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Are the post-crisis statistical initiatives complete? An overview

Overview of the ninth IFC conference[1]

Evelyn Truong and Bruno Tissot[2]

"*Are post-crisis statistical initiatives completed?*" This was the topic of the ninth conference of the Irving Fisher Committee on Central Bank Statistics (IFC), hosted at the Bank for International Settlements (BIS) on 30–31 August 2018, and attended by almost 150 participants from more than 50 countries. The question is key for today's central bank statisticians. The Great Financial Crisis (GFC) of 2007–09 brought to light the need to address a wide range of data issues, such as the information requirements associated with globalisation, non-bank financial intermediation, complex interbank relationships, and macroprudential policy needs. This has led to **numerous statistical initiatives** (Borio (2013)), a number of them still in their implementation phase a decade after the GFC. Yet, the conference was also an occasion to take stock of more recent developments, especially those related to information-sharing, data dissemination and the impact of technological innovation – such as the digitalisation of the economy and the opportunities and challenges of big data and machine learning in financial statistics.

Statisticians around the world have made considerable progress towards filling known blind spots in data collections since the GFC, as stressed by BIS General Manager Agustín Carstens (BIS) in his opening remarks. Particularly noteworthy have been the efforts of several international organisations, including the BIS,[3] as well as national authorities in the context of the G20-endorsed Data Gaps Initiative (DGI).[4] However, collecting high-quality data may not be sufficient to promote financial stability and prevent the next financial crisis. What is crucial is **the lens that is applied to the data**: connecting the dots is even more important than collecting them (Caruana (2017)). Moreover, official statistics should be constantly evolving to reflect the changing financial environment. This is of particular relevance in the context of fintech's[5] rapid expansion and the shift to financing via bond markets and non-bank

1 The views expressed here are those of the authors and do not necessarily reflect those of the Bank for International Settlements (BIS), the Reserve Bank of New Zealand (RBNZ) or the Irving Fisher Committee on Central Bank Statistics (IFC).

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3 Especially in the context of the Inter-Agency Group on Economic and Financial Statistics (IAG), which comprises the BIS, the European Central Bank (ECB), Eurostat, the International Monetary Fund (IMF, Chair), the Organisation for Economic Co-operation and Development (OECD), the United Nations (UN) and the World Bank (WB). The IAG was established in 2008 to coordinate statistical issues and data gaps highlighted by the global crisis and to strengthen data collection.

4 See FSB-IMF (2009) for the first phase of the DGI; and FSB-IMF (2015) for its second phase (2016–20).

5 Defined as "technology-enabled innovation in financial services that could result in new business models, applications, processes or products with an associated material effect on the provision of financial services" (FSB (2017)).

financial intermediaries (Shin (2013)). The bottom line is that central bank statisticians should be able to adapt continuously and flexibly to an evolving financial world.

As the global financial environment is changing, so too are policy needs. As emphasised by the IFC Chair, Claudia Buch (Bundesbank), in her keynote address, a lot has happened in the decade since the GFC: data gaps have been closed, new technologies have transformed the production of statistics, and structured evaluations of post-crisis financial sector reforms have started at the G20 level. Yet, in order to sustain these efforts and transform "data" into "information", three points need to be emphasised. First, central bank statistics are of interest to many stakeholders (analysts, researchers, policymakers and private market participants), but they will be used only if they are easily accessible. Communication with stakeholders, a clear legal basis to support data-sharing, the use of joint methodological standards, and measures to protect confidential information are thus crucial (IFC (2015a)). Second, when discussing new data initiatives, the costs and benefits need to be weighed up carefully. Detailed, granular data improve the quality of analytical work, and thus contribute to better policies and public welfare. But reporting of statistical and supervisory information can be costly, particularly if data initiatives are not well coordinated. Improving this trade-off between costs and benefits requires long-term strategic planning and consultation with industry. Third, policy analysis and statistical work can be integrated and coordinated more closely. Before launching policy projects, data needs should be carefully considered, and sufficient time should be budgeted for data work. Statistical initiatives have to take into consideration the type and granularity of data needed to conduct good causal evaluation studies. Both require close coordination between statistical and policy departments in central banks.

The presentations at the conference shed useful light on these various issues. The related papers, spread across nine different sessions[6] and referred to in this overview, are included in this IFC Bulletin. Their findings can be summarised along with **three main messages**. First, significant efforts have already been made to address most of the known post-crisis information gaps, although the related data collection exercises remain unfinished and will take considerable time to be completed. Second, turning data into useful information requires the effective alignment of statistical collections and policy objectives; to this end, one should focus on data-sharing arrangements and techniques for presenting and disseminating information. Third, new data needs have emerged as a consequence of financial digitalisation and technical innovation: these new needs will surely play a major role in shaping central bank statistics looking ahead.

1. Addressing post-crisis data gaps

The past decade of focused and coordinated efforts by the central bank statistical community has substantially improved the scope and quality of financial data

6 Chaired by, respectively, Hock Chai Toh (Central Bank of Malaysia), Robert Kirchner (Deutsche Bundesbank), Naruki Mori (Bank of Japan), Pedro Duarte Neves (Bank of Portugal), Roh Chung Seak (Bank of Korea), Luis Teles Dias (Bank of Portugal), Joe McNeill (Central Bank of Ireland), Gülbin Şahinbeyoğlu (Central Bank of the Republic of Turkey) and Aurel Schubert (Vienna University of Economics and Business).

available. To give a few examples, the understanding of the global interlinkages between both countries and sectors has improved, more granular data have become available for monitoring the banking sector, and better information is being collected to measure the size and the systemic role of non-bank financial intermediaries.

That said, many statistical initiatives to address the information gaps identified in the wake of the GFC are still under way, and time and resources will be needed to complete the related data collection exercises. The conference highlighted three major areas of interest: the impact of globalisation, rising non-bank financial intermediation, and the need for more granular information.

The impact of globalisation

Many of the critical data gaps identified during the GFC were associated with the impact of globalisation, reflecting the **difficulties in measuring the footprint of global groups** outside their jurisdiction of residency (see Tissot (2016a)). As underscored by Peter van de Ven (OECD) in his keynote address, this is a major obstacle hampering the measurement of domestic activity, for instance when calculating the headline indicator for GDP. This calls for the System of National Accounts framework (SNA; European Commission et al (2009)) to be enriched with a far broader set of statistics. Of course, statisticians' efforts should not be limited to the analysis of the impact of globalisation. There is a more general need to better understand the functioning of the economy, for instance by considering unpaid household activities, integrating distributional issues (eg inequalities), and appropriately measuring the transfer of goods and assets across countries allowed by rapid technological advances.

Yet, the most acute challenges for statisticians stem perhaps from the rapid development of financial globalisation (BIS (2017)). For example, the global business model of multinational enterprises (MNEs)[7] makes it difficult to identify the location of corporate decision-making bodies – particularly in the case of **intellectual property products (IPPs)**, such as R&D and software products, which are recorded as intangible produced assets (2008 SNA, #10.98 and #A3.90). IPPs can be transferred across borders (in particular within a single multinational organisation) at low cost and with minimal business impact. The implications can be considerable, as seen in Ireland, where a number of multinational corporations attracted in large part by low corporation tax rates have relocated their economic activities, and more specifically their underlying intellectual property. This caused a large revision in Irish GDP in 2015, resulting in an impressive reported rate of growth (26%; OECD (2016)). But one difficulty related to such intra-group relocations of IPPs is to distinguish between legal and economic ownership, noting that the SNA recommends that assets be recorded on the balance sheets of the economic rather than the legal owner (2008 SNA, #2.47).

Another important issue is associated with the growing use of **special purpose entities (SPEs)**, which are legal entities typically used by companies as financial vehicles. This poses important challenges, especially in small open economies. One notable statistical caveat relates to the asymmetrical accounting treatment between resident firms and MNEs: in general, SPEs do not satisfy the definition of an

[7] See 2008 SNA, Chapter 21 (#21.47–48).

institutional unit in the SNA because they lack the ability to act independently from their parent corporation.[8] But when the parent company is a foreign entity, SPEs have to be recorded in line with the application of the domestic residency principles of the SNA – and this can be challenging for national accountants.

Several presentations at the conference touched on a particular aspect of these **broad statistical issues posed by the prevalence of multinational firms, the incentives to locate businesses in low-tax jurisdictions, and the growing use of offshore financing vehicles**. For instance, an estimation by the Federal Reserve Board showed that nearly one third of measured US cross-border portfolio investment can be distorted by standard reporting conventions (see Bertaut et al, session 1). Fortunately, it would seem that much work is going on to address such issues. For example, the Bank of France has developed a number of methodologies for estimating household portfolio investments in securities not covered by national reporting (see Gervais and Quang, session 1). Similarly, the Bank of Italy is "looking through" cross-border positions in investment funds so as to get a more representative description of the composition of portfolio investments (see Della Corte et al, session 3). Turning to the IMF, it has undertaken a long-term project to compile from-whom-to-whom[9] information for cross-border portfolio securities, taking advantage of its position as a central repository of international data (see Harutyunyan and Sánchez Muñoz, session 1). Furthermore, analysts at the Netherlands Bank are combining from-whom-to-whom data from financial accounts with information on international investment positions (IIPs) to build a sectoral network model for financial analysis (see Bijlsma et al, session 2).

One promising avenue seems to organise the **collection of globally integrated data sets** capturing group-level activities both within domestic jurisdictions and outside national borders. For instance, the Bank of Portugal has developed a business database which depicts the group structure of Portuguese firms and covers their resident and non-resident affiliates (see Pinto et al, session 2). Similarly, the Bank of France has designed a survey methodology to capture firms' involvement in the global economy, supporting the compilation of statistics on balance of payments (BOP) and IIPs (see Golfier, session 1).[10] Turning to the BIS, several initiatives have been launched to better understand the complex interconnections between entities located in different jurisdictions. One is to combine complementary statistical approaches to identify the residency of the ultimate holders of debt securities, which are sometimes difficult to allocate across countries (see He and Filkova, session 2). Another approach developed jointly by the BIS and the Bank of Portugal is to use so-called mirror data to improve information on the external sector in general and on cross-border banking claims (see Falcão Silva and Pradhan, session 1).

Filling data gaps does not require collecting new data in every instance. In some circumstances, unique combinations of existing data sets can be used to derive needed information. For example, one can mobilise publicly available information on

[8] See 2008 SNA Chapter 4, especially #4.55–56: "There is no common definition of an SPE but some of the following characteristics may apply (…). Such units often have no employees and no non-financial assets. They may have little physical presence" (…) and "are often resident in a territory other than the territory of residence of the related corporations".

[9] For an introduction to from-whom-to-whom tables in financial accounts, see Tissot (2016b).

[10] For a description of the BOP statistical framework, see IMF (2009), and for a review of current challenges related to external sector statistics, see IFC (2018a).

loans to construct a database on cross-country banking exposures (see Serena Garralda, session 2). Similarly, existing IIP data have been used at the Deutsche Bundesbank to calculate the impact of exchange rate changes on the domestic value of assets and liabilities for German residents (see Arz et al, session 1).

Non-bank financial intermediation

Another statistical shortcoming highlighted by the GFC was related to the activities of non-bank financial intermediaries, for which there was too little information available for policymakers despite their growing significance in the financial sector. These data needs were obvious from the perspectives of both monetary policy, especially to shed light on monetary transmission mechanisms, and financial stability, because of potential systemic risks building up in unregulated sectors that could spill over to the banking sector. Particular attention was paid to the shadow banking sector, which saw a substantial increase in its assets relative to those of banks in the run-up to the GFC.[11]

The conference provided ample evidence that the statistical community is developing **new data sets to better understand and measure the activities of non-bank financial institutions**. The Bank of Japan has recently compiled and released data on "Other Financial Corporations" – that is, the non-depository institutions which are often not subject to prudential requirements comparable with those applied to banks[12] – making full use of existing statistics including micro data sources (see Date et al, session 3). In Europe, the focus has been on greater data harmonisation and completeness, with ongoing work at the ECB to broaden the coverage and consider those financial institutions that are not already captured by existing standardised reporting schemes (see Agresti and Giron, session 3). More generally, many central banks have been investigating those particular aspects of non-bank financial intermediation that might contribute to specific financial stability concerns. One telling example was the research conducted at the Bank of Ireland related to the recent rise of Irish real estate investment funds and the implications of their activities (see McCarthy, session 3).

A number of presentations also shed light on **ongoing structural changes in the financial system**. One topic related to derivatives operations, in which non-financial corporations (and not just financial institutions) are increasingly involved. Micro, firm-level data can elucidate the characteristics of entities making use of derivatives, for instance, in terms of size, sector and financial structure. Going deeper and analysing even more granular data, one can assess firms' trading preferences in relation to different types of derivative contract using transaction-level information collected under the European Market Infrastructure Regulation (EMIR; see Benatti and Napolitano, session 3). A second important topic regarding the functioning of the financial system is related to the demand of currency in circulation. Some countries (eg Sweden) have seen a steady decline in the amount of cash transactions in recent

[11] See the FSB monitoring of non-bank financial entities' involvement in credit intermediation that could pose financial stability risks such as maturity/liquidity mismatches and excessive leverage (FSB (2018)).

[12] In the SNA framework, financial corporations are divided into three broad classes: financial intermediaries; financial auxiliaries; and other financial corporations (defined as "institutional units providing financial services, where most of their assets or liabilities are not available on open financial markets" (2008 SNA, #4.101)).

years, but there are many differences across countries, and paper-based payments such as cheques and cash still play important roles (Jakobsen (2018)). But assessing demand for cash is particularly challenging in a monetary union, and alternative approaches need to be followed (see Dias, session 4). Another issue discussed at the conference was Islamic finance, which can significantly alter financial intermediation patterns, for instance, by shifting the composition of banks' assets towards instruments financing physical assets and discouraging leverage creation. Yet the reporting practices of Islamic financial institutions vary substantially across jurisdictions, reflecting different types of business model, which calls for the development of more adequate international statistical guidelines – for instance, as regards the measurement of financial intermediation services and the characteristics of underlying Islamic financial products (see Goh, session 7).[13]

Collecting more granular data

Another lesson from the GFC was the need for more granular, institution-level data, and in particular for financial balance sheet information. Obviously, such data have been in demand to back up authorities in their resolve to tighten microprudential regulation and supervision after the crisis. However, they also help to shed light on the financial system more generally. In particular, there is a general push among central banks to **set up central credit registers (CCRs)**, ie a centralised system for collecting entity-level credit information on loans provided to the economy.[14] For instance, data from the Bank of Korea's consumer credit panel have proved to be particularly useful for supporting policy (see Kim, session 5). Similarly, the Bank of Israel has been developing a central credit registry with a proper disclosure control process (see Mantzura, session 7).

Such registries offer a wealth of information with many **practical applications**. For instance, the experience of the Central Bank of Malaysia is that granular credit data sources can be usefully combined to estimate the supply and demand components of household credit growth (see Soh, session 5).[15] Turning to the National Bank of the Republic of Macedonia, a new, granular credit registry data set is being used to investigate the existence and importance of a risk-taking transmission channel for monetary policy (see Miteski et al, session 4).

But the push for more granular data is **not limited to information on credit provided by banks**. At the ECB, for instance, in addition to the ongoing initiative to establish a European-wide CCR (AnaCredit),[16] important efforts have been made to set up detailed security-by-security data sets. As one of its benefits, this granular information permits an improved analysis of the portfolio rebalancing implications of the Eurosystem's asset purchase programme after the GFC, and the associated distributional effects across household groups (Kavonius and Honkkila, session 5). Another useful source of granular, firm-level information is provided by Central

[13] See 2008 SNA #6.163-6.169 for the issues related to the calculation of the financial intermediation services indirectly measured (FISIM).

[14] For a general discussion on central banks' use of CCRs, see IFC (2017c).

[15] The related paper from the Central Bank of Malaysia on "Disentangling the supply and demand factors of household credit in Malaysia: evidence from the credit register" (Soh (2018)) received the IFC award for the best paper presented at the conference by a young statistician.

[16] "AnaCredit" stands for analytical credit data sets.

Balance Sheet Data Offices (CBSOs), which generally provide a wealth of details covering firms' individual financial statements (IFC (2017b)). This can be useful for policy evaluation on how companies in different classes are affected by stress episodes (see Artman, session 5).

2. Turning data into information

As noted above, a second theme of the conference was the need to turn data into **information that is useful for policy**. To this end, statistical collection should go hand in hand with economic analysis: statisticians should strive to provide data that is suitable for the needs of analysts, who in turn should have the appropriate lens when interpreting the data collected. This entails two major consequences if one wants to fully reap the benefits of sound data. First, information has to be relevant for authorities, ie it can be fed into applications supporting policy analysis. From this perspective, various elements such as international harmonisation, high-quality standards, and user-friendly dissemination platforms can help to make the data more usable. Second, it should be possible to effectively use this information, that is, it has to be accessible to analysts and policymakers. This calls for proper arrangements for sharing data securely, taking into account confidentiality considerations. Needless to say, good communication between statisticians and other stakeholders is a fundamental building block to ensure progress on these two fronts.

Data for policy analysis

While it is of crucial importance that analysts apply an appropriate lens to the data, it is equally important that the data collected are tailored to their needs. Data requirements should thus be constantly evolving in response to the changing economic environment and new policy needs. This was clearly illustrated by Claudio Borio (BIS) in his keynote address, which discussed the **data requirements associated with evolving macroprudential policies**. A key factor has been the major intellectual shift that occurred after the GFC, with the realisation that episodes of financial instability can be the endogenous consequence of the previous build-up of macro-financial imbalances, and not just the result of exogenous shocks pushing the economy away from its long-term equilibrium.

This shift calls for new analytical frameworks, and in turn new types of data. For instance, granular, institution-level data are required for conducting macroeconomic stress tests and assess the potential resilience of financial institutions to adverse shocks as well as for evaluating the impact of new regulation. At the same time, aggregate measures remain indispensable for monitoring the financial system as a whole, for instance, to assess the stage of the credit cycle.[17] There is thus a clear need to "see the forest as well as the trees" (Borio (2013)), by combining micro and macro data sets (IFC (2016a)). One should note, however, that what constitutes **useful information to policymakers can vary over the financial cycle**: as emphasised by Agustín Carstens in his opening remarks, rough aggregates generally suffice to indicate that imbalances are building, but more granular data are needed for taking

[17] See, for instance, the various credit data sets developed by the BIS to this end, at www.bis.org/statistics/about_credit_stats.htm?m=6%7C380%7C673.

decisions once a crisis breaks out. One way of addressing these issues is to make sure that the new data frameworks are well integrated with central bank functions, such as microprudential regulation, macroprudential supervision of financial stability risks, crisis resolution etc.

The need to establish a link between the data collected and diverse policy needs was emphasised by many participants. For instance, analysis conducted at the BIS shows that CCR data can be useful for analysing both the impact of macroprudential policies and their interaction with monetary policy – two major issues for central banks in the aftermath of the GFC (see Gambacorta and Murcia, session 4). A number of other presentations highlighted the **vast range of policy needs that constantly call for developing new (or re-arranging existing) data sets**. In Brazil, where structural obstacles limiting the development of the domestic financial system are a primary policy concern, the central bank has developed a new set of indicators to support its efforts in lowering the cost of credit through various channels (see Fiorindo et al, session 4). At the ECB, a detailed security-by-security data set has shed additional light on the implications of the Eurosystem's asset purchase programme not only in terms of distributional effects, as noted above, but also as regards its impact on international capital flows (see Bergant and Schmitz, session 4). As another example, work at the central bank of Colombia demonstrates how unanticipated changes in the reference interest rate can affect the price of credit and saving instruments. To better understand the impact of monetary policy on various financial prices, "monetary policy shocks" are derived from a survey of experts' forecasts (and errors) of expected policy decisions (see Christiano-Botia et al, session 9).

Data-sharing and dissemination

Statisticians have faced a **difficult trade-off since the GFC**. On the one hand, there has been a steady demand for micro information. On the other hand, the more granular the data, the more challenging it is to address confidentiality concerns. Session 6 of the conference dealt with the issues posed by the management of granular financial data. This was a welcome opportunity to introduce the recently formed International Network for Exchanging Experience on Statistical Handling of Granular Data (INEXDA).[18] INEXDA aims to facilitate the international use of granular data for analytical, research and policy purposes, first by providing a forum for exchange of information and ideas on those issues and, second, by offering a framework for investigating possibilities to harmonise data access procedures for external stakeholders. An exchange of country experience has been awaited to address the statistical challenges associated with the GFC. To this end, INEXDA members have decided to develop a shared metadata scheme that can be applied to granular data sets from different countries (see Bender, Hausstein and Hirsch, session 6). This represents a useful first step in moving towards greater harmonisation and standardisation across countries as regards the procedures to access granular data from outside the central banks.

In parallel, important work has been going on to develop **technical solutions for sharing information** with external stakeholders while preserving anonymity and satisfying privacy protection laws. At the Bank of Italy, cryptographic techniques have been applied to link anonymised data sets (see Bruno et al, session 6). In particular,

[18] See Bender et al (2018).

four different types of data-sharing arrangement have been identified using these techniques. Addressing the same issue, but from a different perspective, various masking techniques have been developed at the Central Bank of the Republic of Turkey with the aim of providing user-friendly software tools to generate anonymised data sets. Work is under way to assess the impact of these techniques on the accuracy of the statistical operations conducted on such transformed data sets, as well as the degree of protection against potential attempts to uncover masked information (see Başer et al, session 6). Another example is the Bank of Israel's newly developed credit registry, which is supported by an in-house framework for anonymisation and control (see Mantzura, session 7).

Of course, the **challenges posed by sharing granular data** under confidentiality constraints do not relate only to external researchers, they are also relevant within central banks as well as between central banks and (domestic and foreign) authorities.[19] As regards the situation within central banks, a key issue is to establish a proper information management system to ensure that users have access to adequate data; this is indeed one important lesson of Bank of Mexico's 15 years of experience in collecting and sharing granular financial data (see Gaytan González et al, session 6). As regards sharing between central banks, a number of successful cooperative approaches have been implemented, such as the initiative by the Deutsche Bundesbank and the Bank of France for sharing data reported by complex multinational enterprises (see Mosquera Yon and Walter, session 5).

Moreover, confidentiality and privacy constraints are not the only factors that limit access to information. In order to be useful to analysts and policymakers, **data need to be clearly structured, presented in a manageable format, and communicated clearly** via a user-friendly system. To address these issues and improve its internal data-sharing capabilities effectively, the ECB has developed a Data Intelligence Service Centre (DISC). This central technology platform for organising, storing, and managing data is compatible with many common software tools for statistical analysis. The aim is to provide quick and easy access to data for internal users, including complex granular data sets (see Witt and Blaschke, session 7). The Deutsche Bundesbank's experience is that the success of such initiatives relies on setting up a well thought-out process for data integration to address the challenges posed by huge data volumes (see Müller, session 8) – noting that these data are neither well organised nor complete, with the increasing importance of "found" data, as distinct from "designed" data (that is, data collected for a specific statistical purpose).

From a similar perspective, but focusing more on the external users, the Reserve Bank of New Zealand and the Central Bank of the Republic of Turkey have explored user-friendly online graphical tools to **enhance the actual dissemination of publicly available central bank data**. In both cases, the general public can access tools to get "dashboard views", with customised reports and graphs, on an interactive basis. While for Turkey the system covers broad economic aggregates and is designed primarily to promote financial literacy (see Eken et al, session 7), the New Zealand tool focuses on the disclosure of banking statistics, disaggregated at the firm level, and is particularly designed to support market discipline in the banking sector (see Irrcher, session 7). One interesting issue relates to increasing demand for long consistent data

19 On the general data-sharing issues faced by central banks, see IFC (2016b). For a recent example of international data-sharing related to the monitoring of global systemic institutions in the context of the DGI, see Bese Goksu and Tissot (2018).

series, while in reality break-adjusted series are rarely published, especially for data on stocks or positions. To address this need, the Netherlands Bank has introduced a policy to foster the compilation and publication of break-adjusted series, with adequate documentation on the methodology used (see van der Helm and Bartman, session 7).

3. New technological frontiers in statistics: big data, machine learning, and automation

Rapid technological change is **transforming central banks' internal statistical capabilities** (for instance, in storing and analysing data) **as well as data requirements** (for instance, to measure the development of fintech). As a result, big data and machine learning techniques have become increasingly relevant to the design of their information systems. Central bank statisticians are already using data derived from internet activities (eg Google searches) and applying machine learning techniques (eg principal component analysis, clustering). Yet interest in exploring these areas has clearly increased since the GFC, together with the actual capability to do so (thanks to increased computing power), and the availability of large data sets, both structured and unstructured. Indeed, in 2015 two thirds of the central banks surveyed by the IFC said they were actively discussing and investigating the use of big data, even though fewer than one third were already using big data sources in a meaningful way.[20]

As usual when innovation emerges, one risk is that these new techniques and data sources may disappoint those expecting major breakthroughs in official statistics (and for central bank information systems). Since more data are not necessarily better data, analysts and statisticians need to be aware of the limitations surrounding big data sets, especially as regards their accuracy and representativeness, which is sometimes overstated. **Understanding such limitations** is particularly important in the world of financial big data, where a clear feedback loop affects the information collected, the design of policy measures, and actions taken by market participants in response – implying that any move to measure a phenomenon can lead to a change in the underlying reality.[21] Furthermore, there are challenges associated with communicating results derived from "black-box calculations", especially for authorities who want to be transparent about their decision-making process. Hence, as emphasised by Professor Ruggeri (Vice President, International Statistical Institute (ISI)), one needs to be careful in using machine learning tools and to take **a balanced approach**. On the one hand, these techniques can be very useful in predicting and classifying, especially when one has to deal with a large number of parameters. On the other hand, they cannot solve all problems and it can sometimes be more appropriate to rely on a stochastic modelling approach to understand "what is going on". Addressing this trade-off requires a combination of these two types of technique; from this perspective, "statistical machine learning" would be a valid approach, but the range of solutions is still limited in practice.

[20] See IFC (2015b).

[21] Representing an application of the famous Lucas critique to the field of micro-financial statistics (Lucas (1976)).

Thus, a key message from the conference was that central bank analysts and statisticians **must cautiously explore the new opportunities** provided by technology innovation and be clear about the type of estimation being made, as well as its aims and limitations – in other words, "demystify" the concepts at stake (see Mehrhoff, session 8). At the same time, the conference was also an opportunity to present several **examples of big data applications in the central bank context**, suggesting that (i) there is a clear potential for big data sources to complement official statistics; and (ii) new, powerful statistical techniques can help users to navigate through the increasing amount of granular data collected since the GFC (IFC (2017a)).

As regards first the **potential for new data sources**, the possibility of applying indicators derived from internet activities in a central bank setting has already been well explored (Cœuré (2017)). For instance, the Deutsche Bundesbank is using Google data to produce a synthetic indicator for "nowcasting" mortgage market developments (see Oehler, session 8). "Financial big data sets" comprise not only the "internet of things", but also the wide range of granular data sets from commercial activities (eg credit card operations), financial markets (eg "tick-by-tick" price data), and administrative data sets (eg registers),[22] all of which can be usefully explored. One example from the Bank of Japan was related to detailed inter-dealer transactions data, which have helped new liquidity indicators to be constructed for the Japanese sovereign bond market (see Sakiyama and Kobayashi, session 8). Another area of interest relates to the development of text-mining techniques to access digitalised but unstructured information. For instance, the Bank of Canada has used a text analytics tool to develop a labour market conditions index for China, providing a useful complement to the (limited) official statistics (see Bailliu et al, session 8). Similarly, the Bank of Indonesia has developed an indicator based on text information produced by the media to assess general public expectations about policy rate decisions (see Andhika Zulen and Wibisono, session 9).

Turning to the second aspect, ie the **new tools provided by big data/machine learning/artificial intelligence technologies**, the central bank statistical community has shown a growing interest for them. One important application is to employ these new methods when the size of the data set is too big for "more conventional" tools. For instance, machine learning techniques have been used at the Bank of Greece to perform credit risk analysis derived from a very large loan-level data set (see Petropoulos et al, session 9).

Yet another promising avenue is to use these techniques to **improve existing data collections**. For instance, a BIS-developed algorithm for imputing missing data has proved capable of outperforming existing alternatives under certain conditions (see Kwon, session 9). Similarly, recent ECB work shows that techniques based on both supervised and unsupervised machine learning can be effective for outlier detection and missing data imputation (see Benatti, session 9). In addition, these new tools can support large-scale data cleaning exercises as currently undertaken at the ECB, for instance, to address the quality issues encountered with the collection of derivatives transactions reported by EU-based trade repositories (TRs). This is of particular interest because of the double-sided reporting requirements of the European EMIR Regulation: both counterparties of a trade are obliged to report this transaction to a

[22] For the use of administrative data sources for official statistics, see for instance Bean (2016) in the UK context.

TR, and statisticians manage data quality by comparing the resulting reports through an automated pairing and matching of the two-sided reports collected (see Pérez-Duarte and Skrzypczynski, session 9, as well as IFC (2018b)).

4. Conclusion: are post-crisis statistical initiatives complete?

The conference proved a **useful opportunity for taking stock** of the many statistical initiatives developed to address the information gaps identified in the wake of the GFC. Significant progress has already been made in terms of data collections, especially as regards the impact of globalisation on the financial system, activities related to non-bank financial intermediaries, and the need for more granular institution-level data especially on financial balance sheets. Yet the event was also a useful reminder that collecting data is a necessary but not a sufficient condition for knowledge. It is also crucial to turn data into information that is useful for policy, and this puts a premium on enhancing the dialogue between data compilers and analysts, especially within central banks. The goal is, first, to ensure that the statistics collected are effectively feeding into policy work, and, second, that the information is adequately shared with and disseminated to users. A third important message was related to the opportunities (and risks) associated with the rapid pace of technological change, especially since the GFC: new big data sources have emerged that can be of interest to central bank statisticians; and more sophisticated techniques are available to deal with the increasing amount of information at their disposal.

From this perspective, can one thus say that post-crisis statistical initiatives have been completed? The conference's concluding panel[23] showed that the **jury is still out**: a lot has been achieved over the past decade, but many more things remain to be done and this may perhaps take just as long. The following considerations were seen as particularly relevant for central bank statisticians looking ahead:

- **The requirement to fill known information blind spots cannot, by definition, be a finite exercise**. There is an ongoing, recurring cycle involving data compilation and data analysis, implying that statistical requirements will have to be continuously adapted to meet evolving policy needs. Cases in point relate to fintech and globalisation, two major sources of disruption in terms of future information requirements.
- Yet the **costs and benefits** of any new statistical initiative need to be carefully weighed up: data collections are, ultimately, burdensome exercises that warrant effective coordination with the stakeholders involved as well as careful long-term planning.
- Moreover, **statistics are not an end in themselves**. Collecting statistics is a necessary first step, but it is equally important to break down any barriers standing in the way of information-sharing and dissemination to users. This puts a premium on data standardisation, strong legal frameworks, anonymised data-sharing technologies and, most importantly, good communication both across country borders and between agencies working

[23] IFC Chair Claudia Buch was joined by Peter van de Ven (Head of National Accounts, OECD), Fabrizio Ruggeri (Vice President, International Statistical Institute), and Aurel Schubert (Vienna University of Economics and Business, and former Director General Statistics, ECB).

within the same jurisdictions. The ultimate goal should be to facilitate the integration of statistical work in policy analysis.

- **The future of central banks statistics depends on how the role of central banks will evolve**. From this perspective, policy data needs cannot be predicted with perfect foresight, which calls for central bank statisticians to be agile and responsive, while continuously seeking to produce statistics that are fit for purpose and aligned with users' needs.
- **International cooperation is crucial**. Improving the quality and use of available statistics is invaluable, through knowledge-sharing and the exchange of experiences. It is also necessary to ensure proper convergence across jurisdictions in terms of data collection and harmonisation, which is a key requirement given the global nature of the financial system.
- **There are clear potential benefits from ongoing technological innovation**. One should be aware of the risk of over-investing or adopting new tools for novelty's sake,[24] but central banks should actively explore the new opportunities offered by the big data revolution. Given limited resources, this also puts a premium on **cooperation both across countries as well as disciplines**. As a committee representing almost 100 jurisdictions that is associated with the ISI, the IFC can certainly help to promote such cross-country and cross-disciplinary fertilisation.

[24] Highlighting the importance for central banks of "looking beyond the hype", as can be argued in the case of cryptocurrencies (BIS (2018)).

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Are post-crisis statistical initiatives completed? Taking stock

Opening remarks by Agustín Carstens
General Manager, Bank for International Settlements

Ninth Biennial Irving Fisher Committee (IFC) Conference

Basel, 30 August 2018

Good morning, ladies and gentlemen, and welcome to the ninth biennial conference of the Irving Fisher Committee on Central Bank Statistics (IFC). The IFC is a forum for central bank economists, statisticians and others wishing to discuss statistical issues of interest to central banks. It is one of the five committees established and governed by the international central banking community and operating under the auspices of the BIS.

First, let me thank the IFC executives, members, authors and presenters for their contribution to this meeting. I would also like to take this opportunity to extend my special thanks and welcome to Claudia Buch, Vice President of the Deutsche Bundesbank and Chair of the IFC. Claudia will address you in just a few minutes. But before handing over to her, I propose to take a moment to reflect on why we are here today, and what we hope to achieve.

The theme of this conference poses a pertinent question: are the post-crisis statistical initiatives completed? Every financial crisis leads to calls for new data to be collected, and it is natural for policymakers to focus first on filling the data gaps for those aspects of the crisis that were not on their radar before. Not surprisingly, the Great Financial Crisis of 2007–09 set in train a broad-based expansion of financial statistics. Now, one decade on, we ask ourselves: have we achieved all we set out to accomplish in the wake of the crisis? And if the answer is yes, can we hope that the newly available data will help policymakers anticipate and manage the next crisis?

I shall argue that we have come a very long way towards achieving many post-crisis statistical objectives and have removed many of the known blind spots in our data collection. However, it is the lens through which we view the data that matters: it takes purposeful analysis to turn data into information. Today, we have access to more data than ever before, but having more data does little to promote financial stability if there is not an appropriate focus and perspective. So while we should congratulate ourselves on our statistical achievements to date, we must recognise that they will not be sufficient to prevent future crises or to manage them. To make the most of the data at their disposal, policymakers need to gear their institutional knowledge towards greater awareness of the build-up and manifestations of risks.

What's more, as our environment and policy needs constantly evolve, so too do our data requirements. Therefore, the challenge that we face is not only to collect information to fill known data gaps, but also to constantly assess our data collection against our needs, and develop it to reflect the changing environment. This approach requires that we remain cognisant of both the cyclical variations in our information needs and the fundamental developments in the financial environment, which will have a long-term impact on our data requirements and data collection capabilities. In order to prepare for future events, statisticians and policymakers alike must constantly survey the horizon and adapt flexibly to changes in the financial environment.

The G20 Data Gaps Initiative

The global nature of the Great Financial Crisis has spawned a coordinated data collection effort, centred on the G20 Data Gaps Initiative.[1] The BIS and IMF play key roles alongside other international organisations, central banks and supervisory authorities. The effort addresses major gaps in the international coverage of statistics concerning individual institutions and international financial markets.

Thanks to this joint effort, some aspects of costly boom-bust cycles no longer remain in a blind spot. Specifically, the BIS has overseen the expansion of statistics covering international banking and credit default swap markets, and it now publishes internationally comparable data on residential and commercial property prices – an asset class that plays a central role in financial cycles. Furthermore, most global systemically important banks (G-SIBs) now report their bilateral risk exposures to, and funding dependencies on, their largest individual counterparties to the BIS International Data Hub. They also report data on their maturity and currency mismatches, both on- and off-balance sheet. At the IMF, more than 100 countries now submit financial soundness indicators, and 35 report additional details on concentration and tail risk. The coverage of international portfolio holdings has been extended to major financial centres and has become more timely. The World Bank launched a public sector debt database, and the OECD links national accounts with detailed sectoral data.

But with this wealth of data, where do we look for the next source of vulnerabilities?

Information requirements over the cycle

As my deputy Luiz Pereira da Silva argued in his recent panel remarks at the Ninth ECB Statistics Conference,[2] it takes the right lens to see the relevant developments in statistics. Closing the data gaps identified in the last cycle is certainly important, but every boom and bust comes in a new guise. Generally, rough aggregates suffice to indicate that imbalances are building. Once a crisis breaks out, however, more granular data are needed for taking decisions. What constitutes useful information to policymakers thus depends on the circumstances and varies over the financial cycle. It is not always immediately obvious where policymakers should focus their attention.

On the one hand, BIS work suggests that aggregate data are most useful for identifying the build-up of emerging risks. One thing we have learned is that simple credit-to-GDP gaps can help to identify credit booms that often end in a crisis, even if the approach is agnostic about the mechanisms at work.[3]

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[1] The 20 data gap recommendations are set out in IMF and FSB, *The financial crisis and information gaps: report to the G20 Finance Ministers and central bank Governors*, October 2009. The completion of the first phase and the work plan for the second are described in FSB and IMF, *Sixth progress report on the implementation of the G-20 Data Gaps Initiative*, September 2015.

[2] See L Pereira da Silva, "Data for financial stability: collecting and connecting the dots", remarks at the Ninth European Central Bank Statistics Conference "20 years of ESCB statistics: what's next?", July 2018.

[3] See C Borio, "The Great Financial Crisis: setting priorities for new statistics", *Journal of Banking Regulation,* vol 14, no 3–4, July 2013; and M Drehmann and M Juselius, "Evaluating early warning indicators of banking crises: satisfying policy requirements", *International Journal of Forecasting*, vol 30, no 3, July 2014. Using imperfect data available in 2002, the first paper in this line of research underlines the importance of choosing the right lens: see C Borio and P Lowe, "Asset prices, financial and monetary stability: exploring the nexus", *BIS Working Papers*, no 114, July 2002.

In addition, when looking for financial vulnerabilities, gross stocks are often more informative than net flows.[4]

Another lesson is that financial strains are best measured in consolidated statistics, with data that group institutions by their nationality, not by residence.[5] The common theme is that balance sheet aggregates expand procyclically, reflecting the risk-taking of financial intermediaries. Moreover, it is important to consider the full scope of a firm's financial activity, including its full derivatives exposure as well as its offshore funding.[6] At the BIS, we have been leading the way in collecting such statistics, which can usefully complement the traditional framework of national accounts and balance of payments.[7]

On the other hand, the management and resolution of failed institutions requires much more timely and granular supervisory data. On the verge of the Lehman bankruptcy in September 2008, the major banks could not measure their consolidated exposures to the collapsing investment bank. The uncertainty surrounding exposures to failing banks and toxic assets induced market panic and complicated the policy response.

From this perspective, we have made much progress. In sharp contrast to 10 years ago, the interconnections between G-SIBs are now known to supervisors, and a growing share of OTC derivatives and repo trades are centrally cleared and recorded. The availability of such data does not replace asking hard questions in daily supervisory practice. But it certainly facilitates decision-making in a crisis. And with enhanced data, better measurability of risk exposures should in turn improve risk management and market discipline, eg in setting initial margin or pricing credit default swaps.

Of course, granular data must be collected, structured and analysed before they are relied upon for critical policy decisions. International sharing of data and analytical results has also improved with the establishment of supervisory colleges, the European Single Supervisory Mechanism and the International Data Hub. And the data coming out of the data gaps initiative are increasingly used to support financial stability analysis and macroprudential policy at the national and international level.[8]

An ongoing quest: responding flexibly to evolving policy needs

Despite our considerable progress, challenges remain for statisticians and policymakers. While we have been busy filling the data gaps identified in the last crisis, the financial world has moved on. To illustrate, consider two recent developments.

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4 See the BIS Global Liquidity Indicators (www.bis.org/statistics/gli.htm); and N Tarashev, S Avdjiev and B Cohen, "International capital flows and financial vulnerabilities in emerging market economies: analysis and data gaps", note submitted to the G20 International Financial Architecture Working Group, August 2016.

5 See P McGuire and G von Peter, "The US dollar shortage in global banking and the international policy response", *International Finance*, vol 15, no 2, 2012; and S Avdjiev, R McCauley and H Shin, "Breaking free of the triple coincidence in international finance", *Economic Policy*, vol 31, no 87, July 2016.

6 Despite recent progress, various aspects of international funding remain to be better analysed. For instance, non-banks outside the United States owe trillions of dollars through the use of FX swaps and forwards; see C Borio, R McCauley and P McGuire, "FX swaps and forwards: missing global debt?", *BIS Quarterly Review*, September 2017. And non-financial corporations from emerging market economies have increased their external borrowing significantly through the offshore issuance of debt securities; see S Avdjiev, M Chui and H S Shin, "Non-financial corporations from emerging market economies and capital flows", *BIS Quarterly Review*, December 2014.

7 See B Tissot, "Globalisation and financial stability risks: is the residency-based approach of the national accounts old-fashioned?", *BIS Working Papers*, no 587, October 2016.

8 See FSB and IMF, op cit; and BIS, *Annual Economic Report 2018*, June 2018, Chapter IV.

First, the post-crisis shift to financing via bond markets and non-bank intermediaries has forced policymakers and supervisors to think beyond banking. Do asset managers or central counterparties pose systemic risk? To what extent do they rely on banks for committed lines of credit in extreme circumstances? The fragmented and inconstant nature of liquidity poses major informational challenges.

Second, rapid innovation has taken the financial system into uncharted waters. Identifying financial stability risks in this environment of next-generation fintech, cyber-security threats and cryptoassets will require new efforts. Policymakers should seek to imagine the many ways in which technological change may disrupt core financial system functions and collect the corresponding data. One area is the potential erosion of credit standards as new underwriting procedures and mechanisms of certification take hold. Another is the uncertain liquidity implications of algorithmic trading and other technologies. Yet another area is the possible threat to the integrity of payment systems as the use of digital currencies expands.

To stay abreast of new developments, it will be necessary to collect and share novel types of data, such as a register of cyber-attacks, or data on external cloud service providers. And expanded data collection needs to go hand in hand with scenario analysis. Integrated risk assessments should focus on multiple sources of threats. In the supervisory context, that would entail running a broad range of scenarios for stress tests, knowing that any single scenario represents but one small part of an infinite range of possible futures.

While rapid developments in fintech have led to a series of new challenges, new technologies also present us with promising opportunities. Suptech and regtech – terms to describe digital innovations for financial regulation – are fast becoming incorporated into our regulatory vocabulary. Similarly, the term "datatech" might be used to refer to the range of innovations applying artificial intelligence, machine learning and other automated processes to collect, process, analyse and disseminate official statistics. With the aid of these technologies, we should focus not only on closing known data gaps, but also on expanding information frontiers – extending our knowledge base so as to better prepare ourselves for future developments.

Conclusion

To conclude, we have come a very long way towards completing the key statistical initiatives undertaken a decade ago. Certainly, some significant efforts are still required, and these data collections are likely to occupy us for many years to come. But our task is not a finite one – it is an ongoing quest to provide data to meet our evolving needs. Our work consists of a continuous cycle of identifying data requirements, collecting new data and applying a suitable lens.

Thanks to the international efforts in regulatory reform and the associated statistical initiatives, the core financial system is now more resilient than a decade ago. So I am convinced that the combination of enhanced regulation, supervision and information-sharing will help better prepare us for the next financial crisis.

That being said, despite best efforts to have better data at our disposal, attempts to identify risks in real time will invariably fall short. Financial booms and busts have been with us for centuries. Their commonalities notwithstanding, future booms and busts will come in new guises. Central banks should thus continue to remain alert and to probe areas that have the potential to undermine the stability of the financial system. Ultimately, we need to cultivate our ability to better match our data collection to our information needs, and to make better sense of the data we collect.

Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

Are post-crisis statistical initiatives completed?[1]

Claudia Buch, IFC Chair and Vice President,

Deutsche Bundesbank

[1] This keynote address was prepared for the meeting. The views expressed are those of the author and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

Claudia Buch: Keynote address – "Are post-crisis statistical initiatives completed?"

Keynote address by Prof Claudia Buch, IFC Chair and Vice-President of the Deutsche Bundesbank, at the Ninth IFC Conference "Are post-crisis statistical initiatives completed? ", Basel, 30 August 2018.

* * *

Let me welcome you to the 9th biennial conference organised by the Irving Fisher Committee. We are very glad to welcome speakers and participants from IFC central banks and from international organisations. I would especially like to welcome the authors of the seven papers which are being considered for this year's "Young Statistician Award". A panel of experts will choose a winner who will be announced towards the end of the conference.

Ten years have elapsed since the financial crisis. Central banks statistics have contributed significantly to our understanding of the financial system, systemic risks, and potential vulnerabilities. Against this backdrop, this conference asks: Are post-crisis statistical initiatives completed?

Statistical initiatives are not an end in themselves: They need to address demand for information among the general public, academics, and policymakers. They need to balance the costs and benefits of collecting information. And they need to make best use of the available technology. Before going into these issues, let me give a quick refresher on post-crisis statistical initiatives.

1. What has happened since the crisis?

The global financial crisis highlighted significant gaps in data needed to understand financial stability risks and implications for the real economy. Post-crisis reforms under the G20 Data Gaps Initiative (DGI) thus focused on:[1]

- the assessment of international and cross-sector relationships,
- the monitoring of risks in the financial sector,
- better communication of official statistics.

The first phase of the DGI in the years 2009-15 focused on conceptual work. Key deliverables include

- revised Financial Soundness Indicators,
- the FSB's annual Global Shadow Banking Monitoring Report[2], and
- a standardised data template for the collection of data on global systemically important banks (G-SIBs).

The second phase, which started in 2015, is focusing on implementation and data collection. Emphasis is being placed on monitoring of risk in the financial sector, vulnerabilities, interconnections and spillovers.

Linkages and contagion effects

As regards understanding cross-border and cross-sector linkages, we have made progress in terms of analysing contagion effects. The first three sessions of the conference will address contagion effects and their measurement through reporting from multinational enterprises, identification of international exposures and international flows of funds, and managing cross-border impacts on financial accounts.

The IFC has highlighted the usefulness of nationality-based indicators. Nationality-based indicators complement residency-based statistics. For example, they help understand who takes the underlying economic decisions, who is exposed to final risks, and in which countries the ultimately responsible unit resides. This work was conducted in cooperation with international organisations, in particular the OECD.

Granular data and information systems

Shocks affecting individual banks or firms can have significant aggregate effects (Gabaix 2011, Amiti and Weinstein 2018). Yet, the collection of sufficiently granular statistics on individual banks and firms can be difficult and costly. Although a lot of granular information is potentially available, using and merging different datasets has been complicated by a lack of harmonised identifiers or the existence of legal constraints.

In 2017, the IFC and the European Committee of Central Balance Sheet Data Offices (ECCBSO) published a report which highlights the usefulness of firms' individual financial statements (IFC 2017a). The report shows that the coverage of firm-level balance sheet information has improved. Yet, comparing data across different jurisdictions, and matching balance sheet data with other statistics, remains challenging.

The report also indicates that the use of granular financial data is often constrained by confidentiality considerations. It is important for us to improve information systems. The International Network for Exchanging Experience on Statistical Handling of Granular Data (INEXDA)[3] is one example of such information sharing.

One area where granular data are particularly relevant is the surveillance of risks to financial stability. By their very nature, financial stability concerns arise whenever risks to individual institutions or sectors threaten the stability of the financial system as a whole. In 2017, the IFC therefore co-organised a workshop with the National Bank of Belgium to share views on data collection for macroprudential analysis.[4]

Understanding how shocks propagate within the financial system requires entity-level information on interlinkages and spillovers. This information is needed to monitor risks and to assess the effects of post-crisis financial sector reforms.[5] Important data gaps, however, are still a major obstacle to the effective assessment of the impact of post-crisis reforms (ESRB 2016, Eurostat 2017, and OECD 2017). Among them are the measurement of prices in the real estate sector, the assessment of household vulnerabilities, and new developments such as related to FinTech.[6]

2. Data and policy evaluation

Collecting data is not, and should not be, an end in itself. We need to join the dots, not just collect them. Data provide information about the structure and state of the financial system, and they can be used to assess the effects of post-crisis financial sector reforms.

After the crisis, several major reform initiatives were launched, which aim at enhancing the stability and resilience of the global financial system. So far, national and international bodies have focused on monitoring the implementation of these reforms (FSB 2016). To answer the question of how financial sector reforms have affected market dynamics and the real economy, we need to go a step further. In 2017, the G20 leaders have thus adopted a framework for the evaluation of reform effects (FSB 2017). The framework has three elements: causally attributing observed trends in financial markets to reforms, understanding relevant heterogeneities across banks, countries, and over time, and understanding general equilibrium effects.

One crucial objective of policy evaluation is to make a distinction between the effects of reforms on individual firms, and the effects on the financial system. (Short-term) costs of reforms for the private sector, such as costs of compliance, are often more visible and easier to measure than longer-terms benefits for society as a whole. Some of these benefits arise through shifts in costs from the public to the private sector: withdrawing implicit public guarantees for financial institutions increases the costs of debt, because creditors cannot rely on bailouts and thus demand higher risk premia. This will show up as a private cost. Yet, society as a whole benefits if the financial system becomes more stable and if risk is not shifted to the public sector.[7]

To see why structured policy evaluation is needed, take the effects of increased capital requirements. Better capitalised banks are more resilient and can lend more to the real economy. At the same time, post-reform trends in bank lending have differed across countries, banks, and industries. This raises a number of questions: Has lending declined because of weaker credit demand? Do banks lend more prudently? What has been the impact of regulations on stability and growth? Does bank lending support sectoral reallocation – and thus growth? Aggregate time trends in lending do not answer these questions. Rather, micro data and empirical methods for (causal) identification are the basis for well-informed policy decisions.

A good data strategy is crucial for policy evaluation. Data on trade repositories have, for example, been an important element of a recent evaluation of derivatives market reforms. The Financial Stability Board (FSB) recently released a consultative report on the impact of post-crisis reforms on incentives for central clearing.[8] Many of the insights in this report are based on trade repository data, but the report also mentions important shortcomings in the use and availability of data.

In 2017, the IFC conducted a survey to investigate data collected by trade repositories. The report, which will be released soon, contains interesting insights:

- Data from trade repositories are useful for macroprudential risk assessment, for analysing market transparency, and for microprudential risk assessment.
- Most jurisdictions collect some data on derivatives, but there are still considerable gaps.
- Using these data for policy work remains limited due to incomplete coverage, reporting lags, and the complexity of the existing data.

3. Data and new technologies

The arrival of new technologies and data sources has been another structural change. New data sources – typically summarised under the label "Big Data" – can provide information that complements or even replace traditional statistics. New technologies such as machine learning can allow making better use of existing data and improve the efficiency of producing statistics. Let me briefly review the key trends as they are reflected in the work of the IFC.

Big Data and machine learning

Big Data has become a buzzword. It can open up new business opportunities and information sources, but it also raises concern about data confidentiality and privacy. In 2015, the IFC thus reached out to central banks to learn about the relevance of Big Data to central banks. Big data are flexible and available in real time. They thus complement existing statistics and support policy analysis. Yet central banks' actual involvement has remained limited, given the costs of handling and using Big Data. The IFC has decided to start pilot projects, related not only to the internet but also to the various large micro datasets that are already available (eg administrative, commercial and financial market datasets). Conferences and workshop events in this area have been co-organised in 2017 and 2018 with the Bank of Indonesia.

Another area in which technological advances are delivering new opportunities for central bankers and statisticians is the realm of machine learning. For example, the Bundesbank currently tests a neuronal network for generating forecasts on price movements in US-

Treasuries over short time horizons (1-10 days) in order to support and inform the decision making process in portfolio management. Other projects explore the use of machine learning for quality assurance, record linkages, or merging datasets. The IFC continues to support cross-institutional collaboration in this space through conferences such as this one.

FinTech

The central banking world is also increasingly engaged in understanding the impact of FinTech on the financial system and financial stability. FinTech can be defined as technologically-enabled financial innovation that could result in new business models, applications, processes or products with an associated material effect on the provision of financial services. It is rapidly modifying the structure of financial markets, by eg fostering new forms of credit (peer-to-peer lending), leading to the emergence of cryptocurrencies, and prompting changes in payments systems. The rapid innovation of FinTech means risks are constantly changing and there are many avenues to explore.

In response to these developments, the IFC has committed to undertaking further work in this area to support central banks' understanding of risks and opportunities related to FinTech. Yesterday, the IFC Committee agreed to set up a task force to work on data issues related to FinTech, in close cooperation with international standard setters including the Basel Committee on Banking Supervision (BCBS) and the Committee on Payments and Market Infrastructures (CPMI).

4. Summing up

A lot has happened in the ten years that have elapsed since the crisis: Data gaps have been closed; new technologies transform the production of statistics; structured evaluations of post-crisis financial sector reforms have been kicked off at the G20 level.

In order to sustain these efforts and to transform "data" into "information", let me emphasise a few points:

First, central bank statistics are used by many stakeholders: analysts, researchers, policymakers, and private market participants. These stakeholders will use our statistics only if they are easily accessible. Communication with stakeholders, a clear legal basis to support data sharing, the use of joint methodological standards, and measures to protect confidential information are thus crucial (IFC 2015).

Second, when discussing new data initiatives, the costs and benefits need to be weighed up carefully. Detailed, granular data improve analytical work, and thus contribute to better policies and public welfare. But reporting of statistical and supervisory information can be costly, in particular if data initiatives are not well coordinated. Improving the trade-off between costs and benefits requires long-term strategic planning and consultation with industry.

Third, policy analysis and statistical work can be integrated and coordinated more closely. Before launching policy projects, data needs should be carefully considered, and sufficient time should be budgeted for data work. Statistical initiatives have to take into consideration the type and granularity of data needed to conduct good causal evaluation studies. Both require close coordination between statistical and policy departments in central banks.

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1 For details, see FSB and IMF (2016) and FSB and IMF (2017).

2 For details, see www.fsb.org/2018/03/global-shadow-banking-monitoring-report-2017/

3 See www.bundesbank.de/Navigation/EN/Bundesbank/Research/RDSC/INEXDA/inexda.html?https=1

4 For details, see IFC (2017b).

5 www.fsb.org/2017/07/framework-for-post-implementation-evaluation-of-the-effects-of-the-g20-financial-regulatory-reforms/

6 For details, see www.fsb.org/2017/06/financial-stability-implications-from-fintech/

7 Recent evidence shows that, between 1970 and 1985, franchise values of US banks were not high, market-to-book values of bank equity were closely aligned, and implicit government guarantees were small (Atkeson, d'Avernas, Eisfeldt, and Weill 2018). Between 1996 and 2007, market values of bank equity rose, banks took on more risk, and the value of government guarantees increased.

8 For details, see www.fsb.org/2018/08/fsb-and-standard-setting-bodies-consult-on-effects-of-reforms-on-incentives-to-centrally-clear-over-the-counter-derivatives/

Ninth IFC Conference on “Are post-crisis statistical initiatives completed?”

Basel, 30-31 August 2018

Globalisation and digitalisation[1]

Peter van de Ven,

Head of National Accounts, OECD

[1] This presentation was prepared for the meeting. The views expressed are those of the author and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

GLOBALISATION AND DIGITALISATION

9th Biennial IFC Conference "Are post-crisis statistical initiatives completed?"

BIS, Basel, August 30 – 31, 2018

Peter van de Ven (OECD)

BETTER POLICIES FOR BETTER LIVES

Introduction

- Currently two most prominent topics on the agenda of the System of National Accounts:
  - Globalisation
  - Digitalisation
- A combination of measurement issues and conceptual challenges

Globalisation:
What Are the Main Problems?

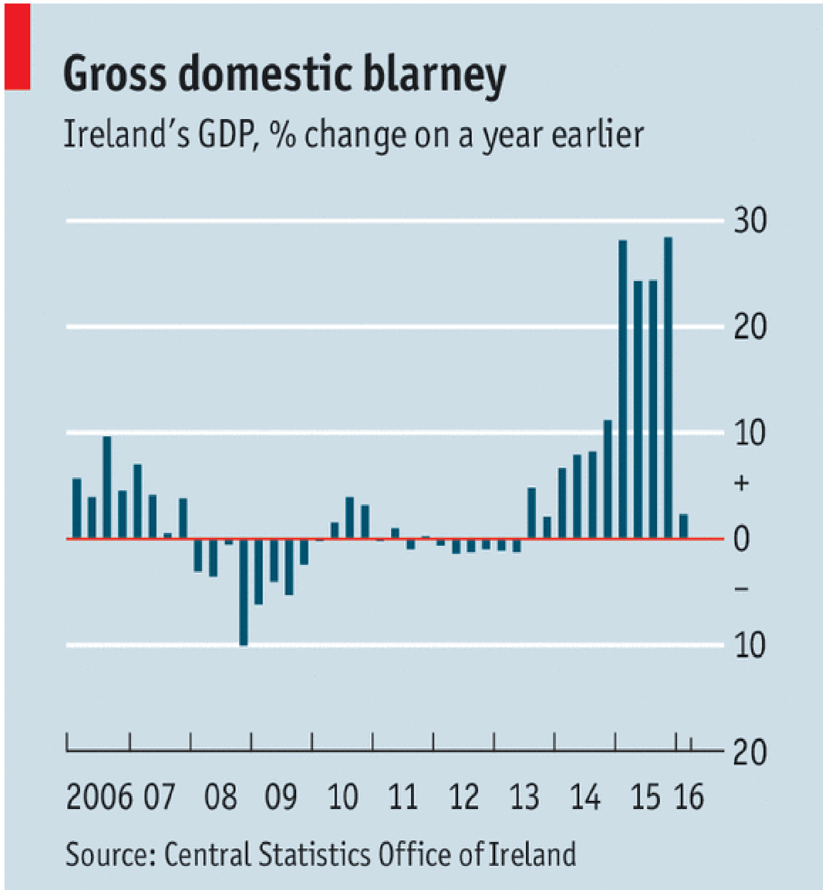
Have They Gone Mad?

Irish GDP up by 26.3% in 2015!

"Ireland's Economists Left Speechless by 26% Growth Figure" (Bloomberg)

"Why GDP growth of 26% a year is mad" (Economist)

"It's complete bullshit, it's Alice in Wonderland economics" Colm McCarthy, University College Dublin)

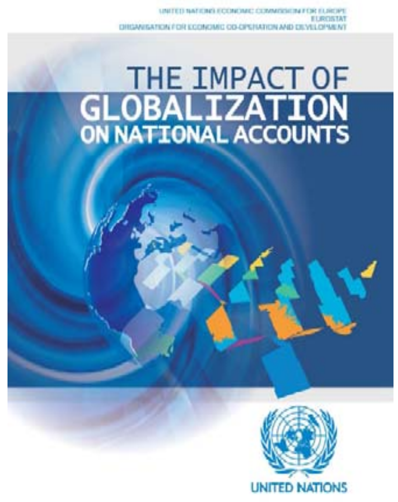


Economist.com

Global production versus national statistics

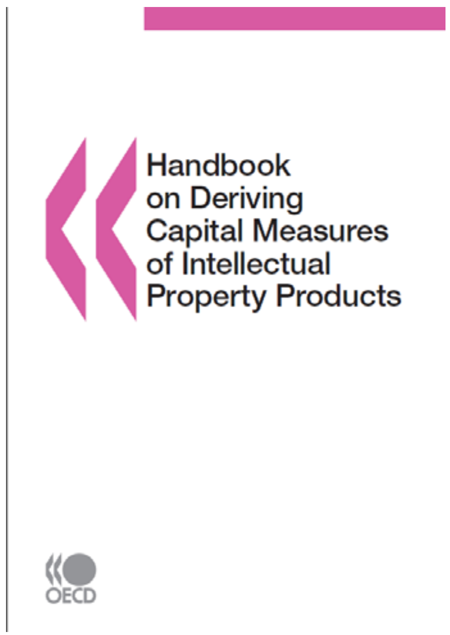
- **Global production arrangements** between firms and within MNEs
- **Quickly evolving, even minor organisational rearrangements can have significant impact**
- **Statistical complications have long been recognised** and discussed:
  - Goods for processing/merchanting
  - Transfer pricing
  - Special Purpose Entities
  - Relocations/reorganisations
  - Asymmetries in trade data
- **Clear friction between national statistics based on residency and global behavior of MNEs** (also in the area of monitoring risks and vulnerabilities)

www.oecd.org/trade/valueadded



Adding IPPs and digitalisation

- Challenges exacerbated when **globalisation meets IPPs and digitalisation**
- **IPPs have no physical and local constraints => relatively easy to relocate from one country to another**
- Impact can be large, especially in small economies
- **Is GDP still valid** as a measure of domestic production? For **designing** monetary, fiscal and structural **policies?**



Ratio of Profit-type Return to Compensation of Employees

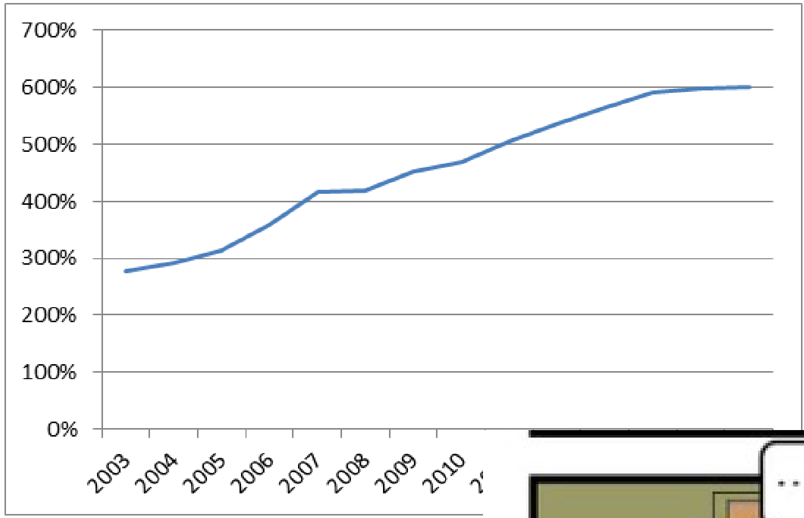
All countries	**0.840**
Canada	**0.848**
Europe	**0.579**
Ireland	6.639
Netherlands	0.878
Switzerland	1.614
Latin America and Other Western Hemisphere	**1.555**
Central & South America	0.978
Other Western Hemisphere	11.709
Barbados	34.967
Bermuda	36.062
United Kingdom Islands, Caribbean[1]	8.833
Western Hemisphere, n.e.c.[2]	6.347
Middle East	**1.837**
Other Middle East[3]	9.403
Asia Pacific	**1.178**
Hong Kong	0.953
Singapore	2.978

Source: Robert E. Lipsey: Measuring the Location of Production in a World of intangible Productive Assets, FDI, and Intra-Firm Trade (NBER Working Paper 14121)

Special Purpose Entities in the Netherlands

Balance sheet totals of "special financial institutions" in NL, 2003 – 2016

% of GDP



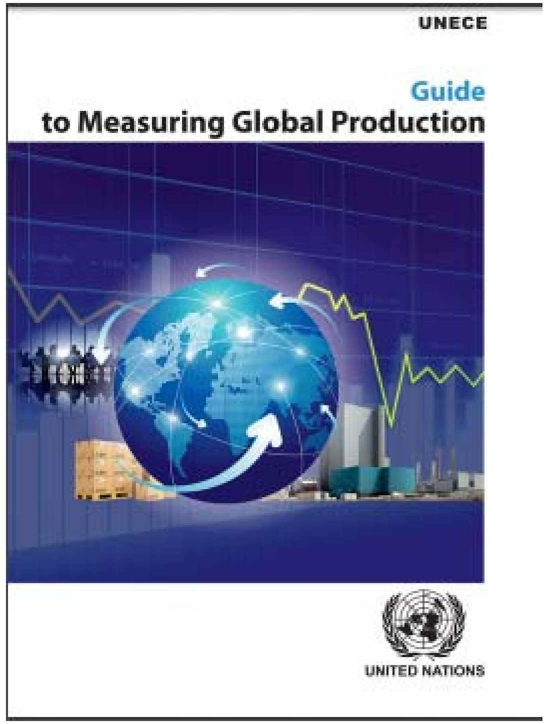
Source: De Nederlandsche Bank (2018)

Globalisation:

Solutions within the Current International Standards

Improved accounting

- **Better accounting for global production arrangements**
- **Improving consistency at national level** (e.g. by establishing Large Case Units)
- **Improving international consistency of recording MNE-activities** (EuroGroups Register, Early Warning System, etc.)



Emphasising existing complementary indicators, …

- **National Accounts ≠ GDP**
- The System of National Accounts is a framework from which a **variety of indicators** can be derived
- **Some indicators** such as NNI and Household Disposable Income **hardly/not affected** by e.g. relocations
- Better use and communication needed

…, including greater granularity, …

- **Proposed additional breakdowns** in supply and use tables and/or in institutional sector accounts:
  - **By type of ownership:**
    - Public corporations
    - National private corporations, not part of domestic MNE
    - **National private corporations, part of domestic MNEs**
    - **Foreign-controlled corporations**
      - **Of which: Special Purpose Entities (SPEs)** (Note: may only be relevant for some countries)
  - By type of firm:
    - Factoryless producers, merchanters, contract manufacturers, processors
    - By business function?

…, and possibly defining additional indicators and datasets

- **Additional indicators:**
  - **GNI*** (= GNI minus retained earnings of re-domiciled firms minus depreciation of categories of foreign-owned domestic capital assets (such as IP capital assets))
  - **Contributions of inputs to (growth of) GDP** (e.g. separating value added from IPPs and other movable assets, from labour and other assets)

- **Creating global datasets on multinational enterprises**, to better monitor and understand economic behaviour

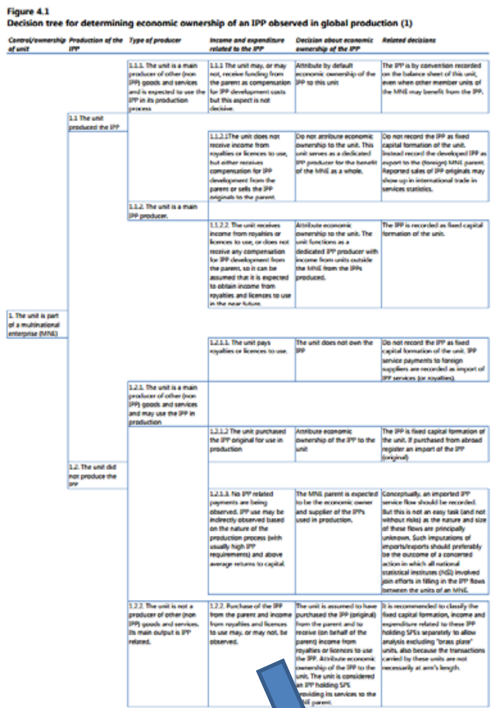
Globalisation:

Challenges with and Implication for the Current International Standards

Main characteristics of IPPs

- **No physical or local constraints**
- **Often no direct link to the production process** (e.g. basic research)
- **Often no direct link between today's stock of assets and today's production of goods and services**
- **Often concern the whole value chain, not a particular part of the process** (e.g. product and process innovations)
- Once produced, they are usually **easily scalable**
- …

Who owns the IPPs?



- 2008 SNA makes **distinction between economic (*risks and rewards*) and legal ownership**
- But, despite best efforts, **guidance on identifying economic ownership arguably falls short**

1.2.2. The unit is not a producer of other (non IPP) goods and services. Its main output is IPP related.	1.2.2. Purchase of the IPP from the parent and income from royalties and licences to use may, or may not, be observed.	The unit is assumed to have purchased the IPP (original) from the parent and to receive (on behalf of the parent) income from royalties or licences to use the IPP. Attribute economic ownership of the IPP to the unit. The unit is considered an IPP holding SPE providing its services to the MNE parent.	It is recommended to classify the fixed capital formation, income and expenditure related to these IPP holding SPEs separately to allow analysis excluding "brass plate" units, also because the transactions carried by these units are not necessarily at arm's length.

Way Forward?

- **More prescriptive guidance on economic ownership**
- **As a default option, to always consider, conceptually, the parent as the economic owner**, …
- … meaning that current measures of **(distributed and reinvested) earnings would shift from GNI to GDP** in the parent economy
- Note: In current national accounts, payments for services and property income often blurred

Consolidating SPEs

- SPEs are typically **pass-through types of units**, often set up to minimize global tax burden
- **No economic substance; often brass plates**
- Currently treated as separate institutional units, because associated corporation is located in another country
- If not located in another country, they would **not be considered as separate institutional units** and would be consolidated
- Assigning e.g. ownership of IPPs to these units is matter of legality or practicality
- **Consolidate SPEs with the ultimate owner?**

A panacea or a sticking plaster? Who is the ultimate parent?

- **Centre of economic decisions** = location from where decisions are made on:
  - global arrangements of production
  - R&D and other corporate investments
  - corporate finance
  - appointment at senior management level
  - etc.
- **Location of board of directors**
- …
- Corporate inversion by setting up a holding type of SPE to minimise tax burden would thus not affect centre of economic decisions

*"In between dream and act there are hindering laws and practical issues" **

- **Solutions require extensive exchange of individual enterprise information at the international level**
  - **Top-down approach** (e.g. BEPS-data, or alternative/additional collection of data on MNEs at the international level)
  - **Bottom-up approach** (monitoring and analysis of MNEs primarily based on collection of data on the national level)
- But … we already have **major problems in arriving at consistency at the national and international level**
- **Need for enhancing (the possibilities for) international co-operation and co-ordination**

* Quote from the poem "The Marriage" by Willem Elsschot

Digitalisation:
What Are the Main Problems?

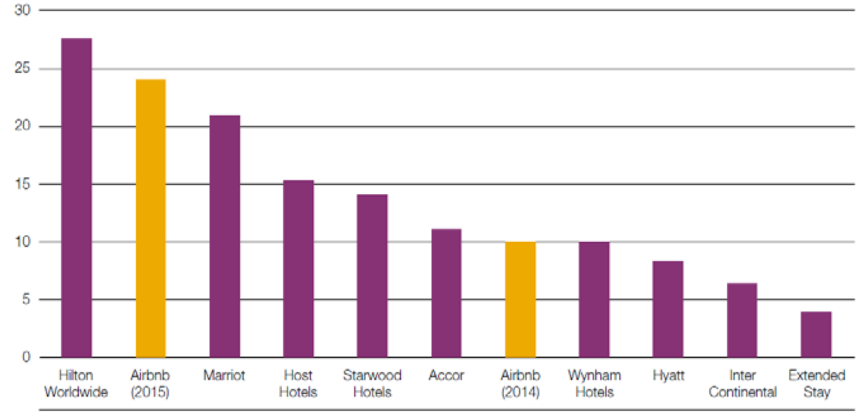
Background

Increased prevalence of 'new' transformative (digital) technologies

But …

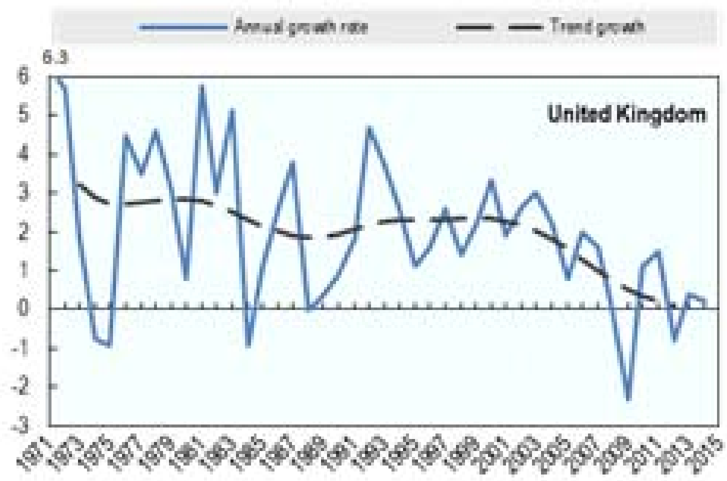
… declining productivity

Market capitalisation of Airbnb (£ Billions)



Source: Davidson, L., (2015). 'Airbnb boss calls the UK the "centre of the sharing economy",' The Telegraph.

Trend labour productivity growth



Very present in the public debate

Charles Hulten: *"Valuing the Net and the wide range of applications… is challenging…. and their omission or undervaluation surely affects GDP."*

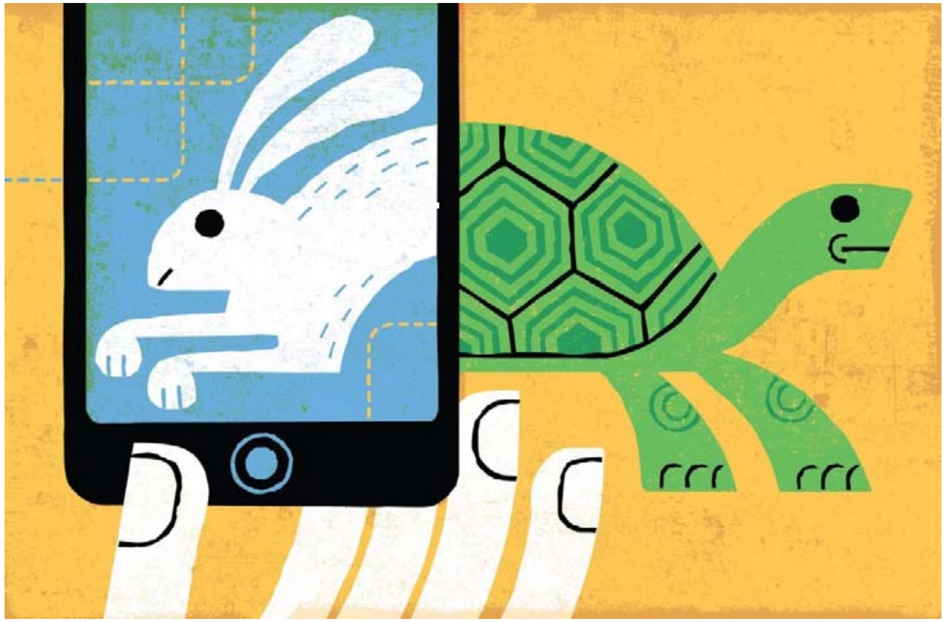
Charles Bean: *"statistics have failed to keep pace with the impact of digital technology"*

Diane Coyle: *The pace of change in OECD countries is making the existing statistical framework decreasingly appropriate for measuring the economy*

THE WALL STREET JOURNAL.

Silicon Valley Doesn't Believe U.S. Productivity

The U.S. Underestimates Growth



FINANCIAL TIMES

The internet and the productivity slump

ComputerWeekly.com

Why we're measuring the digital economy in the wrong way

The Economist

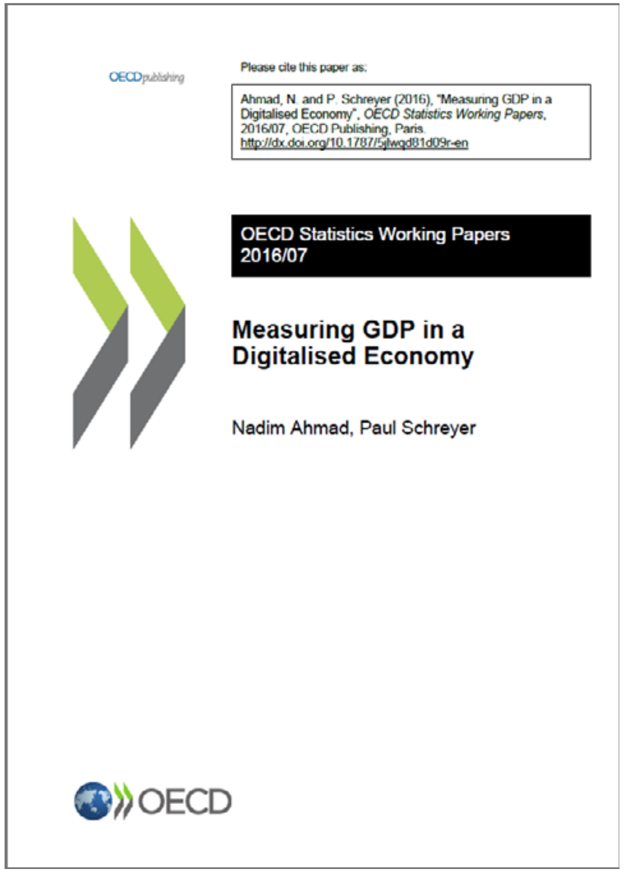
Some optimists argue instead that the problem is one of measurement. Technological progress often raises productivity in ways that statistical agencies struggle to detect

The ill-defined nature of the issue has not helped

There is often confusion between:

- **Conceptual** vs. **Empirical** issues
- **Production** vs. **Consumer Surplus** vs. **Welfare**
- **Volumes** vs. **prices**

Recent OECD paper reviews these issues more systematically


OECDpublishing

Please cite this paper as:

Ahmad, N. and P. Schreyer (2016), "Measuring GDP in a Digitalised Economy", *OECD Statistics Working Papers*, 2016/07, OECD Publishing, Paris.
http://dx.doi.org/10.1787/5jlwqd81d09r-en

OECD Statistics Working Papers
2016/07

Measuring GDP in a Digitalised Economy

Nadim Ahmad, Paul Schreyer

OECD

Digitalisation:

Some examples of new products and services

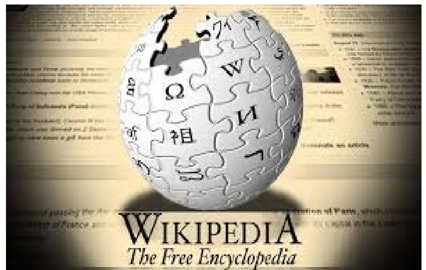
New forms of intermediation

- **Digital platforms** provide intermediation services for supply and demand
- **Not new**, but more **pervasive** and **provided differently**:
  - Taxi reservation service => *Uber*
  - Travel agent => *Booking.com*
  - Hilton online reservations => *Airbnb*
  - Banks =>*Peer-to-peer lending and crowdfunding*
  - Payment services => *PayPal, Adyen*
- **No conceptual issues, but possible measurement issues** (e.g., occasional self-employed, intermediator may be located in the rest of world)

Alibaba.com™

Consumers as producers

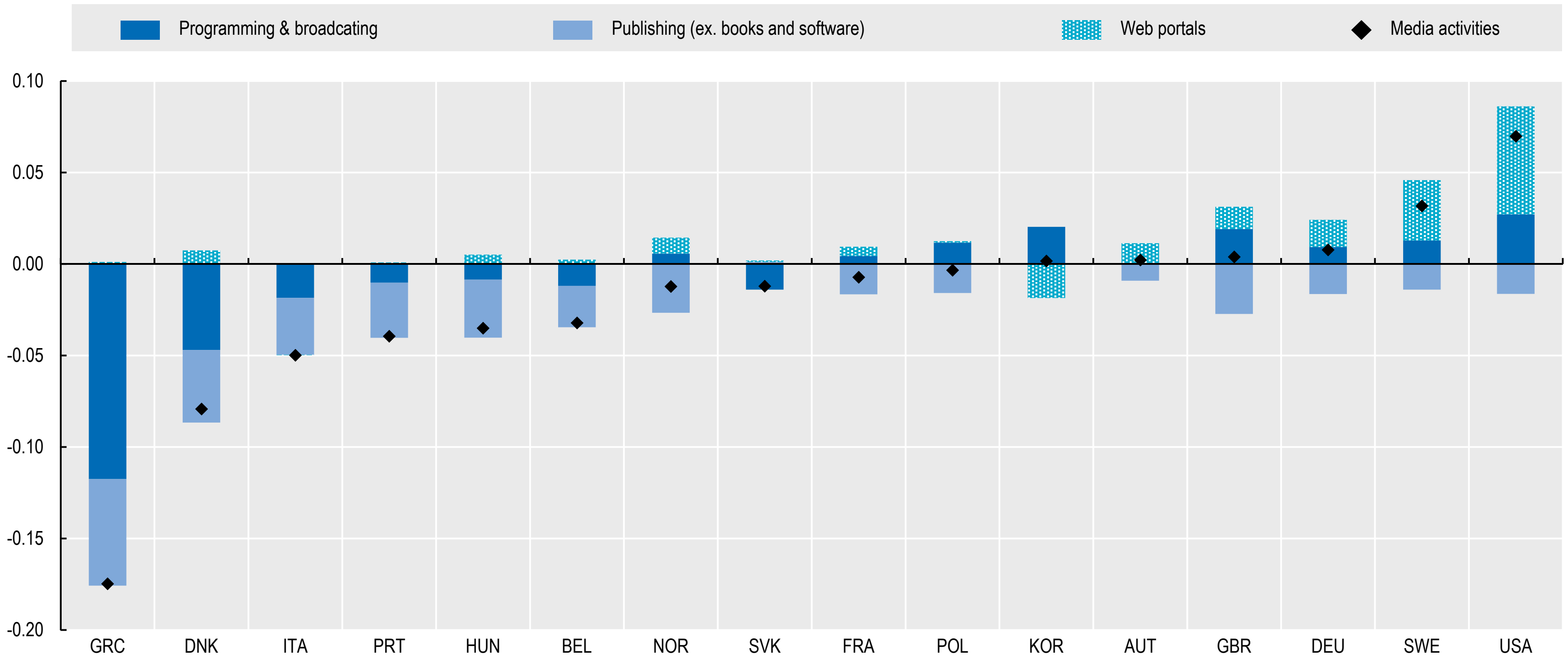
- Internet access by households has led to **blurring between household production for market purposes, own account production, consumption, leisure**:
  - Own booking of hotels, or flights by households
  - Self-service at supermarkets
  - On-line banking
- In common: movement **from dedicated market producers out of market**
- Furthermore, households generate **free assets**: Wikipedia, Linux
- Not captured in GDP
- **Old problem of dealing with unpaid household activities =>**
  Further elaboration in satellite account



Free and subsidised consumer products

- **Free apps, search capacity** by Google, etc., **social networking** through Facebook, Tencent, etc.
- Financing via **advertisements** or **data**
- Frequently cited as **output that goes unnoticed** despite contribution to consumer welfare
- Some debate about **imputation of additional output and value added** of “information services”
- **Again old problem (e.g. broadcast television and radio) =>**
  Further elaboration in a satellite account

Impact of free media activities on GDP growth, 2009-2013



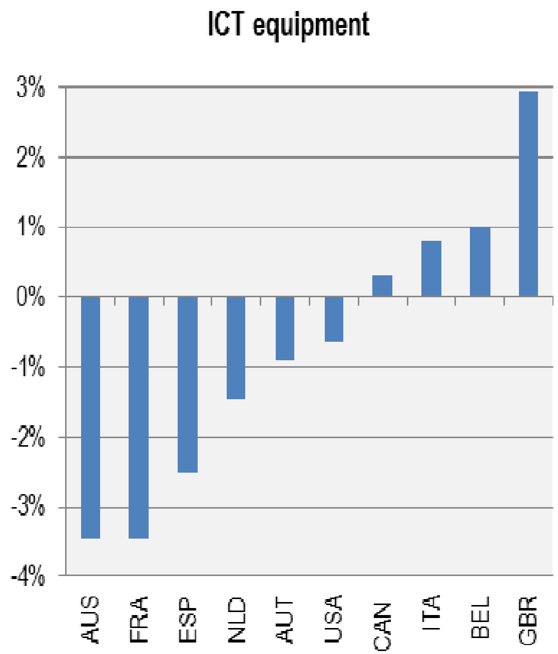
Average 2009-2013, percentage points

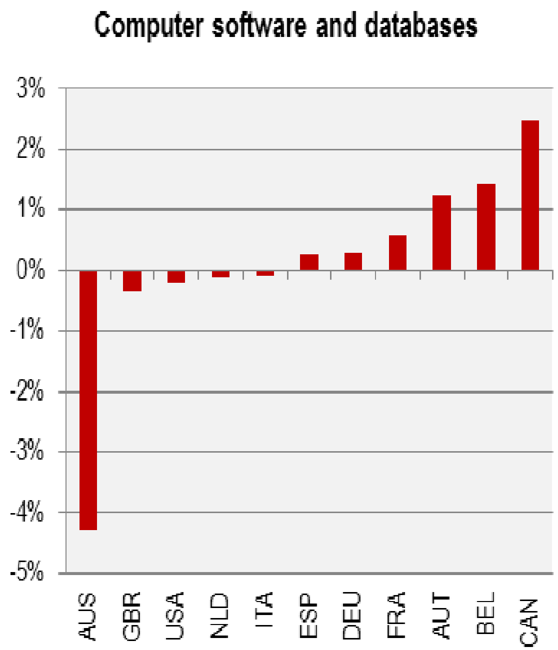
Notes: Data for BEL, KOR and POL refer to 2012-2013, for FRA, GRC to 2010-2013 and for the USA to 2011-2013.

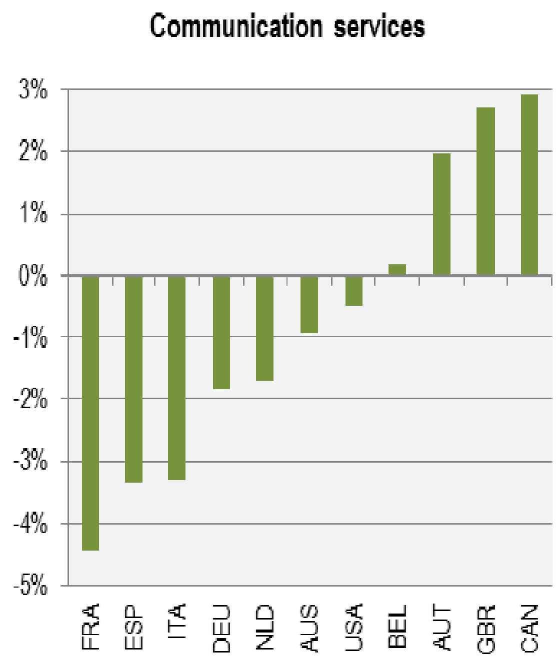
Source: OECD calculations based on data from OECD SDBS database, OECD Annual National Accounts database and US Census Bureau data. The GDP deflator was used for deflation purposes.

Volume and price measurement

Average annual growth rate in percentage, 2010-2015 (or latest available year)







Notes: Data reported for Spain for ICT equipment and Computer software and database correspond to the period 2010-2014. Data reported for Austria for Communication services correspond to the period 2011-2015.
Source: OECD National Accounts Statistics, OECD Productivity Database, OECD Prices and Purchasing Power Parities database, Australian Bureau of Statistics, U.S. Bureau of Economic Analyses and Statistics Canada, February 2017

Potential impact on GDP growth

Average annual growth rate in percentage, 2010-2015 (or latest available year)

Country	GDP growth, unadjusted	Adjusted GDP growth minus Unadjusted GDP growth		
		Scenario I: M=0	Scenario II: FD=0	Scenario III: FD and M from SUT
Australia	2.761%	0.023%	-0.001%	0.022%
Austria	1.047%	0.294%	-0.103%	0.191%
Belgium	0.996%	0.400%	-0.184%	0.216%
Canada	2.148%	0.286%	-0.093%	0.194%
France	0.943%	0.157%	-0.034%	0.123%
Germany	1.572%	0.122%	-0.044%	0.077%
Italy	-0.641%	0.200%	-0.091%	0.109%
Netherlands	0.748%	0.367%	-0.118%	0.250%
Spain	-0.235%	0.176%	-0.058%	0.117%
UK	1.978%	0.365%	-0.193%	0.172%
US	2.072%	0.208%	-0.046%	0.162%

Notes: Using lower bound price indices; Data reported for Austria (communications) correspond to 2011-2015 and Spain (ICT goods and software) correspond to 2010-2014.
Source: OECD calculations based on OECD National Accounts Statistics, OECD Prices and Purchasing Power Parities database, OECD Supply and Use Tables database, Australian Bureau of Statistics (ABS), Bureau of Economic Analysis (BEA), Statistics Canada, Office for National Statistics (UK), February 2017

Digitalisation:
Main conclusions and way forward

Conclusions

- **Good measurement is key in a digital economy**, but mismeasurement unlikely to explain productivity and growth slowdown
- **Conceptually, national accounts appear up to the task, but …**
- **… measurement in some areas may require improvement, especially in the area of volumes and prices**
- GDP is a measure of (market) production, not an indicator of welfare

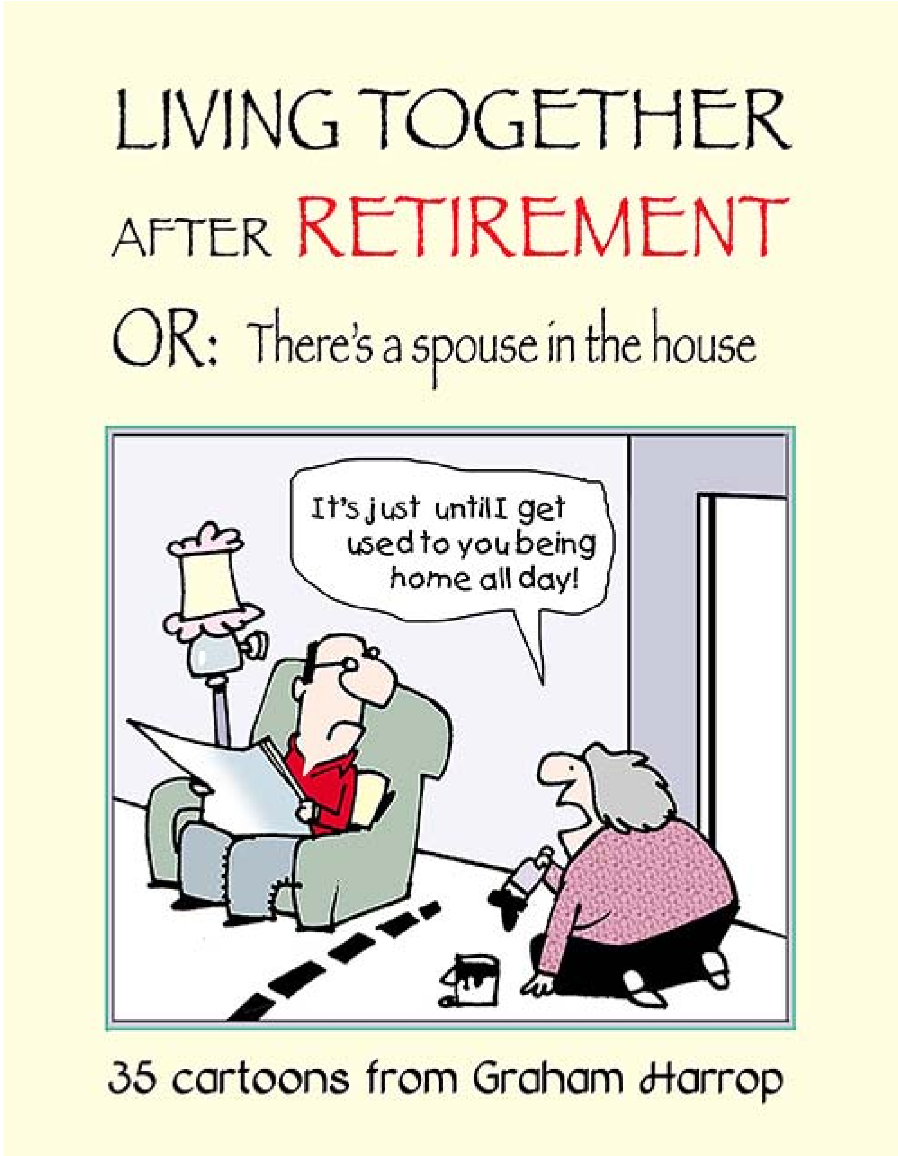
Way forward

- OECD's project **"Going Digital"**
- **Planned work** of the Advisory Group on Measuring GDP in a Digitalised Economy:
  - Further work on assessing the **effects of possible bias in price indices** on measured productivity and growth
  - Further work on assessing the impact of **"free goods and services"**
  - Further work on **the role of data, including its recording**
  - **Developing and compiling a satellite account for the digital economy**
  - **Developing indicators to monitor the digital economy**

Final considerations

Final considerations

- **Lots of critique and renewed debate on the adequacy of the core framework of national accounts**
- **Challenging issues** on the table, in addition to issues like the measurement of well-being, sustainability, (financial) risks and vulnerabilities, etc.
- **Lots of fun!**
- **No time to retire soon!**



Thank you for your attention!

Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

Macroprudential frameworks: experience, prospects and a way forward[1]

Claudio Borio,

Head of Monetary and Economic Department,

Bank for International Settlements

[1] This presentation was prepared for the meeting. The views expressed are those of the author and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

BANK FOR INTERNATIONAL SETTLEMENTS

Macroprudential frameworks: Experience, prospects and a way forward

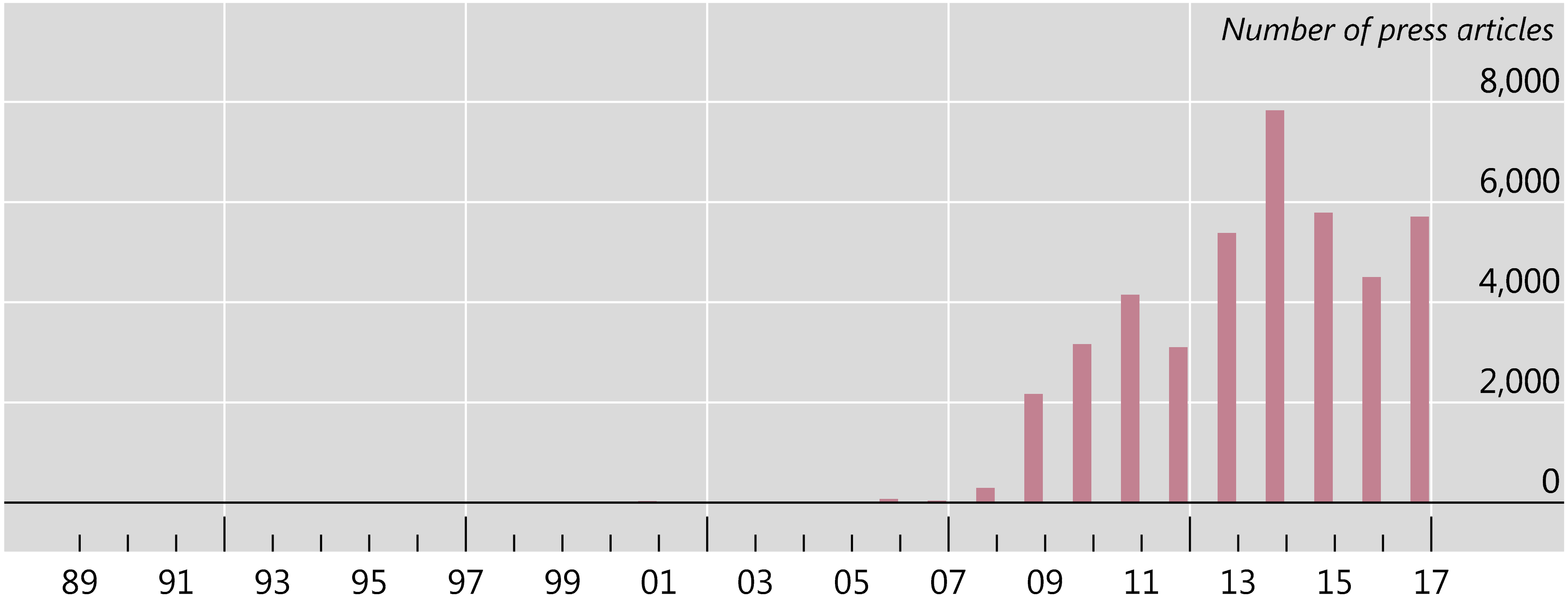
Claudio Borio
Head of the Monetary and Economic Department

9th biennial IFC Conference
BIS, Basel 31 August 2018

Introduction

- Macroprudential (MaP) frameworks
  - A key new element of the post-crisis financial reforms

Growing popularity of the term "macroprudential"



Themes and takeaways

- Macroprudential (MaP) frameworks
  - A key new element of the post-crisis financial reforms

- Two questions:
  - What has been the experience so far?
  - What is the way forward?

- Definition: use of (primarily) prudential tools targeting systemic risk
- Focus: time dimension (procyclicality)

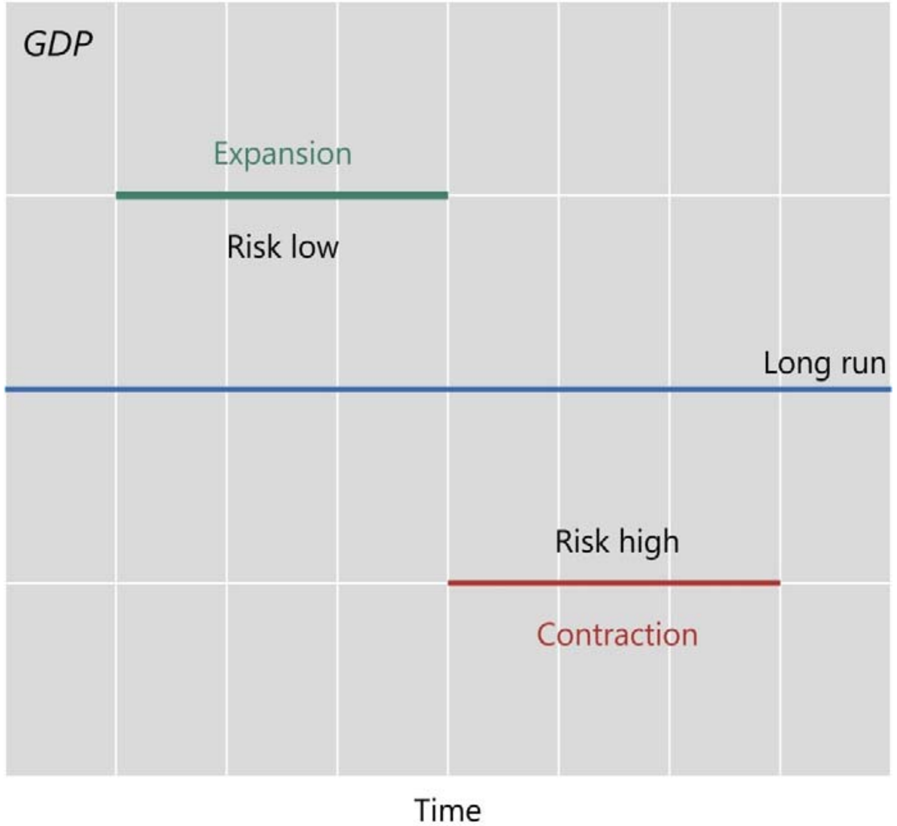
- Three takeaways
  - MaP frameworks have brought about a welcome major intellectual shift
  - Substantial progress has been made, but more needs to be done
  - MaP to be embedded in broader macro-financial stability frameworks

Structure of the remarks

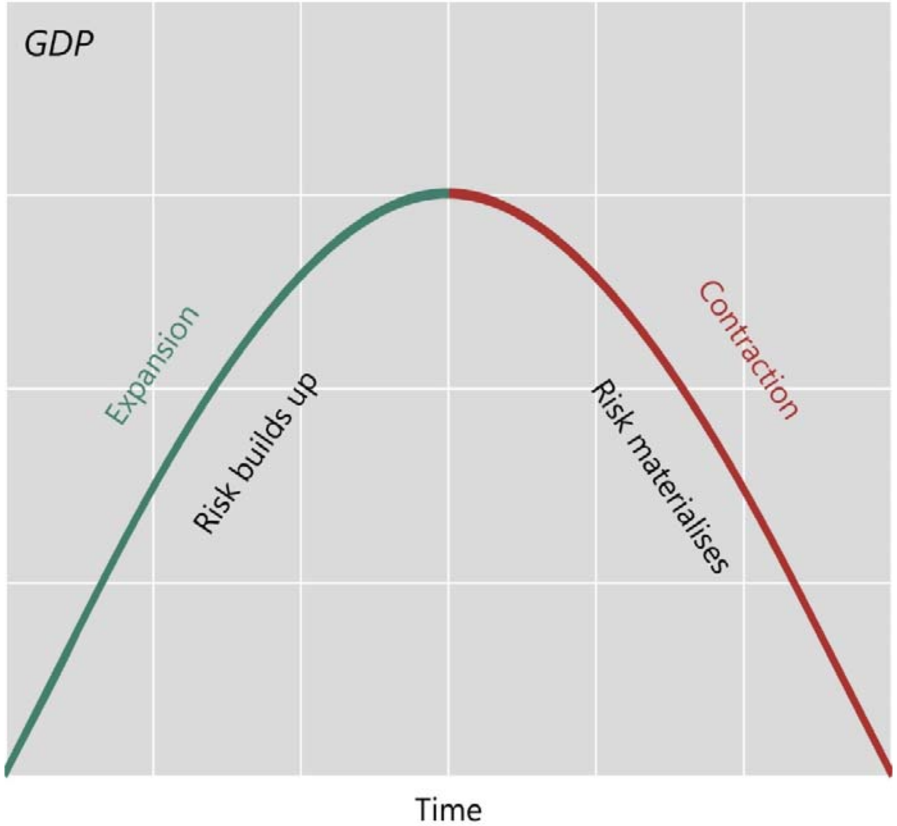
- The MaP intellectual shift
  - A major enduring gain
- Implementing MaP framework
  - Good progress, but more needed
- Beyond MaP frameworks
  - Towards a more holistic macro-financial stability framework

Two conceptions of risk

Prevailing pre-crisis

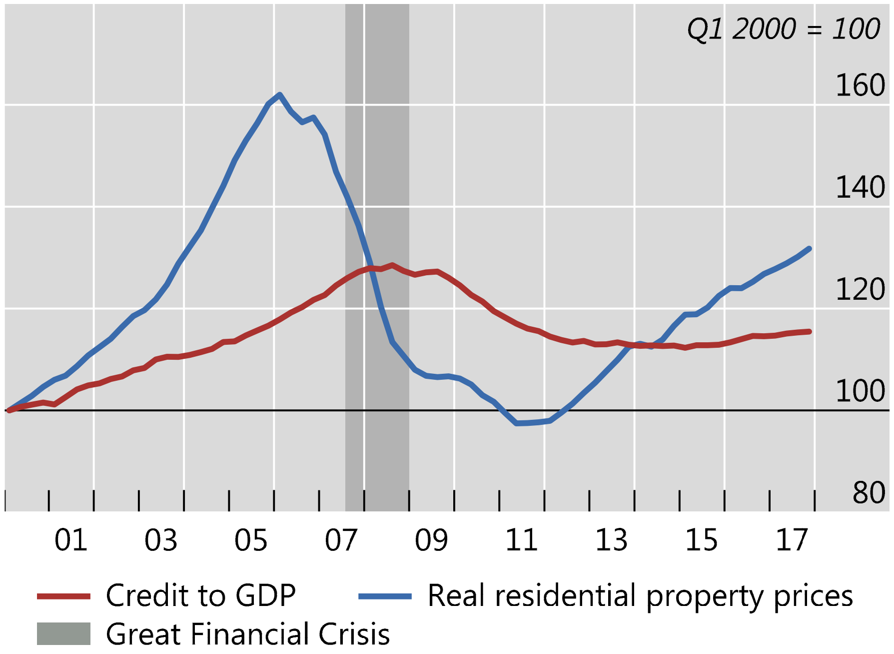


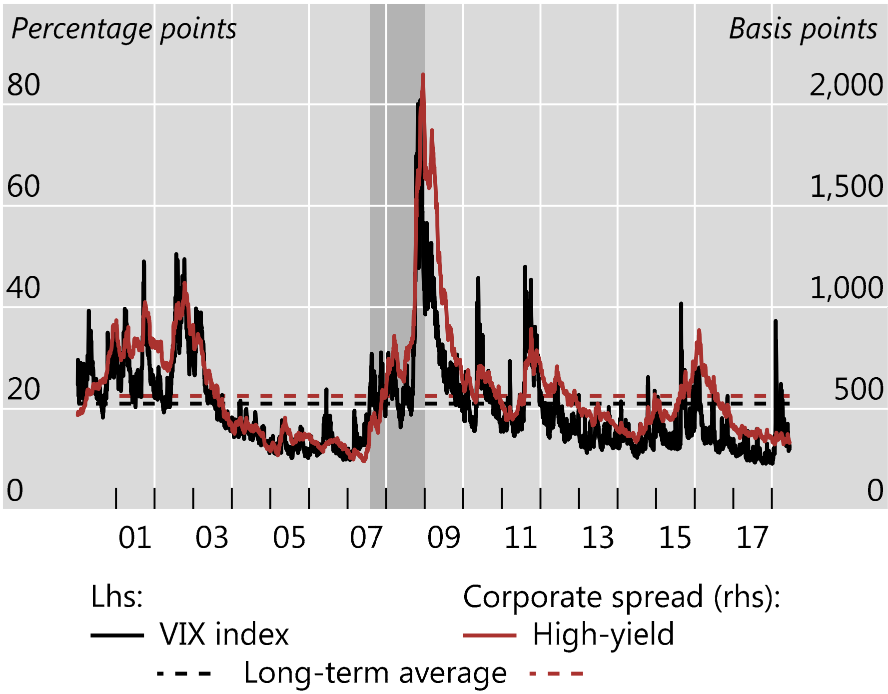
Macroprudential



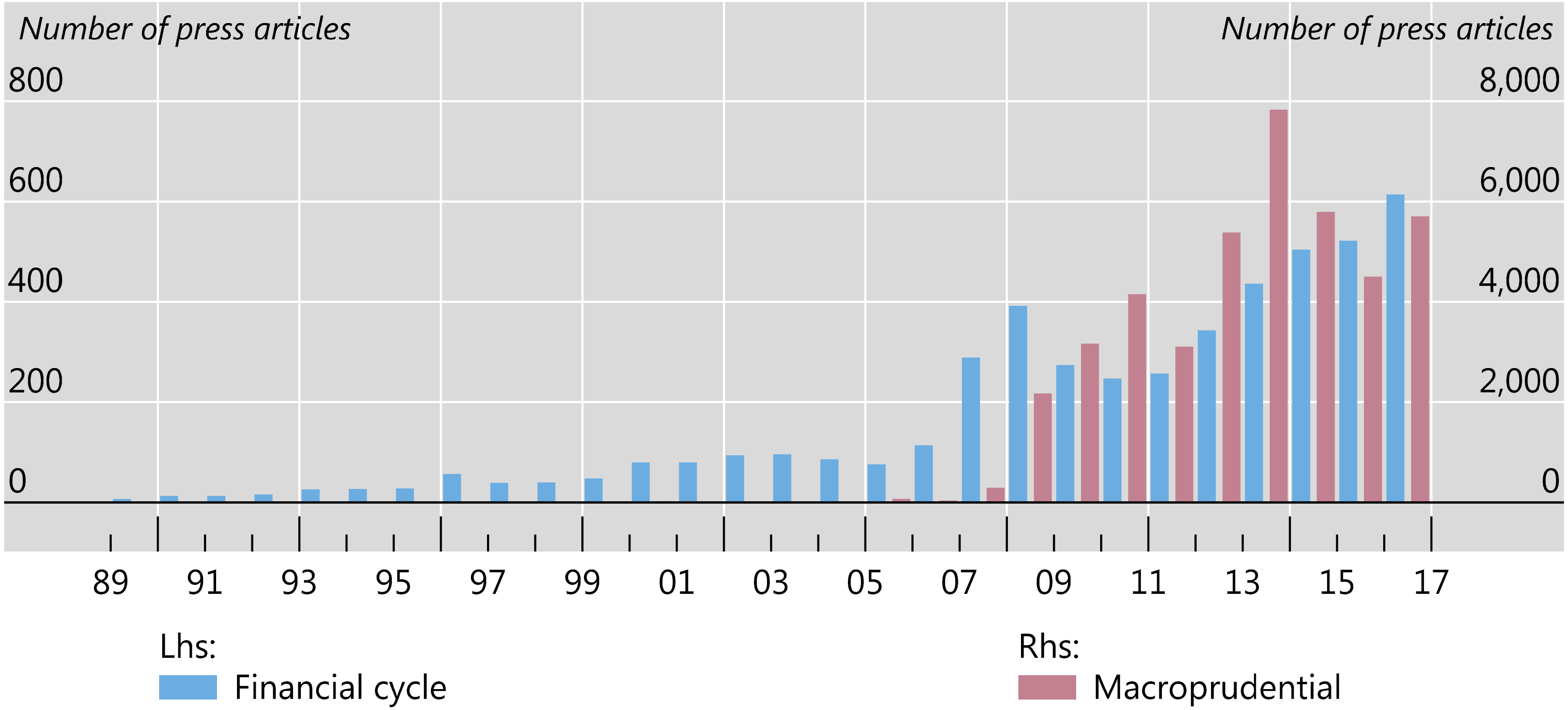
Financial booms, low spreads and volatility are signs of high risk-taking

US example





Growing popularity of the terms "macroprudential" and "financial cycle"



Structure of the remarks

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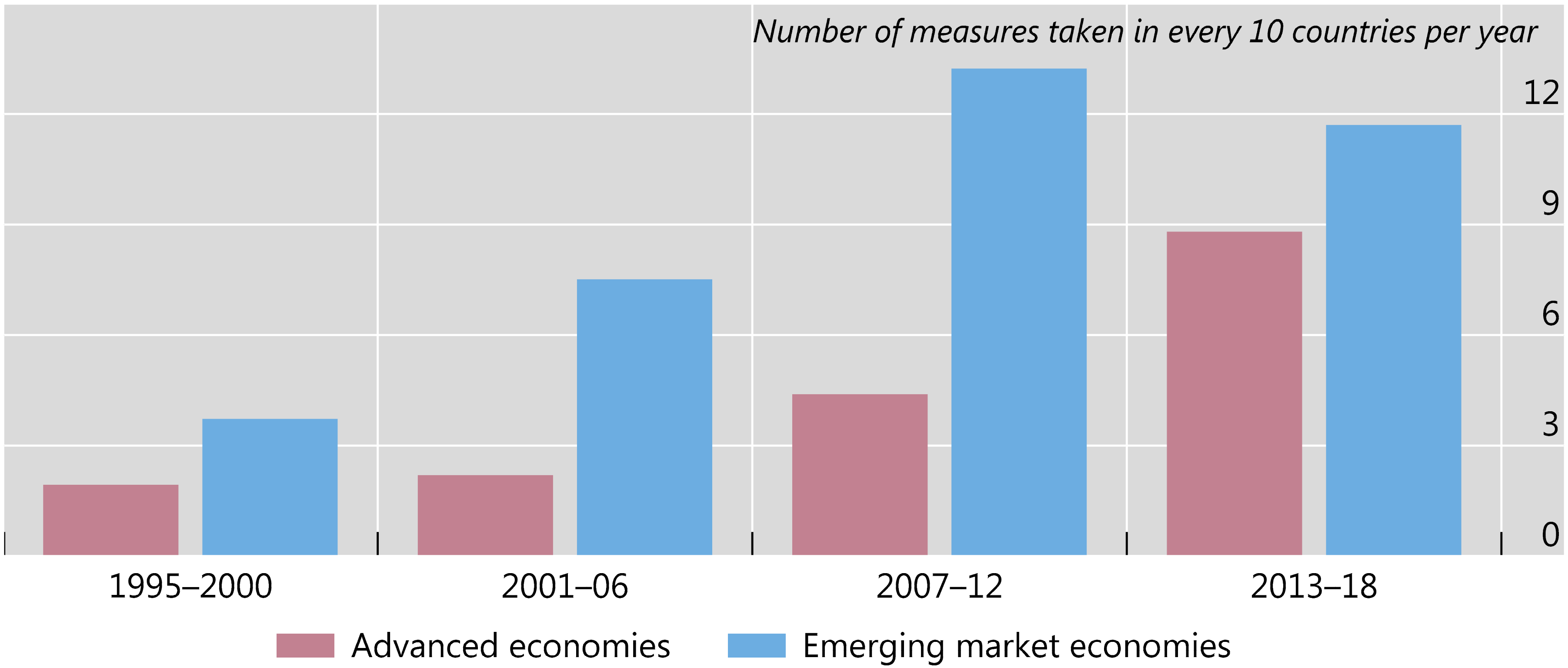
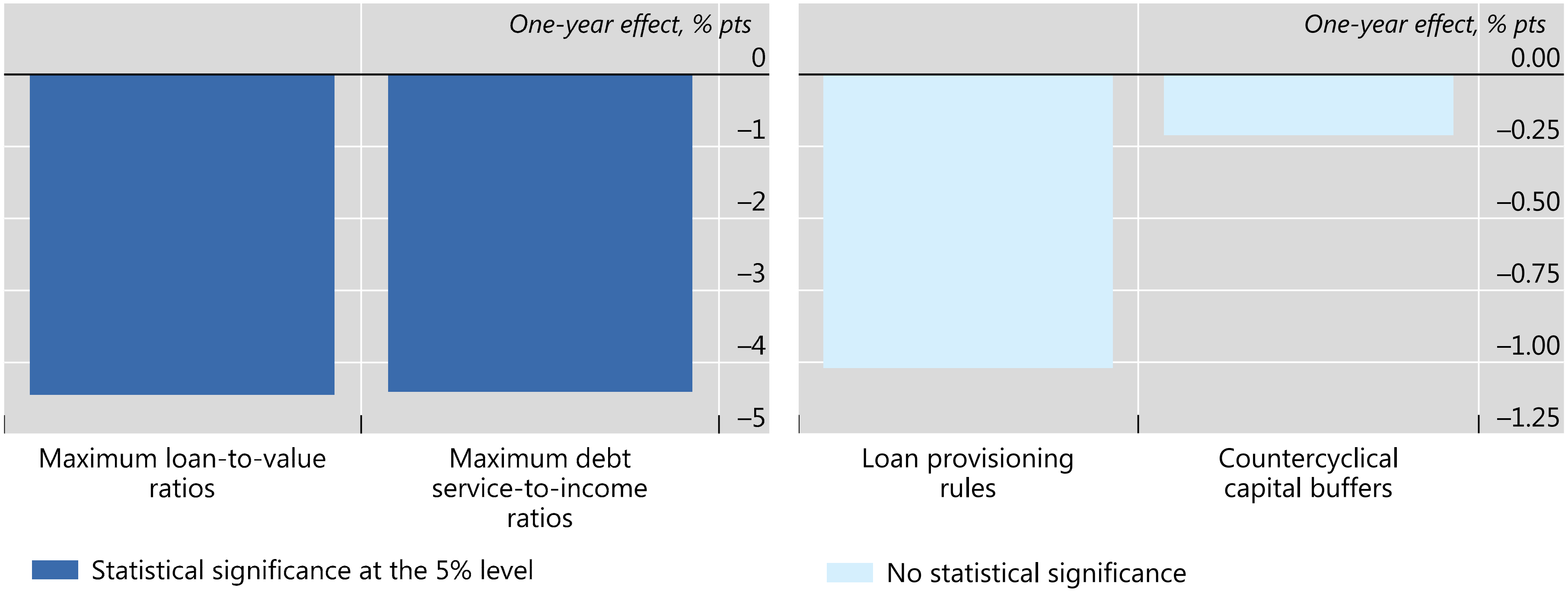
Macro stress tests: strengths and limitations

Macroprudential: growing use of measures over time

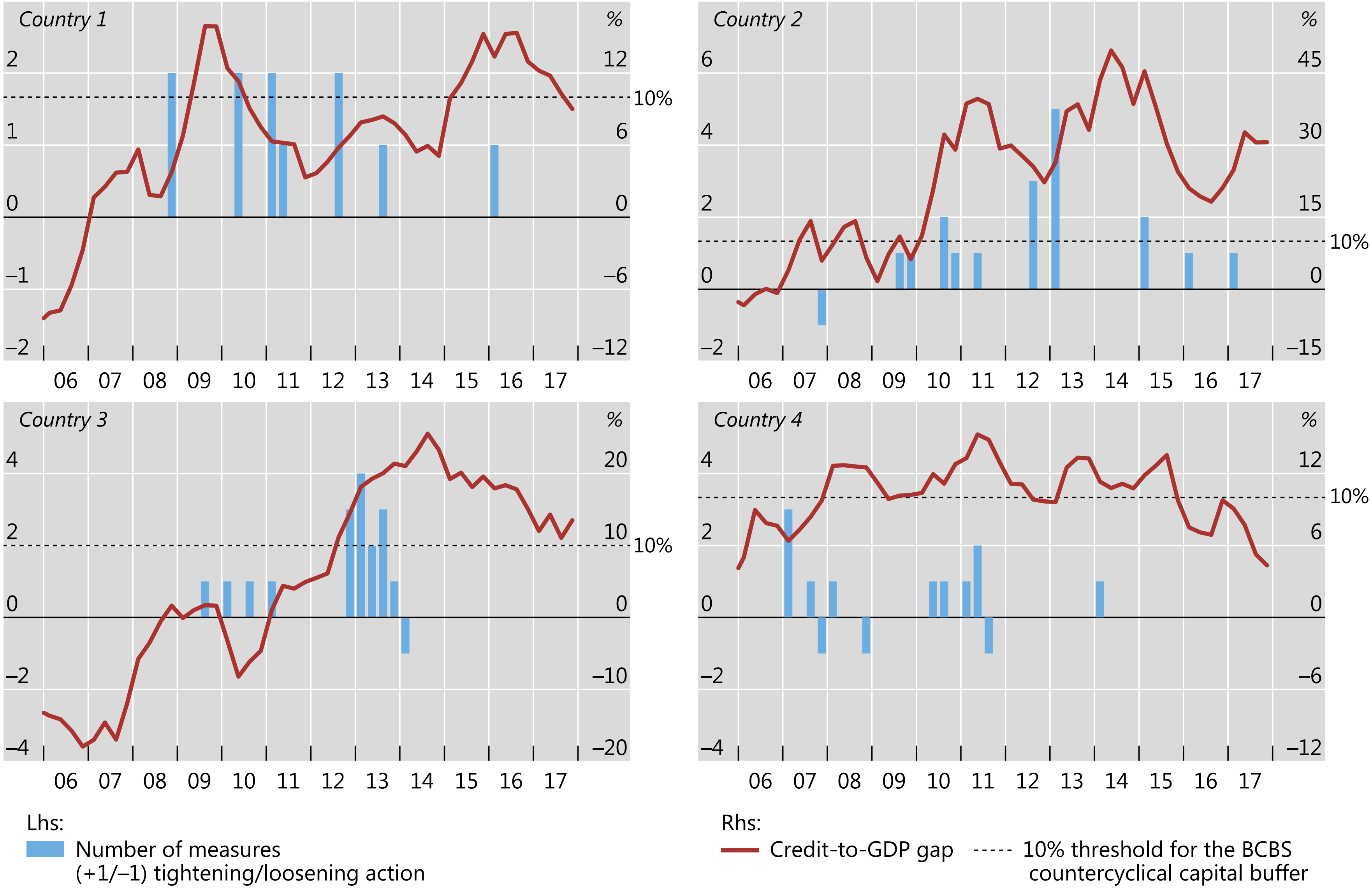


Impact of macroprudential measures on bank credit

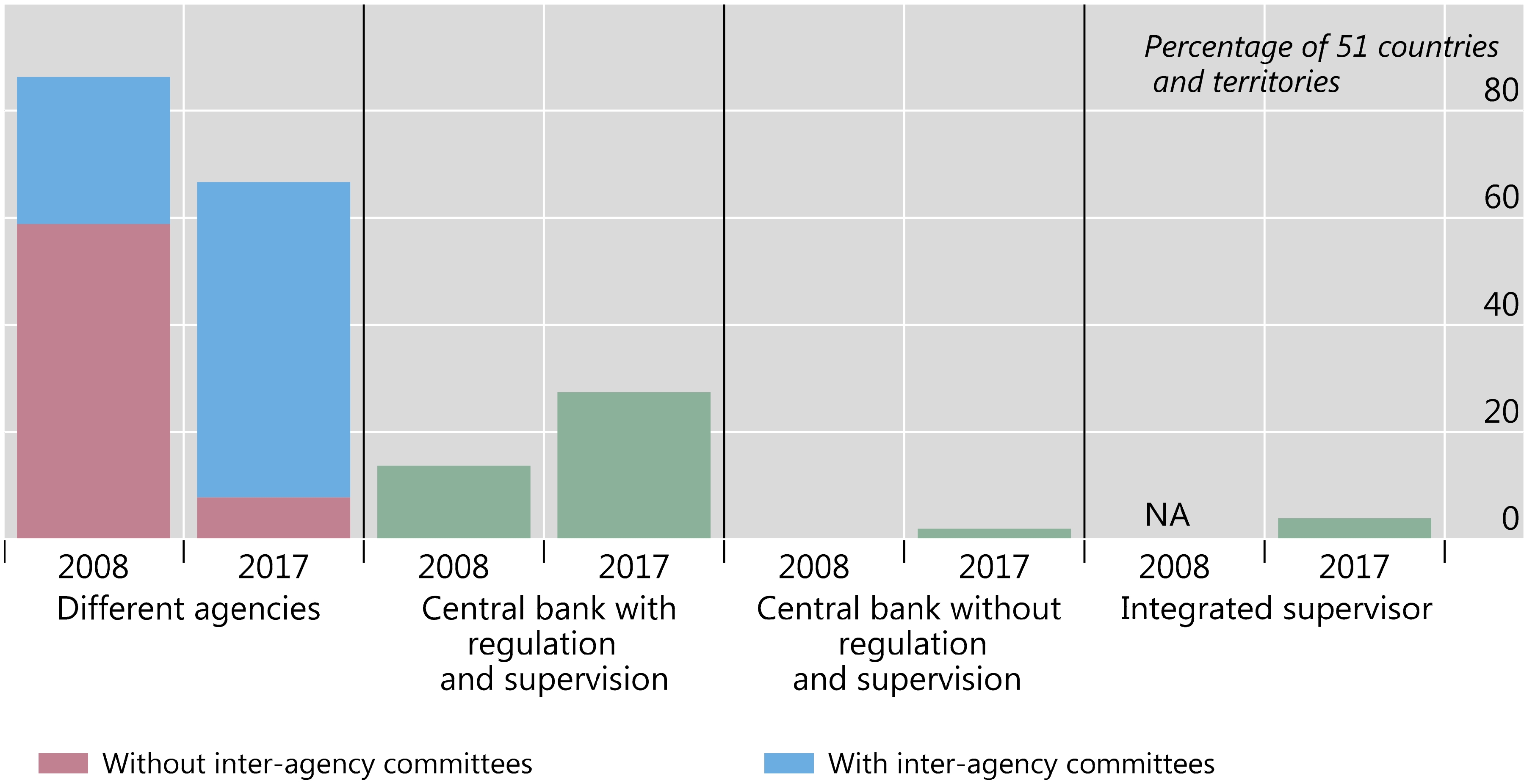
Impact of tightening



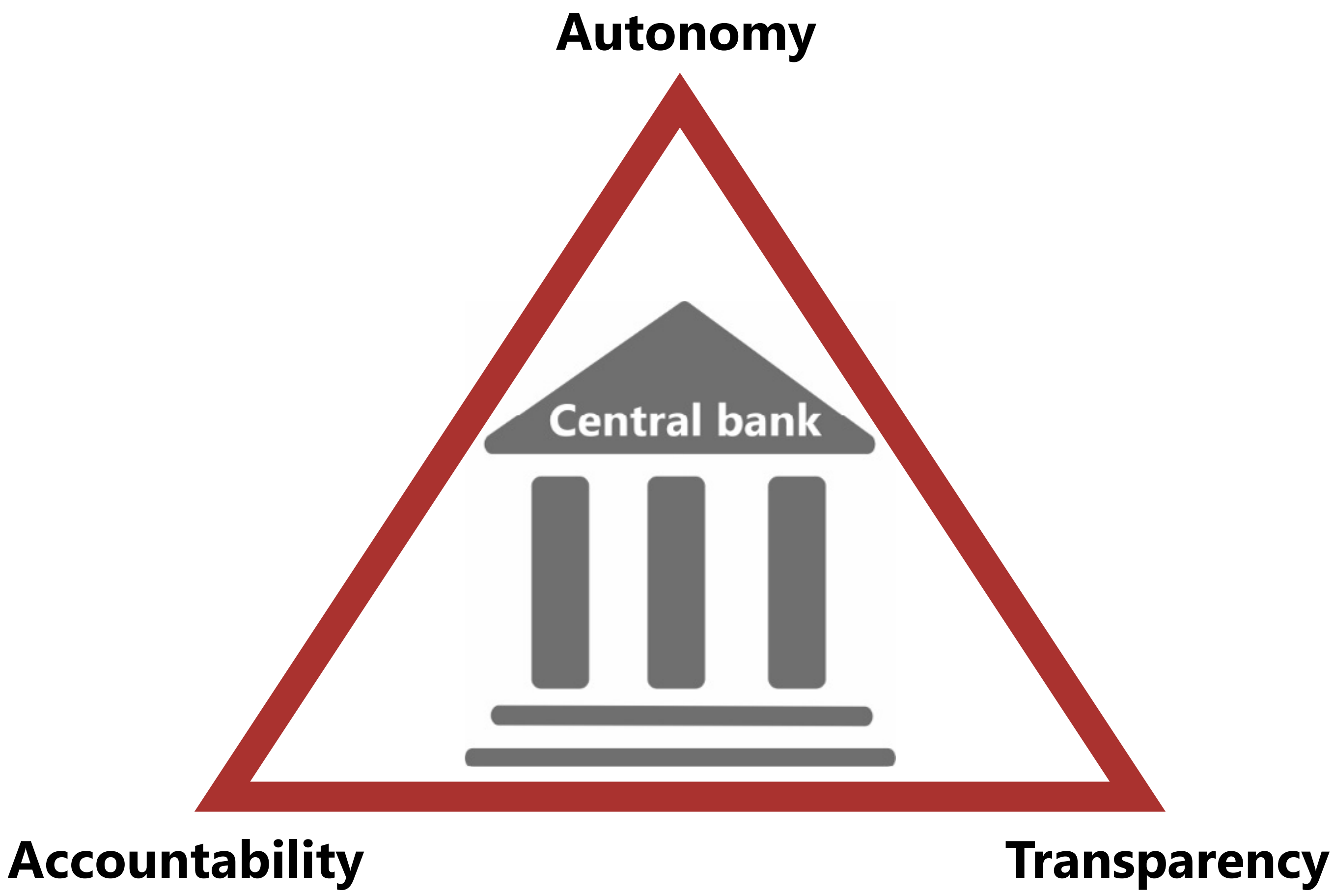
Some signs of financial imbalances even where measures used actively



Who is responsible for macroprudential measures?



A case for autonomy in MaP frameworks



Structure of the remarks

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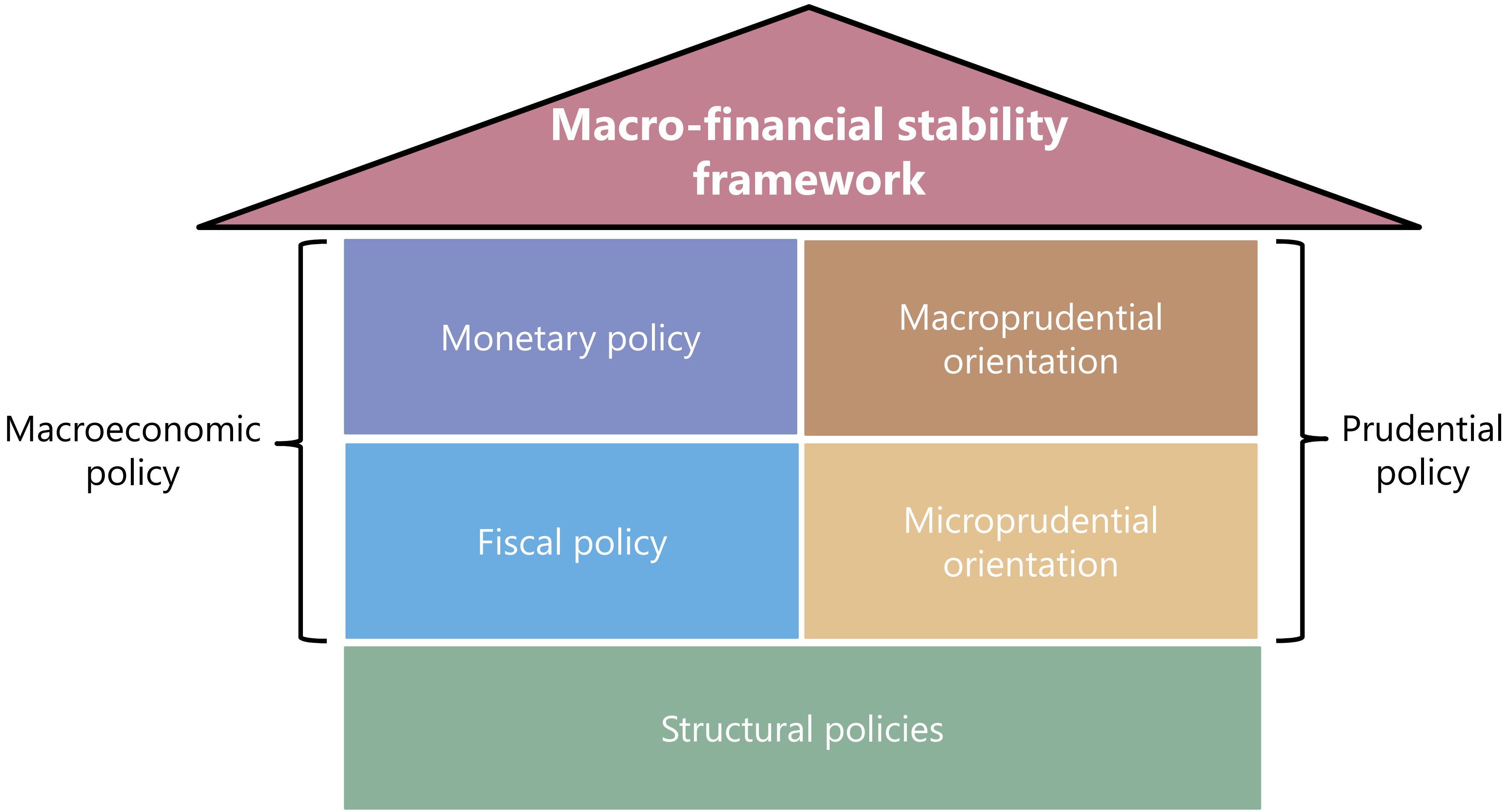
Towards a macro-financial stability framework



Conclusion

- The MaP intellectual shift
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Thank you!

Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

Macroprudential frameworks: experience, prospects and a way forward[1]

Claudio Borio,

Head of Monetary and Economic Department,

Bank for International Settlements

[1] This paper was presented at the meeting. The views expressed are those of the author and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

BANK FOR INTERNATIONAL SETTLEMENTS

Macroprudential frameworks: experience, prospects and a way forward

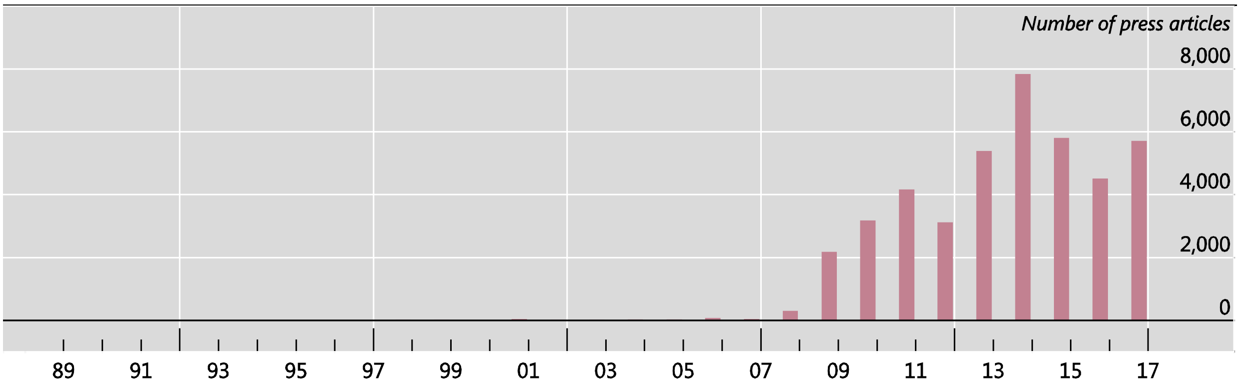
Speech by Claudio Borio
Head of Monetary and Economic Department

on the occasion of the Bank's Annual General Meeting
in Basel on 24 June 2018

Good afternoon, ladies and gentlemen.

As Agustín mentioned, macroprudential frameworks have become a key new element of the post-crisis financial reforms designed to ensure financial stability. This is very welcome. As you know, while the concept of "macroprudential" regulation and supervision goes back to the 1970s and was refined in the early 2000s, it became popular only post-crisis, thanks in part to the support of the G20. Graph 1, tracing the increase in the number of press articles mentioning the term "macroprudential", underlines the point. There were hardly any articles before 2008 and they surged thereafter.

Growing popularity of the term "macroprudential" Graph 1



Source: Factiva.

In my remarks today, based on the Annual Report's special chapter, I would like to take stock of where we stand in the implementation of macroprudential frameworks and suggest a way forward. This is a particularly good time to do so: macroprudential measures can play a key role in supporting monetary policy along its normalisation path, enhancing its room for manoeuvre. The window of opportunity should not be missed.

A couple of clarifications before I start.

First, I will define macroprudential frameworks as the use of (primarily) prudential tools to target specifically systemic risk and mitigate its macroeconomic costs. Thus, the macroprudential approach to regulation and supervision differs from the more traditional microprudential one. The latter focuses on the assessment of the risks institutions face on a standalone basis, with little regard for the financial system as a whole or the macroeconomy.

Second, I will focus only on the so-called "time dimension" and leave out the "cross-sectional" (or structural) dimension. The time dimension addresses how systemic risk evolves over time. The key concept here is the "procyclicality" of the financial system, ie its tendency to amplify financial expansions and contractions, which in turn can amplify business fluctuations. The financial cycle is a reflection of such forces. By contrast, the cross-sectional dimension addresses how risk is distributed in the financial system at a given point in time. In particular, it focuses on common exposures and interlinkages. Think, for instance, of capital surcharges for global systemically important banks or of central counterparties

There are three takeaways from my presentation:

First, we should not underestimate the intellectual shift macroprudential frameworks have brought about in how to ensure financial stability. This shift is now taken for granted, but its influence goes way beyond regulation and supervision.

Second, substantial progress has been made, but more needs to be done. The best way forward is to combine ambition in implementation with realism as to what we should expect the frameworks can achieve on their own.

Finally, to ensure financial stability, and hence sustainable growth, macroprudential measures should be embedded in a more holistic macro-financial stability framework. This framework, in addition to prudential policies, involves also monetary, fiscal and even structural policies.

I will take each point in turn.

I – The intellectual shift

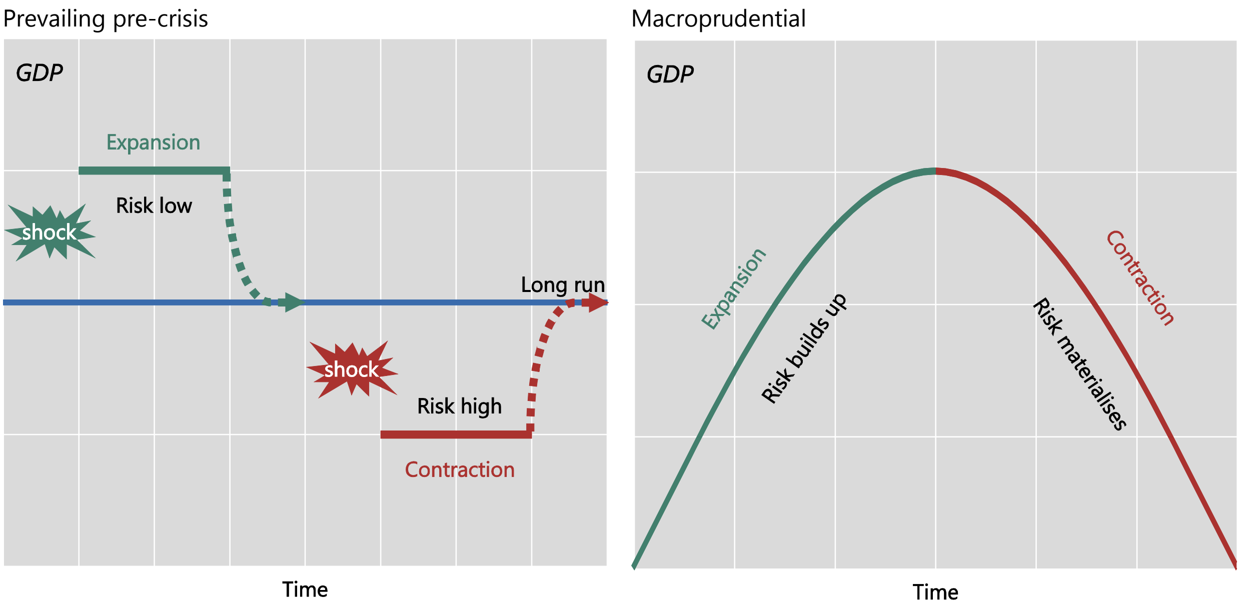
So, the intellectual shift first.

We now take it for granted; it has become, as it were, part of the furniture. But the conception of risk brought about by the macroprudential approach differs markedly from the one prevailing pre-crisis. Admittedly, this conception is an old one, but it had largely gone out of fashion during the heady atmosphere of the so-called Great Moderation.

At the time, it seemed obvious that "risk is low in a boom and high in a bust" (Graph 2, left-hand panel). But the macroprudential approach turned this dictum on its head, stating that "risk builds up in a boom and materialises in a bust" (same graph, right-hand panel). What we see in a bust or a recession is simply the result of what precedes it.

The notion prevailing at the time took root in the idea that the economy switched from states of expansion and contraction as a result of unforeseen ("exogenous") shocks, and then swiftly returned to equilibrium (Graph 2, left-hand panel). By contrast, the macroprudential conception saw the economy as evolving in response to self-reinforcing ("endogenous") forces that might take it away from equilibrium (same graph, right-hand panel). And it was the prevailing notion of the time that hindered the recognition of the risk build-up ahead of the Great Financial Crisis (GFC).

Two conceptions of risk — Graph 2

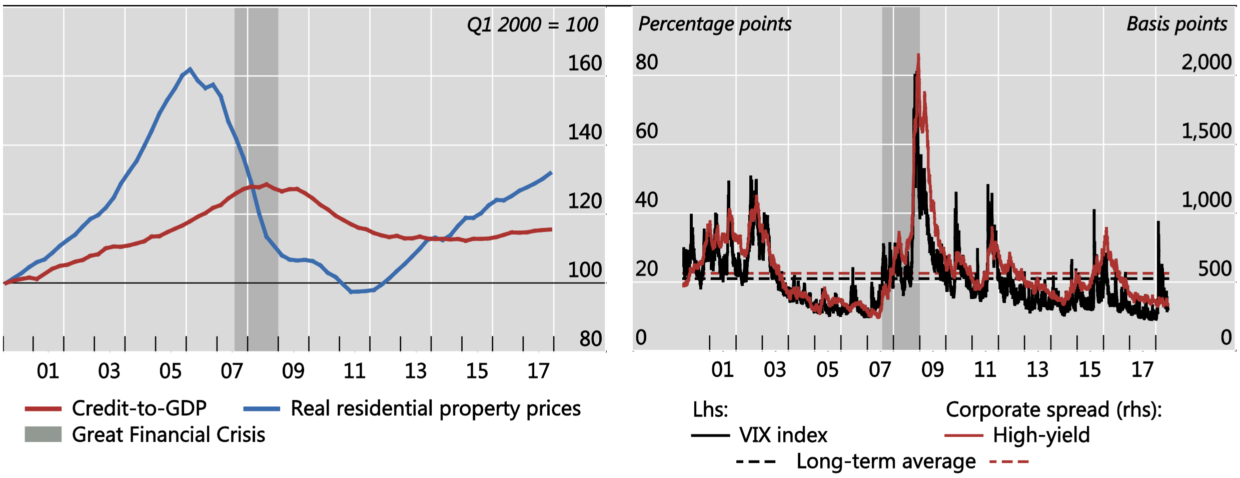


Source: BIS.

Now things have changed radically, very much informed by that experience (Graph 3). Unusually strong increases in credit and asset prices, ie a financial cycle boom, are taken as a sign of growing risk, not of a healthy expansion (left-hand panel). And highly compressed spreads and subdued volatility are taken as a sign of high risk-taking, not of low risk (right-hand panel).

Financial booms, low spreads and volatility are signs of high risk-taking

US example — Graph 3



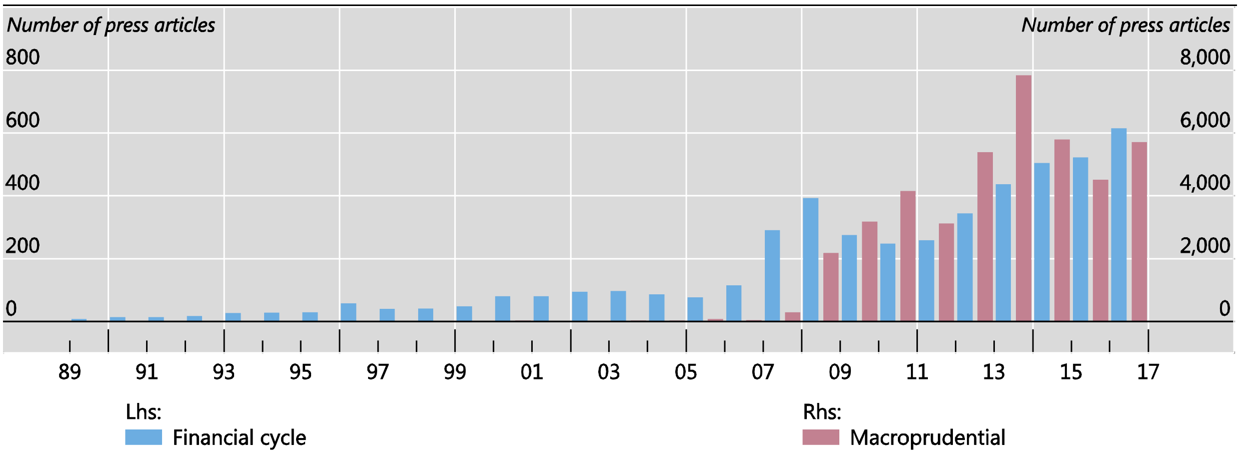
Sources: Bloomberg; ICE; national data: BIS calculations.

To be sure, one may legitimately wonder whether this fundamental intellectual shift has been sufficiently embedded in the current vintage of macroeconomic models. Personally, I doubt it: the issues are inherently complex. But it has definitely spread to other policymaking areas, not least monetary policy.

That all this is now taken for granted is simply testimony to how entrenched the intellectual shift has become. For instance, alongside the term "macroprudential", the term "financial cycle" has grown increasingly familiar. This is indicated in Graph 4, which traces the term's increasingly frequent appearance in the press (blue bars), largely mirroring the pattern for the term "macroprudential".

This intellectual shift is extremely welcome and probably the major gain.

Growing popularity of the terms "macroprudential" and "financial cycle" Graph 4



Source: Factiva.

II – Macroprudential frameworks: progress and outlook

Let me now turn to the assessment of the implementation of macroprudential frameworks.

Post-crisis, we have been gaining considerable experience with the frameworks, including with the identification of risks, the deployment of tools, the impact of the measures, and governance arrangements. In all of these areas, substantial progress has been made. I shall mention just a few points about each; you can read more about them in the chapter.

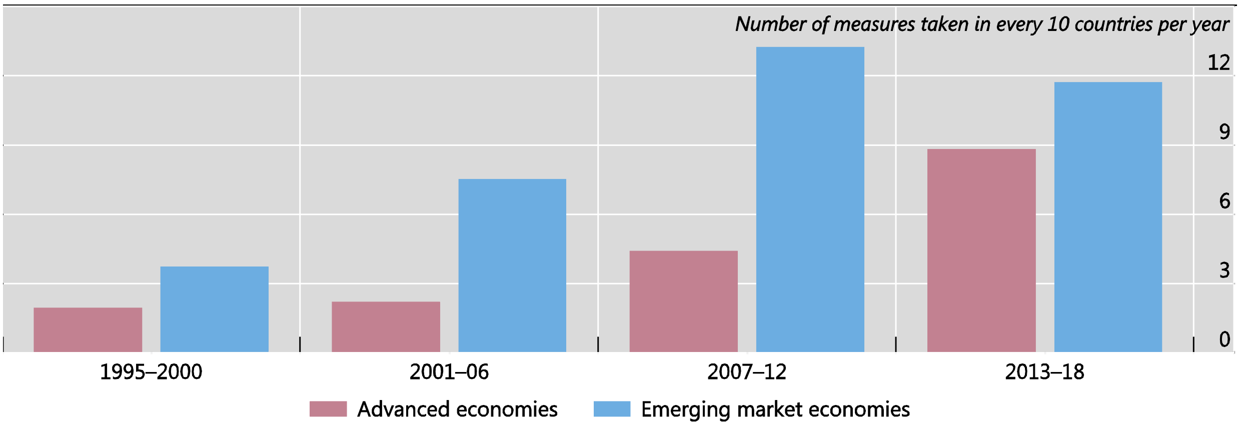
While identifying the build-up of risks remains a challenge, the authorities can now rely on a broad range of tools. These include: aggregate early warning indicators of possible stress a few years in advance, typically based on the notion of the financial cycle; banking system-wide (or financial system-wide) stress tests (so-called macro stress tests); and more qualitative analyses based on a wide array of information.

What are the key takeaways from the experience so far? One takeaway is that there is a need to regard the aggregate analysis only as a starting point for more refined and comprehensive assessments. These may, for instance, look at how debt burdens are distributed across the population of households and firms.

Another takeaway is that macro stress tests are helpful, but have their limitations. In fact, none of them identified the serious risks ahead of the GFC. Technical difficulties in capturing second-round effects loom large, not least as a result of the weaknesses of current macro models. Thus, if improperly used, macro stress tests could even foster a false sense of security. By contrast, they have proved much better as devices to enforce the required recapitalisation after a crisis. Moreover, stressing balance sheets has also been useful in calibrating tools, such as maximum loan-to-value ratios (LTVs) and debt service-to-income ratios (DSTIs).

Turning next to the deployment of tools, it has become clear that this is subject to a number of constraints, of a technical as well as a political economy nature. For instance, vulnerabilities build up only very slowly, so that there is a high risk of being seen as crying wolf and taking unnecessary measures. Similarly, the near-term costs are obvious, at least to some interest groups, while the long-term benefits, though very large, are hard to measure, even ex post. Still, while the risk of an "inaction bias" is real, it has not prevented the more frequent use of measures. This is shown in Graph 5. We see that the number of measures has tended to increase, especially in advanced economies, but that they are more frequently used in emerging market economies.

Macroprudential: growing use of measures over time | Graph 5



Sources: BIS calculations; work done for the BIS Annual Economic Report 2018.

The impact of the tools varies. Naturally, most of them are very useful in building buffers and hence the financial system's resilience. That said, they differ in their ability to restrain the growth in credit and asset prices. In particular, maximum LTVs and DSTIs have proved to have a larger and more discernible effect than, say, countercyclical provisions or the countercyclical capital buffer.

This is illustrated in Graph 6. The light blue bars for provisions and the countercyclical capital buffer indicate that their impact is not statistically significant. This result has been confirmed by policymakers' own assessment of their experience and contrasts with the impact of LTVs and DSTIs (dark blue bars). This is both economically and statistically significant.

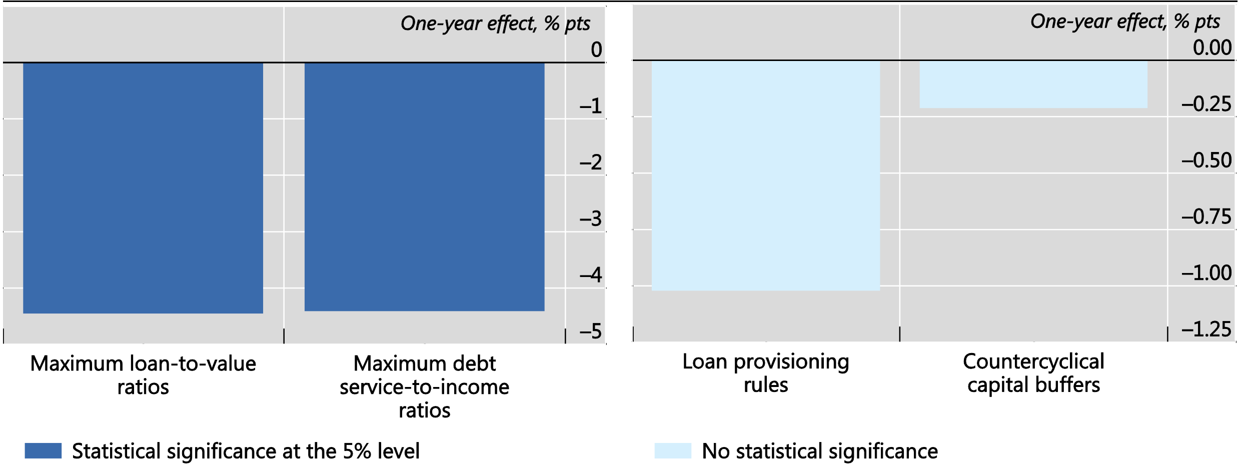
In addition, macroprudential instruments in general have some limitations. Most of them apply only to the banking sector. They can leak, ie they are subject to regulatory arbitrage, both within and across countries, possibly pushing activity into the darker corners of the financial system. And, at least *as used so far*, they have not necessarily prevented the emergence of familiar signs of financial imbalances – for instance, in the form of outsize credit growth. This is illustrated in Graph 7, which indicates how the use of the tools (blue bars) did not prevent credit growth from exceeding long-term averages by a large margin (specifically, a highly positive credit-to-GDP gap, red line): the red line is above the dotted horizontal line, which refers to the ceiling for the activation of Basel III's countercyclical capital buffer.

From all this, I draw a number of implications concerning instruments. The analysis suggests that: it is desirable to better identify risks and calibrate macroprudential tools accordingly; to develop more tools that target the non-bank sector, such as asset managers and capital markets more generally; to consider implementing further mechanisms to address cross-country leakages, analogous to the reciprocity clauses of the countercyclical capital buffer; and to complement macroprudential measures with other policies. I will come back to this last point in a moment.

Impact of macroprudential measures on bank credit

Impact of tightening[1]

Graph 6

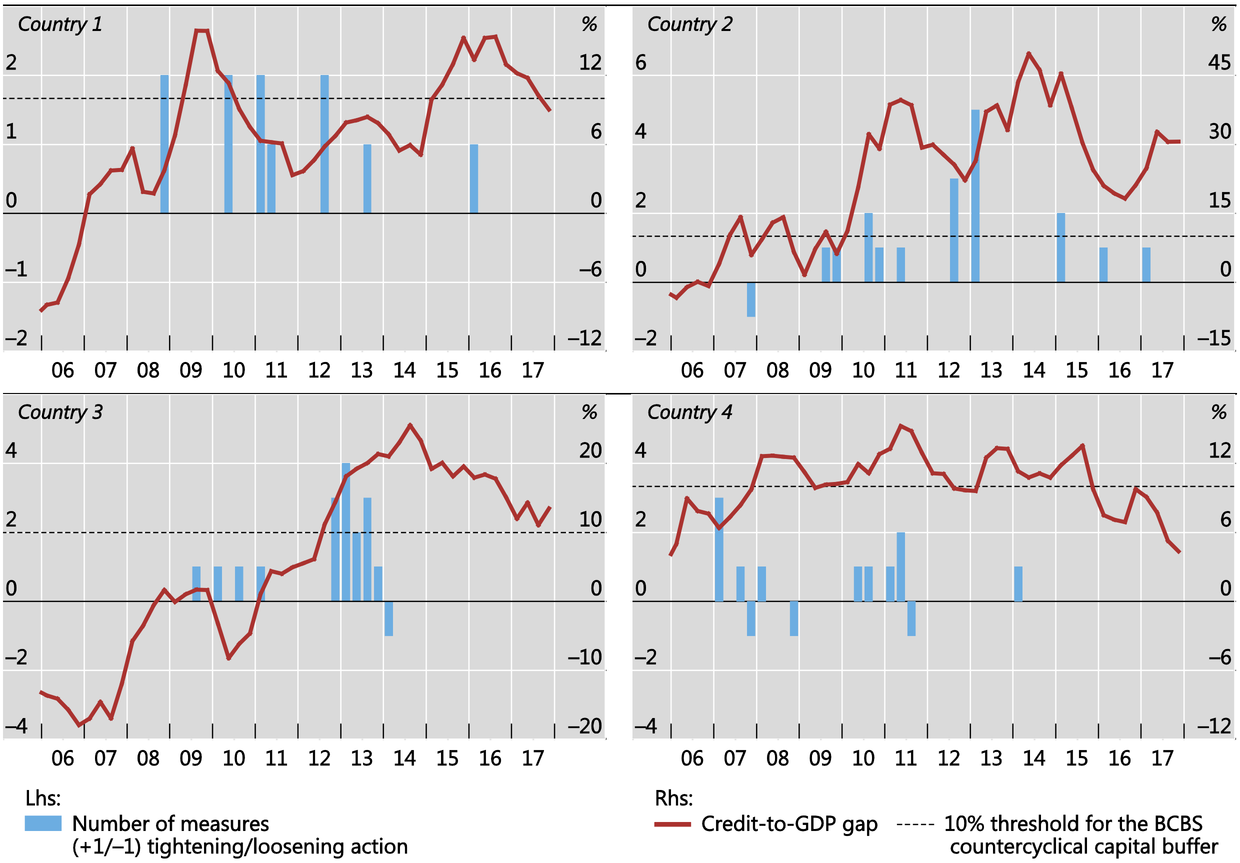


[1] For maximum loan-to-value ratios, maximum debt service-to-income ratios and loan provisioning, impact on housing credit growth; for countercyclical capital buffers, impact on bank credit growth.

Sources: BIS calculations; work done for the BIS Annual Economic Report 2018.

Some signs of financial imbalances even where measures are used actively

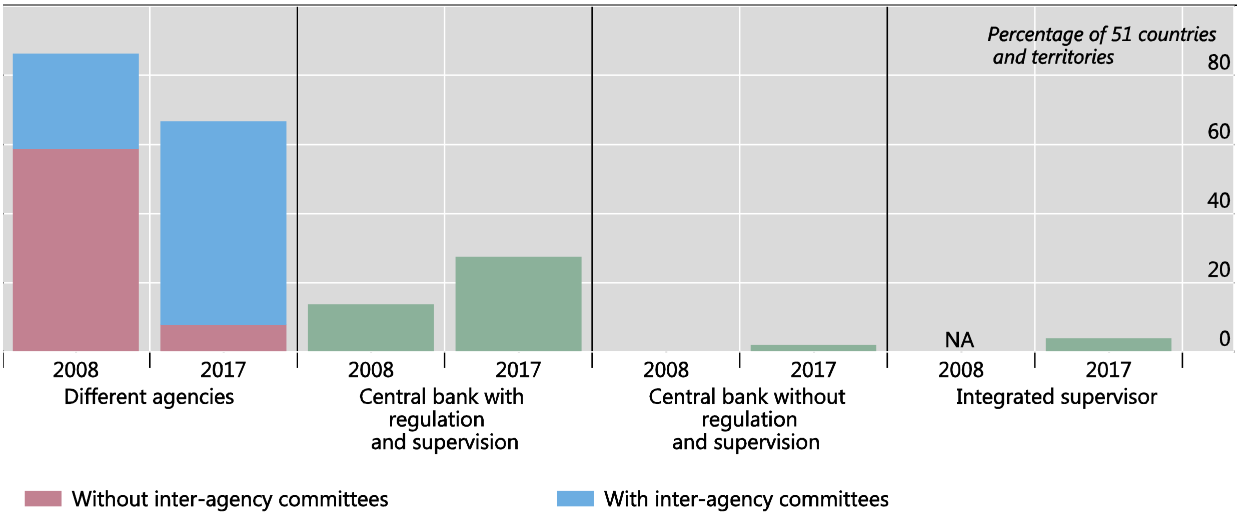
Graph 7



Sources: BIS; BIS calculations; work done for the BIS Annual Economic Report 2018.

Finally, what about governance arrangements? Experience indicates that there is no one-size-fits-all, as they vary a lot across countries. As Graph 8 shows, the most common arrangement is a committee bringing together various authorities (the blue segments of the two bars on the far left). The second most common is entrusting the central bank with responsibility for both the regulation and supervision of individual institutions and macroprudential measures (next set of bars from the left). In general, central banks play a prominent role, making them even more essential for financial stability.

Who is responsible for macroprudential frameworks? Graph 8



Source: BIS surveys.

So far, the experience with governance arrangements has been mixed. For instance, a BIS survey of central banks suggests that coordination through inter-agency committees has not always worked well.

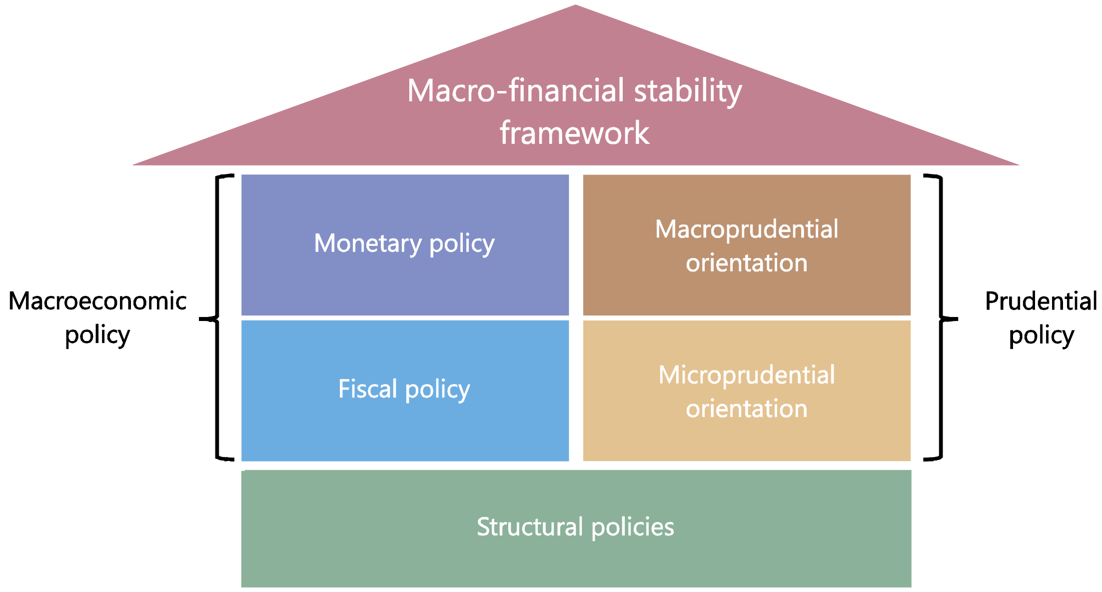
In passing, let me also note a point concerning the need for policymakers' autonomy in this area. My sense is that, in *crisis prevention*, as opposed to *crisis management*, the need for autonomy from the government has been underestimated. True, compared with an inflation-oriented monetary policy, the measures have more obvious distributional implications and the objective is fuzzier. But the lag between actions and effects on the ultimate goal is longer, and there is hardly any constituency against the inebriating feeling of getting richer during a boom. Thus, taking away the proverbial punchbowl is, if anything, even harder than in monetary policy.

My bottom line from all this? If we are to make further progress in implementing effective macroprudential frameworks, we need a pragmatic mix of ambition and realism. Ambition to develop tools further, to target them better, to overcome any inaction bias and, where needed, to coordinate internationally. Realism to understand the tools' and frameworks' limitations, and hence not to entertain overly optimistic expectations about what they can do on their own.

III – Towards a macro-financial stability framework

This naturally brings me to my last point: the need to embed macroprudential frameworks in a broader macro-financial stability framework. As illustrated in Graph 9, such a framework also involves other policies, including monetary, fiscal and even structural ones, underpinned by strong (microprudentially oriented) regulation and supervision of individual institutions.

Towards a macro-financial stability framework Graph 9



Source: BIS.

This should have two advantages. First, ensuring a more balanced policy mix, so as not to overburden macroprudential measures. And second, improving the chances of achieving lasting financial and macroeconomic stability and hence more sustainable growth.

The precise balance between the various policies is still subject to debate. More analysis is no doubt needed. Since we have already discussed the role of these policies in some detail in previous Annual Reports, here let me just mention a few key points for each.

The role of monetary policy is still quite controversial. It is generally agreed that monetary policy and macroprudential measures interact closely, that monetary policy can affect the build-up of financial imbalances – after all, it operates partly by influencing credit, asset prices and risk-taking – and that monetary policy can complement macroprudential measures because it can reduce leakages, since it is much more pervasive. But views about its role depend on the degree to which one considers macroprudential and microprudential measures sufficient to ensure stability as well as on assessments of any collateral damage that monetary policy may have.

Clearly, the room to use monetary policy increases once central banks' anti-inflation credibility is established. This is because, at a minimum, a more financial stability-oriented monetary policy requires a certain tolerance for deviations of inflation from objectives and a lengthening of the policy horizon.

Moreover, using monetary policy involves not only interest rates but also foreign exchange intervention. Just as with other macroprudential tools, leaning with foreign exchange intervention can help build up precautionary buffers in good times so as to run them down in bad times. And it may also help constrain the build-up of imbalances, at least as long as market participants do not perceive it as providing insurance.

The role of fiscal policy, too, is multifaceted. The tax code can be used to influence credit and asset prices. In particular, it would be very helpful to reduce the tax bias that typically favours debt over equity. In addition, it is important to ensure sufficient fiscal space to address any crises that might materialise: as we know, the sovereign's balance sheet is the ultimate backstop for the financial sector. Ensuring fiscal space requires full recognition of the flattering effect that financial booms have on the fiscal accounts, obscuring their underlying strength.

Finally, structural policies can help too. For instance, regulations that artificially constrain land supply can amplify property price booms and busts. And more generally, inflexible labour and product markets reduce an economy’s resilience to macroeconomic downturns.

Conclusion

Let me sum up. Substantial progress has been made in implementing macroprudential frameworks. But challenges remain. And they will require action well beyond the bounds of the narrow macroprudential sphere itself.

Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

Globalization and the geography of capital flows[1]

Carol Bertaut, Beau Bressler, and Stephanie Curcuru,

Board of Governors of the Federal Reserve System

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[1] This paper was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

Globalization and the Geography of Capital Flows

Carol Bertaut, Beau Bressler, and Stephanie Curcuru[1]

This version: November 21, 2018

Abstract:

The growing use of low-tax jurisdictions as locations for firm headquarters, proliferation of offshore financing vehicles, and growing size, number, and geographic diversity of multinational firms have clouded the view of capital flows and investor exposures from standard sources such as the IMF Balance of Payments and the Coordinated Portfolio Investment Survey. We use detailed, security level information on U.S. cross-border portfolio investment to uncover the extent of distortions in the official U.S. statistics. We find that roughly $3 trillion – nearly a third of U.S. cross border portfolio investment – is distorted by standard reporting conventions. Moreover, this distortion has grown significantly in a little over a decade. Expanding to consider global implications, we estimate that roughly $10 trillion – about one-fourth – of the stock of global cross-border portfolio investment is similarly distorted. Our results have implications for conclusions we draw about the factors influencing flows to emerging markets, trends in home bias, and the sustainability of the U.S. current account deficit.

Keywords: Balance of Payments, Capital Flows, Financial Globalization, Foreign Assets, International Financial Data

JEL classification: F30, F32, G15

[1] The authors are, respectively, Deputy Associate Director, Senior Research Assistant, and Assistant Director in the Division of International Finance at the Board of Governors of the Federal Reserve System. Matthew Guse, Patrick Kennedy, and Andrew Watrous provided excellent research assistance. The views expressed are solely the responsibility of the authors and should not be interpreted as reflecting the views of the Board of Governors of the Federal Reserve System or of any other person associated with the Federal Reserve System.

1. Introduction

After the global financial crisis, the G20 supported several efforts to produce improved global capital flow and investment statistics, with the goal of a better understanding of cross-border linkages and investor exposures. With respect to cross-border portfolio investment – cross-border flows and positions in bonds and equity – these initiatives included increased participation in the IMF's Coordinated Portfolio Investment Survey (CPIS), and efforts to increase both frequency and granularity of the CPIS, including providing detail on issuer and investor sectors.

However, these efforts to improve the matrix of global portfolio assets and liabilities are not sufficient to gain a thorough understanding of global capital movements due to an ongoing fundamental limitation: These statistics use the official balance of payments (BOP) framework that collects cross-border flows and positions according to *legal residence*. This legal residence concept is increasingly uninformative in a world of increasing globalization and growth in and use of offshore financial centers and tax havens, because there is an increasing disconnect between the legal residence and the economic exposure. Firms issuing securities may not do any business at that legal residence, and thus ownership of such securities may say little about the actual exposures investors face. Thus, even if efforts to improve the country coverage are successful, official statistics will still provide an increasingly distorted view of linkages and economic exposures. Lane and Milesi-Ferretti (2017) provide an overview of the distortionary effects of increasing offshore issuance and financial center intermediation on properly assessing external exposures.

There appear to be two main causes of the firm behavior that lead to the distortions between country residence and economic exposure we observe in the cross-border capital flows and position data. The primary cause is tax considerations. When able, multinational firms locate in the jurisdiction with the lowest tax rate (see for example the survey on the tax competition literature in Keen and Konrad 2013). This is most common for firms with substantial intangible and other portable assets (Desai, Foley, and Hines 2006, Hebous and Johannesen 2016, Pomeroy 2016, Devereaux and Vella 2017, among others). This relocation is responsible for the elevated reported capital flows associated with firms incorporated in Luxembourg and other low-tax jurisdictions. These tax havens are associated with neither firm production nor expenses, so inferring country exposure from standard cross-border statistics is incorrect.

Another main driver of the distortions is firms seeking to improve their access to capital markets and the pool of global bond investors. Many firms, particularly those in emerging market economies (EMEs), issue corporate bonds using a subsidiary firm located in markets outside their home country. For this debt, the residence-based statistics will attribute transactions to the location of the subsidiary. There are many factors driving the use of offshore subsidiaries. Black and Munro (2010) find that companies located in countries with relatively small bond markets issue bonds offshore to improve pricing, access foreign investors, and to issue larger, lower-rated or longer-maturity bonds. Serena and Moreno (2016) identify a pickup in offshore issuance by firms in EMEs following the global financial crisis, which they attribute to declining financing costs and the less developed state of EME financial markets more generally. However, the longer-term trend since the Asian Financial Crisis in the late 1990s has been away from offshore issuance, which is generally denominated in hard currencies, to local-currency issuance in the domestic bond market (Black and Munro 2010, Mizen et al 2012, Hale et al 2016). While we observe a pick up in the amount of offshore issuance by EMEs, the amount of issuance in the local market is growing even more rapidly.

A separate source of distortion in global statistics arises from the growing importance of mutual funds as a vehicle for cross-border investment. Under international standards, holdings of investment fund shares are classified as equity holdings, and, for cross-border fund holdings, to be assigned to the country of fund incorporation. These standards apply regardless of the focus of the investment fund in terms of either the type of assets that the fund invests in or country of investment focus.

In this study, we construct different measures of country-level holdings and estimates of economic exposures to understand the extent of distortions in existing residence-based portfolio statistics. Many questions of interest to economists and policymakers concern inter-country economic exposures. Similarly, when deciding where to invest, international investors make their decisions based on the economic exposure of a firm, rather than where it is incorporated. For the reasons mentioned above the official statistics are an increasingly poor proxy for economic exposure. To address these concerns, we assign U.S. portfolio holdings to specific countries by three classifications: residence, nationality, and economic exposure. Residence is the standard BOP framework of the legal residence of the entity issuing the security. We define nationality as the location where the ultimate parent of the entity has its center of operations. Finally, we define economic exposure by where the firm does business, in terms of the shares of its sales.

We map the underlying security-level data on U.S. portfolio holdings, collected on a residence basis for the Balance of Payments, to commercial data sources to calculate U.S. holdings on these alternative classifications. First, we use commercial country level investment products designed for international investors, along with ultimate parent data for offshore debt issuance, to convert U.S. portfolio holdings to a nationality basis. Second, we use detailed firm-level information on the geographic distribution of firm sales to provide preliminary estimates of the actual country-level economic exposures of U.S. investors.

We use information on U.S. cross-border investments as a case study, but our results can be generalized to draw conclusions about the extent of global distortions. We find that roughly \$3 trillion – nearly a third of U.S. cross border portfolio investment – is distorted when we compare our nationality-based measures to the standard BOP reporting conventions. Moreover, this distortion has grown significantly in a little over a decade. Expanding to consider global implications, we estimate that roughly \$10 trillion – about one-fourth – of the stock of global cross-border portfolio investment is similarly distorted in our current statistics. Our results have implications for conclusions we draw about the factors influencing flows to emerging markets, trends in home bias, and the sustainability of the U.S. current account deficit.

The remainder of this paper is organized as follows. Section 2 discusses our findings on the extent of distortion in reported cross-border investment in detail. 2a focuses on U.S. cross-border holdings of bonds and 2 b. on equity. Section 2c extends our analysis to estimate the extent of distortion in global cross-border portfolio investment. In section 3, we discuss implications of documented mismeasurement for analysis of cross-border portfolio flows, and section 4 outlines implications for measures of home bias and factors affecting cross-border portfolio decisions. Section 5 discusses our preliminary findings of economic exposure based on where firms actually do business when we consider the full U.S. equity portfolio, including holdings of domestic securities. Section 6 concludes with a discussion of implications more generally for our interpretations of financial flows and various components of the current account.

2. The extent of the problem: distortions in cross-border portfolio statistics

2a. Increasing use of offshore financing arms and implications for cross-border holdings of long-term debt

The international debt securities statistics produced by the Bank for International Settlements (BIS) illustrate the growing disconnect between residence and nationality measures of debt securities issued via offshore financing arms. International debt securities are primarily those issued in a market other than the home country.[2] Figure 1a shows international issues of corporate debt outstanding for a selected number of EMEs, with country attribution on the standard balance-of-payments residence basis. According to these statistics, internationally issued corporate debt of these countries totaled about $900 billion in 2016. The largest EM corporate borrowers in this market were Mexico and Korea, although China has had the fastest growth. Figure 1b shows international corporate debt securities for the same EMEs, but this time with country attribution assigned on a nationality basis. The total amount of bonds outstanding for these countries is now much higher, at nearly $2 trillion. China is by far the largest issuer, followed here by Brazil and Russia. Figure 1c shows the current differences in these measures.

These differences between the residence- and nationality-based statistics arise because Chinese, Brazilian, and Russian companies primarily issue international debt securities via financing arms located in financial centers, such as the Cayman Islands, Ireland, and Luxembourg. On a residence basis, these securities are allocated to the

[2] For a detailed discussion of recent enhancements to the BIS international debt securities statistics, see Gruic and Wooldridge (2012) https://www.bis.org/publ/qtrpdf/r_qt1212h.pdf. BIS securities statistics are available at https://www.bis.org/statistics/secstats.htm

country where the financing arm is legally resident, similar to the IMF BOP statistics. On a nationality basis, they are recognized as being securities of the ultimate parent firm.

We find that reported cross-border holdings of U.S. bond investors are similarly misrepresented. We conduct our analysis by exploiting the underlying security-level data from the comprehensive reports on U.S. Portfolio Holdings of Foreign Securities, conducted as of end-December 2001 and then annually since 2003.[3] These data are collected for BOP purposes, and thus country attribution is assigned on a residency basis. But because we observe the actual securities held, we are able to map U.S. investor holdings from a residence basis to nationality basis.[4] To investigate the extent of distortion in debt securities, we focus on U.S. investors' holdings of foreign-issued corporate debt, as government debt typically is unaffected by offshore issuance.

Figures 2a and 2b illustrate the growing divergence between the residence- and nationality-based country attribution of U.S. investor holdings. On a residence basis (figure 2a), U.S. holdings of foreign-issued corporate debt securities have risen from about $300 billion in 2001 to about $1,700 in 2016. By 2016, roughly 40 percent of total holdings consisted of securities issued out of offshore centers or tax havens, an increase from roughly 30 percent in the early 2000s. Holdings of EME corporate debt account on average for about 8 percent of U.S. holdings of foreign corporate debt.

On a nationality basis (figure 2b), however, holdings of foreign corporate debt securities have risen less, reaching only about $1,300 billion in 2016. The lower value largely reflects increased issuance by financing arms of U.S. corporations established in offshore centers. Bonds of such U.S. entities accounted for nearly a quarter of "foreign" issued debt held by U.S. investors in 2016. That said, U.S. holdings of the debt of some other countries and regions are substantially understated. In particular, EME corporate debt holdings are notably higher on a nationality basis and have grown faster in recent years. By 2016, our estimate of U.S. investment in EME corporate debt is 60 percent higher than under the residence-based statistics. Overall, offshore issuance currently distorts the geography of more than a third of U.S. holdings of foreign corporate debt.

Figures 2c and 2d illustrate how residence-based statistics can distort estimates of changes in investor preferences and portfolio allocations. On a residence basis

[3] These surveys are conducted through the Treasury International Capital System, a joint undertaking of the U.S. Treasury Department, the Federal Reserve Bank of New York, and the Board of Governors of the Federal Reserve System. Earlier surveys were also conducted in 1994 and 1998. Although referred to as "surveys", data reporting is mandatory. Further information about the surveys, including the survey reports and instructions, are published on the U.S. Treasury's website: https://www.treasury.gov/resource-center/data-chart-center/tic/Pages/index.aspx

[4] We are grateful to our colleague Seung Jung Lee and his coauthors for their fuzzy text matching code to enable us to identify and match the individual securities, as many were not reported with standard security IDs, especially in earlier years. See Cohen et al (2018).

(figure 2c), U.S. investors appear to have allocated a much larger share of their portfolios to Mexican corporate debt than to Brazilian corporate debt, and own essentially no Russian corporate debt. On a nationality basis (figure 2d), however, U.S. investors' holdings of Brazilian debt rival and at times exceed those of Mexican debt.[5] The nationality-based holdings also show that U.S. investors have non-trivial holdings of the Russian corporate sector, a finding completely missed in residence-based holdings statistics.

2b. Distortions in cross-border equity holdings

For cross-border equity holdings, two factors contribute to the major disconnect between residence-based statistics and economic exposures. First, as noted in the introduction, many large multinational firms have found it advantageous to incorporate in tax-favored jurisdictions, which becomes their legal residence. For many firms there are little or no operations or sales in the country of incorporation, so there is no economic exposure to that country. Second, investment fund holdings are attributed to the countries where the funds are incorporated, which is often driven by tax considerations. These country allocations are also often unrelated to actual investor exposures. We estimate the distortions created by these two factors below by mapping residence-based holdings to nationality-based portfolios.

2b1. Common Stock

Distortions in estimates of exposure based on the residence-based geography of U.S. cross-border equity holdings arising from large multinationals incorporating in lower-tax jurisdictions is not a new phenomenon. For example, Schlumberger – long one of the largest 100 global firms – has been operating in the U.S. since the 1930's and is headquartered in Houston, Texas, but has been incorporated in Curaçao since 1956.[6] As a result, the U.S. cross-border statistics show that U.S. investors have had large holdings of Netherlands Antilles/ Curaçao equity for some time. These distortions have become more pronounced in recent years following a wave of cross-border mergers and corporate "inversions", whereby former U.S.-resident firms have become foreign-resident firms after the merger.[7] For example, following recent high-profile inversions in the pharmaceutical industry such as Actavis/Allergan and Medtronic/Covidien, the equity of several major U.S. firms is now considered "Irish"

[5] Note, however, that our estimates of total U.S. holdings of Mexican corporate debt are most likely somewhat understated in the pre-crisis years, even on a nationality basis, because at that time Petroleos Mexicanos (PEMEX) also issued debt out of a U.S. (Delaware) financing arm, PEMEX Project Master Funding Trust. Ideally, we would want to include U.S. investor holdings of these Delaware-issued PEMEX bonds to our estimates of Mexican corporate debt on a nationality basis. Unfortunately, the U.S. claims surveys that are the basis of our analysis do not include securities issued from Delaware financing arms, because such securities are considered U.S. securities.

[6] http://www.fundinguniverse.com/company-histories/schlumberger-limited-history/

[7] "Inversions" refer to M&A activity where the acquiring firm is typically larger than the target firm. After the merger, the combined firm "inverts" to establish its residence in the country of the target firm, which is typically a lower-tax jurisdiction.

equity according to official statistics. Adding to these distortions has been the increasing presence of EME firms incorporated in the Caribbean. This is especially notable for some large Chinese firms including Alibaba, Baidu, and Tencent.

Residence-based statistics for cross-border equity holdings are thus imperfect estimates of portfolio exposures. Commercially available country-level investment products designed for international investors do not rely on residence for determining country allocation, and instead match firms to countries based primarily on the location of operations. This leads to large differences between the country-assignment of firms in the residence-based statistics and mutual fund industry benchmarks such as MSCI or FTSE Global indexes. MSCI continues to treat Medtronic as a U.S. firm despite its incorporation in Ireland since its merger with Covidien in 2015, because its operations are largely U.S.-based and its shares continue to trade on the NYSE. And since December 2015, MSCI has included Alibaba and Baidu in its EME/China indexes, although they are both incorporated in the Cayman Islands and their shares trade on the NYSE and the NASDAQ, respectively.

Similar to our exercise for reassessing country exposures by reassigning bonds issued offshore to the country of ultimate parent, we use the underlying security-level data to reassign U.S. holdings of foreign common stock according to constituent information for the MSCI. We are able to do so for the years 2005 through 2016.

Figures 3a and 3b show the evolution of U.S. holdings of foreign common stock according to standard residence-based country attribution (figure 3a) and nationality-based attribution (figure 3b). As we found with U.S. investment in foreign bonds, an increasing source of distortion arises from firms that the MSCI classifies as "U.S." but are legally incorporated outside the United States. This share has grown from less than 10 percent in 2005 to 16 percent in 2016, totaling more than $900 billion. U.S. holdings of EME equity are also considerably larger by MSCI definitions, in large part reflecting the classification to EMEs of large Chinese firms incorporated in offshore centers. Overall, we find that by 2016, roughly $1.3 trillion – nearly a fourth – of U.S. holdings of foreign common stock was attributed by official statistics to a country different from its country of nationality as classified by MSCI.

2b2. Fund shares

Fund shares add additional layers of distortion. International standards call for holdings of investment fund shares to be reported as equity holdings, and, for cross-border fund holdings, to be assigned to the country of fund incorporation. These standards apply regardless of the focus of the investment fund in terms of either type of assets the fund invests in (stocks, bonds, commodities, derivatives, money market instruments, or mixed allocations) or country of investment focus. So for fund shares, there is a mismatch between the country of residence and country of nationality, similar to what we observe for bonds and equities. But there is the additional problem of misallocation to security type.

To investigate the potential distortions in fund share holdings, we again use the detailed holdings from the U.S. claims surveys. About 15 percent of the foreign equity held by U.S. investors – $1.2 trillion as of 2016 – is in the form of fund shares and types of equity other than common stock. The fund and other equity share is much higher for equity holdings in financial centers: 77 percent for the Cayman Islands, 82 percent for the British Virgin Islands, and 53 percent for Luxembourg. The underlying data indicate that U.S. investments in foreign-issued funds consist of a wide variety of assets and exposures, including ETFs that track the S&P 500 and other U.S. stock indexes, funds that invest in U.S. Treasuries, and a variety of real estate focused funds, emerging markets funds, and commodities-focused funds. About $450 billion consists of securities of various private equity funds. These funds are especially opaque in their portfolio allocations, but it is unlikely that they represent exposures to the Cayman Islands, for example. Indeed, many of these private equity holdings may reflect corporate investments in the United States.

We can gain some information on the underlying investments of Cayman Islands-based investment funds from Cayman Island's submissions to the CPIS.[8] Beginning in December 2015, these submissions have included assets held by investment funds resident in the Cayman Islands. Total reported cross-border portfolio holdings are roughly $1.6 trillion as of December 2016, with more than half (a little over $900 billion) in debt securities and the remainder in cross-border equity. About 70 percent of these holdings are of U.S. securities. About 15 percent is securities issued by other advanced economies and the residual 15 percent all other countries, including EMEs.[9]

Similar information on the assets underlying fund shares held by global investors is available for Luxembourg. The Central Bank of Luxembourg publishes monthly information on the broad asset classes held by non-monetary funds established in Luxembourg.[10] Total assets of these funds amounted to nearly $2.9 trillion at end-2016. As a share of total assets held, just under a third of these funds are as equity funds, a slightly larger share (36 percent) are bonds funds, and just under a quarter are mixed bond-equity funds. The remaining 10 percent are hedge funds, real estate funds, and other funds. For equity, bond, and mixed funds, the data indicate that only about a third of securities held as assets of the fund were issued in the euro area. About 27 percent are U.S. securities. Another 10 percent are securities issued by other European Union countries, about 4 percent were Japanese securities, and about a quarter from other countries including emerging markets.

While it is difficult to determine precisely the nationality-based country exposures that U.S. holdings of foreign fund shares represent, it is clear that that they are not primarily exposures to the economies of the Cayman Islands or Luxembourg, where the majority of these funds are located. To quantify the distortion in total U.S. investment in foreign funds and other types of equity, we make a conservative assumption that only U.S. holdings of fund shares and other equity located in the

[8] Details on CPIS reporting results are available at this link: http://data.imf.org/?sk=B981B4E3-4E58-467E-9B90-9DE0C3367363.

[9] Prior to the inclusion of the holdings of investment funds, the Cayman Islands reported only security holdings of Cayman-resident banks, and consequently their total reporting to the CPIS was much lower. For example, the Caymans reported only $61 billion in cross-border assets to the CPIS in June 2015.

[10] http://www.bcl.lu/en/statistics/series_statistiques_luxembourg/13_investment_funds/index.html

Caribbean and only half of such equity located in European countries reflects underlying assets of another location. Even under these conservative assumptions, fund share holdings add nearly $1 trillion to the distortion in U.S. foreign portfolio statistics in 2016.

Combining our findings for U.S. cross-border investment in bonds, common stock, and fund shares, we estimate that nearly $3 trillion of the total $9.6 trillion in foreign portfolio securities held by U.S. investors in 2016 reflected exposures to countries other than as reported in the official statistics (table 1). Comparing 2016 results with 2005 shows how much these distortions have increased in just over a decade: In 2005, only a little over $800 billion of U.S. holdings of foreign securities reflected investment in a different country of exposure.

2c. Implications for global cross-border distortions

Global statistics provide similarly misleading estimates of country exposures. While U.S. and foreign investor portfolios certainly differ in terms of portfolio allocations and country concentrations, geographic misallocations arise primarily through holdings of securities issued via offshore centers. Because U.S. investors in aggregate are likely representative of global investors in terms of these offshore holdings, we are comfortable in drawing conclusions about global distortions from our analysis of U.S. holdings.

Overall, we estimate that nearly a quarter – almost $10 trillion – of the aggregate cross-border holdings of bonds and equity as reported in the IMF's CPIS for 2016 likely reflect holdings of a different country than reported (table 2).[11] For bonds, we estimate that more than $2.5 trillion of the roughly $20 trillion reported is affected. Distortions are larger for global cross-border equity holdings, in large part because of the growing importance of fund shares, as evidenced by the growing importance of holdings in Luxembourg and the Cayman Islands. These two countries are the second and third largest destinations for cross-border equity investment after the United States, according to the CPIS. We estimate that more than $7 trillion of the roughly $20 trillion in cross-border equity and investment fund holdings reported in the CPIS for end-2016 are distorted by residence-based reporting.

Estimates for some countries and regions of particular interest to global policy makers are especially distorted. We estimate that global holdings of EME bonds and equity in the CPIS are understated by about $1.5 trillion, reflecting both corporate bonds issued via offshore financing arms and the growing market cap of emerging market firms incorporated in offshore centers. Global holdings of U.S. securities are also understated, owing to the legal incorporation of U.S.-based multinationals in low-tax jurisdictions, as well as the investments of funds located in offshore centers. Securities holdings of other advanced economies, including Germany, Italy, and Spain are also likely understated, because their firms frequently issue debt securities via Luxembourg and Netherlands financing arms.

[11] We exclude SEFER (reserves) holdings from this analysis. Foreign exchange reserves holdings are primarily invested in sovereign debt, which is largely unaffected by these considerations.

3. Implications of geographical distortions in interpreting balance of payments flows:

These differences between as-reported country of residence and country of nationality are important for how we interpret developments in capital flows. Figures 4a and 4b show total U.S. purchases of foreign bonds and foreign stocks on a residence basis. The figures decompose purchases into those of "true" foreign securities and those of securities where the ultimate parent or center of operations is actually in the United States.

Figure 4a illustrates that in the lead-up to the 2007-2009 global financial crisis, roughly a third of the foreign bonds acquired by U.S. investors were actually purchases of U.S. assets. In large part, these were purchases of asset-backed securities issued by special purpose vehicles established by U.S. financial institutions in the Cayman Islands, and of which the underlying assets were U.S. mortgages. Purchases of "true" foreign bonds did increase over this period, but not as dramatically as the residence-based statistics indicate. The adjusted flows also paint a somewhat different picture of U.S. purchases of foreign bonds in more recent years: purchases of "true" foreign bonds are a noticeably weaker in 2014 and 2016 and more than account for the foreign bond sales in 2015. Figure 4b shows that purchases of "true" foreign equity – excluding securities of firms that MSCI includes as U.S. – are also smaller. Indeed, they are only about half as large in the past couple years.

However, there are also differences within our adjusted purchases of foreign securities. Figures 4c and 4d show purchases of EME bonds and stocks on both a residence and nationality basis. On a nationality basis, U.S. purchases of EME bonds are stronger in earlier years, but sales in recent years are also somewhat larger. Purchases of EME equity are larger through 2015 (especially in 2014 and 2015), but indicate that U.S. investors actually sold EME equity in 2016.

4. Implications of distortions for measures of home bias and our understanding of global investment decisions

4a. Measures of Home Bias

The distortions we identify affect how we think about evolving investor preferences, including measures of "home bias" and the drivers of portfolio allocations. "Home Bias" refers to the lack of diversification of international investors relative to the optimal holdings implied by the International Capital Asset Pricing model (ICAPM). The ICAPM predicts that in a world with frictionless markets the optimal asset allocation is the world portfolio; in other words, investors should spread their wealth among global equities according to each asset's share of global market capitalization. For example, since U.S. equities currently make up about 40 percent of global market capitalization, about 40 percent of U.S. investors' equity holdings should be in U.S. stocks.

The basic calculation for home bias thus compares portfolio allocations in foreign (to the investor) equity to shares in global market capitalization:

$$\frac{\frac{(holdings\ of\ foreign\ equity)}{(total\ equity\ portfolio)}}{\frac{(foreign\ equity\ market\ cap)}{(world\ equity\ market\ cap)}}$$

Note that if portfolio shares are close to or equal market capitalization shares, this ratio will be close to one. This ratio is typically subtracted from 1 to measure "home bias", so that the larger this ratio, the greater the extent of home bias:

$$1-\frac{\frac{(holdings\ of\ foreign\ equity)}{(total\ equity\ portfolio)}}{\frac{(foreign\ equity\ market\ cap)}{(world\ equity\ market\ cap)}} \tag{1}$$

In reality, investors in the U.S. and across the globe hold much larger shares of their wealth in domestic assets than predicted by the ICAPM. There is a large literature on the potential causes of home bias, which include hedging motives arising from exchange rate and other risks, and frictions such as transactions costs as well as easier access to and better information about domestic markets. Coeurdacier and Rey (2013) provide a comprehensive survey of this literature. This literature focuses on factors that affect investor demand for exposure, and the associated characteristics of investment in different countries. Thus, there can be a mismatch between the theory and home bias calculations calculated using residence rather than nationality-based measures.

Research into home bias generally finds that factors such as better information (as proxied by common language and trade linkages) as well as easier market access (for example, through issuance of depository receipts and cross-listing) help reduce home bias. Indeed, several studies have shown that measures of home bias have declined over time, consistent with easier access to information about foreign markets (Sorensen et al. 2007, Bakaert and Wang 2009, Cooper et al. 2013).

However, our results indicate that residence-based statistics have tended to overstate recent declines in U.S. home bias. Figure 5 shows our estimates of U.S. home bias in common stock, where the definition of "foreign" is computed on both a residence basis and on an nationality basis as designated by MSCI. We draw a couple relevant conclusions. First, U.S. home bias in equity is more pronounced on the nationality basis than on a residence basis, reflecting the fact that equity of large multinationals considered "foreign" to the U.S. on a residence basis are considered to be investment in the U.S. by MSCI. Second, home bias has not declined materially by either measure, at least not since the financial crisis. In fact, home bias appears to have been drifting back up in recent years, especially on the nationality basis, casting doubt on the narrative that improved access to information about foreign markets has contributed to a decline in home bias more recently.

We find that U.S. home bias in bonds is similarly more pronounced on a nationality basis than on a residence basis (figures 6 a-d), though by both measures there is a declining trend. Home bias in financial sector bonds has declined less post-crisis on an ultimate parent basis (figure 6c), with a noticeable gap opening up between the two years. Home bias has declined more noticeably for nonfinancial corporate debt (figure 6d) on both measures, but the level is decidedly higher on an ultimate parent basis. This is because, as shown in figure 2b, a significant amount of what is reported in the residence-based statistics as U.S. holdings of foreign debt is actually debt issued by U.S. nonfinancial firms through an offshore subsidiary. There has been essentially no decline in home bias in government bonds (6b), which are unaffected by residence versus ultimate parent considerations.

4b. Implications for understanding the factors influencing cross-border portfolio allocations

We can shed some further light on how conclusions about the drivers of home bias and international portfolio flows more generally may be misleading when based on residence-based statistics by looking at country-level *relative* portfolio weights. As with overall home bias, we can construct measures of relative portfolio weights in different countries as:

$$\frac{\frac{(holdings\ of\ country\ i\ equity)}{(total\ equity\ portfolio)}}{\frac{(country\ i\ total\ equity\ market\ cap)}{(world\ equity\ market\ cap)}} \qquad (2)$$

Larger values again imply weights closer to the market cap shares, and smaller weights imply greater underweighting relative to market cap shares. These measures can differ on a residence and exposure basis through differences in the share of the portfolio assigned to $country_i$.

To illustrate how the differences between residence-based and nationality-based weights can affect the conclusions one might draw about the factors affecting portfolio decisions, we estimate a simple gravity-type model of U.S. relative weights in foreign equity, similar to that of Fidora et al. (2007). Our left hand side variable is the measure of relative portfolio weight in a given county's equity given by equation (2). We construct this measure two ways: on a standard BOP residence basis, and on our recalculated MSCI country of nationality basis. We include variables standard in the gravity model literature including distance, measures of "information" and market access, financial development, and trade shares. Following Fidora et al. (2007), we also add measures of equity market and GDP correlation to control for diversification motives.[12] Our resulting panel is for roughly 40 countries and 12 years. An appendix lists the estimation model and describes the independent variables.

The conclusions inferred from the model estimation about the drivers of international portfolios are different using the BOP versus MSCI country allocations. Table 3 summarizes our results. Trade linkages appear far more important (both

[12] Our goal is not to defend this particular model (for example, we are not able to control for cross-listing or other measures of market access found to be important in similar portfolio weight regressions by Ahearne, Griever, and Warnock (2004)), but rather to point out how strikingly different the results are simply by our different relative weight measures.

statistically and economically) in the MSCI nationality regressions than in the standard BOP residence regressions, whereas the opposite is true for the diversification measures. Most tellingly, proximity, common language, and common legal origin are all far more important in the residence-based regressions. These results suggest that these particular factors may be more important for the choice of where firms incorporate, and tell us less about what matters for investors' portfolio allocations.

4c. Additional implications for analysis of capital flows to Emerging Markets

Our results have additional implications for how we think about factors influencing capital flows to EMEs. For example, there has been much focus on the global impact of the extraordinary policy actions undertaken by advanced economy central banks in the wake of the global financial crisis. Of particular emphasis has been how these monetary policies spill over into emerging markets and how asset prices in emerging markets will react when these policies are reversed (Bowman et al 2015, Fratzscher et al 2018, Curcuru et al 2018). Our results showing the mis-measurement of capital flows to EMEs – with stronger flows when policy was especially accommodative and somewhat weaker flows as policy has begun to tighten – suggest that the impact may be understated.

Additionally, our results weaken the argument that capital flows arising from foreign direct investment (FDI) are generally preferable because they are less volatile than portfolio flows. Reasons in support of this conclusion are that FDI is harder to expropriate (Albuquerque 2003) and driven by pull rather than push factors (Eichengreen et al 2018). However, these arguments assume that portfolio flows in the BOP accounts fully capture investment in a country's securities. When foreign residents buy bonds issued onshore, these purchases will show up as portfolio investment inflows. When corporations issue bonds via offshore affiliates, however, funds borrowed through the offshore entities are funneled back to the parent firm in the form of lending or "reverse investment" in the parent firm. These flows will appear as FDI inflows. These funds are effectively no different from typical portfolio flows, and will be just as volatile. Growing reliance on offshore financing vehicles for debt issuance could thus confound our understanding of the resilience of different types of cross-border financial flows.

Our results also raise some potential flags for interpreting conclusions on the effectiveness of capital controls for preventing portfolio inflows to emerging markets (Forbes and Warnock 2012; Ahmed and Zlate 2014; Forbes et al. 2014; Forbes et al 2015; Pasricha et al. 2015). Foreign investors may still be able to gain exposures to countries via offshore-issued bonds, which typically are unaffected by controls. But because their purchases are not classified as portfolio inflows to these countries, the effectiveness of the controls may be overstated.

5. Determining economic exposure in terms of where firms actually do business

Thus far, we have documented significant challenges in understanding investor motivations and portfolio allocations by comparing the results of our restated nationality-based statistics with standard residence-based country allocations. However, even these restated portfolios do not fully capture country exposures, because investors gain additional exposures through the global activities of multinational firms. To provide a sense of how important these full exposures are, we take the additional step of calculating the geography of economic exposures of individual firms, focusing on common stock equity of firms for which we have access to information on the geography of their sales.

For this exercise, we consider the full U.S. equity portfolio, including holdings of foreign as well as domestic stocks, as in our calculations of home bias. We map our firm-level individual securities to firm-level Worldscope data to identify the major geographic regions of each firm's sales.[13] We then allocate U.S. investor equity holdings by three broad regions: the United States, emerging markets, and other foreign countries.

Figure 7 compares our results for the aggregate U.S. portfolio by each of our three classifications: residence, nationality, and sales exposure. Overall, we are able to classify a total U.S. portfolio of roughly $25.6 trillion as of December 2016. On a residence basis, holdings of U.S. firms amount to about $21 trillion. On a nationality basis, holdings of U.S. firms increases to $21.7 trillion, reflecting our reclassification of the holdings of equity of U.S. multinationals incorporated in offshore centers, as discussed in section 2b1 above. Holdings of emerging market equity are also slightly larger, as also discussed previously.

In contrast, estimated economic exposures to the United States based on sales are considerably smaller at $16.3 trillion, though they remain the largest portion of the total portfolio. This smaller share reflects the fact that large-cap U.S. firms are global in reach and thus holding their shares provides considerable international exposure. Estimated exposures to EMEs and other foreign countries are correspondingly higher. Of course, the reduced exposure to the United States from these calculations is offset in part by a reallocation of some of the holdings of foreign equity: foreign multinationals often have significant operations in the United States, and thus U.S. investors acquire some U.S. exposure through their holdings of foreign stocks.

Our results here thus raise questions about how investors view their equity portfolios in terms of actual country-level economic exposures, and how readily they adjust their portfolio holdings of both domestic and foreign securities when faced with foreign shocks. For example, stock prices of internationally-exposed U.S. firms certainly respond to foreign shocks and developments such as dollar appreciation (see Bertaut and Sinha 2015). These calculations also raise questions about the notion of "home bias" and how it has evolved over time, as large-cap domestic firms that make up the bulk of investor portfolios are increasingly global in scope. Extending

[13] Our claims surveys only collect security-level information on U.S. holdings of securities issued by foreign-resident firms. To estimate U.S. investor holdings at the security level of U.S.-resident firms, we start with the market capitalization of each firm, and subtract those security-level holdings that we know are held by foreign investors from the complementary annual U.S. portfolio surveys of foreign investors.

these exposure-based estimates back through time should provide further insights to these questions, and is the subject of ongoing research.

6. Concluding remarks: Implications of globalization for the analysis of the composition of financial flows and for Current Account sustainability

We have shown that as-published statistics on cross-border portfolio flows and measures of investor exposures are increasingly distorted by firms' choices of where to establish legal residence and from what location to issue securities. We have highlighted some of the ways these distortions can affect conclusions we draw about the factors influencing investor decisions and portfolio allocations. These distortions also have broader implications for how we think about the composition of financial flows and other components of the international accounts.

In addition to the implications discussed in section 4, our results have implications for other areas of international finance. They are relevant to the long-standing Lucas (1990) paradox, which arises from differences between the theoretical prediction of movements between developed and developing countries, and what is observed. Theory predicts that capital should move toward economies with lower levels of capital per worker. Contrary to this theory, most studies find that capital does not flow from more to less developed economies; rather, it flows in the other direction (see Alfaro et al. 2008, among others). Our results suggest that advanced economy exposure to EMEs is larger than previously believed, which resolves some portion of this puzzle. This is perhaps especially evident when we consider the global reaches of large multinational firms.

Finally, our results are relevant for analysis of the sustainability of the U.S. current account deficit. For example, future values of the U.S. net international investment position depend importantly on the composition of the underlying assets and the income generated by them (for example, see Ahmed et al. 2018). The net impact on sustainability is not clear, as some of the large investment income received by U.S. multinationals would be offset by the effect of a lower trade deficit in the absence of large transfers of intangible assets to foreign subsidiaries (Guvenen et al. (2017)). This important issue requires further study.

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Figure 1a. BIS International Debt Securities Corporate Debt Outstanding for Selected EMEs:
By Residence

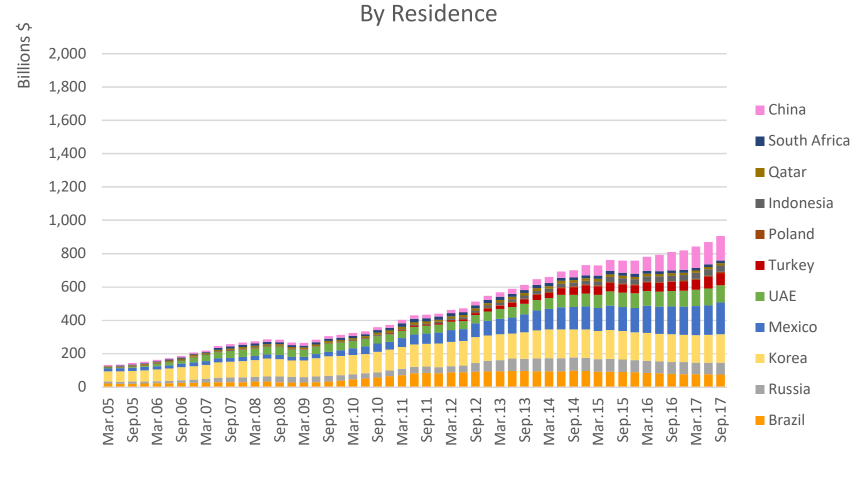


Figure 1b. BIS International Debt Securities Corporate Debt Outstanding for Selected EMEs:
By Nationality

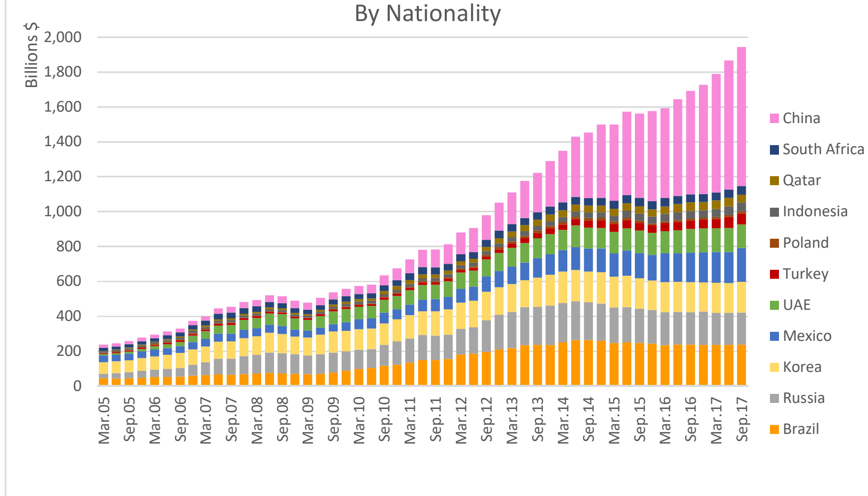
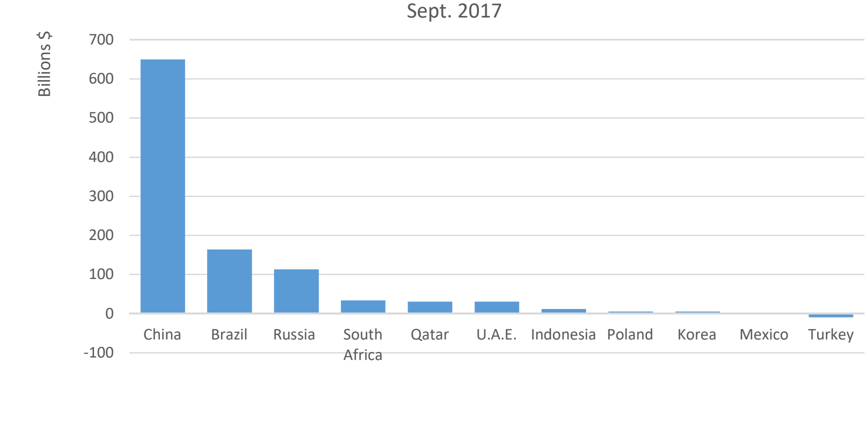


Figure 1c. Difference in International Corporate Debt Securities Outstanding, Residence vs Nationality Basis, for selected EMEs
Sept. 2017



Source: BIS debt securities statistics, International Issuances, https://www.bis.org/statistics/secstats.htm

Figure 2a. U.S. holdings of foreign corporate debt, by residence (Billions of $)

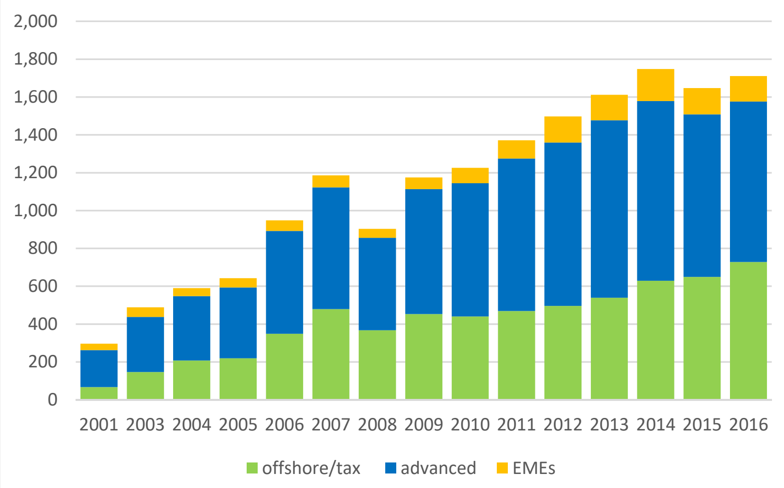


Figure 2b. US holdings of foreign corporate debt, by nationality (Billions of $)

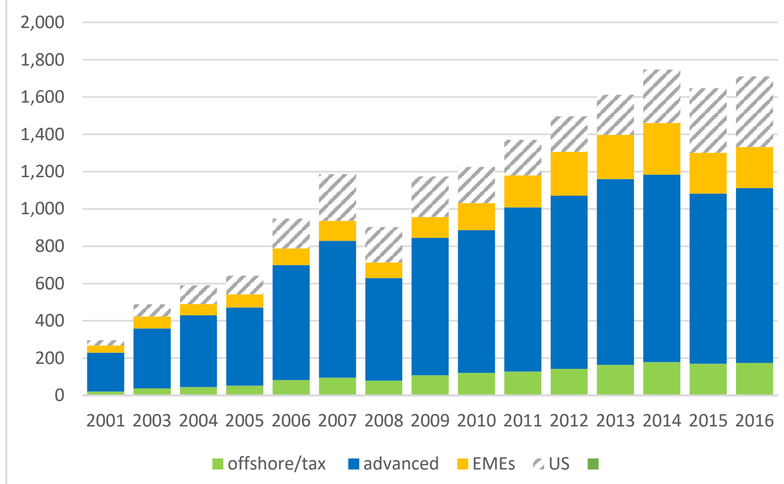


Figure 2c. U.S. holdings of selected EME corporate debt, by residence (millions of $)

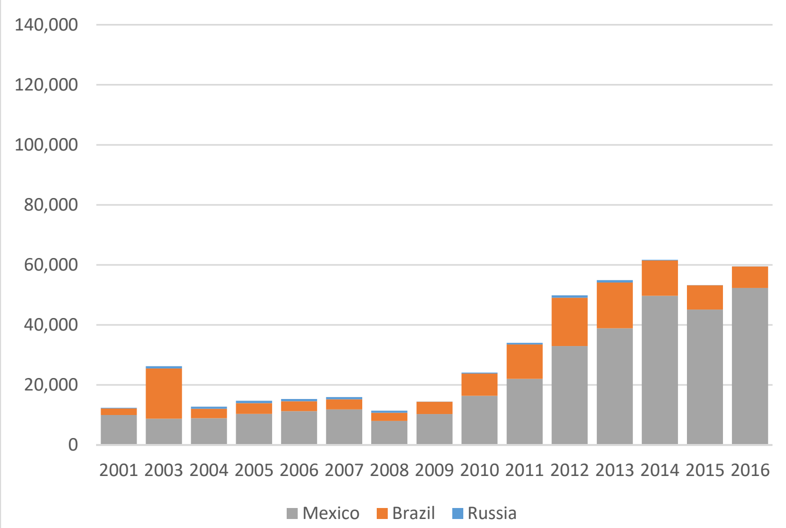
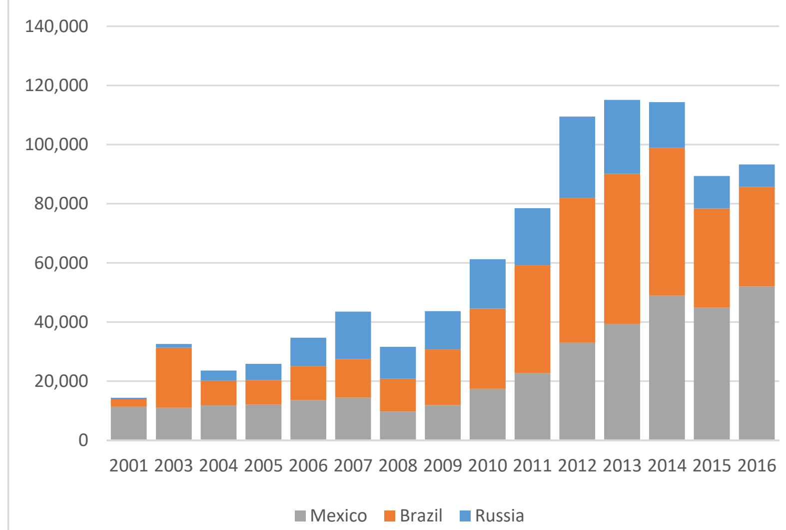
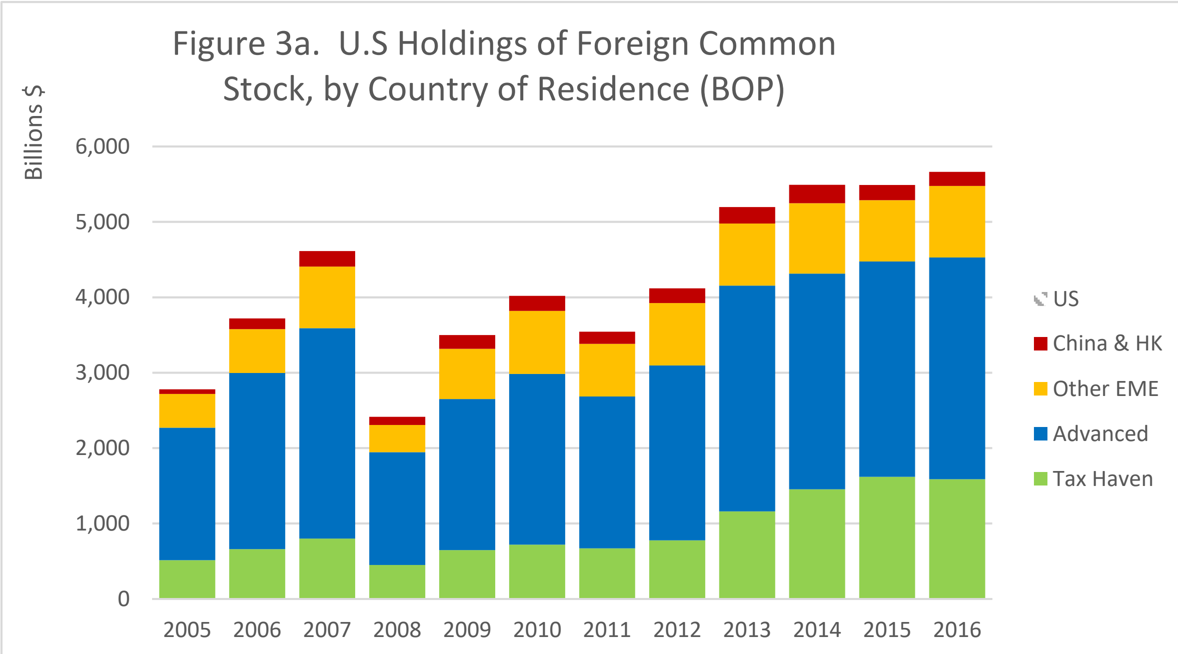
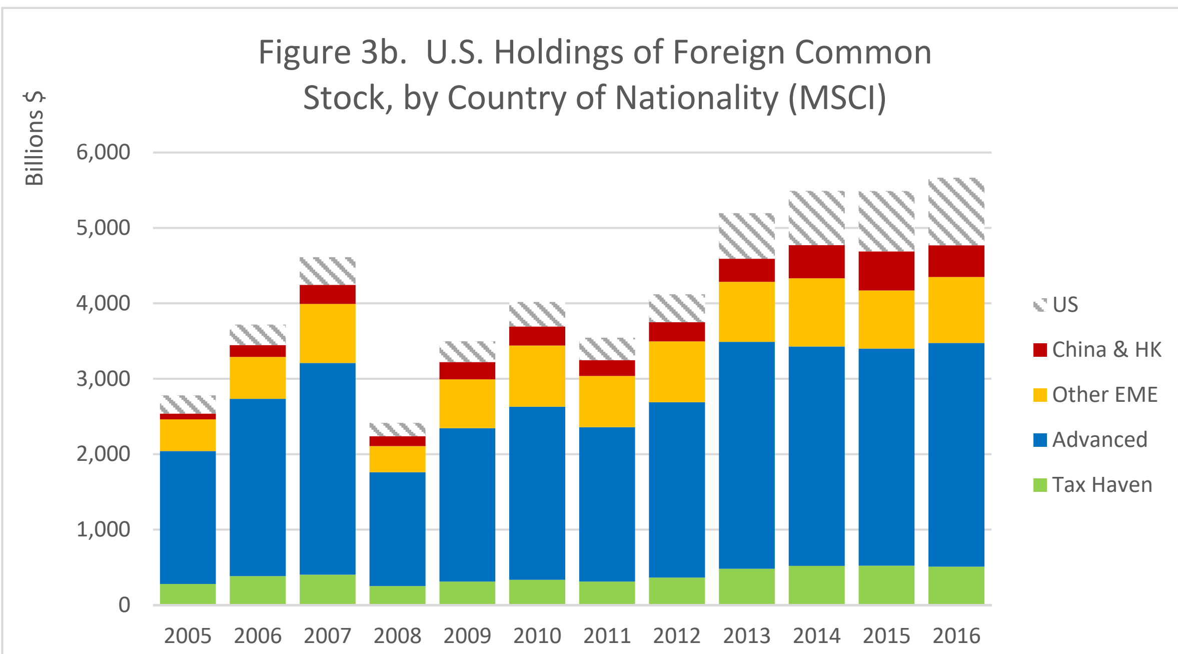


Figure 2d. U.S. holdings of selected EME corporate debt, by nationality (millions of $)

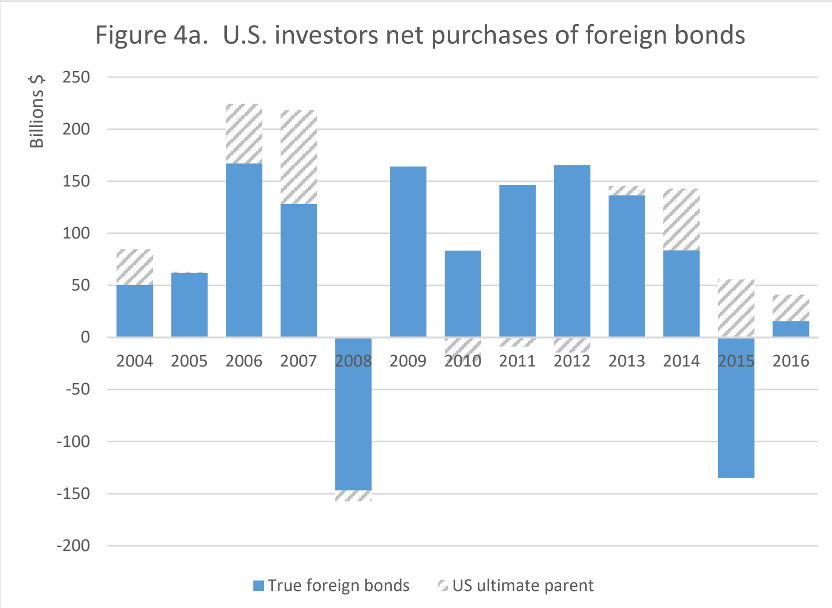


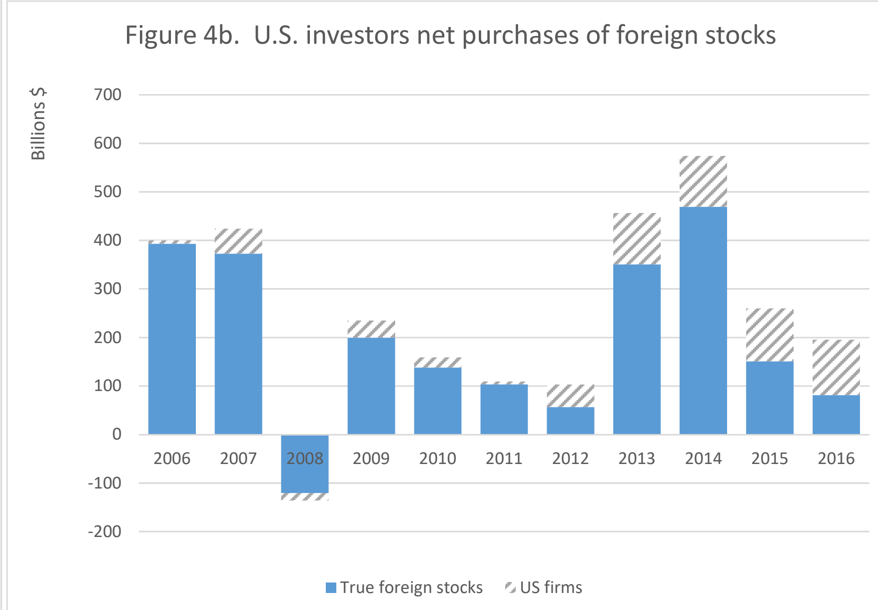
Source: Authors' calculations from Treasury International Capital, Surveys on U.S. Portfolio Holdings of Foreign Securities, various years.

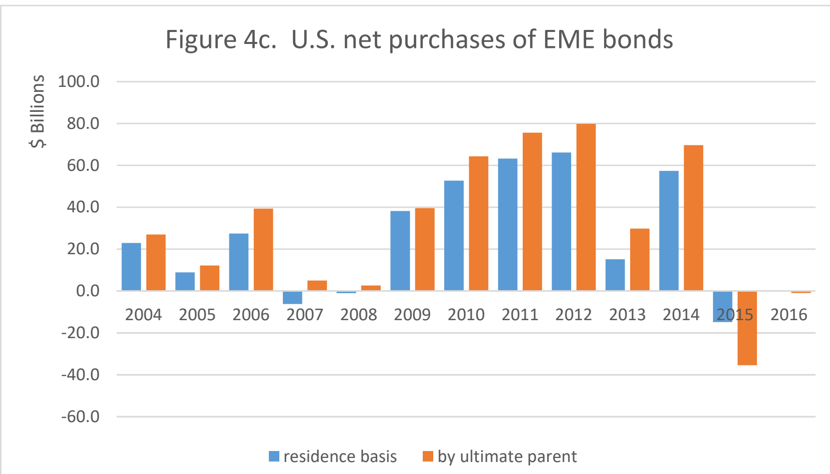


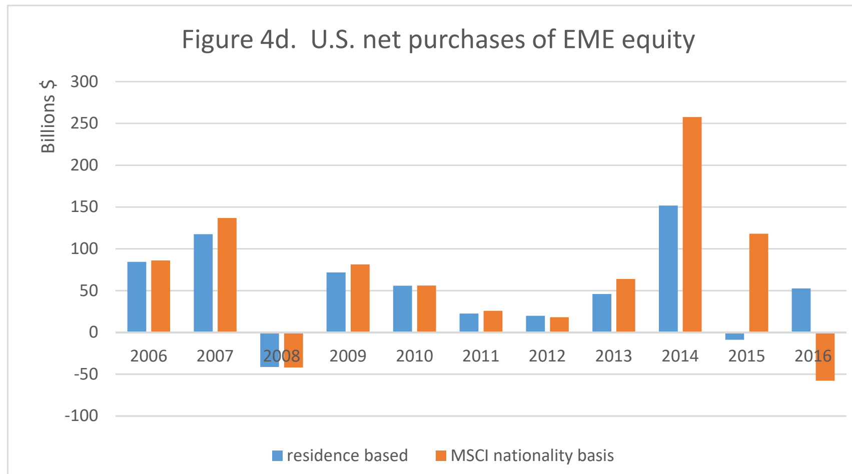


Authors' calculations from Treasury International Capital, Surveys on U.S. Portfolio Holdings of Foreign Securities, various years.









Source: Authors' calculations from Treasury International Capital, Surveys of U.S. Portfolio Holdings of Foreign Securities, various years.

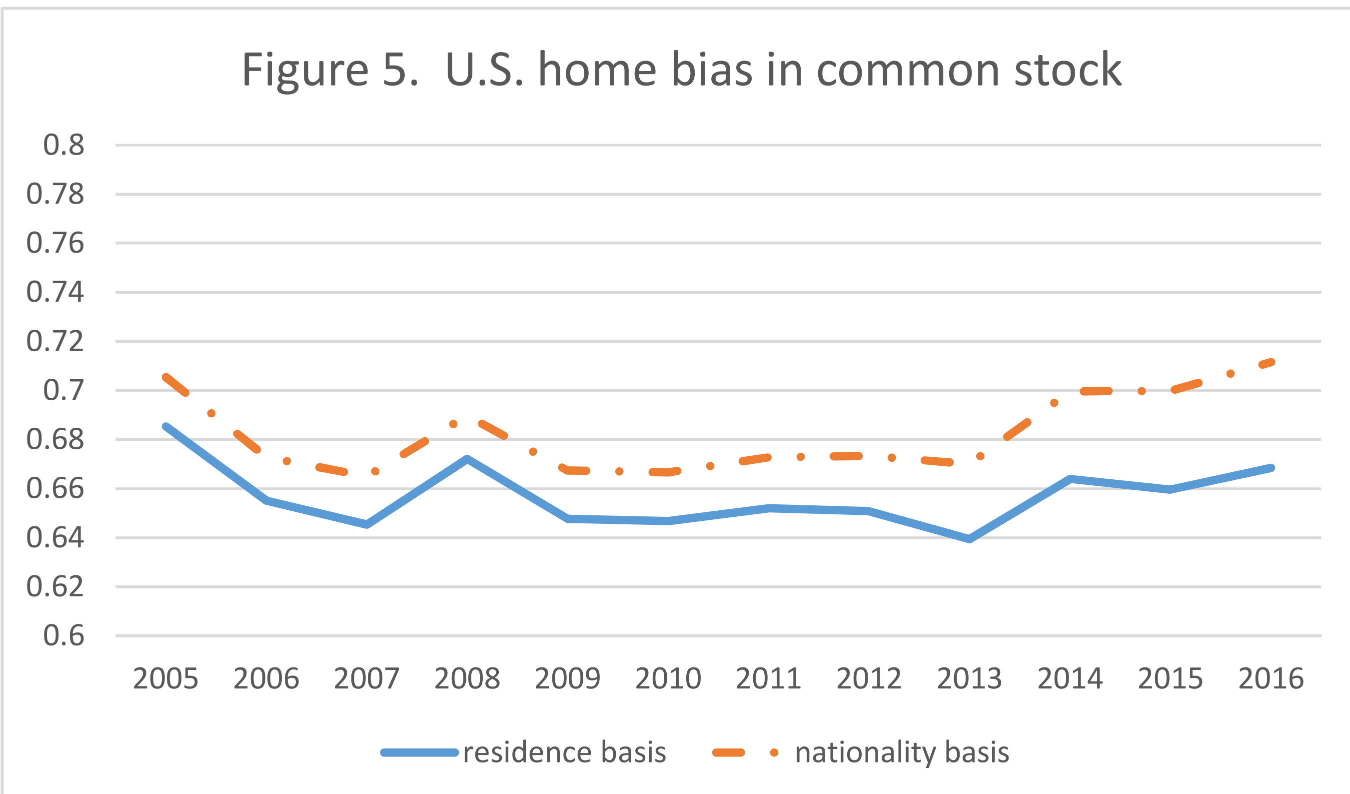


Figure 5. U.S. home bias in common stock
0.8
0.78
0.76
0.74
0.72
0.7
0.68
0.66
0.64
0.62
0.6
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
residence basis
nationality basis

Figure 6a. US home bias in total bonds

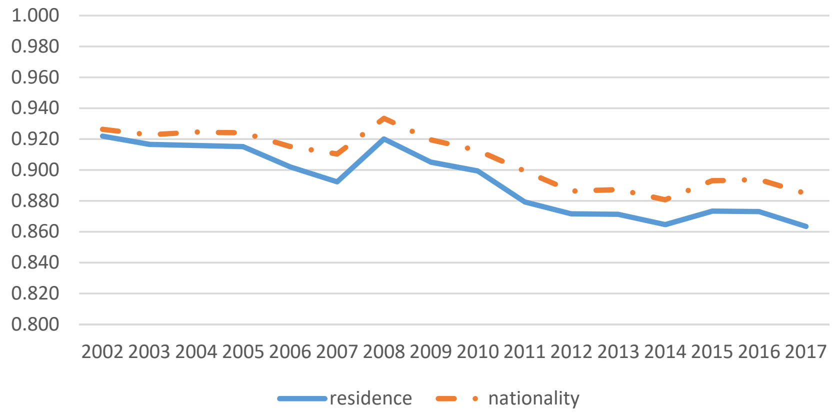


Figure 6b. US home bias in government bonds

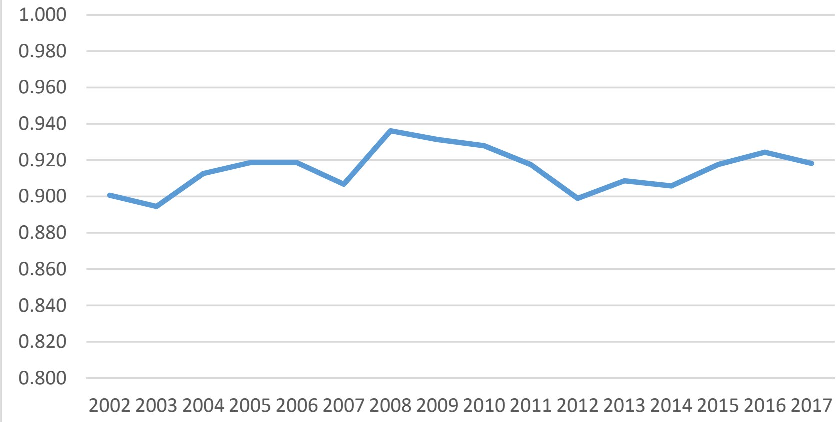


Figure 6c. US home bias in financial bonds

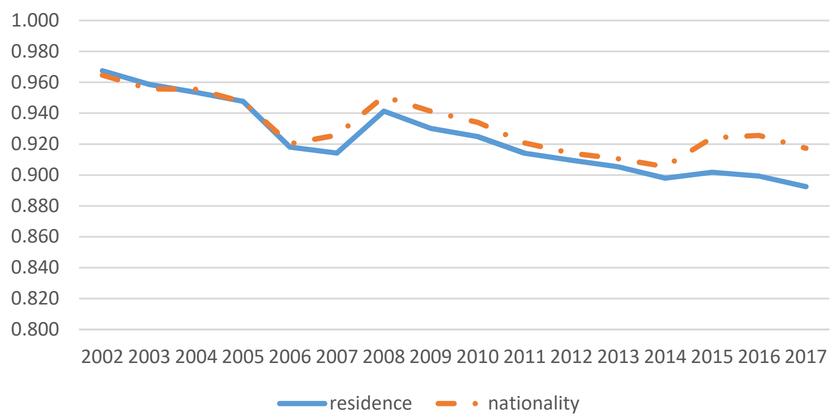
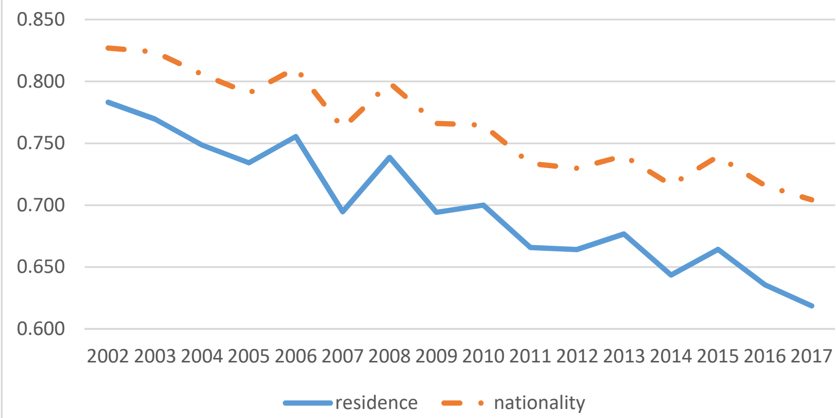
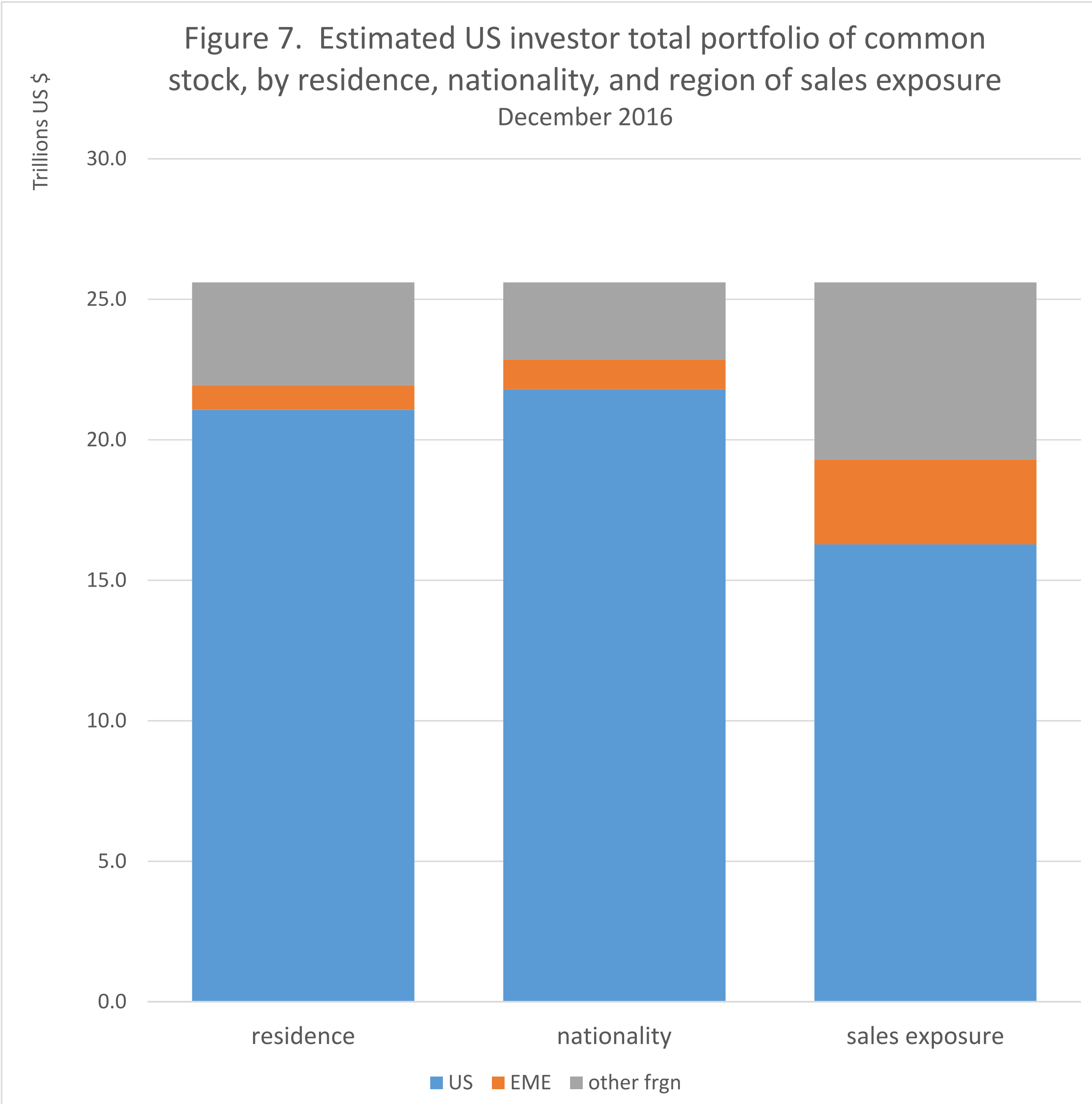


Figure 6d. US home bias in nonfinancial bonds





Source: Authors' calculations from Worldscope and Treasury International Capital, Surveys on U.S. Portfolio Holdings of Foreign Securities (December 2016)

Table 1. U.S. Portfolio Holdings of Foreign Securities As Reported and Amounts with Different Country of Nationality

Billions of Dollars

	2016		2005	
	As reported	With different country of nationality	As reported	With different country of nationality
Long Term Debt	2,437	631	1,028	184
Common Stock	5,918	1,333	3,224	612
Funds and other equity	1,229	991	94	38
Total	9,583	2,955	4,346	834

Authors' calculations from Treasury International Capital, Surveys of U.S. Portfolio Holdings of Foreign Securities

Table 2. Global cross-border equity and bond holdings as reported in the IMF Coordinated Portfolio Investment Survey, December 2016, Billions of US Dollars

	Total	LT Debt	Equity
Total cross-border portfolio investment holdings (excluding reserves holdings)	42,566	19,389	23,177
Totals reported to Caribbean & other offshore centers	4,165	1,025	3,140
Totals reported to Luxembourg, Netherlands, and Ireland (countries for incorporation of financing arms and investment funds)	5,643	1,599	4,044
Country of nationality other than as reported	9,522	2,457	7,065

Notes: other offshore centers include Guernsey, Jersey, Isle of Man, Liberia, Mauritius, and the Marshall Islands
Totals reported by all economies in the CPIS, excluding SEFER and SSIO holdings

Source: Authors' calculations from IMF Coordinated Portfolio Investment Survey, December 2016.

Table 3. Regression results for U.S. relative portfolio weights in foreign country equity

	(1) Nationality (MSCI) portfolio weight	(2) Residence (BoP) portfolio weight	(3) Nationality (MSCI) portfolio weight	(4) Residence (BoP) portfolio weight
(sd) exchange_rate	0.00450	0.0102	0.00114	0.00607
	(1.68)	(1.22)	(0.56)	(0.86)
Individuals using the internet (%)	0.00247***	0.00310*	0.00300***	0.00427**
	(7.04)	(2.56)	(8.55)	(2.85)
log_listed_companies	-0.00926	-0.0627**	-0.0254***	-0.0663**
	(-1.43)	(-2.92)	(-4.17)	(-3.25)
log_distance	-0.0122	-0.123*	-0.0164	-0.169*
	(-1.06)	(-2.29)	(-1.36)	(-2.57)
1=Common official or primary language	0.0932***	0.223***	0.0491***	0.230***
	(6.49)	(4.23)	(3.88)	(3.85)
1=Common legal origins after transition	-0.0242	0.261**	-0.00587	0.318***
	(-1.61)	(3.25)	(-0.40)	(3.60)
1=Destination is a EU member	0.0557***	0.367**	0.0366*	0.445**
	(3.72)	(3.11)	(2.07)	(3.12)
tax_haven	0.204***	1.188***	0.194***	1.270***
	(7.50)	(4.67)	(7.09)	(4.71)
GDP growth in previous year (annual %)	-0.00702**	0.0443	-0.00620*	0.0488
	(-2.77)	(1.26)	(-2.46)	(1.35)
share_of_trade	1.066***	-0.00301	0.919***	0.0418
	(4.93)	(-0.00)	(4.05)	(0.06)
Monthly equity returns correlation			0.0323	-0.352**
			(0.95)	(-2.59)
Rolling GDP correlation			0.0352	-0.546*
			(0.86)	(-2.16)
Constant	0.184	1.209**	0.276*	2.189**
	(1.58)	(2.78)	(2.08)	(3.11)
Observations	467	467	433	433
R^2	0.500	0.441	0.572	0.458

Robust standard errors (t statistics in parentheses)
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix

Portfolio Weight Regression Specification

$$PortfolioWeight^{1} = \beta_0 + \beta_1 SD(D\_ExchangeRate)_{i,t} + \beta_2 InternetUse_{i,t} + \beta_3 Ln(Distance_i) + \beta_4 Ln\left(NumListedCompanies_{i,t}\right) + \beta_5 CommonLanguage_i + \beta_6 CommonLegalOrigin_i + \beta_7 EUMember_{i,t} + \beta_8 TaxHaven_i + \beta_9 GDPGrowth_{i,t-1} + \beta_{10} ShareofTrade_{i,t} + \beta_{11} EquityReturnsCorrelation_{i,t} + \beta_{12} GDPCorrelation_{i,t}$$

Variable	Definition	Source
SD(D_ExchangeRate)	The standard deviation of the month-on-month percent change in country *i*'s exchange rate in year *t*.	Bloomberg
InternetUse	The percentage of individuals using the internet in country *i* in year *t*	World Bank World Development Indicators
Distance	Geographic distance between New York City and the largest city in country *i*.	CEPII's *GeoDist* database[2]
NumListedCompanies	The number of listed companies in country *i* in year *t*.	World Bank Financial Structure Database
CommonLanguage	Dummy variable indicating whether country *i* shares an official or primary language with the US.	Source: CEPII's *Language* database[3]
CommonLegalOrigin	Dummy variable indicating whether country *i* has shared legal origins with the US.	CEPII's *Gravity* database[4]
EUMember	Dummy variable indicating whether country *i* was an EU member during year *t*.[5]	CEPII's *Gravity* database
GDPGrowth	Country *i*'s year-on-year GDP growth in year *t-1*.	World Bank World Development Indicators
TaxHaven	Dummy variable indicating whether a country is a tax haven.	Author designation[6]
ShareofTrade	The share of United States trade in year *t* that occurs with country *i*.	U.S. Census Bureau's Foreign Trade statistics
EquityReturnsCorrelation	8-year rolling correlation between monthly equity returns in country *i* and in the US	Bloomberg
GDPCorrelation	20-year rolling correlation between annual GDP in country *i* and in the US.	CEPII's *Gravity* database

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[1] Countries that appear in our sample: United Arab Emirates, Argentina, Australia, Austria, Belgium, Brazil, Canada, Switzerland, Chile, China, Colombia, Cyprus, Czech Republic, Germany, Denmark, Egypt, Spain, Finland, France, United Kingdom, Greece, Hong Kong, Hungary, Indonesia, India, Ireland, Israel, Italy, Jordan, Japan, South Korea, Luxembourg, Morocco, Mexico, Malaysia, Nigeria, Netherlands, Norway, New Zealand, Peru, Philippines, Poland, Portugal, Qatar, Russia, Saudi Arabia, Singapore, Sweden, Thailand, Turkey, South Africa

[2] See Mayer and Zignago (2011).

[3] See Melitz and Toubal (2014).

[4] See Head et al (2010) and Head and Mayer (2014).

[5] Only Croatia and Bulgaria change EU designation in the sample period.

[6] The countries that we designate as tax havens are Aruba, Bahamas, Bermuda, British Virgin Islands, Cayman Islands, Curacao, Guernsey, Isle of Man, Jersey, Netherlands Antilles, Nauru, Marshall Islands, Ireland, Netherlands, Luxembourg, and Switzerland. Only Ireland, Netherlands, Luxembourg and Switzerland are ultimately in the regression sample.

Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

Globalization and the geography of capital flows[1]

Carol Bertaut, Beau Bressler, and Stephanie Curcuru,

Board of Governors of the Federal Reserve System

[1] This presentation was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

Globalization and the Geography of Capital Flows

Carol Bertaut, Beau Bressler, and Stephanie Curcuru

Division of International Finance
Board of Governors of the Federal Reserve System

This presentation is prepared for the
9th biennial IFC Conference
"Are post-crisis statistical initiatives completed?"
Basel, Switzerland, August 30-31 2018

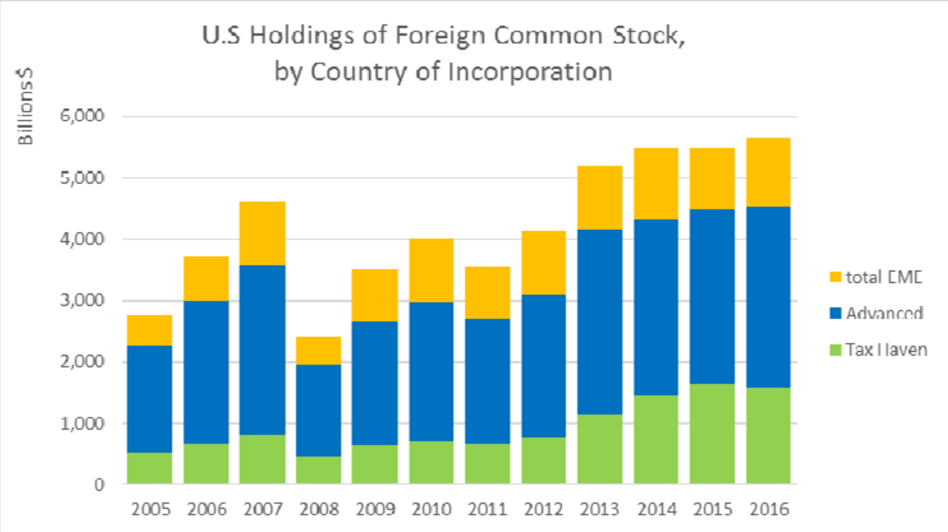
Official statistics on capital flows, portfolio holdings provide an increasingly distorted view of actual investor exposures and cross-border linkages

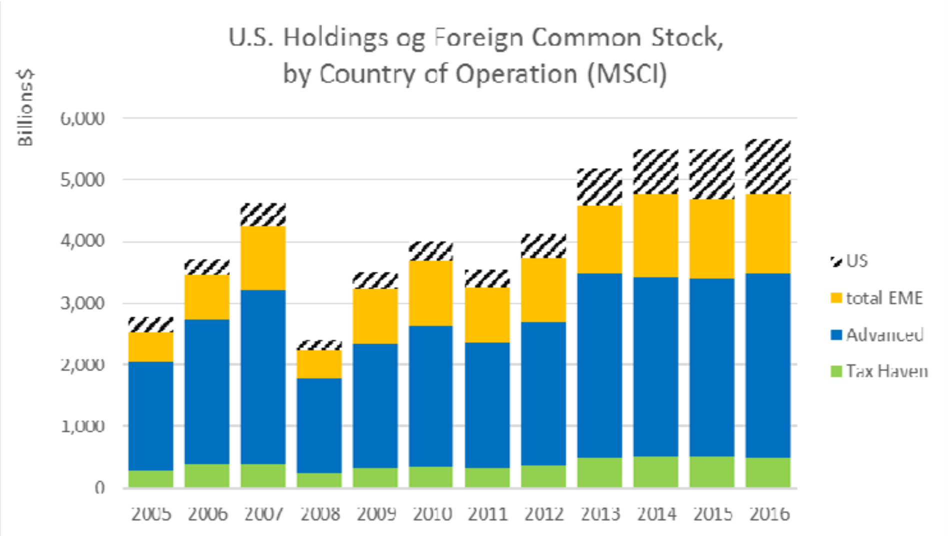
- Post-crisis initiatives for CPIS: greater participation, more granularity (issuer/holder sectors), more frequent (semi-annual)
- These data are still based on BOP framework of **legal residence**
- Country assignment may not convey useful information about investor exposures, because firms may not do any business in that residence.
  - Multinationals incorporate in tax havens, especially when intangibles important
  - Firms issue debt out of financing arms in offshore centers for improved market access
  - Mutual funds established in tax havens
- Increasing recognition of problem:
  - Lane & Milesi-Ferretti (2017): increasing distortionary effects of financial center intermediation for assessing external exposures
  - BIS banking statistics: post-crisis locational-by-nationality initiatives
  - BIS international debt securities on both residence & nationality basis

Our Study

- We combine underlying security-level data on U.S. foreign portfolio investment with a variety of commercial data sources designed for investors to monitor portfolios relative to benchmarks
  - Allows us to map U.S. investor holdings from **residence** basis to **nationality** basis (based on location of parent, or firm's center of operations)
  - Ongoing work: map holdings to fuller **exposure** basis based on where firms actually do business from firm level data on location of sales
- We find that distortions in the U.S. portfolio data just from **residence** to **nationality** are large, and growing
  - ~$3 trillion, nearly 1/3 of U.S. cross-border portfolio in 2016
- Global portfolios becoming similarly distorted
- Distortions have important consequences for researchers and policy makers:
  - drivers of portfolio allocations and capital flows
  - spillovers of monetary policy
  - resilience of different types of capital flows
  - effectiveness of capital controls
  - components of and sustainability of current account

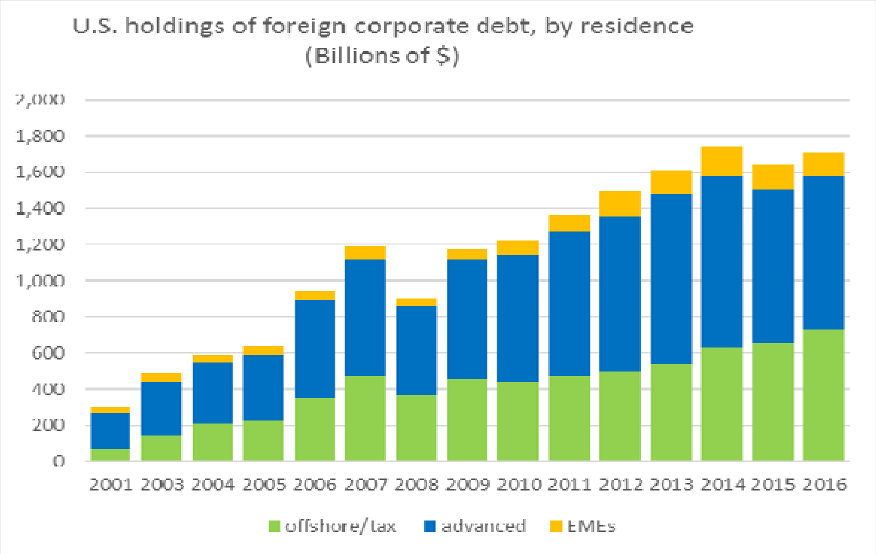
U.S. investor holdings of foreign common stock: residence versus nationality basis

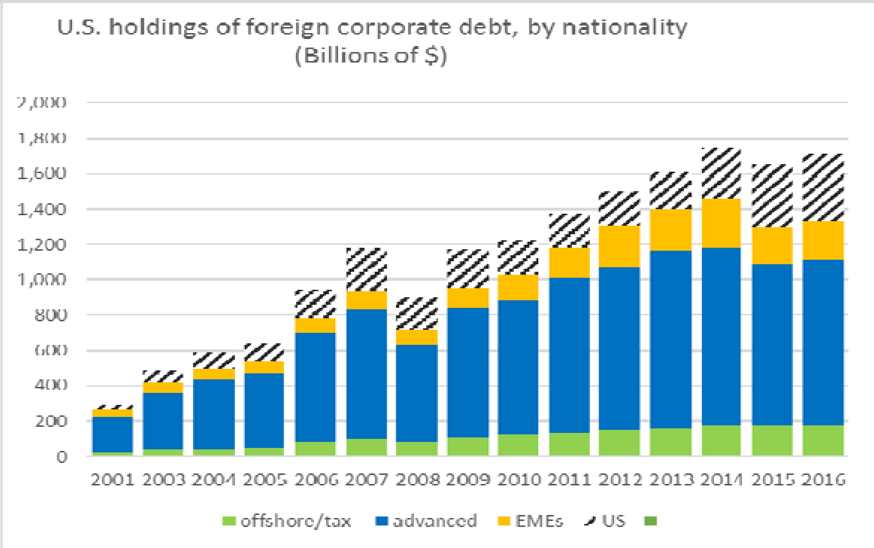




- Residence basis: $5.6 trillion in 2016
  - $1.6 trillion is in tax havens
- Use MSCI constituents to map to nationality
- $900 billon is considered U.S. by MSCI
  - U.S. multinationals incorporated in tax havens abroad
  - Recent increases: U.S. M&A/ corporate inversions in Ireland
- Within foreign: more EME holdings by nationality, especially Chinese firms incorporated in Caymans
- Only common stock holdings. Fund shares add additional layers of distortion: in terms of type of assets, in addition to country
  - Holdings disproportionally in the Cayman Islands, British Virgin Islands, Luxembourg
  - Adds another $1 trillion in distortion

U.S. investor holdings of foreign corporate bonds: Residence versus nationality





- Focus on corporate bonds because government bonds not typically affected by offshore financing arms
- Residence basis: foreign corporate debt: $1.7 trillion by 2016
- 40% is from offshore centers and tax havens
- Nationality basis: total holdings of foreign corporate bonds smaller at $1.3 trillion
- EME holdings larger because of EME firms that issue out of offshore centers
  - Especially true for Chinese, Brazilian, Russian firms

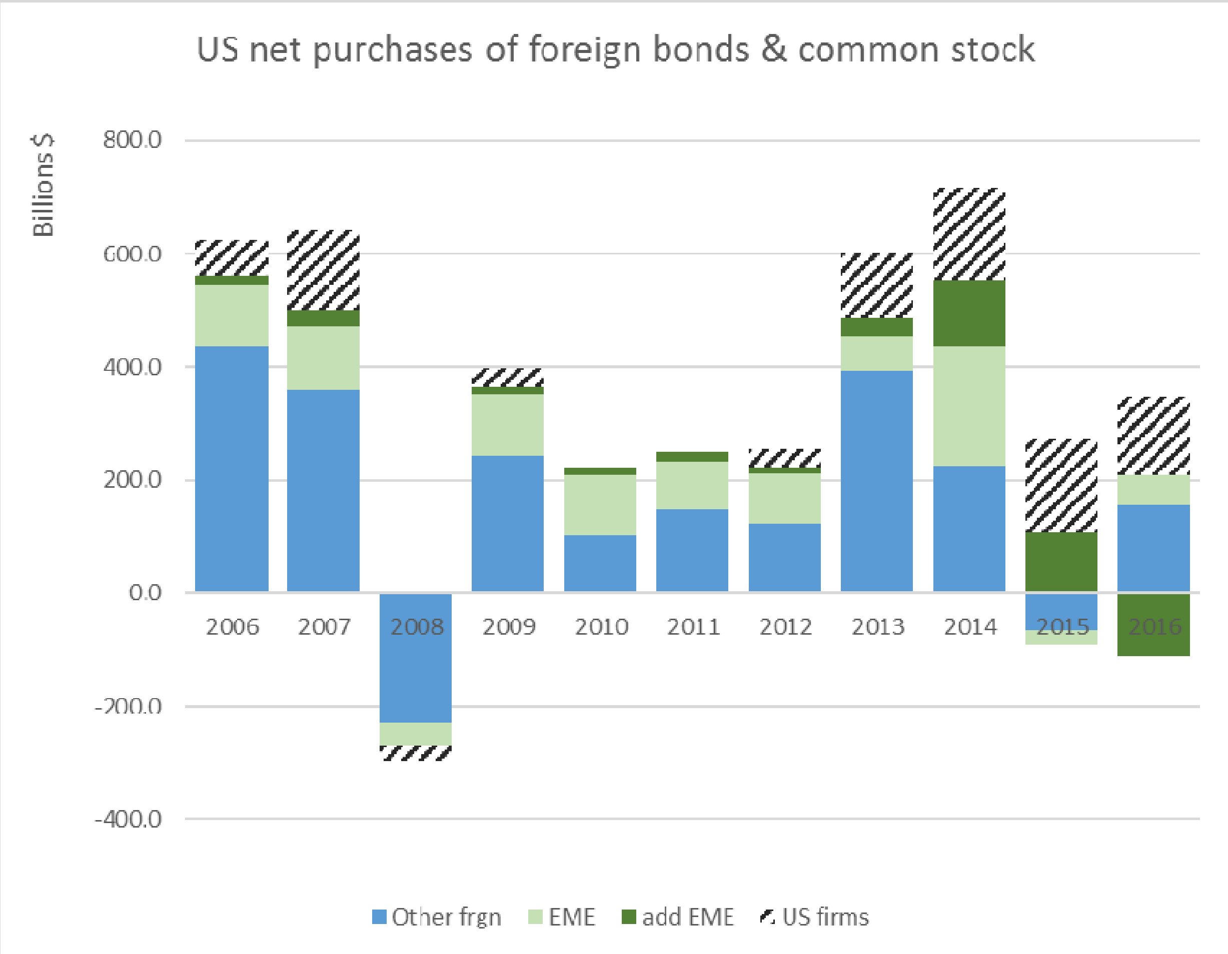
Global Distortions: $9.5 trillion in 2016 (nearly a quarter of total cross-border holdings)

Global cross-border equity and bond holdings in IMF CPIS December 2016, Trillions of US Dollars			
	Total	LT Debt	Equity
Total cross-border portfolio investment holdings (excluding reserves holdings)	**42.6**	**19.4**	**23.2**
Caribbean & other offshore centers	4.2	1.0	3.1
Luxembourg, Netherlands, and Ireland	5.6	1.6	4.0
Estimated holdings with a different country when reported as nationality instead of residence	**9.5**	**2.5**	**7.1**

Notes: other offshore centers include Guernsey, Jersey, Isle of Man, Liberia, Mauritius, and the Marshall Islands

Totals reported by all economies in the CPIS, excluding SEFER and SSIO holdings

Restated flows: U.S. net purchases of foreign stocks and bonds on residence versus nationality basis

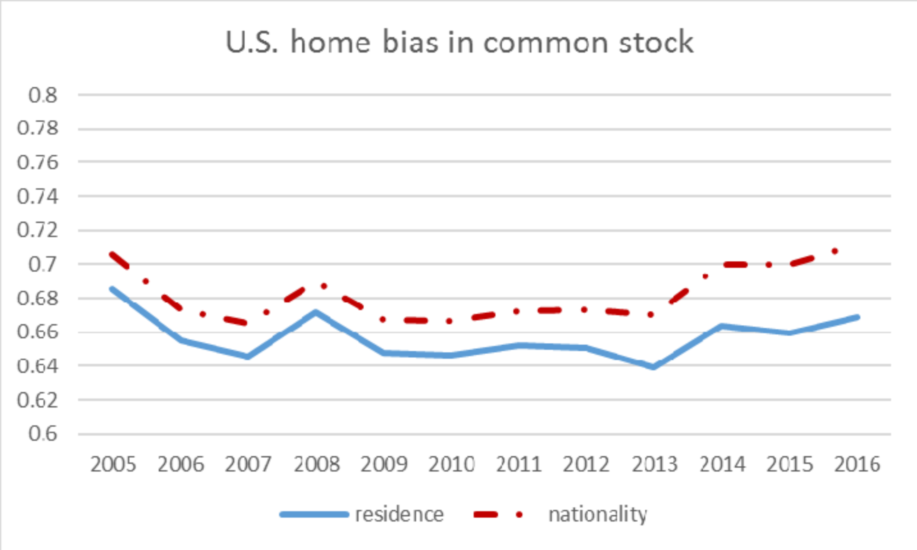


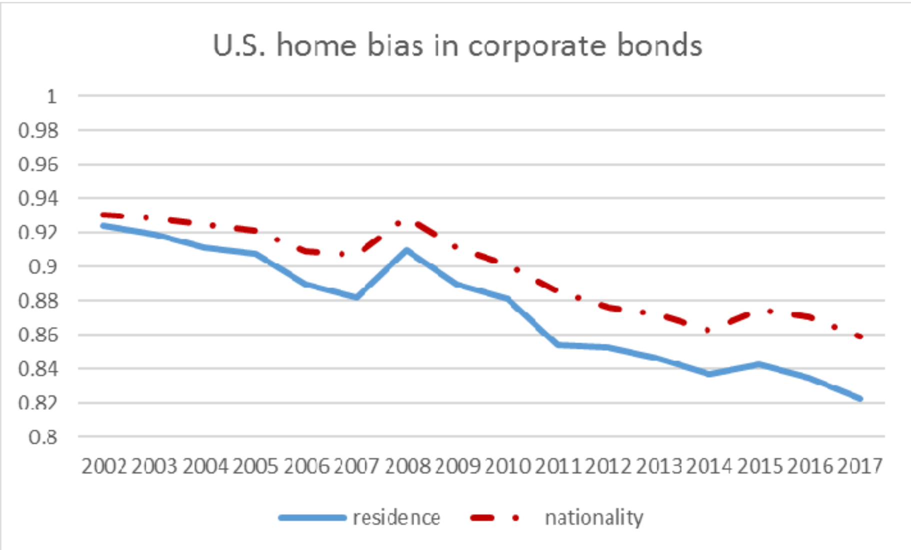
- U.S. purchases foreign assets on ***nationality*** basis are not as large as reported in lead-up to crisis, and not as large in last few years
- Differences within purchases of foreign securities: more EME purchases initially post-crisis, larger sales of EME assets last year

Implications of differences in flows (especially to EMEs)

- Spillovers of accommodative policy in advanced economies and implications for its removal:
  - Post-crisis, U.S. portfolio flows to EMEs have been larger than reported, but sales also larger in last couple years
- Purchases of bonds issued via offshore centers will result in FDI, not portfolio, inflows
  - FDI flows often considered more stable than portfolio flows, but offshore issuance means FDI increasingly "portfolio – like"
- Could misrepresent effectiveness of capital controls if focus on portfolio flows but purchases switch to offshore bonds
- More generally: Potentially gets us closer to answering Lucas paradox why doesn't capital flow from AEs to EMEs, if EME flows understated
- Has contributed to current configuration of U.S. current account
  - Large direct investment receipts from affiliates in tax havens, but larger trade deficit because exports do not embody value of intellectual property/intangibles
  - Implications for how we think about CA sustainability

Implications for global portfolio allocations & "Home Bias"





- ICAPM: in frictionless world, global investors should hold market cap in portfolio:

$$\frac{\dfrac{(holdings\ of\ foreign\ equity)}{(total\ equity\ portfolio)}}{\dfrac{(foreign\ equity\ market\ cap)}{(world\ equity\ market\ cap)}}$$

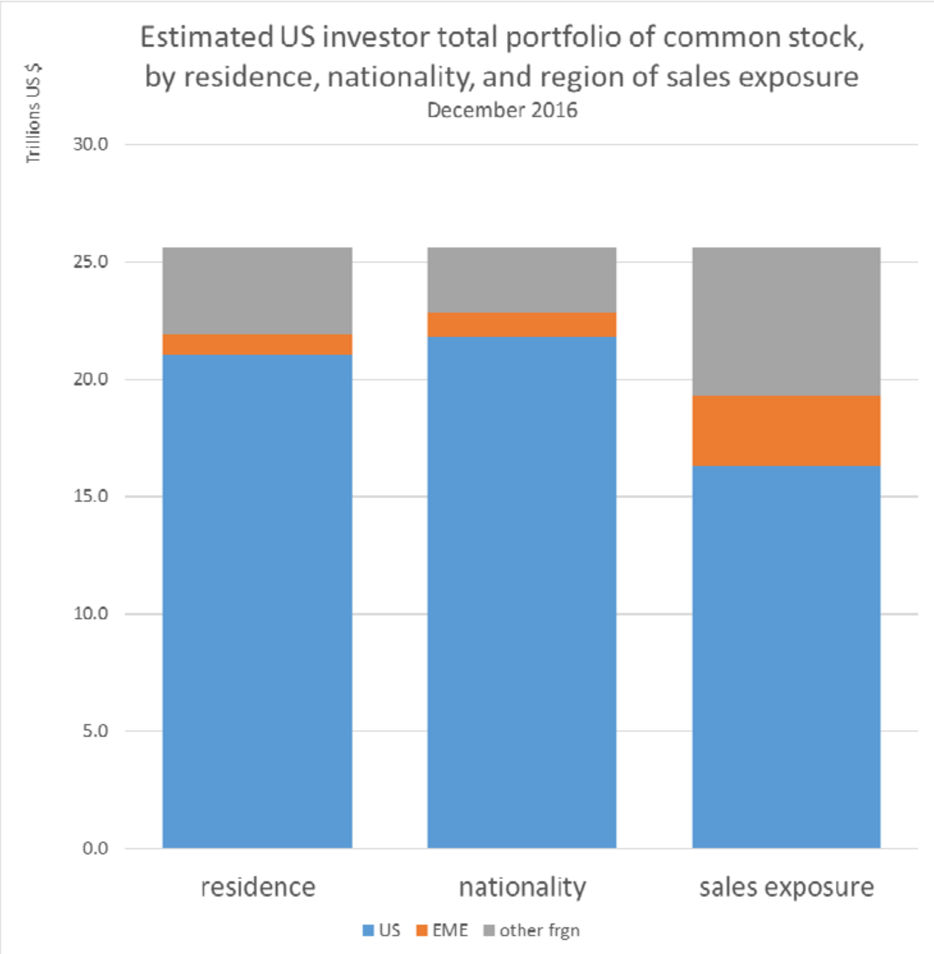
- But investors don't: widespread "home bias"
- Literature: frictions, hedging costs, market access, information advantages of home country firms
- We find U.S. measures of home bias are higher, and have come down by less in recent years, when measured by nationality
- Has implications for what drives home bias and investor allocations

Cross-country relative portfolio weights: Similar to home bias concept; shares of country *i* equity in portfolio and in market cap

	Nationality (MSCI) portfolio weight	Residence (BoP) portfolio weight
(sd) exchange_rate	0.00114	0.00607
Individuals using the internet (%)	0.00300***	0.00427**
log_listed_companies	-0.0254***	-0.0663**
log_distance	-0.0164	-0.169*
1=Common official or primary language	0.0491***	0.230***
1=Common legal origins after transition	-0.00587	0.318***
1=Destination is a EU member	0.0366*	0.445**
tax_haven	0.194***	1.270***
GDP growth in previous year (annual %)	-0.00620*	0.0488
share_of_trade	0.919***	0.0418
Monthly equity returns correlation	0.0323	-0.352**
Rolling GDP correlation	0.0352	-0.546*
Constant	0.276*	2.189**
Observations	433	433
R^2	0.572	0.458
t statistics in parentheses		
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$		

- Estimate gravity model to explore differences in US investor allocations across countries
- Panel data, ~40 countries ~12 years
- LHS variable is relative weight in each country
- Create relative country weights 2 ways:
  - residence
  - nationality
- Would draw different conclusions about factors that influence portfolio decisions: ie importance of trade vs diversification variables
- Would conclude that distance, common language, legal origin matter more if used residence specification
  - These results may say more about what matters for where firm locates than what influences investor choices

But even nationality basis still doesn't address "exposures" more broadly, in terms of where multinationals actually do business



- Consider full common stock portfolio of US investors: holdings of domestic equity as well as foreign equity
- Map firm-level holdings to firm-level Worldscope data on location of revenues to determine international exposures
  - Large U.S. multinationals have considerable sales in foreign locations: U.S. investors have foreign exposure through these holdings
  - Partially offset by increased U.S. exposure from foreign multinationals that do business in the United States
- Implications for how we think about home bias

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BANK FOR INTERNATIONAL SETTLEMENTS

Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

Uses of mirror data: examples from the BIS international banking statistics and other external statistics[1]

João Falcão Silva, Bank of Portugal,

and Swapan-Kumar Pradhan, Bank for International Settlements

[1] This paper was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

Uses of mirror data: examples from the BIS international banking statistics and other external statistics[1]

João Falcão Silva[2] and Swapan-Kumar Pradhan[3]

Abstract

This study examines the data elements that are common to the BIS international financial statistics and other external statistics such as the Balance of Payments, International Investment Position and Coordinated Portfolio Investment Survey. We enlist several conceptual relationships between various data sources and demonstrate the validity of relationships with country data at an aggregate level. In addition, the differences between mirror data items provide deeper insight into relevant data sets.

The paper's approach elucidates the methodological framework and data gaps, helping users to properly use the information. It also addresses quality issues and the statistical links between different domains.

Keywords: balance of payments, data collection and data estimation methodology, international banking, international financial data.

JEL classification: C82, C800, F42, F300.

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Contents

A. Introduction

Mirror data refer to different sources that capture similar concepts. They involve the comparison of different statistical data that can be analysed mainly in two perspectives – within one country between different statistical domains with similar concepts; or between reporting countries aiming to compare the same statistical data under a dual perspective.[4] For example, creditor banks' assets should equal to debtor banks' liabilities when valued using the same method.

The concept of mirror data is an important statistical tool that also allows common data items to be validated across statistical domains, which can help to fill gaps in related data sets. In addition, it promotes consistency and accuracy, helping to raise statistical quality standards. Consistent and high-quality data are crucial for economists, analysts and policymakers who need to explore statistical information.

This paper focuses on external statistics, comparing creditor as well as debtor data sources. In particular, it explores linkages within and between two data sources of the BIS international banking statistics, as well as linkages with the BIS international debt securities statistics, the IMF International Investment Position (IIP) and the IMF Coordinated Portfolio Investment Survey (CPIS).

The paper seeks to identify statistical consistency tests between the BIS's international banking statistics and other external statistics domains. At a first stage, it aims to compare published data between these different domains. Second, it identifies the methodological aspects that may explain some differences. Finally, it offers guidance on the types of discrepancy that should be avoided. The country experiences include the Portuguese case, and also benefit from contributions provided by other reporting countries.

We propose to develop this joint work in several stages. After identifying the consistency tests (in this paper), we will present them at the BIS workshop for compilers in November 2018 and ask for additional suggestions. In order to address different compilation practices among countries, we intend to collect the relevant metadata from all the compilers and list the main methodological differences. Subsequently, consistency tests for individual reporting countries and bilateral comparisons at a granular level could be constructed.

This document consists of five sections. After the introductory Section A, data sources are described in Section B. The methodological framework for linkages between pairs of mirror data sources and results with explanations are provided in Section C for loans and deposits, and in Section D for debt securities. Section E concludes with proposed future work. The annex provides statistics tables by country for each of the mirror concepts; and also the list of names of ISO country codes used in the texts and tables.

[4] Swapan-Kumar Pradhan (BIS) and Jana Sigutova, who was visiting from the Bank of Canada, were the first to jointly explore the mirror relationships between the BIS international banking statistics and other data sets. The topic was presented for discussion in the Biennial Meeting of the Central Bank Experts, 8–9 February 2017, Basel.

B. Description of data sources

This study covers two different dimensions: an internal one comparing the BIS international banking and financial statistics (IBFS) data sources and an external dimension comparing the international banking statistics (IBS) with other external data sources. In regard to the first dimension, we recognise linkages between the locational banking statistics (LBS), the consolidated banking statistics (CBS) and the international debt securities (IDS).

The LBS and CBS are the two BIS data sets on international banking activities. The LBS measure claims and liabilities including the inter-office positions of banking offices resident in reporting countries. They record the instruments (loans and deposits, debt securities, and other assets and liabilities), currencies, bank nationalities, counterparty sectors (eg intragroup, central banks, unrelated banks and non-banks) and the composition of resident banks' balance sheet by their counterparties' geographical location. Complementing this perspective, the CBS measure the worldwide consolidated claims of banks headquartered in reporting countries, including claims of their foreign affiliates but excluding inter-office positions.

The LBS comprise two data subsets, the LBS by residence (LBS/R) and the LBS by nationality (LBS/N). Broadly speaking, the LBS/R include an instrument breakdown for banks' on-balance sheet claims/liabilities, while the LBS/N provide the same information on the basis of reporting banks' nationality. The CBS are also presented in two different formats – on an immediate counterparty basis (CBS/IC), which aggregates claims based on the contractual obligation of banks' immediate counterparty countries, and on an ultimate risk basis (CBS/UR). The latter are aggregated on the basis of ultimate obligor, after taking into account risk transfers. Common elements (breakdowns) exist within and between the two LBS data sets, and the LBS/N are also comparable with the CBS/IC since both abide by the principle of immediate counterparty on a residence basis and aggregated by the nationality of banks.[5]

The IDS are a security-by-security data set built by the BIS using information from commercial data providers. They describe securities issued outside the local market of the country where the borrower resides and/or securities issued under international law. They capture eurobonds and foreign bonds but exclude negotiable loans. The securities are aggregated, among other criteria, by issuer's sector, currency, nationality and issuer's residence. The residence of the issuer is the country where the issuer is incorporated, whereas the nationality of the issuer is the country where the issuer's parent is headquartered. In principle, the cross-border debt securities liabilities of banks in the LBS/R should be comparable with the IDS issued by the banks' sector in the same location (residence). However, information may be incomplete if the ownership of securities changes through secondary market transactions.

According to the 'Reporting guidelines and practices for BIS international banking statistics', the LBS statistics are consistent with the Balance of Payments (BoP)

[5] The latest version of the 'Reporting guidelines and practices for BIS international banking statistics', as well as reporting templates and other documents explaining how to report the BIS international banking statistics, are available on the BIS website.

and International Investment Position (IIP) methodology, as they correspond to claims/liabilities of one country vis-à-vis those of non-resident countries. In addition, the LBS are best suited for macro analysis of economic and financial stability issues. The linkages with these and other statistical domains cannot be disregarded and should be part of the IBS statistical analysis.

To address the second dimension, external statistics are used. Under the IMF, Balance of Payments and International Investment Position Manual (sixth edition) (BPM6), the IIP is a statement that shows, at a given point in time, the value of financial assets (liabilities) of residents in one economy that are claims (debts) on non-residents or are gold bullion held as reserve assets. Our analysis focuses on the linkages between LBS/R and the IIP loans, deposits and debt securities of deposit-taking corporations excluding central banks, among all functional categories.

We also compared the debt securities liabilities of banks from the LBS/R with the bank-issued debt securities liabilities that are reported as assets in the IMF CPIS, which is a voluntary data collection exercise conducted by the IMF.

C. Methodological framework and results for loans and deposits: Linkages between LBS and other statistical domains

One of the most important ways to validate data consistency is to analyse interlinkages with other data sources, and help to improve data quality as well as coverage. In addition, such linkages send an important message to data analysts and decision-makers: namely, that statistical information should be used to complement economic analysis from different perspectives. This section presents three broad categories, with subcategories within each, for loans and deposits.

Loans and deposits (LD)

LD1: Comparison of bilateral interbank claims and interbank liabilities from the BIS LBS/R

This mirror exercise corresponds to the comparison between interbank claims and interbank liabilities for loans and deposits, both sourced from the LBS/R (hereafter referred as interbank claims and interbank liabilities). The LBS/R provide instrument breakdown of claims/liabilities of resident banks in a reporting country, with a full country breakdown of counterparties including currencies and counterparty sectors.

The main motivation in this case is that the claims of reporting banks in country "*i*" on counterparty banks in country "*j*" should be a good proxy of the liabilities of reporting banks in country "*j*" to banks in country "*i*".[6] Similarly, the liabilities of

[6] According to the valuation principles defined in the 'Reporting guidelines and practices for BIS international banking statistics', loans (both claims and liabilities) should be valued in accordance with the reporting country's accounting standards and, in principle, at nominal (or contractual) values. It is recognised, however, that national accounting rules may require different valuation methods for particular positions.

reporting banks in country "i" to counterparty banks in country "j" should be a good proxy of the claims of reporting banks in country "j" on banks in country "i".

From the perspective of country "i", the tests can be described as:

$$Interbank\ claims_{i;j}^{LBS/R} \approx Interbank\ liabilities_{j;i}^{LBS/R}$$

and

$$Interbank\ liabilities_{i;j}^{LBS/R} \approx Interbank\ claims_{j;i}^{LBS/R}$$

The above comparison is only possible among LBS reporting countries. We use reported bilateral positions and aggregate to overall positions. The net interbank claims of all countries are defined by:

$$Net\ interbank\ claims = \sum_{i=1}^{x}\left[\sum_{\substack{j=1\\i\neq j}}^{x}(Claims_i^j - Liabilities_j^i)\right]$$

and

$$Net\ interbank\ liabilities = \sum_{i=1}^{x}\left[\sum_{\substack{j=1\\i\neq j}}^{x}(Liabilities_i^j - Claims_j^i)\right]$$

Where the inner sum represents net interbank claims/liabilities for reporting country "i" and x is the number of reporting countries in respective quarter. The value of x could be different depending on count of LBP reporting countries, with inclusion of new ones over the years.[7] Tables 1 and 2 (Annex) illustrate how net interbank claims and liabilities were derived in our exercise from underlying bilateral claims and liabilities for banks in reporting countries.

One crucial aspect which is ignored in most research using interbank claims and liabilities, even at the aggregate level, is that the LBS counterparty bank sector includes central banks (or official monetary authorities) which are not included in the reporting banks.[8] Therefore, a fair comparison between interbank claims and liabilities is valid only if the counterparty bank sector excludes central banks. Until Q3 2013, such an exclusion was possible only at the aggregate cross-border positions level, but hardly any analysis using aggregate level data on interbank claims/liabilities considered this aspect when comparing mirror positions.[9] The importance of positions vis-à-vis central banks in reconciliation of interbank claims/liabilities is demonstrated with actual reported data in Table 3.

7 x =38 in 2004, 39 in 2005/2006, 40 in 2007, 41 in 2008, 42 in 2009, 43 in 2010 to 2014, 45 in 2015 and 47 in 2016/17.

8 Data structure definition of LBS is available at www.bis.org/statistics/dsd_lbs.pdf#page=2.

9 Committee on the Global and Financial System (CGFS) Stage 1 and 2: "Improving the BIS international banking statistics", CGFS Papers, no 47, BIS, November 2012.

Positions vis-à-vis counterparty bank sector and, of which, central bank

Actual reported positions, as of Q4 2017, in USD millions — Table 3

Position	Reporting country (RC)	Interbank sector including CBs	Interbank sector excluding CBs
Claims	RC1 on RC2	28,393.0	8,155.0
Liabilities	RC2 to RC1	8,720.7	8,600.8
Net interbank claims of RC1 on RC2		**19,672.3**	**–455.8**

Position	Reporting country (RC)	Interbank sector including CBs	Interbank sector excluding CBs
Liabilities	RC1 to RC2	31,499.0	9,334.0
Claims	RC2 on RC1	11,736.1	8,020.6
Net interbank liabilities of RC1 to RC2		**19,762.9**	**1,313.4**

In our analysis, we exclude bilateral positions vis-à-vis central banks, which are reported with enhanced data from Q4 2013[10] subject to availability (a few countries started providing enhanced data in subsequent quarters). Using reported bilateral data and the methodology described above, Table C1.1 and Table C1.2 (Annex) respectively reveal results by country for positions in total of all currencies.[11] Both Tables show the comparison of net bilateral interbank claims and net bilateral liabilities for the same set of 44 individual reporting countries between two periods: Q4 2011 (before CGFS enhancements) and Q4 2017.[12]

Between 2011 and 2017, the size of net claims differences, at the level of all reporting countries, fell from USD –322.8 billion to USD –162.5 billion, which corresponds to a decline from –2.2% to –1.5% of the stock of net interbank claims (Graph C1 left-hand panel and Table C1.1).

At an aggregate level, this is represented with the opposite sign for net interbank liabilities (Graph C1 right-hand panel and Table C1.2 (Annex)). Of the 25 countries shown individually in the table, net interbank claims improved for 16 countries between 2011 and 2017, and also for nine of other 19 countries not shown individually. This trend is also observed for net interbank liabilities across countries with some exceptions.

10 According to the march 2013 'Reporting guidelines and practices for BIS international banking statistics' which incorporates Stage 2 enhancements, sub-sectors within the banking sector should be reported in both sets of locational statistics.

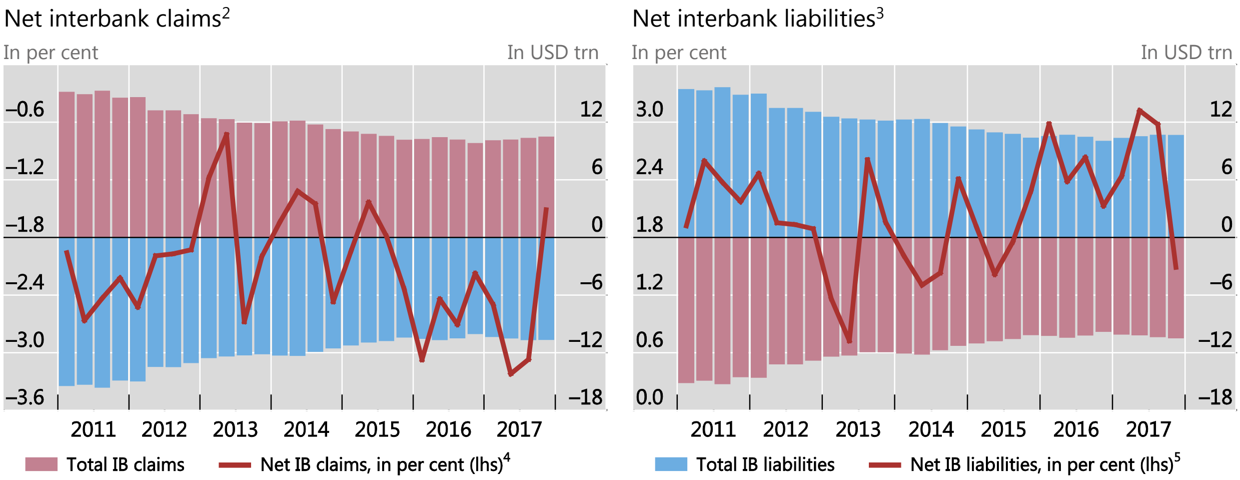
11 We also examined total differences by currency – total, euro and dollar – but results in tables are for all currencies.

12 Three countries (China, Russia and the Philippines) joined after Q4 2011 and are excluded for the comparison from these two tables.

Cross-border net interbank claims and liabilities in reporting countries[1]

Excluding positions vis-à-vis central banks

Graph C1



[1] Interbank positions of banks in 44 reporting countries; CN, PH and RU started reporting after 2011 and are excluded. [2] Sum of all bilateral claims of banks in one reporting country vis-à-vis banks in the other 43 reporting countries minus sum of all bilateral liabilities by banks in the other 43 reporting countries to banks in a reporting country. [3] Sum of all bilateral liabilities of banks in one reporting country to banks in the other 43 reporting countries minus sum of all bilateral claims by banks in the other 43 reporting countries on banks in a reporting country. [4] Net claims (=total Interbank claims minus total Interbank liabilities) as a percentage of total Interbank claims. [5] Net liabilities (=total Interbank liabilities minus total Interbank claims) as a percentage of total Interbank liabilities.

Source: BIS locational banking statistics by residence (QR June 2018, Released database).

It is noteworthy that the accuracy of the results also depends on the availability of data reported on positions vis-à-vis central banks (CB), a subcategory of the total banks sector. Graph C2 represents the share of the central bank sector in total claims/liabilities, interbank claims (loans) and interbank liabilities (deposits) vis-à-vis the counterparty bank sector. It shows that global cross-border interbank claims and interbank liabilities are highly concentrated within BIS reporting countries (about 95% for claims and 92% for liabilities).

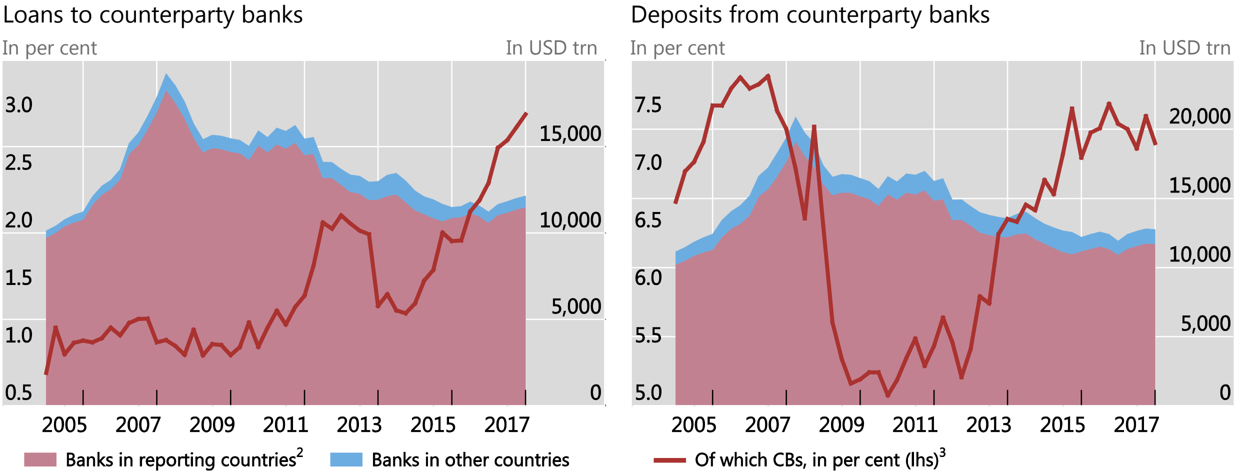
On the other hand, the share of the CB subsector has been increasing over time with respect to loans and after 2009 for deposits. In 2017 the percentage of central bank (CB) loans and deposits was 3% and 7.5%, respectively, in the total amount of the "banks" sector.

We further analysed the loans to CBs and deposits from CBs by counterparty country location from Q4 2013 (Graph C3). The bilateral cross-border loans of reporting banks to CBs (left) are shown by location and for deposits of CBs (right) placed with reporting banks. Between 2014 and 2017, cross-border loans to CBs have increased from USD 177 billion to USD 368 billion, whereas for cross-border deposits from CBs increased from USD 898 billion to USD 929 billion. It can also be seen that in the case of loans, counterparty CBs located in reporting countries correspond to 80% of the total amount (compared with 14% in non-reporting countries and the remaining 6% undisclosed by location for confidentiality reasons). In the case of deposits, counterparty CBs in reporting countries correspond to only 37% (and 35% from CBs in non-BIS reporting countries and a remaining 28% undisclosed by location for confidentiality reasons).

Global cross-border interbank loans and deposits vis-à-vis bank sector[1]

Counterparty banks in all countries

Graph C2



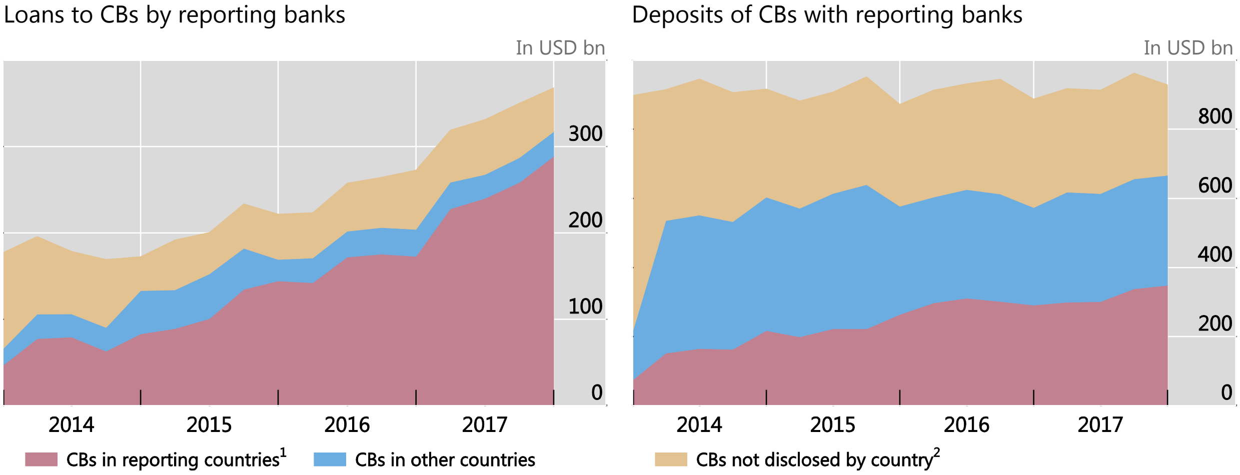
[1] In the locational banking counterparty sector, "banks" includes central banks. [2] Among all counterparty countries in the world, the set of counterparties as reporting countries and as other countries adjusted in each quarter, depending on countries that contributed to the LBS in the respective quarter, ie 38 in 2014 and 47 in Q4 2017. [3] Share in total claims/liabilities vis-à-vis bank sector.

Source: BIS locational banking statistics by residence (QR June 2018, Released database).

Cross-border loans and deposits vis-à-vis central banks

By location of counterparty CBs

Graph C3



[1] Among all counterparty countries in the world, the set of counterparties as reporting countries and as other countries adjusted in each quarter, depending whether countries contributed to the LBS in the respective quarter, ie 44 in 20014 and 47 in Q4 2017. [2] Cross-border positions not allocated by country either to counterparty reporting countries or to other countries, mainly on account of confidentiality restrictions.

Source: BIS locational banking statistics by residence (QR June 2018, Released database).

When we consider the Portuguese case, net claims differences fell from USD –1.8 billion (end-2011) to USD –0.9 billion (end-2016). We investigated the interbank claims/liabilities of banks in Portugal vis-à-vis banks in other reporting countries between 2004 and 2017. We find that the loan claims and deposit liabilities of Portuguese banks are mostly vis-à-vis the bank sector in other reporting countries. Although the positions vis-à-vis the CB subsector in the case of banks in Portugal were immaterial, the exclusion of these positions, starting in 2014 when data became available, further diminished the already negligible differences between compared claims and liabilities. This also means that the quality of interbank data reported by Portugal (vis-à-vis other reporting countries) and by other reporting countries (vis-à-vis Portugal) has improved over time.

Differences identified in Table C1.1 and C1.2 indicate that the interbank assets/liabilities reported by countries may not be consistent with derived liabilities/assets provided by counterparty reporting countries. However, this does not necessarily mean that there are gaps or errors for the reporting country concerned. Some issues can be adduced to explain the differences:[13]

1. **Coverage** – incomplete coverage of the counterparty banks – eg banks in a reporting country may have claims on a specific bank located in another reporting country that exclude the bank from its reporting population.
2. **CB's positions** – not all concerned countries disclose bilateral positions vis-à-vis CB (official monetary authorities). These positions, if not excluded, will widen the gap in the reconciliation of interbank positions.
3. **Definition of bank sector** – a few countries include building societies or post-banks in their reporting banks but they are non-bank counterparty for other reporting countries. Non-bank financial institutions are also included in some reporting populations (eg development banks and export credit agencies).
4. **Instrument breakdown** – in some cases, there are gaps in instrument breakdown as well as issues with the inclusion/exclusion of items within loans and deposits. For example, non-negotiable debt instruments should be reported under loans and deposits, not in debt securities. By contrast, loans that become negotiable should be reported under debt securities (provided that a secondary market exists for the trading of such loans).
5. **Valuation** – varying valuation methods. According to the BIS guidelines, loans and liabilities (eg deposits) should be valued at nominal (or contractual) values rather than at market prices. However, it is recognised that national accounting rules may require different valuation methods for particular positions.
6. **Banking laws** – treatment of instruments could differ due to accounting or other reasons (eg Islamic banking).
7. **Legal/confidentiality restrictions** – country legal restrictions preventing the disclosure of bilateral loans/deposits for confidentiality reasons, even to the BIS.
8. **Different reporting practices** – with regard to fiduciary instruments (credit on a trust basis).

[13] The relative importance of each issue will vary according to the reporting country.

LD2: Comparison domestic claims, local claims in all currencies and local liabilities of domestic banks between the LBS/N and CBS/IC[14]

We compare domestic claims in all currencies, local claims in all currencies and local liabilities in local currency vis-à-vis residents of the respective reporting countries using data reported in the CBS/IC and LBS/N.

Domestic claims are those vis-à-vis residents of a country, regardless of whether the claims/liabilities are booked by domestic banks' offices inside the country (local claims) or by offices outside the country (cross-border claims). In the LBS/N domestic claims are those vis-à-vis residents of the parent country and are reported by host LBS countries, while in the CBS/IC those vis-à-vis residents of the country that compiles/reports the data.

On the other hand, local claims and local liabilities of domestic banks are those vis-à-vis residents of country where banking offices are located, be in the reporting country or abroad. In our test, we consider local claims and local liabilities vis-à-vis residents of the reporting country that compile both data sets. In the LBS/N, both local claims and local liabilities are available with a currency breakdown into local (or domestic) and foreign currencies. However, in the CBS/IC local liabilities vis-à-vis residents are available only in local currency and are collected as a memo item. That is why we can compare domestic claims (local plus cross-border) and local claims from LBS/N (both excluding intragroup positions) with the reported figures in CBS/IC but only the local liabilities in local currency (defined as liabilities booked in the domestic currency of, and with a counterparty located in the reporting country in both the LBS/N and CBS/IC).

The intuition is that the above positions[15] of country "i" banks (domestic banks) in the consolidated banking statistics on an immediate counterparty basis vis-à-vis residents of country "i"[16] should be a good proxy for the domestic position, excluding intragroup, of country "i" banks in the locational by nationality statistics.

This test can be described for both claims and liabilities by the following:

$$LBS/N\ claims_i^{DomesticAll} \approx CBS/IC\ claims_i^{DomesticAll}$$
$$LBS/N\ claims_i^{LocalAll} \approx CBS/IC\ claims_i^{LocalAll}$$
$$LBS/N\ liabilities_i^{LocalLocal} \approx CBS/IC\ liabilities_i^{LocalLocal}$$

The results are shown in Tables C2.1, C2.2 and C2.3 (Annex). Domestic claims and liabilities in the LBS are available from Q2 2012 under enhanced requirements, while domestic claims are available in CBS/IC from Q4 2013.

Table C2.1 reveals that the differences in domestic claims between the LBS/N and CBS/IC diminished at an aggregate level in percentage terms from 16.6% in Q4 2014 to 15.9% in Q4 2017. It was possible to reveal figures in all cells for 19 countries but not for all countries due to data confidentiality or data gaps. The amounts between

[14] Domestic claims in all currencies, local claims in local currency and local liabilities in local currency, potentially include financial instruments (eg debt securities) in addition to loans and deposits.

[15] Positions vis-à-vis banks and non-banks located in the same country of residence of the reporting banking office.

[16] Available in the enhanced CBS/IC data from Q4 2013, and from Q2 2012 in the LBS/N data.

the two data sets are either almost the same or differ by less than 10% for 13 of the 19 reporting countries. On the other hand, relatively large differences exist for a number of countries

Table C2.2 compares local claims in all currencies on residents of the reporting countries by domestic banks located in the same country of residence as that of the reporting country. In the total of 16 countries, the difference increased from USD 3,603 billion (12.4%) in Q4 2014 to USD 3,716.3 billion (14.6%) in Q4 2017. However, the individual behaviour is heterogeneous, with a number of countries posting almost the same amount in both data sets.

Table C2.3 compares local liabilities in local/domestic currency between the LBS/N and CBS/IC. The table shows that the amounts between the two data sets are either the same or differ by less than 6% for a number of reporting countries while, for other countries, the gap between the two data sets has increased between 2014 and 2017.

Differences between the LBS/N and CBS/IC may relate to several different issues:

1. **Coverage** – the CBS/IC have a much broader coverage than the LBS/N data. In addition, while the CBS reporting population may exclude smaller banks and include non-financial subsidiaries (excluding insurance), the LBS/N population may include non-bank affiliates such as building societies, credit unions and other financial institutions that take deposits or issue a close substitute for deposits.
2. **Different criteria** – the LBS and CBS/IC use different criteria for the classification of domestic banks. Some countries classify banks with a private foreign ownership as non-domestic banks in the LBS/N but classify them as domestic banks in the CBS for supervisory purposes.
3. **Geographical breakdown** – domestic claims are aggregated by nationality in the LBS/N data (excluding inter-office claims) by the BIS, whereas they are reported by the concerned country in the CBS/IC. Different data sources, particularly inter-office positions, may not be completely consistent or correctly reported. In certain cases, inter-office positions may include those vis-à-vis non-bank affiliates.
4. **Reporting issues** – in the case of local liabilities in the CBS/IC, a number of countries report only loans and deposits, whereas other positions such as debt securities are also included in the LBS/N. Debt securities issues by counterparty country are also difficult to report under the CBS.
5. **Different scope/coverage** – in some countries, such as Austria and Finland, a very large number of small banks are not consolidated by a parent. If these very small banks have a reporting obligation only for the LBS/N, whereas in the CBS only "internationally active banks" are included, the local/domestic claims and liabilities are prone to differ. In such a case, the CBS's focus on internationally active banks might actually lead to a situation where the LBS/N provide a broader coverage of domestic/local business, whereas the CBS are broader in their coverage of international banking businesses.
6. **Different scope of consolidation** – the "artificial consolidation" applied in this test by excluding intragroup positions is only applied to claims/liabilities from banks, whereas the scope of consolidation in the CBS is usually wider

in scope (often a prudential scope of consolidation is used, also including various kinds of financial intermediaries). As a result, the LBS/N part of the test usually includes claims and liabilities that would be consolidated by the reporting bank in the CBS. Additionally, it is usually very hard for central banks to classify liabilities/debt securities as intragroup, which would not allow them to "artificially consolidate".

There are varying experiences across countries. In Portugal, the main discrepancies for the recent periods are related to the geographical breakdown on interest owed but not yet paid. Austria explains that the difference is mainly due to the sample of reporting banks, in that only internationally active banks are included in the CBS. Another important difference between the LBS/N and CBS for liabilities for Austria is how debt securities are treated: while they are not included in local liabilities in the CBS, they are included in the LBS/N and assigned to a counterparty based on an estimation of the holder of the securities (based on the Securities Holdings Statistics or SHS data). In the Swiss case, interbank positions in the CBS are netted between the parent company and its subsidiaries/affiliates (netting in both directions) but, in the LBS/N, positions against parent companies or "sister" companies are not included in the counterparty sector "intragroup".

LD3: Comparison of loans and deposits between the BIS LBS/R and the IMF IIP

We examine the loans and deposits of deposit-taking institutions excluding CB between the LBS/R and the IMF IIP

We consider that cross-border loans and deposits for both claims and liabilities on the accounts of reporting banks in the LBS/R should be comparable with the country's International Investment Position assets and liabilities for the functional category "other investment" comprising currency, deposits and loans for the deposit-taking corporations, excluding central banks.

This test can be summarised as follows:

$$LBS/R\ assets_i^{Loans\ and\ deposits} \approx IIP\ assets_i^{Loans\ and\ deposits}$$
$$LBS/R\ liabilities_i^{Loans\ and\ deposits} \approx IIP\ liabilities_i^{Loans\ and\ deposits}$$

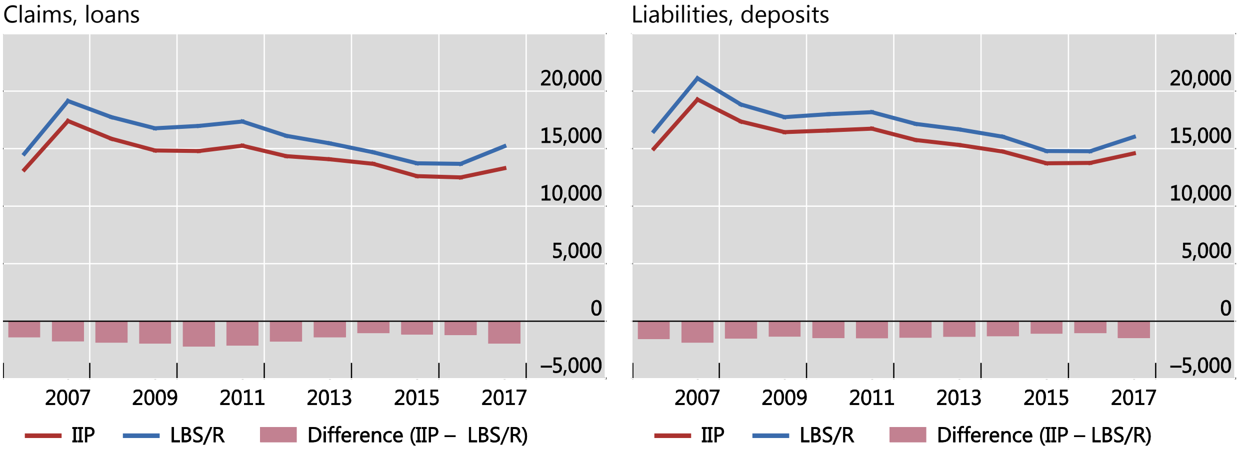
Graph C5 shows the evolution of LBS/R and IMF IIP claims and liabilities between 2006 and 2017. Note that loans and deposits have declined for these countries after the 2007–09 Great Financial Crisis. In addition, LBS/R amounts are higher than the IIP for this period.

We also compare LBS/R data with the IIP by country for two different periods – Q4 2014 and Q4 2017. Of the 47 reporting countries in the LBS/R, IIP data for loan claims and deposit liabilities of deposit-taking corporations are not available for 12 LBS/R reporting countries.[17] We thus make the comparisons for the remaining 35 LBS/R reporting countries.

17 The IIP data on loans and deposits are not available for 12 LBS/R reporting countries (BS, BH, CN, CW, GG, IM, JE, KY, MO, MY, SG and TW).

Cross-border loans and deposits between the BIS LBS/R and the IMF IIP[1]

In billions of US dollars | Graph C5



[1] Claims and liabilities in the IIP comprise "Other investment" on account of currency and deposits, and loans of deposit corporations excluding central banks. This graph shows comparison for total loans and deposits for the 24 countries for which IIP data have been available since Q4 2006. The countries are AT, AU, BE, BR, CA, CH, CL, DE, DK, ES, FI, FR, GB, GR, IN, IT, JP, KR, LU, NL, PA, SE, TR and US. The latest available IIP data for GB related to Q4 2015 and were copied to Q4 2016 and Q4 2017. A number of other countries that started reporting IIP data after Q4 2006 are excluded from this graph (details in Table C3.1 and Table C3.2).

Source: BIS locational banking statistics by residence (QR June 2018, Released database) and IMF International Investment Positions (IIP, 2018 M06 release)

Table C3.1 and C3.2 (Annex) confirm that, except in some instances, data on loans and deposits between LBS/R and the IIP reporting systems are complementary to each other as the differences are limited for most countries. While both sets exist for different purposes (eg granularity in the LBS/R, frequency), there are a number of benefits in such complementary data sources. For instance, the short-term and long-term split, not available in the LBS/R, can be found in the IMF IIP database.

In the case of loans claims, the difference in the total of all countries increased from –6.9% in Q4 2014 to –9.1% Q4 2017. The difference between the two mirror sources fell for most other countries. In the case of deposit liabilities, the difference in the total of all countries fell from –7.7% in Q4 2014 to –6.7% in Q4 2017, and, except in a few cases, the differences between the two mirror sources also narrowed in the latest period of Q4 2017.

In the Portuguese case, the differences between the IIP and LBS/R for claims amount to USD –0.2 billion in Q4 2014 and USD –1.5 billion in Q4 2017 (Table C 3.3, Annex). These differences are mainly related to the geographical breakdown on interest owed not yet paid. The larger values for the Swiss IIP are related to the calculation from the monthly balance sheet survey, which includes more than 240 banks (larger than number of reporting banks in the LBS/R data). However, the difference between the IIP and LBS/R for Switzerland fell in Q4 2017 compared with Q4 2014. Canada's main differences on the assets side are related to the inclusion of inter-office positions – equity and retained earnings in the LBS/R loans and deposits. On the liabilities side, the discrepancy is caused by the exclusion of repo transactions in the IMF IIP and the inclusion of covered bonds in the LBS/R.

D. Methodological framework and results for debt securities: Linkages between the LBS and other statistical domains

In this section, we discuss three broad categories of mirror relationship with subcategories for the debt securities claims/liabilities. Debt securities claims and liabilities (DS)

DS1: Comparison of cross-border debt securities claims between the BIS LBS/R and the IMF IIP

We examine the cross-border debt securities claims between the BIS LBS and the IIP of deposit-taking corporations excluding the CB of that country.

The cross-border debt securities claims of deposit-taking corporations, except for those of CB, should, in principle, be comparable between the BIS LBS/R and the IMF IIP. The presumption in this case is that the cross-border debt securities assets of reporting banks in the LBS/R should be similar to the portfolio investment net acquisition of financial assets amounts of deposit-taking corporations (excluding those of central banks).

This test can be described by the following formula:

$$LBS/R\ assets_i^{Cross-border\ debt\ securities} \approx IIP\ assets_i^{Debt\ securities}$$

The IMF IIP data on portfolio investment debt securities claims are available for 34 of 47 countries with latest available data for Q4 2017 (2018 M06 release).[18] In the LBS/R, two countries (Bahrain and Curaçao) do not report cross-border debt securities claims and, of the remaining 45 countries, the data for two countries are not disclosed.

Graph D1 shows the relationship between the LBS/R and IIP for these two periods. It is noteworthy that almost all reporting countries are aligned between the two data sets. However, there are some exceptions for countries with larger LBS/R and IIP amounts.

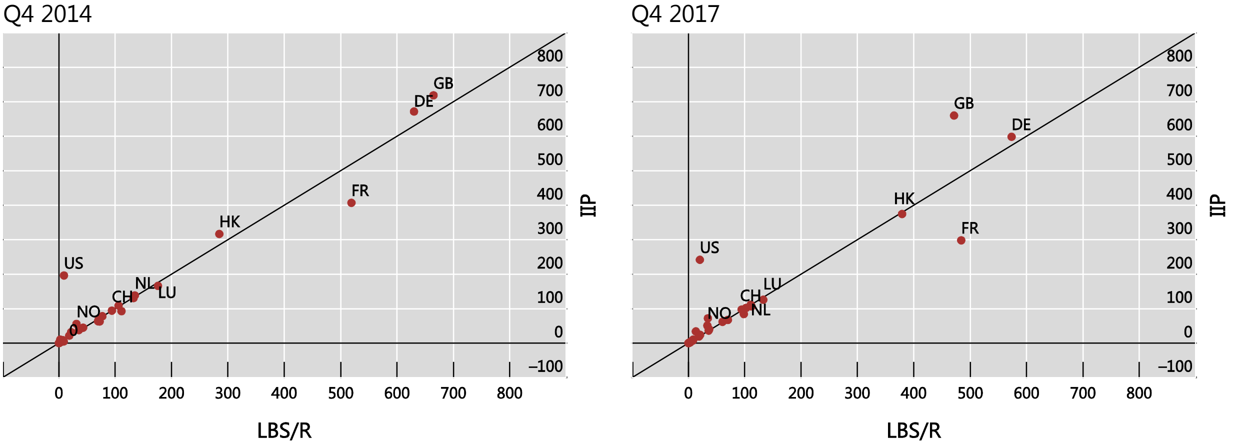
In particular, data are exactly or almost the same or they differ by less than 5% for 14 countries. On the other hand, large differences exist for three countries (GB, JP and US). A time series comparison shows high volatility in the data for the most recent quarters in a number of countries (eg Australia and France), which may be due to the provisional nature of the data. Further investigation is needed, with the help of reporting countries, to understand the underlying reasons and resolve any issues relating to concepts, coverage or reporting. A few large exceptions resulted in a broader gap in the total of 34 countries. Nevertheless, a comparatively good consistency between the two mirror sources for a large number of countries offers the added benefit that cross-border debt securities claims from the IIP are available with a maturity breakdown into short- and long-term.

[18] IIP data on cross-border debt securities claims are not available for 13 LBS reporting countries (BH, BS, CA, CN, CW, GG, IM, JE, KY, MO, MY, SG and TW).

Cross-border debt securities claims between the BIS LBS/R and the IMF IIP[1]

In billions of US dollars

Graph D1



[1] The IMF IIP data for debt securities claims are available for 34 of the 47 LBS/R reporting countries. The graph shows data for 31 of the 34 countries, excluding JP, PH and RU (data of JP are not public whereas those for PH and RU are not available in Q4 2014). Further details provided in the footnote of Table D1.

Source: BIS locational banking statistics by residence (QR June 2018, Released database) and IMF international investment positions (IIP, 2018 M06 release).

There are country-specific reasons for differences in the cross-border debt securities claims of deposit-taking corporations (except those of CB between the two sources. The main reasons for the differences between the two data sources are listed below:

1. **Coverage** – while debt securities issued by internationally active banks are included in the LBS, the IIP covers those by all deposit-taking institutions excluding central banks.
2. **Sources** – in most countries, the LBS data are compiled by central banks (official monetary authorities) while the IIP is compiled mostly by statistical agencies but CB in some other cases.
3. **Definition** – the definition and treatment of external/cross-border positions might differ between the LBS and the IIP.
4. **Treatment of instruments** – there is the possibility of incorrect classification of instruments by the reporting entities. In particular, debt securities that are held on a custodial basis for customers or acquired without cash collateral should not represent on-balance sheet claims (or holdings of debt securities).

DS2: Comparison of cross-border debt securities liabilities between the BIS LBS/R and the IMF CPIS

We examine the debt securities liabilities of banks by counterparty country between the LBS/R and the CPIS. This section also benefits from information available from the IMF as well as from a few central banks. The concepts of counterparty country and counterparty sector are identical between the LBS/R and the CPIS: both follow the same BoP/IIP treatments or principles. The treatment of instrument classification is almost the same. In both data sets, loans that have become negotiable instruments are reclassified from loans to debt securities.

With regard to our purpose on debt securities liabilities by counterparty country, the main problem is that the issuer of a security (debtor) may not know the residency of the holder. This uncertainty for tradable instruments arises from the fact that foreign custodians or other intermediaries may hold the securities. The CPIS thus provides more reliable detailed cross-border positions because the holder (creditor) will usually know its holdings. We explain below the conceptual framework that could be exploited to use the CPIS source to ascertain counterparty country names and the amounts of bank-issued debt securities liabilities. A further possibility is that the remaining amount could be either proportionally allocated to these known counterparty countries or assigned to unallocated (cross-border or unknown location) in the LBS/R.

The CPIS was first conducted for end-December 1997, but data are comparable annually from 2001 to 2012. From 2013 onwards, the CPIS was published semi-annually (end-June and end-December). According to the CPIS guidelines, a reporting economy provides data on its holdings of portfolio investment securities (separate data are reported for equity and investment fund shares, long-term and short-term debt instruments). Derived portfolio investment liabilities (all economies) by the economy of non-resident holders are also available in this survey.

The coverage of reporting countries in the CPIS has increased over time. Comparing the two sources, we find that 44 of 47 LBS/R reporting countries provide CPIS data to the IMF. The limitation for derived debt securities liabilities is that liabilities would be known only to CPIS reporting countries that voluntarily report holdings of such securities by issuing sector as an "encouraged" contribution. The usefulness of the CPIS is that, using the holding data by issuing sector, it is possible to obtain the derived debt securities liabilities of 120 countries vis-à-vis holders in a maximum of 26 CPIS reporting economies. For example, one can identify the names of a maximum 26 counterparty countries that hold debt securities liabilities of banks located in Australia.

The voluntary reporting in CPIS for holdings of debt securities by issuer sector leads to our intuition that the total cross-border debt securities liabilities of reporting banks in the LBS/R in all currencies should be higher than those derived from the CPIS reporting countries' holdings of debt securities that were issued by deposit-taking corporations (excluding central banks).

This test can be described by the following formula:

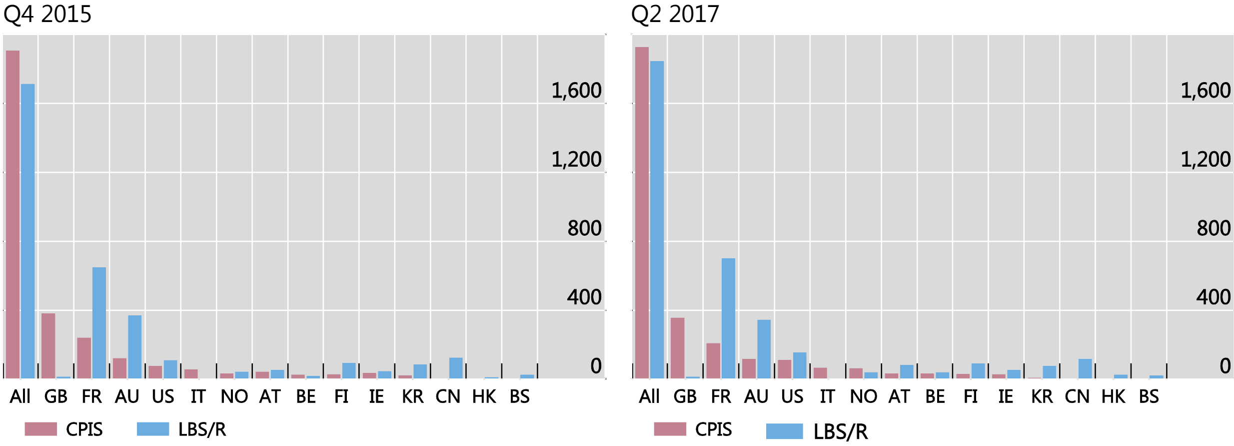
$$LBS/R\ liabilities_{i,j}^{Cross-border\ debt\ securities} > CPIS\ liabilities_{i;j}^{Derived\ debt\ securities}$$

We compare data as of end-December 2015 and end-June 2017[19] (Graph D2) and we demonstrate the results by country in Table D2 (Annex).

[19] The reason for the choice of the first period was that both China and Russia started reporting LBS data from Q4 2015.

Cross-border debt securities liabilities of banks by issuing country[1]

Amount outstanding; in billions of US dollars — Graph D2



[1] Countries having more 20 billion USD debt securities outstanding by individual counterparty countries either in CPIS or in LBS/R are shown in the graph.

Sources: BIS locational banking statistics by residence (QR June 2018, Released database) and IMF CPIS survey (15 March 2018 release).

Although the gap in partially reported counterparty country breakdown between the CPIS and LBS/R has fallen by over 50% (from USD 193 billion in Q4 2015 to USD 83 billion in Q2 2017) within one and half years, it is surprising to note that the counterparty breakdowns within the LBS/R are underreported by almost 50% of the total cross-border amount (Table D2, columns 3 and 4 versus columns 7 and 8).

In addition, we investigated the gap between the LBS/R and CPIS for the same set of 47 BIS reporting countries. The derived debt securities liabilities of banks from the CPIS should be lower in amount as compared with the reported data in the LBS/R, because the number of reporting countries providing issuing sector breakdown is limited in the CPIS. There are other reasons that could potentially cause differences, even if all CPIS countries reported the breakdown, as encouraged. Differences between the two sources can be partially explained by valuation. In the case of the CPIS, holdings (from which we derived liabilities of banks in counterparty countries) are reported at market values, whereas the guidelines for the LBS/R reporting recommend the use of nominal (or contractual) values rather than market values. It is also recognised that national accounting rules may require different valuation methods for particular positions. However, additional factors probably need to be invoked to explain the large differences.

In our exercise, we find a number of interesting facts: First, the CPIS data suggest that banks in Bahrain, Curaçao, Greece and Singapore issued debt securities liabilities but these countries did not report such liabilities in the BIS LBS/R. Second, countries with large cross-border debt securities liabilities, such as the Cayman Islands, Germany and the United Kingdom, do not report any counterparty country breakdown in the LBS/R (reported as total cross-border) but country breakdowns are available in the mirror CPIS data (holdings of debt securities). Third, about USD 1.6 trillion are reported in LBS/R against unallocated by location (neither residents nor non-residents/cross-border). The countries with significantly large amounts vis-à-vis unallocated by country are, above all, Denmark, Japan, Luxembourg, the Netherlands Sweden and Switzerland.

The CPIS data on holdings of debt securities (claims) reported by CPIS participating economies vis-à-vis all other economies in the rest of the world (including unallocated) are informative and useful. These claims data by individual counterparty country and by counterparty issuing sector could serve the following needs:

1. They allow the debt securities liabilities of banks in individual countries to be derived vis-à-vis the reporting economies;

2. Reported debt securities liabilities in the LBS/R could be compared with derived debt securities liabilities from the CPIS; and

3. The country breakdown of debt securities liabilities from the CPIS can be used when such a breakdown is not available in the LBS/R, keeping the remaining amount (if any) in the unallocated category. One of the outcomes of this exercise is that the derived country breakdown of debt securities liabilities from the CPIS can be used to enhance data in other data sets (eg the LBS/R).

We also note below some limitations and sources of differences between the two sources:

1. **Frequency** – the CPIS is semi-annual (after 2013) whereas the LBS/R are quarterly.
2. **Vintages** – the CPIS data are available much later than the LBS/R data. Preliminary LBS/R data are available in about 120 days from the reference period but the CPIS data are available only about 250 days from the reference date.
3. **Reporting population** – only 26 countries report holdings of debt securities by issuing sector, whereas debt securities can be held by investors (creditors) in many more countries.
4. **Different sources** – in some cases, the main data sources for the LBS/R are the banks, while for the CPIS custodians and investment managers are the main data providers.
5. **Valuation** – holdings data in the CPIS are valued at market price whereas liabilities in the LBS/R are reported at book value. However, there are exceptions in the LBS/R that some countries report debt securities liabilities on market price (eg China, South Africa).

Finally, it is possible to use the country breakdown of debt securities liabilities from the CPIS and reconcile it with individual positions reported in the LBS/R. In future we plan to undertake such an exercise and demonstrate ways to use CPIS data for the counterparty country allocation of debt securities liabilities. In addition, as suggested by Austrian colleagues, the Centralised Securities Data Base (CSDB) would be also a good benchmark for comparisons within the euro area.

DS3: Comparison of international debt securities liabilities between the LBS/R and IDS

This section deals with the concepts and the comparison of outstanding debt securities between the LBS/R and IDS. Reporting banks in the LBS/R provide information on their debt securities liabilities vis-à-vis resident and non-resident (cross-border) counterparties of concerned reporting countries. When banks do not know the residency of the debt holder, they report amounts against an unknown country. In the case of the IDS, total international debt securities outstanding from the banks are obtained using a security-by-security database,

Using reported data in the LBS/R, we assume that banks' international debt securities outstanding are the sum of debt securities liabilities to non-residents (cross-border) in all currencies, and those to residents and unallocated countries in foreign currencies. We exclude all debt securities in domestic currency that are reported vis-à-vis residents as well as vis-à-vis unallocated countries. We explain below some potential conceptual differences between these two mirror sources and also give our views on the motivation for such comparisons, even with known weak links.

The concept in this case is that the aggregated outstanding debt securities liabilities of banks (LBS/R) should be comparable with the debt securities liabilities of banks from the IDS database. In other words, the international debt securities liabilities (LBS/R) of banks located in reporting country "i" should be similar to the outstanding amount of debt securities issued by public and private banks in the country "i" from the IDS databases.

This test can be described by:

$$LBS/R\ liabilities_i^{international\ debt\ securities} \approx International\ liabilities_i^{debt\ securities}$$

We show the results by groups of countries having outstanding debt securities of more than USD 20 billion as of Q4 2017 in either the LBS/R or the IDS (Graph D3). Since 2007, the debt security differences between the IDS and LBS/R have been falling due mainly to the contribution of developed countries. By end-2017, the differences had fallen to 29.4% from 46.4% in 2007.

Table D3 (Annex) shows the results for Q4 2015 and Q4 2017. The reason for the choice of the first period was that China and Russia started reporting LBS data from Q4 2015. Total percentage differences fell from –7.7% (2015) to –6.7% (2017).

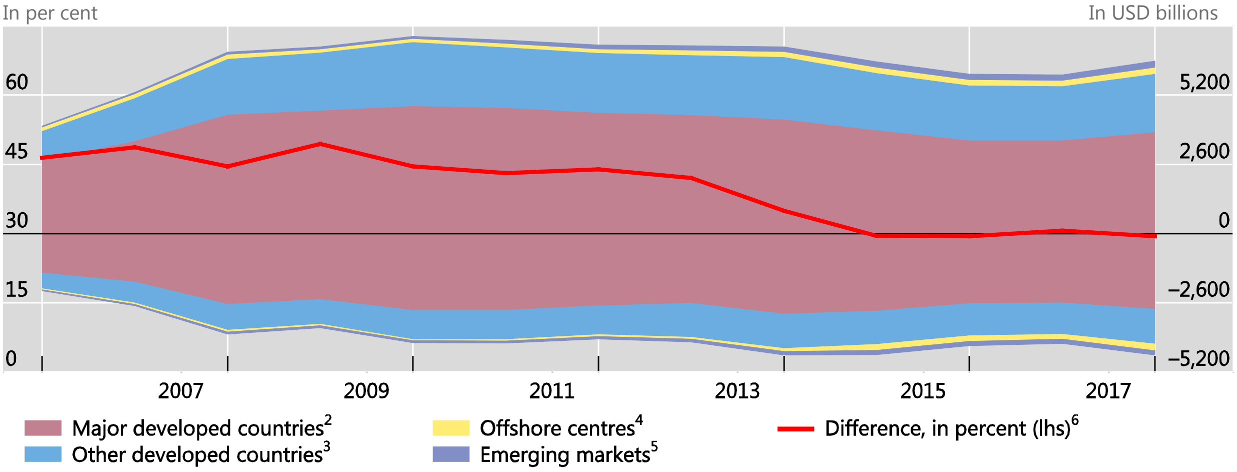
Nevertheless, Table D3 shows large differences for some countries. We examined why amounts in the IDS are always higher for securities denominated in the euro, primarily by banks in the euro area, followed by those denominated in US dollars. IDS statistics are compiled primarily from information on individual securities provided by commercial data sources. Regarding local currency-denominated debt securities (eg euro-denominated in the case of Portugal), the IDS consider a security as international if the governing law is not local and the security is listed on an exchange outside the borders of the country or if the security was issued as a euro bond. Among countries with a lower amount in the LBS/R are some that admittedly underreport debt securities liabilities compared with those in the IDS. There are different reasons for countries having a higher amount in the LBS/R than in the IDS. One reason is that the IDS do not include negotiable loans that are reported as debt securities liabilities in the LBS/R.

In the IDS database, some domestic bonds in local currency are reported as being listed on more than one exchange (for example, in the domestic market and in Luxembourg or London), and other domestic bonds may be subject to a foreign

International debt securities liabilities of banks in LBS/R reporting countries[1]

By issuer region

Graph D3



[1] Countries that either joined after Q4 2005 or do not have issuance recorded in the IDS or have not reported IDS are excluded. [2] Refers to largest issuers and comprises banks in DE, FR, GB, NL and US. [3] Comprises AU, AT, BE, CA, CH, DK, ES, FI, IE, IT, JP, LU, NO, PT, and SE. [4] Comprises BS, BM, KY, HK, MO and PA. [5] Comprises BR, CL, TW, IN, MX, KR and TR. [6] Percentage differences in amounts between IDS and LBS/R with respect to total IDS of the countries mentioned in footnotes.

Source: BIS locational banking statistics by residence (QR June 2018, Released database) and BIS international debt securities statistics (QR June 2018 release)

governing law (issued abroad). In both cases, they are treated as IDS, whereas the LBS/R excludes domestic local currency securities issued locally.

We are aware of conceptual differences between the two mirror sources. First of all, debt securities in the LBS/R should reflect liabilities to investors/buyers as of the reporting date whereas the BIS IDS reflect outstanding by place of issuance. In the LBS/R, a number of reporting countries assign the issuance country as the country of the debt securities holders in the LBS/R (He and Filková (2018) also note this from the country survey). The main reason is that debt securities are traded in the secondary market, and hence the country of the actual holders is usually unknown to the issuing banks. The difficulty of ascertaining the actual holders is also the reason why a number of countries report debt securities liabilities vis-à-vis unallocated by country. Second, in our comparison we followed the standard definition for the LBS/R, which defines the international positions as those that are vis-à-vis non-residents in any currency and vis-à-vis residents in foreign currencies.

On the other hand, the definition of "international" in the BIS IDS is based primarily on the market of issuance (outside the home market) and governing law (international). We have attempted to compare these two sources for two main reasons. First, issuing banks tend to report debt securities in the LBS/R based primarily on the place of issuance (ie cross-border or a foreign country/market where securities were issued) or those issued in the home country but aimed at foreign investors (eg those denominated in a foreign currency irrespective of place). Second, an increasing number of studies combine international/cross-border deposits positions from the LBS/R with debt securities liabilities from the BIS IDS. We thus opted to test if such combinations of sources are meaningful in view of the fact that deposit or debt securities liabilities in the LBS/R are those vis-à-vis actual creditors of banks whereas the IDS reflect only outstanding issuance.

We summarise below the main reasons for differences between the two data sets:

1. **Concepts** – the concepts differ between the two sources. The IDS measure primary market issuance, whereas the LBS/R liabilities are intended to measure holdings (resident vs non-resident holdings).
2. **Definition** – the definition of "international" differs between the LBS/R and the IDS. In the first case, cross-border securities plus local securities in foreign currencies are treated as international, whereas in the IDS debt securities are classified as international if at least one of the following characteristics differs from the country where the borrower resides: registration domain (ISIN), listing place or governing law.
3. **Sources** – LBS/R data are reported by central banks, whereas IDS data are compiled from commercial sources.

E. Conclusion

We demonstrate at an aggregate level that data are available from multiple sources, although with differences in coverage and conceptual aspects. Their usefulness will depend on their granularity and on how widely available the data can be made, with a view to providing tools to validate data quality/reconciliation among reporting countries and fill in data gaps including estimation. Furthermore, mirror sources with good data quality would help provide better estimates of positions for and by non-reporting countries. As an example, the securities holding statistics from the CPIS allow users to obtain derived liabilities for about 120 countries. Similarly, the LBS/R allow BoP compilers in many countries to estimate the claims and liabilities of their residents vis-à-vis banks in BIS reporting countries.

Post-crisis, the enhancements approved by the Committee on the Global Financial System have spurred most of the reporting countries to improve data quality and coverage. These countries have closed reporting gaps and provided new breakdowns, and are reporting bilateral data with or without restrictions. The enhanced data have also allowed a better comparison of interbank positions for the first time. We hope that reporting countries will provide not only the recommended breakdowns at a granular level but will also consider providing encouraged breakdowns with lower confidentiality restrictions to relevant international institutions such as the BIS and the IMF.

Finally, it is important to clarify that this work is a first step towards identifying possible data gaps including limitations and confidentiality issues. These we do not intend to highlight, but rather we aim to point out possible ways of looking at the data with a much more consistent approach, making appropriate use of complementary information to fill in incomplete data. Another conclusion is that countries should work closely together in order to help to identify missing data/reporting errors or bilateral asymmetries. Nevertheless, international institutions should also make comparable analyses to help reporting countries identify these situations. In this endeavour, the BIS could play a major role by encouraging and involving reporting countries to reconcile data between mirror sources. This will be no easy task, but if the similarities and differences between different data domains are explored and explained, all data users would be helped towards a better understanding of the correct use and interpretation of statistical data.

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G. Annex: Statistical tables

Table	Description
Table 1	Illustration of bilateral interbank claims and liabilities
Table 2	Illustration for derived total and net interbank claims and liabilities
Table C1.1	Net bilateral interbank claims by reporting country
Table C1.2	Net bilateral interbank liabilities by reporting country
Table C2.1	BIS LBS/N vs BIS CBS/IC: Domestic claims of domestic banks vis-à-vis reporting countries
Table C2.2	BIS LBS/N vs BIS CBS/IC: Local claims in all currencies of domestic banks vis-à-vis reporting countries
Table C2.3	BIS LBS/N vs BIS CBS/IC: Local liabilities in local currency of domestic banks vis-à-vis reporting countries
Table C3.1	BIS LBS/R vs IMF IIP: Loans claims of deposit-taking corporations excl. central banks
Table C3.2	BIS LBS/R vs IMF IIP: Deposit liabilities of deposit-taking corporations excl. central banks
Table D3.3	BIS LBS/R vs IMF IIP: Loans and deposits of banks located in Portugal
Table D1	BIS LBS/R vs IMF IIP: Cross-border debt securities claims of deposit-taking corporations excl. central banks
Table D2	BIS LBS/R vs IMF CPIS: Counterparty country breakdown of cross-border debt securities liabilities of banks excl. central banks
Table D3	BIS LBS/R vs BIS IDS : International debt securities liabilities of banks
Table E	ISO codes and country/jurisdiction names

Illustration of reported bilateral interbank claims/liabilities and derived net interbank claims/liabilities

For simplicity, we assume that there are only three reporting countries: Austria, Belgium and Portugal. Table 1 identifies bilateral claims (loans) and liabilities (deposits) of reporting banks vis-à-vis banks in the other two counterparty reporting countries. The actual reported bilateral positions are unpublished and mostly either restricted or confidential. Using these underlying data, we derived aggregated interbank positions and net positions (Table 2).

Illustration of bilateral interbank claims and liabilities[1]
In USD

Table 1

Reporting country (i)	Counterparty country (j)	Claims i,j	Liabilities j,i
AT: Austria	PT: Portugal	10	15
AT: Austria	BE: Belgium	15	12
BE: Belgium	AT: Austria	20	16
BE: Belgium	PT: Portugal	25	28
PT: Portugal	AT: Austria	15	24
PT: Portugal	BE: Belgium	35	28
Total		120	123

[1] Numbers are for illustration only.

Table 2 also demonstrates that while net interbank claims/liabilities for individual countries might differ, the total net interbank claims must be equal to total net liabilities, of all countries combined.

Illustration for derived total and net interbank claims and liabilities

In USD billions — Table 2

Reporting country (net interbank claims)	Total claims [1]	Comparable liabilities of other countries [2]	Net claims [3] =[1]+[2]
AT: Austria	25	–40	–15
BE: Belgium	45	–40	+5
PT: Portugal	50	–43	+7
Total	**120**	**–123**	**–3**

Reporting country (net interbank liabilities)	Total liabilities [4]	Comparable claims of other countries [5]	Net liabilities [6]=[4]+[5]
AT: Austria	27	-35	-8
BE: Belgium	44	-50	-6
PT: Portugal	52	-35	+17
Total	**123**	**-120**	**+3**

Net bilateral interbank claims by country

In USD billions — Table C1.1

Reporting country (ISO Code)	End-2011				End-2017			
	Interbank claims [1]	Interbank liabilities [2]	Net claims [3]=[1]+[2]	% Net claims [4]= [3]*100/[1]	Interbank claims [5]	Interbank liabilities [6]	Net claims [7]=[5]+[6]	% Net claims [8]= [7]*100/[5]
All (Total)[1]	**14,529.6**	**–14,852.3**	**–322.8**	**–2.2**	**10,474.5**	**–10,637.0**	**–162.5**	**–1.5**
GB	2,890.7	–3,097.1	–206.3	–7.1	2,280.6	–2,248.6	32.0	1.4
US	2,534.1	–2,350.4	183.7	7.2	1,541.8	–1,466.2	75.7	4.9
DE	1,074.7	–1,175.3	–100.5	–9.4	835.3	–853.1	–17.7	–2.1
FR	1,201.1	–1,081.5	119.6	10.0	818.3	–848.9	–30.5	–3.7
JP	612.1	–517.5	94.6	15.4	565.5	–542.2	23.3	4.1
KY	1,070.6	–1,114.8	–44.3	–4.1	560.8	–552.5	8.3	1.5
HK	362.2	–345.7	16.5	4.6	489.3	–472.8	16.5	3.4
NL	367.0	–367.4	–0.4	–0.1	384.9	–380.0	4.9	1.3
LU	378.8	–487.3	–108.5	–28.6	288.8	–349.1	–60.3	–20.9
SG	274.1	–364.6	–90.5	–33.0	281.9	–351.9	–70.0	–24.8
CA	262.1	–174.7	87.4	33.3	268.8	–182.6	86.2	32.1
SE	200.5	–187.1	13.4	6.7	236.4	–225.7	10.7	4.5
BE	349.4	–318.4	31.0	8.9	224.7	–215.4	9.2	4.1
CH	551.0	–662.1	–111.1	–20.2	200.7	–349.9	–149.3	–74.4
IT	208.9	–211.1	–2.2	–1.1	163.1	–162.6	0.5	0.3
ES	204.3	–200.9	3.5	1.7	139.6	–119.2	20.4	14.6
DK	94.8	–101.8	–7.0	–7.4	134.5	–125.2	9.3	6.9
JE	221.4	–225.2	–3.7	–1.7	125.4	–138.0	–12.6	–10.0
IE	222.5	–234.0	–11.5	–5.2	120.5	–131.0	–10.5	–8.7
AU	72.6	–120.7	–48.1	–66.2	116.4	–133.6	–17.2	–14.8
GG	109.1	–110.7	–1.6	–1.5	93.9	–91.8	2.0	2.2
TW	43.5	–56.4	–12.9	–29.8	81.5	–86.9	–5.5	–6.7
BS	539.6	–507.1	32.5	6.0	81.0	–87.5	–6.4	–7.9
NO	67.4	–82.1	–14.7	–21.9	47.6	–58.1	–10.5	–22.1
FI	69.0	–68.6	0.4	0.5	43.3	–45.9	–2.6	–6.0
Others(19)	547.9	–689.9	–142.0	–25.9	349.8	–418.0	–68.2	–19.5

[1] Total of all 44 BIS reporting countries, excluding CN, PH and RU. These three countries (CN, PH and RU) were excluded from bilateral pairs and we kept the other comparable 44 reporting countries in both periods (Q4 2011 and Q4 2017). Of the 25 countries in shown in the table, net interbank claims improved for 16 countries between 2011 and 2017, and also for nine of the other 19 countries.

Source: BIS locational banking statistics by residence (QR June 2018, Released database).

Net bilateral interbank liabilities by country

In USD billions

Table C1.2

Reporting country (ISO Code)	End-2011				End-2017			
	Interbank liabilities [1]	Interbank claims [2]	Net liabilities [3]=[1]+[2]	% Net liabilities [4]= [3]*100/[1]	Interbank liabilities [5]	Interbank claims [6]	Net liabilities [7]=[5]+[6]	% Net liabilities [8]= [7]*100/[5]
All (Total)[1]	**14,852.3**	**–14,529.6**	**322.8**	**2.2**	**10,637.0**	**–10,474.5**	**162.5**	**1.5**
GB	3,042.5	–3,113.9	–71.4	–2.3	1,820.2	–1,730.5	89.7	4.9
US	2,694.5	–2,484.2	210.3	7.8	1,796.4	–-1,658.7	137.6	7.7
JP	781.9	–579.9	202.0	25.8	1,030.9	–841.4	189.5	18.4
FR	1,240.5	–935.6	304.9	24.6	793.2	–912.6	–119.4	–15.1
DE	702.0	–769.4	–67.4	–9.6	672.6	–684.2	–11.6	–1.7
KY	831.6	–870.4	–38.8	–4.7	512.2	–500.7	11.5	2.2
HK	368.3	–329.0	39.4	10.7	410.1	–399.2	10.9	2.7
NL	451.7	–495.7	–44.0	–9.7	377.3	–416.4	–39.1	–10.4
SG	305.6	–430.6	–125.0	–40.9	369.4	–461.5	–92.1	–24.9
CH	341.2	–427.8	–86.6	–25.4	327.6	–346.2	–18.6	–5.7
IT	402.4	–394.0	8.4	2.1	264.9	–277.6	–12.6	–4.8
LU	382.6	–452.0	–69.4	–18.1	239.8	–210.0	29.8	12.4
ES	389.5	–352.0	37.5	9.6	205.7	–157.7	48.0	23.3
CA	249.3	–227.6	21.7	8.7	193.4	–199.6	–6.2	–3.2
BE	229.6	–201.1	28.4	12.4	170.1	–149.0	21.1	12.4
SE	164.4	–143.6	20.8	12.6	158.6	–170.7	–12.1	–7.6
NO	127.8	–148.7	–20.8	–16.3	131.9	–143.9	–12.1	–9.2
AU	110.5	–162.0	–51.5	–46.6	128.5	–167.5	–39.0	–30.3
FI	179.0	–148.4	30.6	17.1	112.9	–99.8	13.2	11.7
BR	103.9	–94.3	9.6	9.3	102.9	–74.0	28.9	28.1
IE	347.0	–264.4	82.5	23.8	102.3	–108.8	–6.5	–6.4
TW	56.5	–62.2	–5.7	–10.0	90.1	–83.9	6.2	6.9
DK	128.9	–110.1	18.8	14.6	86.0	–82.5	3.5	4.0
TR	55.9	–57.9	–2.0	–3.5	72.0	–73.8	–1.9	–2.6
BS	434.4	–446.8	–12.4	–2.8	65.0	–56.3	8.7	13.4
Others(19)	730.8	–828.1	–97.3	–13.3	403.1	–468.0	–64.9	–16.1

[1] Total of all 44 BIS reporting countries, excluding CN, PH and RU. These three countries (CN, PH and RU) were excluded from bilateral pairs and we kept the other comparable 44 reporting countries in both periods (Q4 2011 and Q4 2017). Of the 25 countries in shown in the table, net interbank liabilities improved for 19 countries between 2011 and 2017, and also for eight of the other 19 countries.

Source: BIS locational banking statistics by residence (QR June 2018, Released database).

BIS LBS/N vs BIS CBS/IC – domestic claims of domestic banks vis-à-vis reporting countries[1]

Excluding intragroup claims, amounts outstanding in USD billions — Table C2.1

Parent /reporting country	Q4 2014		Q4 2017		Difference (amount) (LBS/N – CBS/IC)		Difference (percentage)	
	LBS/N	CBS/IC	LBS/N	CBS/IC	Q4 2014	Q4 2017	Q4 2014	Q4 2017
	[1]	[2]	[3]	[4]	[5] =[1]-[2]	[6]=[3]-[4]	[7] = [5]*100 /[1]	[8] =[6]*100 /[3]
Total[2]	**46,119.0**	**38,454.3**	**51,196.4**	**43,055.9**	**7,664.8**	**8,140.5**	**16.6**	**15.9**
AT	532.6	371.1	492.2	407.6	161.5	84.6	30.3	17.2
BE	286.6	266.2	357.1	331.4	20.4	25.7	7.1	7.2
CA	1,954.0	1,943.3	2,085.8	2,064.5	10.7	21.3	0.5	1.0
CH	1,165.3	1,172.4	1,382.9	1,390.0	–7.1	–7.1	–0.6	–0.5
CL	170.6	173.6	191.8	191.5	–3.0	0.4	–1.8	0.2
DE	5,447.3	5,222.8	5,568.5	5,435.1	224.5	133.4	4.1	2.4
DK	676.3	629.2	685.7	624.5	47.1	61.3	7.0	8.9
ES	2,357.4	2,164.1	2,090.4	1,943.4	193.3	147.0	8.2	7.0
FI	165.1	78.0	198.1	101.2	87.1	97.0	52.8	48.9
FR	4,051.1	3,761.8	4,602.1	4,426.4	289.3	175.7	7.1	3.8
GB	4,981.1	2,701.2	5,130.9	2,674.9	2,279.8	2,455.9	45.8	47.9
GR	289.9	298.6	247.6	257.1	–8.7	–9.5	–3.0	–3.8
IE	230.4	208.0	184.5	165.9	22.4	18.6	9.7	10.1
IT	3,304.5	2,893.1	3,133.1	2,739.9	411.4	393.2	12.4	12.6
JP	15,498.6	11,913.0	19,272.8	15,123.6	3,585.7	4,149.2	23.1	21.5
KR	1,553.7	1,533.0	1,873.2	1,853.5	20.6	19.7	1.3	1.1
NL	1,623.0	1,436.2	1,619.4	1,401.3	186.8	218.1	11.5	13.5
SE	761.0	695.7	770.8	722.9	65.4	47.9	8.6	6.2
TW	1,070.5	993.0	1,309.4	1,201.3	77.5	108.1	7.2	8.3
HK	57.9	…	65.9	…				
LU	52.4	…	62.9	…				
NO	326.1	…	314.8	…				
AU	2,294.7	NA	2,282.0	2,133.8				
BR	1,943.4	NA	1,722.5	NA				
IN	1,622.0	NA	2,046.7	NA				
MX	162.2	NA	170.2	NA				
PA	NA	NA	NA	NA				

BIS LBS/N vs BIS CBS/IC – domestic claims of domestic banks vis-à-vis reporting countries[1] (cont.)

Excluding intragroup claims, amounts outstanding in USD billions | Table C2.1

Parent /reporting country	Q4 2014		Q4 2017		Difference (amount) (LBS/N – CBS/IC)		Difference (percentage)	
	LBS/N	CBS/IC	LBS/N	CBS/IC	Q4 2014	Q4 2017	Q4 2014	Q4 2017
	[1]	[2]	[3]	[4]	[5] =[1]-[2]	[6]=[3]-[4]	[7] = [5]*100 /[1]	[8] =[6]*100 /[3]
PT	364.0	NA	263.5	224.0				
SG	NA	NA	NA	378.7				
TR	NA	666.2	NA	595.2				
US[3]	$$$	10,062.7	$$$	10,929.3				

[1] NA stands for data either not available or not derived because the home reporting country itself does not report either or both in local or foreign currency (See Section LD2); three dots ("...") stand for suppressed (ie restricted or confidential). [2] Only for countries from AT to TW. [3] The United States does not report local claims/liabilities vis-à-vis residents in LBS/N. The domestic claims of US banks in other BIS LBS reporting countries vis-à-vis US residents were $495 billion and $377 billion as of Q4 2014 and Q4 2017 respectively (shown as "$$$" and not included in the total).

Sources: BIS locational banking statistics by nationality and BIS consolidated banking statistics on an immediate counterparty basis ((QR June 2018, Released database for both sources).

BIS LBS/N vs BIS CBS/IC – local claims in all currencies of domestic banks vis-à-vis reporting countries[1]

Excluding intragroup claims, amount outstanding in USD billions — Table C2.2

Parent /reporting country	Q4 2014		Q4 2017		Difference (amount) (LBS/N – CBS/IC)		Difference (percentage)	
	LBS/N	CBS/IC	LBS/N	CBS/IC	Q4 2014	Q4 20174	Q4 2014	Q4 2017
	[1]	[2]	[3]	[4]	[5]=[1]–[2]	[6]=[3]–[4]	[5]*100/[1]	[6]*100 /[3]
Total[2]	**29,123.6**	**25,520.7**	**30,731.6**	**27,015.4**	**3,602.9**	**3,716.3**	**12.4**	**14.6**
BE	277.7	263.9	352.6	330.1	13.8	22.6	5.0	6.4
CA	1,916.7	1,916.7	2,042.0	2,042.0	0.0	0.0	0.0	0.0
CH	1,145.9	1,156.7	1,351.0	1,371.9	–10.8	–20.9	–0.9	–1.5
CL	170.6	172.7	191.8	190.9	–2.1	0.9	–1.2	0.5
DE	5,276.7	5,166.9	5,475.1	5,373.5	109.7	101.6	2.1	1.9
DK	661.0	628.1	653.8	622.0	32.8	31.8	5.0	4.9
ES	2,327.3	2,160.0	2,073.3	1,937.3	167.3	136.0	7.2	6.6
FI	165.1	78.0	198.1	100.9	87.1	97.3	52.8	49.1
FR	3,903.0	3,611.2	4,506.2	4,329.4	291.8	176.8	7.5	3.9
GB	4,845.9	2,632.5	5,028.5	2,635.9	2,213.5	2,392.6	45.7	47.6
GR	287.2	296.4	246.5	255.5	–9.3	–8.9	–3.2	–3.6
IT	3,249.9	2,856.0	3,091.5	2,707.5	393.9	384.0	12.1	12.4
KR	1,546.8	1,530.4	1,868.8	1,848.2	16.5	20.6	1.1	1.1
NL	1,584.4	1,417.0	1,599.2	1,370.8	167.4	228.4	10.6	14.3
SE	699.1	658.8	748.6	704.5	40.3	44.0	5.8	5.9
TW	1,066.2	975.1	1,304.5	1,195.0	91.1	109.5	8.5	8.4
HK	57.2	…	…	…				
IE	…	206.7	…	165.5				
LU	…	…	61.2	…				
NO	…	…	…	…				
AT	532.3	NA	491.5	406.0				
AU	2,269.2	NA	2,252.5	2,009.1				
BR	1,882.6	NA	1,677.1	NA				
IN	…	NA	…	NA				
JP	15,449.0	NA	19,210.5	NA				
MX	159.0	NA	164.0	NA				
PA	NA	NA	NA	NA				
PT	…	NA	…	…				
SG	NA	NA	NA	…				
TR	NA	NA	NA	NA				
US	NA	9,849.4	NA	10,728.9				

[1] Local claims in currencies on residents of the reporting country by their domestic banks. See additional details in explanatory texts. Cells with "NA" mean data are not reported or not reported and three dots ("…") mean they are suppressed (ie either restricted or confidential).
[2] Only for countries from BE to TW, ie does not include suppressed values or those not available in both data sets in either of the periods.
Sources: BIS locational banking statistics by nationality and BIS consolidated banking statistics on an immediate counterparty basis (QR June 2018, Released database for both sources).

BIS LBS/N vs BIS CBS/IC – local liabilities of domestic banks vis-à-vis reporting countries[1]

Excluding intragroup liabilities, amount outstanding in USD billions

Table C2.3

Parent /reporting country	Q4 2014		Q4 2017		Difference (amount) (LBS/N – CBS/IC)		Difference (percentage)	
	LBS/N	CBS/IC	LBS/N	CBS/IC	Q4 2014	Q4 20174	Q4 2014	Q4 2017
	[1]	[2]	[3]	[4]	[5]=[1]–[3]	[6]=[2]–[4]	[5]*100/[1]	[6]*100/[2]
Total[2]	**22,505.7**	**17,345.8**	**23,748.5**	**18,382.9**	**5,159.8**	**5,365.6**	**22.9**	**30.9**
BE	297.9	267.0	355.8	315.6	30.9	40.2	10.4	11.3
CA	1,256.7	1,177.0	1,393.2	1,310.4	79.6	82.8	6.3	5.9
CH	833.3	837.0	933.2	935.6	–3.7	–2.4	–0.4	–0.3
CL	128.7	123.4	146.2	141.6	5.3	4.6	4.1	3.1
DE	5,016.5	4,340.4	5,160.6	4,545.5	676.1	615.0	13.5	11.9
DK	161.9	160.9	171.0	163.5	1.0	7.5	0.6	4.4
ES	1,900.5	2,038.1	1,914.6	1,894.5	–137.6	20.1	–7.2	1.1
FI	102.0	36.1	117.6	52.7	65.9	64.9	64.6	55.2
FR	3,618.0	2,102.2	3,873.3	2,332.8	1,515.9	1,540.5	41.9	39.8
GB	3,851.0	1,873.1	4,076.6	2,062.8	1,977.9	2,013.8	51.4	49.4
GR	267.0	263.9	194.9	192.6	3.1	2.3	1.2	1.2
IT	3,256.4	2,451.1	3,186.8	2,429.0	805.3	757.7	24.7	23.8
KR	1,286.5	1,286.5	1,585.2	1,585.2	0.0	0.0	0.0	0.0
LU	48.6	48.8	58.3	58.4	–0.2	–0.1	–0.3	–0.2
SE	480.8	340.4	581.4	362.9	140.3	218.5	29.2	37.6
HK	58.2	…	68.5	…				
IE	…	135.8	…	137.6				
NL	…	…	…	…				
NO	…	…	…	…				
AT	463.6	NA	440.6	317.4				
AU	1,790.1	NA	1,759.7	1,514.7				
BR	1,692.1	NA	1,542.8	NA				
IN	1,464.4	NA	…	NA				
JP	16,078.2	NA	20,115.9	NA				
MX	121.2	NA	122.5	NA				
PA	NA	NA	NA	NA				
PT	…	NA	…	…				
SG	NA	NA	NA	…				
TR	NA	0.1	NA	0.4				
TW	1,018.6	NA	1,171.5	NA				
US	NA	NA	NA	NA				

[1] Local liabilities in local currency to residents of reporting countries by domestic banks located in the same country of residence of the reporting banking office. See additional details in explanatory texts. Cells with "NA" mean data are not reported and three dots ("…") mean they are suppressed (ie either restricted or confidential). [2] Only for countries from BE to SE, ie does not include suppressed values or those not available in both data sets in either of the periods.

Sources: BIS locational banking statistics by nationality and BIS consolidated banking statistics on an immediate counterparty basis (QR June 2018, Released database for both sources).

BIS LBS/R vs IMF IIP – loans claims of deposit-taking corporations except central bank[1]

Table C3.1

Comparison BIS LBS/R and IMF IIP by country, in USD billions

Country	Q4 2014		Q4 2017		Difference (amount) (IIP – LBS/R)		Differences (percentage)	
	IIP	LBS/R	IIP	LBS/R	Q4 2014	Q4 2017	Q4 2014	Q4 2017
	[1]	[2]	[3]	[4]	[5]=[1]–[2]	[6]=[3]–[4]	[5]*100/[1]	[6]*100/[3]
Total[2]	**15,173.7**	**16,220.8**	**14,810.1**	**16,163.5**	**–1,047.1**	**–1,353.4**	**–6.9**	**–9.1**
AU	236.8	187.0	236.2	238.9	49.8	–2.7	21.0	–1.2
AT	214.2	211.5	166.5	163.6	2.7	2.9	1.2	1.7
BE	367.8	372.0	338.8	341.7	–4.2	–2.9	–1.1	–0.9
BM[3]	3.0	4.6	2.6	3.6	–1.6	–1.0	–53.7	–40.5
BR	17.1	46.8	8.5	26.0	–29.7	–17.5	–-173.6	–205.3
CA	257.7	419.0	347.9	537.6	–161.3	–189.7	–62.6	–54.5
CL	9.1	9.6	7.0	7.5	–0.5	–0.5	–5.4	–7.8
HK[4]	825.3	859.8	967.0	974.6	–34.5	–7.6	–4.2	–0.8
CY	26.1	26.5	17.8	19.4	–0.4	–1.6	–1.7	–8.9
DK	153.1	149.1	193.1	189.4	4.0	3.7	2.6	1.9
FI	129.3	128.7	49.0	49.0	0.6	0.0	0.5	0.1
FR	1,441.7	1,457.9	1,456.8	1,474.7	–16.2	–17.9	–1.1	–1.2
DE	1,594.9	1,594.2	1,443.8	1,442.9	0.7	0.9	0.0	0.1
GR	38.0	36.5	21.4	20.8	1.5	0.6	4.0	2.6
IN	11.4	31.1	20.3	60.5	–19.7	–40.2	–172.8	–198.6
ID	9.7	9.3	11.6	11.2	0.4	0.4	4.4	3.4
IE	220.0	220.0	191.8	194.9	0.0	–3.1	0.0	–1.6
IT	234.2	226.4	247.8	249.0	7.8	–1.2	3.3	–0.5
JP	690.5	688.5	758.2	784.5	2.0	–26.3	0.3	–3.5
KR	117.5	136.3	134.4	157.9	–18.8	–23.5	–16.0	–17.5
LU	531.3	531.5	479.5	479.4	–0.2	0.1	0.0	0.0
MX	10.3	10.0	11.8	16.4	0.3	–4.6	3.0	–38.6
NL	763.4	762.8	765.1	764.1	0.6	1.0	0.1	0.1
NO	116.0	110.5	109.0	106.1	5.5	2.9	4.7	2.7
PA	39.8	42.4	36.5	37.9	–2.6	–1.4	–6.4	–3.9
PH	14.7	14.7	15.3	16.4	0.0	–1.1	0.0	–7.1
PT	52.5	52.7	29.3	30.8	–0.2	–1.5	–0.4	–5.2
RU	189.5	189.5	134.2	134.5	0.0	–0.3	0.0	–0.2
ZA	33.3	32.9	32.7	32.5	0.4	0.2	1.3	0.5
ES	195.0	200.3	226.5	262.3	–5.3	–35.8	–2.7	–15.8

BIS LBS/R vs IMF IIP – loans claims of deposit-taking corporations except central bank[1] (cont.)

Comparison BIS LBS/R and IMF IIP by country, in USD billions

Table C3.1

Country	Q4 2014		Q4 2017		Difference (amount) (IIP – LBS/R)		Differences (percentage)	
	IIP	LBS/R	IIP	LBS/R	Q4 2014	Q4 2017	Q4 2014	Q4 2017
	[1]	[2]	[3]	[4]	[5]=[1]–[2]	[6]=[3]–[4]	[5]*100/[1]	[6]*100/[3]
SE	312.7	300.0	349.4	331.4	12.7	18.0	4.0	5.1
CH	541.5	453.6	455.0	438.5	87.9	16.5	16.2	3.6
TR	26.5	19.9	41.8	35.3	6.6	6.5	24.9	15.6
GB[5]	3,989.0	4,030.7	3,690.7	3,740.0	–41.7	–49.3	–1.0	–1.3
US	1,760.8	2,654.5	1,813.0	2,790.2	–893.7	–977.2	–50.8	–53.9

[1] Claims in IIP comprise "Other investments" on account of currency and deposits, and loans of deposit corporations excluding central banks, which is similar to LBS/R instrument G "Loans and deposits" including currency balances. [2] For the purposes of comparison, LBS/R total in Q4 2014 includes IIP amounts for PH and RU as both countries started reporting after Q4 2014 (PH from Q4 2016 and RU from Q4 2015). [3] Reports IIP data at annual frequency (Q4 of each year). [4] Data for Q4 2017 relate to that of Q4 2016 for both LBS/R and IIP (as IIP data not available for Q4 2017). [5] Data for Q4 2017 relate to that of Q4 2015 for both LBS/R and IIP (as IIP data not available for Q4 2016 and Q4 2017).

Sources: BIS locational banking statistics by residence (QR June 2018, Released database) and IMF IIP data from data set "Balance of Payments (BoP), 2018 M06" release.

BIS LBS/R vs IMF IIP – deposit liabilities of deposit-taking corporations excl. central bank[1]

Comparison BIS LBS/R and IMF IIP by country, in USD billions | Table C3.2

Country	Q4 2014		Q4 2017		Difference (amount) (IIP – LBS/R)		Differences (percentage)	
	IIP	LBS/R	IIP	LBS/R	Q4 2014	Q4 2017	Q4 2014	Q4 2017
	[1]	[2]	[3]	[4]	[5]=[1]–[2]	[6]=[3]–[4]	[5]*100/[1]	[6]*100/[3]
Total[2]	**16,376.0**	**17,642.2**	**16,125.5**	**17,207.9**	**–1,266.2**	**–1,082.4**	**–7.7**	**–6.7**
AU	204.4	174.0	239.1	216.2	30.4	22.9	14.9	9.6
AT	130.2	128.4	96.9	95.2	1.8	1.7	1.4	1.8
BE	331.2	344.4	302.1	301.6	–13.2	0.5	–4.0	0.2
BM[3]	6.6	2.0	6.6	3.3	4.6	3.3	69.8	50.2
BR	115.4	130.2	95.0	105.6	–14.8	–10.6	–12.8	–11.1
CA	395.6	467.2	516.7	517.4	–71.6	-0.7	–18.1	-0.1
CL	13.1	13.3	16.2	15.5	–0.2	0.7	–1.5	4.6
HK[4]	851.1	842.4	942.9	931.8	8.7	11.1	1.0	1.2
CY	29.3	30.5	23.4	25.6	–1.2	–2.2	–4.1	–9.3
DK	173.1	171.5	151.8	151.7	1.6	0.1	0.9	0.1
FI	176.7	176.5	135.1	135.2	0.2	–0.1	0.1	–0.1
FR	1,391.9	1,414.2	1,591.5	1,593.1	–22.3	–1.6	–1.6	–0.1
DE	1,015.1	1,005.1	1,088.7	1,077.7	10.0	11.0	1.0	1.0
GR	88.9	61.2	38.6	29.3	27.7	9.3	31.2	24.1
IN	114.8	113.0	129.1	135.6	1.8	–6.5	1.5	–5.1
ID	23.2	27.4	23.1	25.8	–4.2	–2.7	–18.0	–11.6
IE	240.1	240.1	162.1	164.1	0.0	–2.0	0.0	–1.2
IT	374.5	374.5	353.6	355.4	0.0	–1.8	0.0	-0.5
JP	899.7	1,192.1	1,018.7	1,280.3	–292.4	–261.6	–32.5	–25.7
KR	118.4	59.2	111.4	56.7	59.2	54.7	50.0	49.1
LU	451.7	452.1	405.0	405.3	–0.4	-0.3	–0.1	–0.1
MX	17.9	15.9	13.4	8.1	2.0	5.3	11.2	39.6
NL	711.3	711.3	745.8	745.8	0.0	0.0	0.0	0.0
NO	165.1	151.6	174.0	161.3	13.5	12.7	8.2	7.3
PA	40.4	31.5	41.0	30.2	8.9	10.8	22.0	26.4
PH	16.5	16.5	15.7	17.0	0.0	–1.3	0.0	–8.3
PT	83.7	82.1	58.7	58.2	1.6	0.5	1.9	0.9
RU	160.7	160.7	91.0	95.5	0.0	–4.5	0.0	–5.0
ZA	28.7	28.2	24.9	23.6	0.5	1.3	1.6	5.1
ES	376.2	383.7	321.4	322.2	–7.5	–0.8	–2.0	–0.2

BIS LBS/R vs IMF IIP – deposit liabilities of deposit-taking corporations excl. central bank[1] (cont.)

Comparison BIS LBS/R and IMF IIP by country, in USD billions

Table C3.2

Country	Q4 2014		Q4 2017		Difference (amount) (IIP – LBS/R)		Differences (percentage)	
	IIP	LBS/R	IIP	LBS/R	Q4 2014	Q4 2017	Q4 2014	Q4 2017
	[1]	[2]	[3]	[4]	[5]=[1]–[2]	[6]=[3]–[4]	[5]*100/[1]	[6]*100/[3]
CH	753.0	607.7	744.1	680.6	145.3	63.5	19.3	8.5
TR	144.2	124.8	144.1	128.3	19.4	15.8	13.5	11.0
GB[5]	4,182.5	4,176.6	3,770.1	3,765.3	5.9	4.8	0.1	0.1
US	2,341.3	3,537.6	2,298.6	3,333.0	–1196.3	–1034.4	–51.1	–45.0

[1] Liabilities in IIP comprise "Other investments" on account of currency and deposits, and loans of deposit corporations excluding central banks. [2] For the purpose of comparison, LBS/R total in Q4 2014 includes IIP amounts for PH and RU as both countries started reporting after Q4 2014 (PH from Q4 2016 and RU from Q4 2105). [3] Reports IIP data at annual frequency (Q4 of each year). [4] Data for Q4 2017 relate to that of Q4 2016 for both LBS/R and IIP (as IIP data not available for Q4 2017). [5] Data for Q4 2017 relate to that of Q4 2015 for both LBS/R and IIP (as IIP data not available for Q4 2016 and Q4 2017).

Sources: BIS locational banking statistics by residence (QR June 2018, Released database) and IMF IIP data from data set "Balance of Payments (BoP), 2018 M06" release.

LBS/R vs IMF IIP – loans and deposits of banks located in Portugal[1]

Comparison BIS LBS/R and IMF IIP by country, in USD billions

Table C3.3

	IMF IIP		BIS LBS/R		Difference in amount (IIP – LBS/R)		Percentage difference	
Period	Claims	Liabilities	Claims	Liabilities	Claims	Liabilities	Claims	Liabilities
	[1]	[2]	[3]	[4]	[5]=[1]–[3]	[6]=[2]–[4]	[7]= [5]*100/[1]	[8]= [6]*100/[2]
Q1 2011		179.6	86.2	178.7		1.0		0.5
Q2 2011		172.7	85.4	171.8		0.9		0.5
Q3 2011		154.7	76.5	153.9		0.9		0.6
Q4 2011		136.8	77.0	136.0		0.8		0.6
Q1 2012		135.0	83.5	134.2		0.8		0.6
Q2 2012		123.4	82.3	122.6		0.7		0.6
Q3 2012		119.7	81.8	119.0		0.7		0.6
Q4 2012		118.9	78.6	118.1		0.9		0.7
Q1 2013	74.8	112.9	75.1	112.1	–0.3	0.8	–0.4	0.7
Q2 2013	71.4	111.0	71.0	110.3	0.4	0.7	0.6	0.7
Q3 2013	57.7	95.1	57.4	94.4	0.3	0.7	0.5	0.8
Q4 2013	58.9	97.5	58.5	96.7	0.3	0.8	0.5	0.8
Q1 2014	60.1	95.9	59.7	95.1	0.3	0.8	0.5	0.8
Q2 2014	60.5	97.4	60.1	96.6	0.5	0.8	0.8	0.9
Q3 2014	60.6	83.0	58.4	81.4	2.3	1.6	3.7	1.9
Q4 2014	52.5	83.7	52.7	82.1	–0.2	1.6	–0.4	1.9
Q1 2015	45.5	73.2	45.8	72.0	–0.2	1.3	–0.5	1.7
Q2 2015	46.7	76.6	46.9	75.3	–0.2	1.3	–0.5	1.7
Q3 2015	39.6	70.5	40.0	69.2	–0.5	1.3	–1.2	1.8
Q4 2015	37.4	65.5	38.1	64.2	–0.8	1.3	–2.1	2.0
Q1 2016	36.5	67.2	37.0	65.8	–0.5	1.4	–1.4	2.1
Q2 2016	35.2	67.0	35.8	65.6	–0.6	1.4	–1.7	2.0
Q3 2016	34.4	62.9	35.7	62.4	–1.3	0.5	–3.7	0.7
Q4 2016	30.5	60.6	31.8	59.2	–1.3	1.4	–4.2	2.2
Q4 2017	29.3	58.7	30.8	58.2	–1.5	0.5	–5.1	0.9

[1] Claims in IIP comprise "Other investments" on account of currency and deposits, and loans of deposit corporations excluding central banks, which is similar to LBS/R instrument G "Loans and deposits" including currency balances. On the liabilities side, total liabilities in IIP comprise "Other investments" on account of currency and deposits, and loans of deposit corporations excluding central banks.

BIS LBS/R vs IMF IIP – cross-border debt securities claims of deposit-taking corporations[1]

Amount outstanding, in USD billions

Table D1

Country	BIS LBS/R		IIP		Difference in amount		Percentage difference	
	Q4 2014	Q4 2017	Q4 2014	Q4 2017	Q4 2014	Q4 2017	Q4 2014	Q4 2017
	[1]	[2]	[3]	[4]	[5]=[1]–[3]	[6]=[2]–[4]	[5]*100/[1]	[6]*100/[2]
Total[2]	**3,343.6**	**2,963.3**	**3,558.1**	**3,268.0**	**–214.5**	**–304.7**	**–6.4**	**–10.3**
AU	22.1	34.9	31.6	72.1	–9.5	–37.3	–42.7	–106.8
AT	77.4	60.8	77.9	61.8	–0.5	–1.1	–0.6	–1.7
BE	106.0	94.8	109.4	97.2	–3.4	–2.4	–3.2	–2.5
BM[3]	7.2	8.7	8.9	10.0	–1.7	–1.3	–23.9	–14.8
BR	3.1	4.0	5.3	4.4	–2.2	–0.4	–69.7	–9.7
CL	1.3	1.3	1.0	0.9	0.3	0.4	24.5	28.3
HK	284.9	379.4	316.5	374.3	–31.5	5.2	–11.1	1.4
CY	8.8	2.5	4.8	1.7	3.9	0.7	44.7	29.2
DK	35.7	19.3	38.4	22.2	–2.7	–2.9	–7.5	–14.8
FI	69.7	35.9	63.4	36.3	6.3	–0.3	9.1	–1.0
FR	519.1	484.1	407.4	298.5	111.8	185.6	21.5	38.3
DE	630.4	573.3	671.5	598.3	–41.1	–25.0	–6.5	–4.4
GR	70.9	19.3	71.0	19.3	–0.1	0.0	–0.2	–0.1
IN	0.0	0.3	0.4	0.3	–0.4	0.0		0.1
ID	1.5	1.1	1.7	0.9	–0.2	0.2	–10.2	21.2
IE	132.3	70.3	130.7	67.7	1.6	2.5	1.2	3.6
IT	72.5	112.1	62.6	107.2	9.9	4.9	13.6	4.4
JP	…	…	852.8	861.1				
KR	2.6	13.4	10.4	34.6	–7.8	–21.2	–304.2	–158.7
LU	176.0	133.0	166.3	126.5	9.7	6.5	5.5	4.9
MX	3.9	6.8	3.8	6.9	0.1	–0.1	1.9	–1.4
NL	134.7	110.6	138.2	111.4	–3.5	–0.9	–2.6	–0.8
NO	31.5	33.8	56.1	51.6	–24.7	–17.7	–78.4	–52.4
PA	6.8	8.4	6.8	7.8	–0.1	0.6	-0.9	7.0
PH	NA	9.9	7.3	10.1	–7.3	–0.2		–1.6
PT	18.8	20.8	22.2	24.1	–3.5	–3.3	–18.5	–15.7
RU	NA	38.8	37.7	37.9	–37.7	0.9		2.4
ZA	3.3	3.5	3.0	2.6	0.2	0.9	7.5	24.8
ES	111.4	98.7	93.2	84.7	18.1	13.9	16.3	14.1

BIS LBS/R vs IMF IIP – cross-border debt securities claims of deposit-taking corporations[1] (cont.)

Amount outstanding, in USD billions | Table D1

Country	BIS LBS/R		IIP		Difference in amount		Percentage difference	
	Q4 2014	Q4 2017	Q4 2014	Q4 2017	Q4 2014	Q4 2017	Q4 2014	Q4 2017
	[1]	[2]	[3]	[4]	[5]=[1]–[3]	[6]=[2]–[4]	[5]*100/[1]	[6]*100/[2]
CH	94.2	102.1	94.3	102.1	0.0	0.0	0.0	0.0
TR	0.8	0.8	0.8	0.6	0.0	0.2	–4.9	25.9
GB[4]	664.6	471.6	718.5	659.9	–53.9	–188.4	–8.1	–39.9
US	9.2	20.7	196.7	241.7	–187.5	–221.1	–2,029.0	–1,069.7

[1] The IMF IIP data for debt securities claims are available for 34 of 47 countries. In the BIS LBS/R, two countries (Bahrain and Curaçao) do not report cross-border debt securities claims in the LBS and the data for remaining 11 countries including Japan are either restricted or confidential. [2] Of 34 countries in the table, the total excludes values of JP, PH and RU. [3] IIP data available up to Q4 2016, and hence LBS/R data of Q4 2016 are used in Q4 2017 for fair comparison. [4] IIP data available only up to Q4 2015, and hence LBS/R data used for Q4 2015 are used in Q4 2017 for fair comparison.

Sources: BIS locational banking statistics by residence (QR June 2018, Released database) and IMF international investment positions (IIP, 2018 M06 release).

BIS LBS/R vs IMF CPIS – counterparty country breakdown of cross-border debt securities liabilities between the BIS LBS/R and the IMF CPIS[1]

Amount outstanding, in USD billions | Table D2

Period	CPIS: Cross-border by individual country		LBS/R: Cross-border by individual country		Difference (CPIS – LBS/R)		Memo: LBS/R: unallocated cross-border	
	2015 Q4	2017Q2	2015 Q4	2017Q2	2015 Q4	2017Q2	2015 Q4	2017Q2
	[1]	[2]	[3]	[4]	[5]=[1]–[3]	[6]=[2]–[4]	[7]	[8]
Total	**1,904.2**	**1,925.0**	**1,711.5**	**1,842.4**	**192.7**	**82.6**	**1,541.4**	**1,604.9**
GB	379.5	355.1	12.8	12.3	366.7	342.7	808.2	854.1
FR	238.7	206.2	646.2	699.3	–407.5	–493.2		
AU	120.5	113.6	367.1	342.5	–246.6	–228.9		
US	74.9	108.9	108.3	152.3	–33.4	–43.4		
IT	55.2	64.5	2.7	5.3	52.5	59.2		
NO	30.9	62.0	41.4	38.2	–10.6	23.7	1.7	4.7
AT	41.4	31.0	51.5	79.7	–10.1	–48.8	11.7	
BE	24.4	30.3	16.5	38.9	7.9	–8.6		
FI	26.9	27.7	91.9	88.8	–64.9	–61.1		
IE	33.8	26.6	45.3	52.8	–11.5	–26.2		
KR	20.4	6.5	82.8	75.2	–62.4	–68.7		
GG	11.7	6.7	8.8	9.2	2.9	–2.4		
JE	2.3	6.4	1.7	0.4	0.6	6.1		
BR	7.7	6.2	19.0	13.1	–11.3	–6.9		
CN	1.8	4.0	123.2	115.0	–121.4	–111.1	16.7	15.6
HK	4.0	3.9	9.7	25.4	–5.6	–21.5		
CL	5.3	3.3	9.9	9.2	–4.7	–5.9		
IN	1.7	3.2	2.2	0.3	–0.5	2.9		
PT	5.7	2.7	0.4	0.3	5.4	2.4		
MX	1.9	1.5	11.6	7.9	–9.8	–6.4		
PA	0.7	0.6	16.2	14.4	–15.5	–13.8		
BS	0.6	0.4	25.1	20.7	–24.5	–20.3		
ID	0.3	0.3	4.7	3.6	–4.4	–3.3		
BM	0.1	0.1	0.1	0.1	0.0	0.0		
RU	0.1	0.1	2.0	2.5	–1.8	–2.4	3.8	3.1
MO	0.0	0.1	0.6	3.7	–0.6	–3.6		
PH	0.1	0.0	0.0	1.5		–1.4		
CY	0.0	0.0	0.5	0.1	–0.5	–0.1		
TW	0.2	0.0	1.5	0.3	–1.3			

BIS LBS/R vs IMF CPIS – counterparty country breakdown of cross-border debt securities liabilities between the BIS LBS/R and the IMF CPIS[1] (cont.)

Amount outstanding, in USD billions

Table D2

Period	CPIS: Cross-border by individual country		LBS/R: Cross-border by individual country		Difference (CPIS – LBS/R)		Memo: LBS/R: unallocated cross-border	
	Q4 2015	Q2 2017	Q4 2015	Q2 2017	Q4 2015	Q2 2017	Q4 2015	Q2 2017
	[1]	[2]	[3]	[4]	[5]=[1]–[3]	[6]=[2]–[4]	[7]	[8]
CA	113.8	151.0	0.3	…	113.5			
ES	101.1	78.3	…	…				
MY	4.6	0.2	…	…				
DE[2]	112.6	108.5					646.0	693.9
KY[2]	5.5	2.6					51.4	31.9
ZA[2]	0.2	0.2					2.1	1.7
SG	15.4	17.6						
BH	0.2	0.1						
CW	0.7	0.1						
GR	0.2	0.0						
IM								
NL[3]	233.8	227.3						
SE[3]	111.7	114.7						
DK[3]	60.3	57.6						
JP[3]	19.2	41.1						
LU[3]	23.0	29.7						
CH[3]	6.8	19.9						
TR[3]	4.0	4.3						

[1] CPIS data on holdings of cross-border debt securities issued by deposit corporations excluding central banks. As the sector breakdown of issuers is an encouraged item in the CPIS, only 26 of 85 plus countries report these data. [2] Reports only vis-à-vis unallocated by location without classifying vis-à-vis residents or cross-border. [3] In the LBS/R, amounts are reported almost entirely without any country breakdown (ie only total cross-border amounts are reported).

Sources: BIS locational banking statistics by residence (QR June 2018, Released database) and IMF CPIS survey (15 March 2018 release).

BIS LBS/R vs BIS IDS – international debt securities liabilities[1, 2]

Amount outstanding, in USD billions — Table D3

Period	BIS LBS/R		BIS IDS		Difference in amount (LBS/R – IDS)		Percentage difference	
	Q4 2015	Q4 2017	Q4 2015	Q4 2017	Q4 2015	Q4 2017	Q4 2015	Q4 2017
	[1]	[2]	[3]	[4]	[5]=[1]–[3]	[6]=[2]–[4]	[5]/[1]	[6]/[2]
Total	**4,444.1**	**4,832.8**	**6,227.4**	**6,736.6**	**–1,783.3**	**–1,903.8**	**–40.1**	**–39.4**
AT	68.0	68.1	101.3	83.8	–33.2	–15.7	–48.8	–23.1
AU	372.1	356.6	329.7	338.0	42.4	18.6	11.4	5.2
BE	18.1	49.1	20.1	21.9	–1.9	27.2	–10.7	55.3
BR	20.1	12.5	36.6	28.6	–16.6	–16.1	–82.4	–128.5
BS	26.6	26.6	5.5	7.4	21.0	19.2	79.2	72.1
CA	2.2	5.8	263.8	309.3	–261.6	–303.5	–11,820.0	–5,213.9
CH	21.2	42.8	27.7	34.9	–6.5	7.9	–30.8	18.5
CN	139.9	183.9	48.6	79.1	91.3	104.8	65.2	57.0
DE	678.8	721.8	466.7	570.5	212.1	151.3	31.2	21.0
DK	89.8	97.8	60.0	63.1	29.9	34.8	33.2	35.5
ES	13.0	48.5	131.7	140.5	–118.7	–92.0	–915.1	–189.6
FI	93.3	95.9	65.5	69.9	27.8	26.0	29.8	27.1
FR	662.9	741.9	588.6	648.2	74.3	93.7	11.2	12.6
GB	923.2	1,011.5	1,289.8	1,333.6	–366.6	–322.0	–39.7	–31.8
HK	116.8	160.6	98.7	140.3	18.1	20.3	15.5	12.7
IE	46.0	52.0	115.0	101.2	–69.0	–49.2	–150.1	–94.5
IT	20.6	28.5	266.2	258.3	–245.7	–229.8	–1,193.9	–805.7
KR	85.5	84.3	96.6	99.6	–11.1	–15.3	–12.9	–18.2
KY	51.4	34.5	94.5	96.7	–43.1	–62.2	–83.9	–180.4
LU	31.7	31.7	128.3	136.0	–96.6	–104.2	–305.0	–328.3
NL	269.1	249.7	616.9	636.6	–347.9	–386.9	–129.3	–154.9
NO	45.5	48.3	180.9	188.2	–135.4	–139.9	–297.9	–289.6
RU	9.4	7.6	32.9	29.3	–23.5	–21.7	–251.1	–287.0
SE	299.1	302.0	203.4	208.5	95.7	93.5	32.0	31.0
TR	27.5	34.5	40.5	65.1	–13.0	–30.6	–47.5	–88.7
US	108.3	130.4	550.6	622.5	–442.3	–492.1	–408.4	–377.5
JP	…	…	148.2	222.5				
MY	…	…	13.5	15.5				
Others	115.7	121.9	205.6	187.5	–89.9	–65.6	–77.7	–53.8

1 Banks in five jurisdictions, namely, BH, CW, GR, IM and SG do not report international debt securities in the LBS/R. However, the IDS database shows that BH, CW, GR and SG have issued debt securities in international markets. On the other hand, GG and JE report international debt securities in LBS/R but the IDS database shows no issuances of debt securities in international markets by banks. 2 The cell with "…" means reported data are either restricted or confidential.

Sources: BIS locational banking statistics by residence and BIS international debt securities database (QR June 2018, Released database for both sources).

Table E: ISO codes and country/jurisdiction names

ISO code	Name of jurisdiction		
AT	Austria	IM	Isle of Man
AU	Australia	IN	India
BE	Belgium	IT	Italy
BH	Bahrain	JE	Jersey
BM	Bermuda	JP	Japan
BR	Brazil	KR	Korea
BS	Bahamas	KY	Cayman Islands
CA	Canada	LU	Luxembourg
CH	Switzerland	MO	Macao SAR
CL	Chile	MX	Mexico
CN	China	MY	Malaysia
CW	Curaçao	NL	Netherlands
CY	Cyprus	NO	Norway
DE	Germany	PA	Panama
DK	Denmark	PH	Philippines
ES	Spain	PT	Portugal
FI	Finland	RU	Russia
FR	France	SE	Sweden
GB	United Kingdom	SG	Singapore
GG	Guernsey	TR	Turkey
GR	Greece	TW	Chinese Taipei
HK	Hong Kong SAR	US	United States
ID	Indonesia	ZA	South Africa
IE	Ireland		

Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

Uses of mirror data: examples from the BIS international banking statistics and other external statistics[1]

João Falcão Silva, Bank of Portugal,

and Swapan-Kumar Pradhan, Bank for International Settlements

[1] This presentation was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

USES OF MIRROR DATA
examples from the BIS International Banking Statistics and other external statistics

João Falcão Silva
Swapan-Kumar Pradhan

9th biennial IFC Conference on “Are post-crisis statistical initiatives completed?”
30-31 August 2018

BANCO DE PORTUGAL
EUROSYSTEM

BANK FOR INTERNATIONAL SETTLEMENTS

THE 2 MAIN QUESTIONS: WHY?

WHY MIRROR DATA?

- **Mirror data:** different sources that capture similar concepts
- **Mirror data** are **important statistical tools** that that allows common data items to be validated across statistical domains. Promotes **consistency** and **accuracy**, **raise statistical quality standards**

WHY THIS PAPER?

- Existence of **common data elements**: BIS International Banking Statistics (BIS IBS), International Investment Position (IIP) and other external sources (IMF CPIS, BIS IDS)
- Validity of **mirror relationship** at a country aggregated data level [consistency tests]
- Possible **reasons for differences** between pair of mirror data [fill gaps?]

Background: This topic was discussed in Biennial meeting of central bank experts (2017) on BIS international banking and financial statistics (Swapan with a colleague from Bank of Canada explored the issues). Agreed to jointly explore further, develop methodological framework and provide guidance

CONSISTENCY TESTS

LD1

INTERBANK CLAIMS and **INTERBANK LIABILITIES** comparison for **LOANS** and **DEPOSITS** based on **BIS LOCATIONAL BANKING STATISTICS BY RESIDENCE (LBS\R)**

$$Interbank\ claims\ (liabilities)_{i;j}^{LBS\backslash R} \approx Interbank\ liabilities(claims)_{j;i}^{LBS\backslash R}$$

"i" is the reporting country and "j" the counterparty (reporting) country

This comparison is only possible among LBS reporting countries. We use reported bilateral positions and aggregate to overall positions.

For a give reporting **country *i*,** the **net interbank claims/liabilities** are defined by**:**

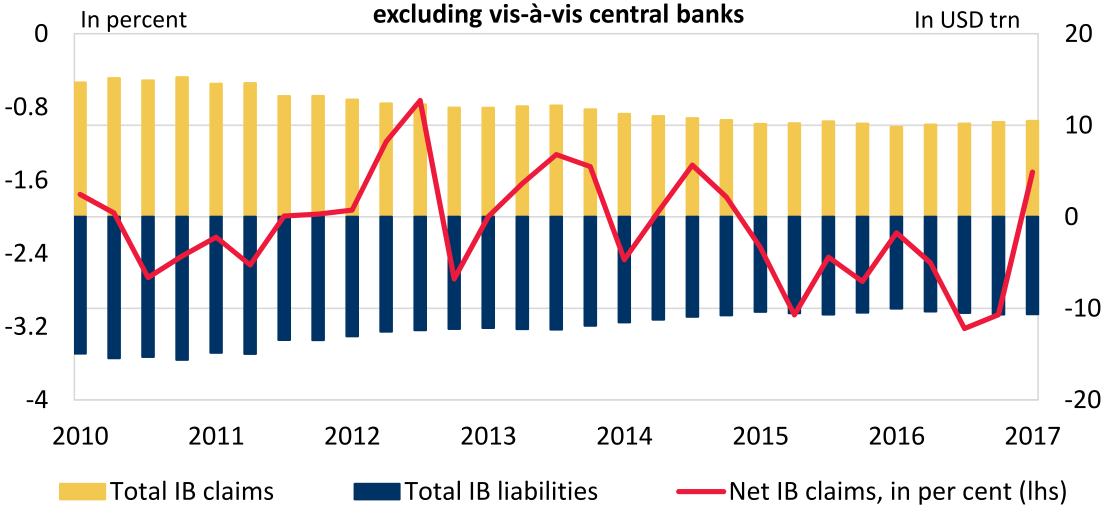
$$Net\ interbank\ claims = \sum_{\substack{j=1 \\ i \neq j}}^{x} Claims_i^j - \sum_{\substack{j=1 \\ i \neq j}}^{x} Liabilities_j^i \qquad \text{and} \qquad Net\ interbank\ liabilities = \sum_{\substack{j=1 \\ i \neq j}}^{x} Liabilities_i^j - \sum_{\substack{j=1 \\ i \neq j}}^{x} Claims_j^i$$

CONSISTENCY TESTS

LD1 | **INTERBANK CLAIMS** and **INTERBANK LIABILITIES** comparison for **LOANS** and **DEPOSITS** based on **BIS LOCATIONAL BANKING STATISTICS BY RESIDENCE (LBS\R)**

CROSS-BORDER NET INTERBANK CLAIMS IN REPORTING COUNTRIES

excluding vis-à-vis central banks



Between **2011** and **2017** the size of **net claims differences**, at the level of all reporting countries, **fell from -2,2% to -1,5%** of the stock of net interbank claims.

POSSIBLE REASONS TO THE DIFFERENCES

- Coverage CB's positions
- Definition of bank sector
- Instrument breakdown
- Valuation
- Banking laws
- Legal/confidentiality restrictions
- Different reporting practises

CONSISTENCY TESTS

LD2

DOMESTIC CLAIMS in **ALL CURRENCIES, LOCAL CLAIMS** in **ALL CURRENCY** and **LOCAL LIABILITIES** in **LOCAL CURRENCY** vis-à-vis residents of the respective reporting countries between **Consolidated Banking Statistics by Immediate Counterparty Basis (CBS\IC)** and **Locational Banking Statistics by Nationality (LBS\N)**

$$LBS\backslash N\ claims_i^{Domestic\ All\ excl.intragroup} \approx CBS\backslash IC claims_i^{DomesticAll}$$

$$LBS\backslash N\ claims_i^{Local\ in\ all\ currencies\ excl.intragrop} \approx CBS\backslash IC\ claims_i^{Local\ \ in\ all\ currencies}$$

$$LBS\backslash N\ liabilities_i^{Local\ in\ local\ currency\ excl.intragroup} \approx CBS\backslash IC\ liabilities_i^{Local\ in\ local\ currency}$$

POSSIBLE REASONS TO THE DIFFERENCES

- Coverage
- Different geographical coverage (CBS\IC vs LBS\N)
- Different scope of consolidation (CBS\IC vs LBS\N)
- Reporting issues

CONSISTENCY TESTS

LD3 | **LOANS** and **DEPOSITS** comparison between **BIS Locational Banking Statistics by Residency (LBS\R)** and **IMF International Investment Position (IIP)**

$$LBS\backslash R\ assets_i^{Loans\ and\ deposits} \approx IIP\ assets_i^{Loans\ and\ deposits}$$

$$LBS\backslash R\ liabilities_i^{Loans\ and\ deposits} \approx IIP\ liabilities_i^{Loans\ and\ deposits}$$

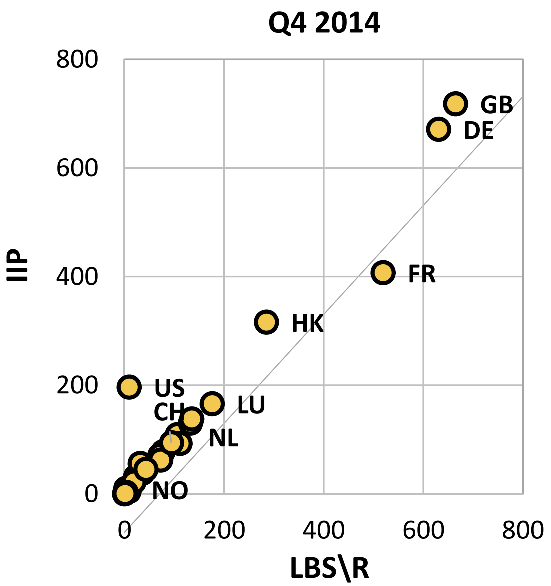
POSSIBLE REASONS TO THE DIFFERENCES

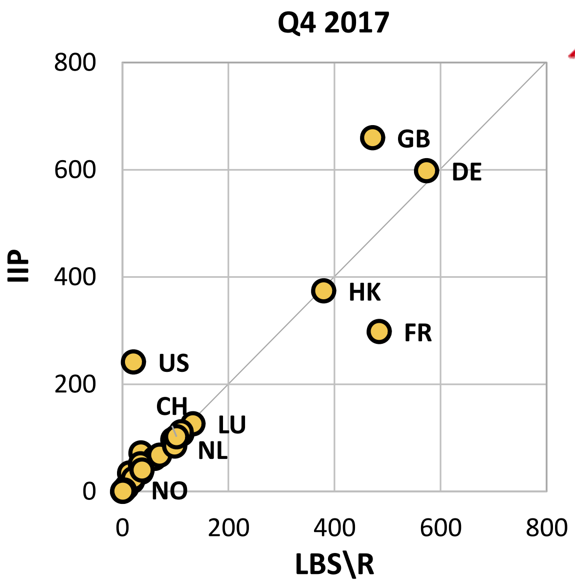
- Geographical breakdown on interest owned not yet paid
- Reporting population may be different
- Inclusion of inter-office positions – equity and retained earnings in the LBS/R loans and deposits
- Exclusion of repo transactions in the IMF IIP and the inclusion of covered bonds in the LBS/R (Liabilities) ==> country specific reason

CONSISTENCY TESTS

DS1 | **CROSS-BOARDER DEBT SECURITIES CLAIMS** comparison between **BIS Locational Banking Statistics by Residency (LBS\R)** and **IMF International Investment Position (IIP)**

$$LBS\backslash R\ assets_i^{Cross-border\ debt\ securities} \approx IIP\ assets_i^{Debt\ securities}$$





POSSIBLE REASONS TO THE DIFFERENCES

- Coverage sources
- Definition treatment of instruments

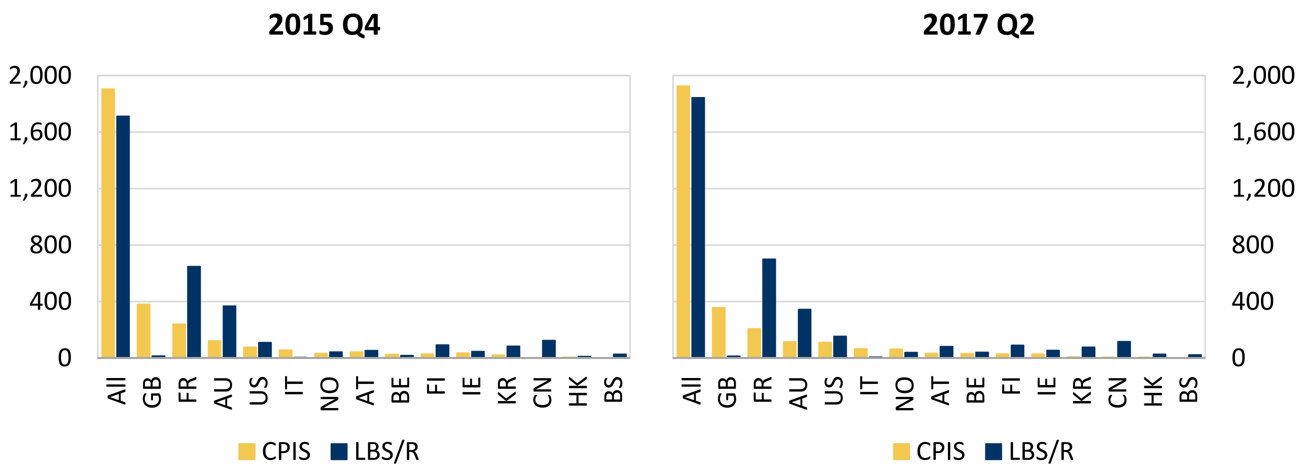
CONSISTENCY TESTS

DS2 | **CROSS-BOARDER DEBT SECURITIES LIABILITIES** comparison between **BIS Locational Banking Statistics by Residency (LBS\R)** and the **IMF Coordinated Portfolio Investment Survey (CPIS)**

$$LBS\backslash R\ liabilities_{i,j}^{Cross-border\ debt\ securities} > CPIS\ liabilities_{i;j}^{Derived\ debt\ securities}$$

CROSS-BORDER DEBT SECURITIES LIABILITIES OF BANKS BY ISSUING COUNTRY

Amount outstanding; in billions of US dollars



POSSIBLE REASONS TO THE DIFFERENCES

- Frequency vintages
- Reporting population
- Practical issues in knowing residency of holder of liabilities (LBS\R)
- Different sources
- Different valuation

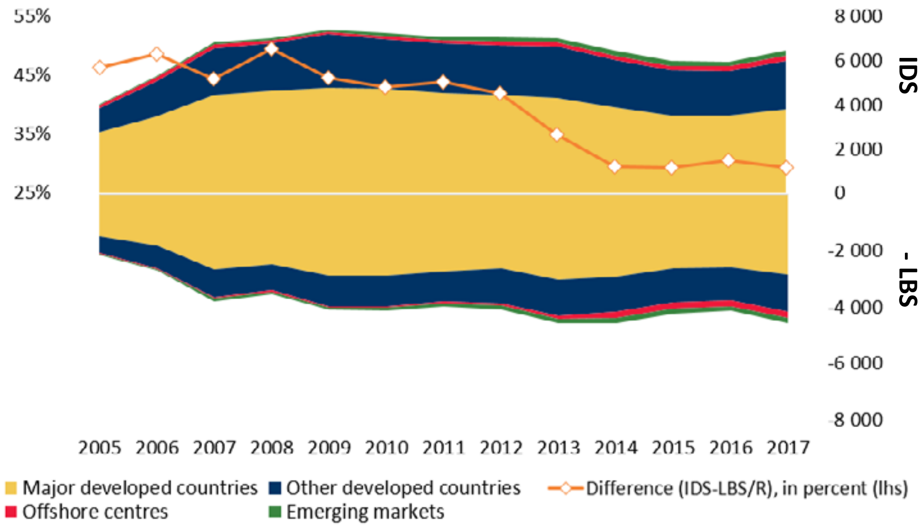
CONSISTENCY TESTS

DS3 | **INTERNATIONAL DEBT SECURITIES LIABILITIES** comparison between **BIS Locational Banking Statistics by Residency (LBS\R)** and the **International Debt Securities (IDS)**

$$LBS\backslash R\ liabilities_i^{international\ debt\ securities} \approx International\ liabilities_i^{debt\ securities}$$

INTERNATIONAL DEBT SECURITIES LIABILITIES OF BANKS IN LBS\R REPORTING COUNTRIES BY ISSUER REGION

in billions of US dollars



POSSIBLE REASONS TO THE DIFFERENCES

- Concepts
- Definition
- Sources
- Practical issues in knowing residency of holder of liabilities (LBS\R)

WHY SHOULD WE USE MIRROR DATA?

1

Improve quality, **better estimates** and **fill-in data gaps** (need granular level details)

2

Data availability in **multiple sources** albeit with **reporting differences**

3

Our approach offers tools and consistency tests to **validate data quality/reconciliation** amongst countries, different datasets aiming to complement statistical analysis

4

Similarities and **differences** between different **data domains**, once explored and explained would help data analysts to a better **understand** of **correctly** use **statistical data**

5

BIS, IMF and other international institutions should play an active role in implementing consistency tests to permit comparable analyses and help countries to improve statistical data

USES OF MIRROR DATA
Examples from the BIS international banking statistics and other external statistics

QUESTIONS?

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How to identify “hidden securities assets” in the Balance of Payments: methods of Bank of France[1]

Emmanuel Gervais and Pierre Bui Quang,

Bank of France

[1] This paper was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

How to identify “hidden securities assets” in the Balance of Payments: Methods of Banque de France

Emmanuel Gervais, Pierre Bui Quang

Abstract

In International Investment Position (IIP) statistics, there is a significant discrepancy between the asset and the liability sides of portfolio investments. This reflects the difficulties faced by Balance of Payments (BOP) national compilers to cover investments of non-financial corporations and households located in other countries (“third party holdings”).

Building on this, the economic literature has used the existing gap between assets and liabilities to measure “hidden” investments. The insight of this stream of research has provided various estimates for the “hidden” wealth of the wealthiest households.

While these results clearly point out the importance of these amounts, the differences between estimation methods also justify some caution when considering how this research can be used for statistical purposes.

Given these considerations, this paper will (i) discuss the gap between assets and liabilities in IIP statistics and how it has been used by the economic literature to identify “hidden” wealth, (ii) assess the relevance of these estimations from a statistical point of view, (iii) present the French methodology for estimating investments in securities not covered by national reportings, and (iv) stress the need for an internationally coordinated effort to improve the coverage of third party holdings.

Contents

1. The gap between assets and liabilities in international portfolio statistics and national BOP data points to "hidden assets" abroad

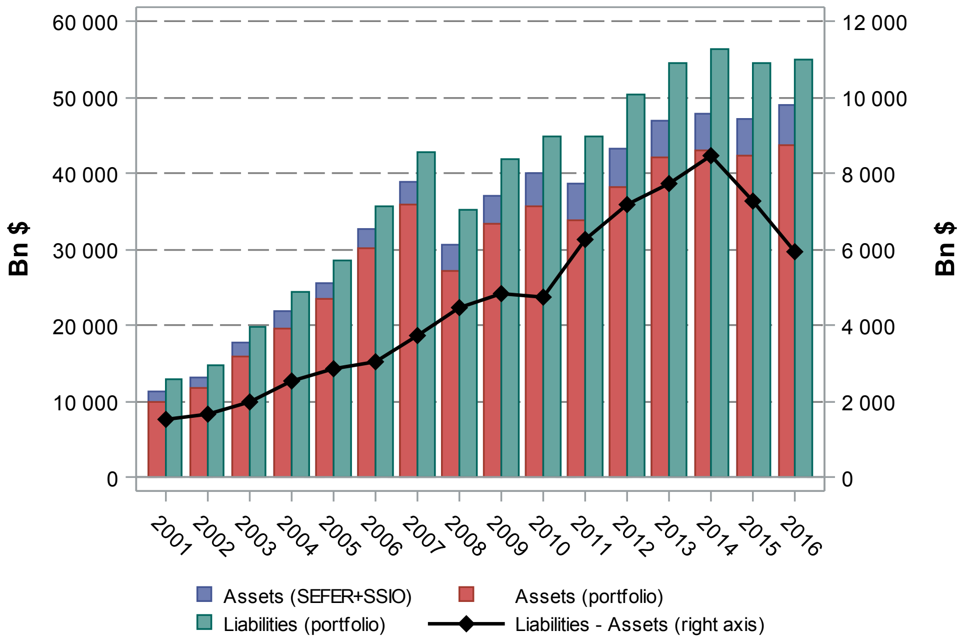
1. "Hidden assets" can explain the inconsistencies in international investment positions (IIP) statistics

Consistency in international statistics requires that global assets equal global liabilities. In securities statistics, this condition is not met. There is a persistent discrepancy between, on the one hand securities held in portfolio and reserve assets, and, on the other hand portfolio liabilities (the former being lower than the latter).

IMF data allows a clear illustration of this point. Aggregated portfolio assets in IIP, augmented with the amount of securities held as reserve assets or held by international organizations (SEFER and SSIO[1], collected by the IMF), miss total liabilities in IIP by around 6 Tn $ in 2016 (see Figure 1). This difference has significantly declined recently - it was close to 8.5 Tn $ in 2014 – indicating a reversal in the previous trend (a steady increase observed since 2001). This recent evolution may notably be attributed to a better coverage in the collection of securities held as reserve assets. Indeed, their amount has grown by 12 % over 2014-2016, while assets held as portfolio investments have grown by only 2 %, and "other reserve assets" (the reserve assets category that includes securities) have declined by 8 %.

[1] SEFER : Securities Held as Foreign Exchange Reserves ; SSIO : Securities Held by International Organizations

Figure 1: Global discrepancy between assets and liabilities in international securities statistics



Sources: IIP, SEFER and SSIO (IMF), authors' calculations

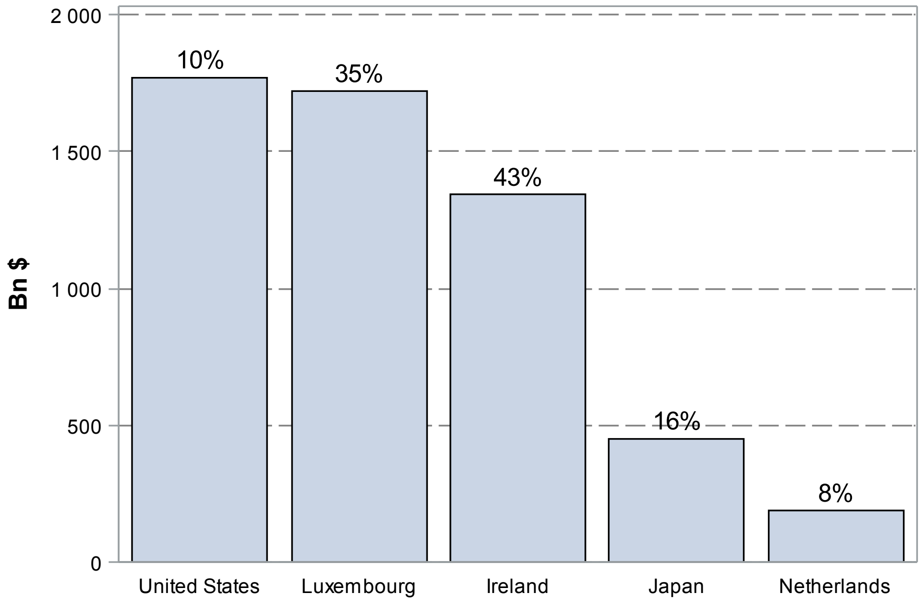
Hence, some of the gap between global assets and liabilities in security statistics may be accounted for by the partial coverage of the SEFER as not all countries participate in the survey. Nonetheless, academic papers that have used estimated amounts of portfolio investments and reserve assets to fill missing data reach the same conclusion. Zucman (2013), using data from Lane and Milesi-Ferretti (2007) and adding other estimated amounts of securities held as reserve assets, estimates the discrepancy to be 4.5 Tn $ in 2008.

Another explanation for this discrepancy lies in the difficulties faced by Balance of Payments compilers to collect data on resident portfolios held in other jurisdictions ("third party holdings"). Indeed, the compilation of portfolio investments positions often relies on information collected from local custodians. Investments in custody abroad may thus be missed by the national compiler, leading to an understatement of assets that would not affect liabilities symmetrically.

Building on this explanation, Zucman (2013) has identified inconsistencies in international investment statistics with households' "hidden wealth", assuming that financial assets are well collected by statisticians except for the part that is owned by households in offshore centers. He has also noticed that the pattern of international investments is consistent with this identification, as most of the assets-liabilities gap is concentrated in financial centers, such as Luxembourg and Ireland, which are more likely to receive investments in custody in offshore securities accounts.

The Figure 2 plots the top 5 countries in differences between liabilities as reported by national compilers and liabilities derived from asset data in the CPIS and SEFER databases in 2016. In value, the largest difference is observed in the US (around 1770 Bn $), but it represents only 10 % of nationally-compiled liabilities in its IIP. Luxembourg and Ireland exhibit differences between nationally-compiled and derived liabilities close to the US level (1720 Bn \$ and 1341 Bn \$, respectively), however much larger in relation to the size of their liabilities (they represent 35 % and 43 % respectively, of nationally-compiled liabilities).

Figure 2: Differences between nationally-compiled liabilities and liabilities derived from counterparts assets

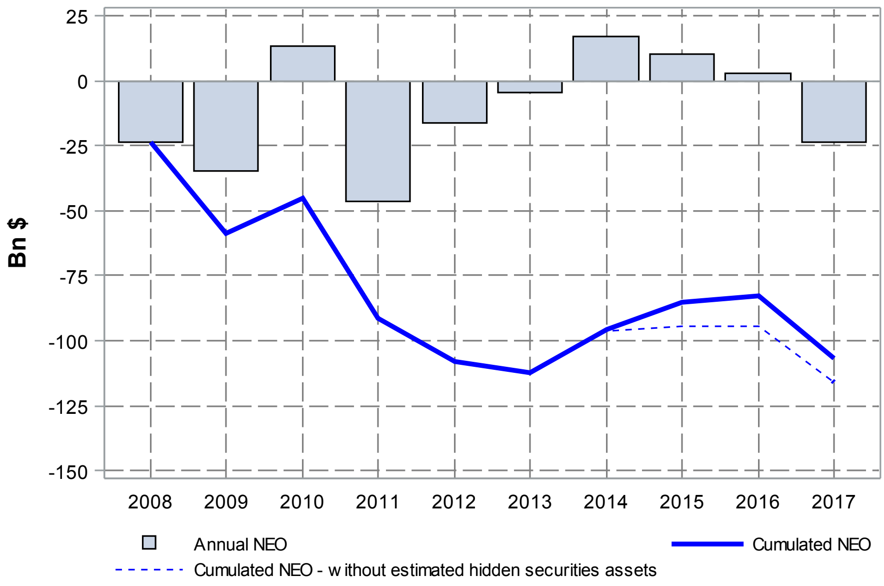


Sources: IIP and CPIS (IMF), authors' calculations

2. "Hidden assets" may also contribute to the French BOP "errors and omissions"

To the extent that their cash counterpart are yet recorded into the financial account of the balance of payments, "hidden investments" may also explain the persisting negative "errors and omissions (NEO)" in the French Balance of Payments. Since 2008, these errors have cumulated to around -100 Bn \$. And portfolio investments, at least arithmetically, are the main BOP counterparts to those cumulated errors and omissions.

Figure 3: Net errors and omissions in the French Balance of Payments



Source: Banque de France

Table 1: Counterparts to the French cumulated net errors and omissions

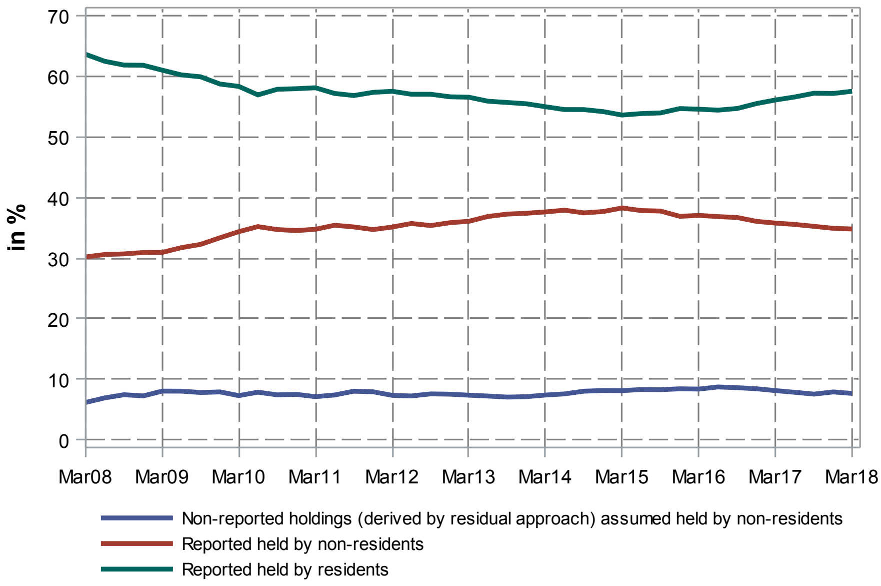
In this table, the balances and net values of each component of the French Balance of Payments are cumulated from 2008 to 2017, with (1)=(2)+(3)+(4)+(5)+(6)+(7)+(8)

Errors and Omissions (1)	Transaction Account (2)	Capital Account (3)	Direct Investment (4)	Portfolio Investment (5)	Derivatives (6)	Other investment (7)	Reserve Assets (8)
-107	173	2	258	-787	-72	309	8

Unrecorded investments by residents holding assets located abroad generate negative errors and omissions in two ways.

First, if invested instruments are debt securities issued by French residents, unrecorded residents' investments would wrongly be identified as inflows from foreign investors. In other words, inflows on the liability side would be overestimated. Indeed, following a common practice in BOP statistics, the residual between the total issued by French residents and the holdings reported by custodians or financial corporations is ascribed to non-residents in the French BOP. However, we deem this error insufficient to account for the negative trends in errors and omissions. First, anecdotal evidence supports the idea that the bulk of resident investments in French securities are entrusted to custodians in France or in the euro zone. Moreover, the share of computed liabilities in the total market value of French securities is quite stable since 2008: it is thus very unlikely that the bias induced by the use of the residual approach would explain the drift in errors and omissions.

Figure 3: Holdings of French securities by source (reported vs derived) and residence of the holder (in % of the total issued - market value)



Sources: Banque de France

Second, and more directly, unrecorded residents' investments with non-resident counterparts entails an underestimation of assets, and thus of outflows. However, this underestimation is mitigated by the fact that, according to ECB Regulation, financial corporations such as credit institutions (i.e. deposit taking institutions in the European context), mutual funds, insurance corporations and financial vehicle corporations are required to report directly to national compilers[2]. Hence, all securities booked in their balance sheet have to be reported, including those in the custody of foreign intermediaries. Regarding non-financial corporations and households, however, such an obligation does not exist and securities holdings statistics rely on information provided by local custodians. Hence, one can assume that "hidden assets" are held by these two sectors.

2. Are academic estimations of households' hidden wealth relevant for statistical purposes?

Recent academic papers have proposed countries' estimates for households' "hidden wealth". The results clearly point out the importance of the "missing wealth" in international statistics. However, the amounts being considered, and the uncertainties in the estimation methods, justify some caution when considering how this research can be integrated in a statistical production framework.

[2] Regulation (EU) No 1011/2012 of the European Central Bank of 17 October 2012 concerning statistics on holdings of securities (ECB/2012/24)

1. The academic literature provides rather large estimates of unrecorded holdings attributed to French households

Alstadsæter, Johannesen and Zucman (AJZ, 2017b) allocate across countries the global households' "hidden wealth" estimated in Zucman (2013). To this purpose, they rely, on the one hand on Swiss data on the ownership of fiduciary deposits, and on the other hand on BIS bilateral banking statistics on deposits owned by non-residents. Although they acknowledge that deposits are only a fraction of offshore financial wealth, they assume that the way they distribute internationally is a good indicator of the distribution of total offshore financial wealth. They obtain that in the case of France in 2007, offshore wealth of households would be as large as 15 % of GDP (i.e. 409 Bn $), whereas the world average would be at 9.8 %. Given the global security/deposit breakdown of "hidden wealth" in Zucman (2013), we may deduce that securities held by French residents in custody abroad would amount to around 300 Bn $. Moreover, they estimate[3] that most of this offshore wealth is owned by the richest households, such that including it would increase the share of wealth owned by the 5% richest households by around 2,5 pp[4].

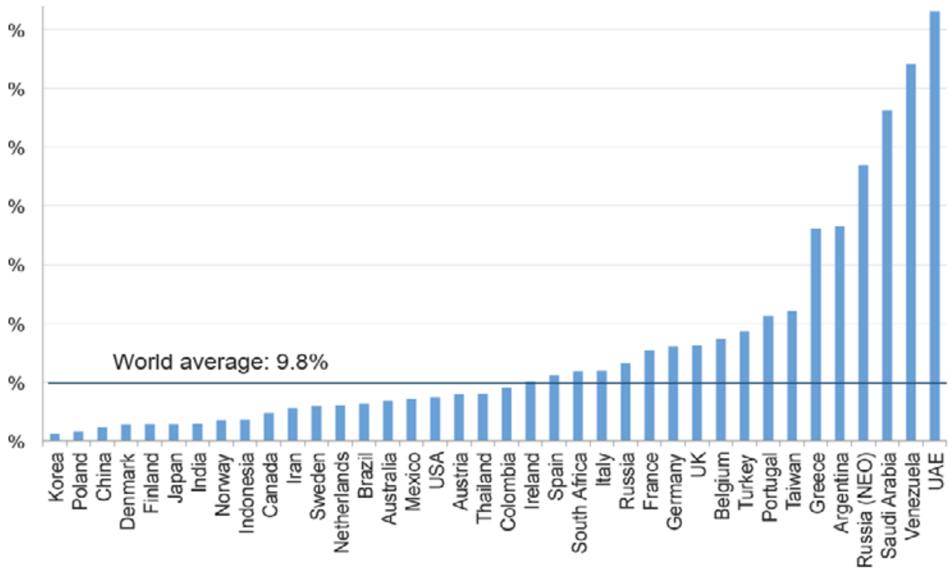
The amount estimated in AJZ (2017b) would almost double French households' holdings of securities (430 Bn $ in 2017 in statistics based on national custodian reporting and data shared within the Eurosystem). Moreover, these estimations radically change the concentration of financial wealth in security holdings. Indeed, the authors estimate that three quarters of the securities in custody abroad are held by 0.1 % of the richest households. And according to BDF custodian statistics, the "large" portfolios (customers owning more than 450 000 euros) – which is a good proxy for first centile of the wealth distribution invested into securities - already account for one third of households' securities holdings[5]. This proportion would more than double if AJZ (2017b) estimations were to be included.

3 Using micro data from the "Swiss Leaks" and tax amnesty data of Scandinavian countries, see also AJZ (2017a).

4 Author's calculations using AJZ estimates provided in online appendix. Bach, Thierman and Zucco (2018) use the "Household Finance Consumption Survey" corrected with public information on French, German and Spanish great fortunes to estimate the parameters of a Pareto distribution that describes the upper tail of wealth distribution. According to their calculation, the share of the top 0.1 % in the total wealth should be revised from 7,3 % to 10,0%.

5 Available via the website of the BDF : http://webstat.banque-france.fr/fr/browse.do?node=5384942

Figure 4: Estimated households' hidden wealth by country (from AJZ 2017b)



This figure shows the amount of household wealth owned offshore as a percentage of GDP, in 2007. The sample includes all the world's countri
iore than $200 billion in GDP in 2007. Offshore wealth is estimated by allocating the global offshore wealth estimated by Zucman (2013), on th
n the geographical distribution of bilateral cross-border bank deposits in offshore centers—see text. For Russia, we also report an alternative estima
ia (NEO)") obtained by cumulating net errors and omissions in the balance of payment, as estimated in Novokmet, Piketty and Zucman (2017
: Appendix Table A.3

Sources: AJZ (2017b)

2. Under-coverage of securities holdings is not limited to households' investments

Despite their interests for unveiling the significance of "hidden assets", these academic findings cannot be directly taken into account in the compilation of BOP statistics for several reasons. First, they must be adjusted to statistical methodologies and concepts. For example, if large households' investments in securities are held via captive vehicles registered abroad, they could be recognized as outward direct investments in their home country whereas portfolio investments should be recorded in the country of residence of the captive vehicle. Second, AJZ (2017b), due to data limitations well explained by the authors and to the need of combining sources referring to different points in time, can only give insights about their recent developments. On the other hand, statisticians have to maintain times series and might prefer consistency over time rather than completeness achieved between too large time intervals.

Third, AJZ (2017b) base their estimations on the assumption of Zucman (2013) that the gap between assets and liabilities at a global level can be identified as households' "hidden assets". From the point of view of a statistician, it is not natural to assume that inconsistencies can be reduced to a single explanation.

On this particular matter, it is somewhat too simplistic to limit under-coverage of securities holdings to households' investments. For many countries, securities in custody abroad held by non-financial corporations, or even by institutional investors, would also be missed by the national compilers, probably to a lesser extent(as large entities are usually subject to higher reporting constraints) but possibly with a significant impact on the gap in international statistics.

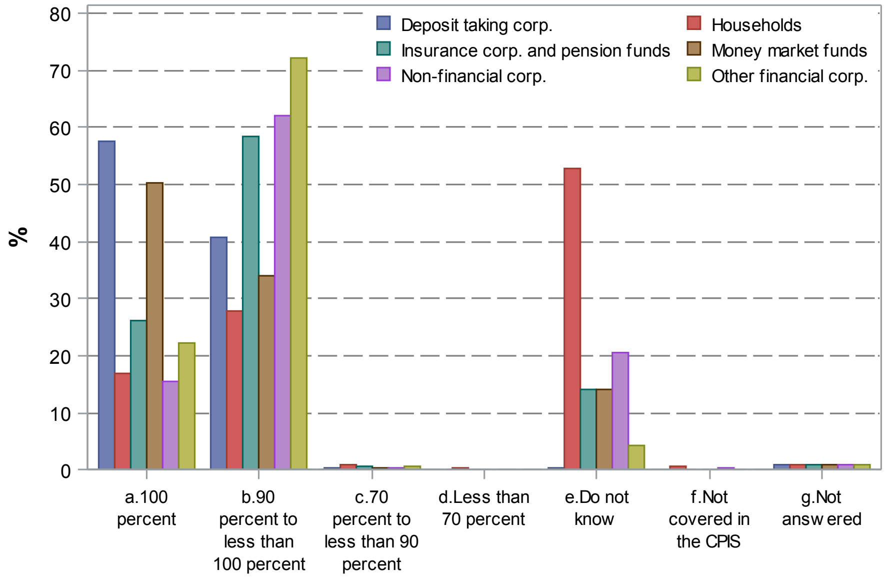
This point is notably illustrated by CPIS metadata[6]. In these metadata, contributing countries are asked to provide an assessment of the coverage of their statistics for the different holding sectors. In the figure below, we have plotted how countries' answers distribute for each holding sectors. Only countries satisfying a consistency condition on the comparison between CPIS assets and IIP portfolio assets are considered, in order to legitimate the claim that these metadata are also a proxy for the coverage in IIP portfolio assets[7]. All countries are weighted by their total IIP portfolio assets, so that the impact of under-coverage on international statistics consistency can be better assessed.

The results clearly confirm that households are the holding sector for which uncertainties regarding statistical coverage are most important. In the sample, countries admitting they "do not know" exactly how well households' holdings of securities are covered account for more than 50 % of the sample's IIP portfolio assets. Those claiming to have a perfect coverage account for less than 20 %.

Nonetheless, other holding sectors are not perfectly covered either. For non-financial corporations, the response "do not know" gathers countries that represent 20 % of the sample's IIP portfolio assets, while the proportion for the response of "90% to less than 100%" is 60 %. For insurance companies and pension funds, the shares are around 15 %, respectively 60 %.

Figure 5: Countries' assessments of the coverage of their CPIS statistics, by holding sectors

These statistics are based on CPIS metadata for a sample of 53 countries accounting for 87 % of total assets in international portfolio positions in 2016.
Plotted bars are referring to assessments' frequencies (in %) for each investing sector, with countries being weighted by their total IIP assets. Otherwise said, they indicate the share of the sample IIP assets that countries reporting the specified coverage rate for the specified investing sectors are accounting for.



Sources: CPIS and IIP (IMF), authors' calculations

6 It is also illustrated by Euro Area mutualized data on securities holdings, see 3.1.

7 The condition is that CPIS assets are between 98% and 102% of IIP portfolio assets.

3. The methodology of the Banque de France for estimating securities located abroad

At the Banque de France, the estimation of securities holdings in custody abroad relies on different methodologies depending on the holding sector.

1. Holdings by non-financial corporations

Concerning the non-financial sector, estimations are based on two sources. Regarding assets located in the Euro Area, they rely on the Eurosystem's Securities Holdings DataBase (SHSDB). Regarding other assets, aggregated positions from NFCs' balance sheet are used.

The integration of securities holdings data collected in partner countries of the Eurozone is the most straightforward way of reducing the under-coverage caused by third party holdings in other euro area countries. According to an ECB Regulation, National Central Banks (NCBs) of the Eurozone are indeed required to collect security-by-security data directly from financial corporations and also from custodians[8]. The latter should identify the sector and the residency of their customers. All third party holdings - that is to say all holdings by non-residents - are covered by this reporting, regardless of the country the issuer of the securities is located in. For example, the German central bank is able to identify Italian securities held by French residents in the custody of German intermediaries. These data are consolidated by the ECB and disseminated to contributing NCBs via a mutualized Securities Holdings DataBase (SHSDB), so that they can be integrated in national statistics[9].

The main advantage of this source is that it is totally consistent with the granular data we use for compiling securities holding statistics. Its drawback is that it does not cover assets located outside the Euro Area. To capture investments in custody outside the Euro Area, the total position of non-financial corporations collected on a granular basis is compared to their balance sheet. These balance sheet data are collected by the Banque de France for NFCs with an annual turn-over greater than 0.75 M€. They contain information on securities assets regardless of the location of the custody. Hence, we can estimate the under-coverage of NFCs by comparing these balance sheet data with securities holdings statistics based on custodian reporting.

8 See https://www.ecb.europa.eu/stats/financial_markets_and_interest_rates/securities_holdings/html/index.en.html.

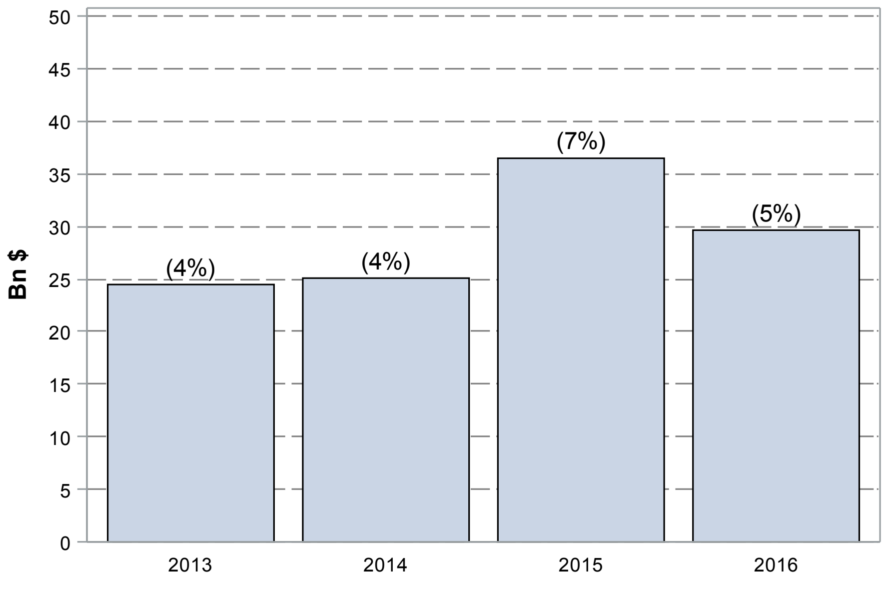
9 See for further information about ESCB holding statistics: https://www.ecb.europa.eu/stats/financial_markets_and_interest_rates/securities_holdings/html/index.en.html.

However, these two sources are not perfectly congruent. First, NFC balance sheet data do not distinguish securities assets according to the counterpart residency. Second, they do not distinguish between types of securities, and in particular, they mix quoted and unquoted shares, whereas securities holdings statistics exclude unquoted shares.

Integrating these data in Balance of Payments statistics thus requires some adjustments to ensure that balance sheet data and custodian reported data are comparable in all extent but the issue of third party holdings. To this end, participating interests[10] are removed from balance sheet data, as they are likely to include mainly unquoted shares. Symmetrically, direct investments (collected independently at the Banque de France) are removed from securities holdings statistics, as well as holdings of quoted shares issued by NFC that are likely to represent participating interests. After these operations, residual mismatches between the two sources are assumed to be largely driven by third party holdings, which are further assumed to be invested in foreign securities. All in all, the combined use of these two sources leads us to add 30 Bn $ of NFCs securities holdings not reported by French custodians (5 % of their total securities holdings, unquoted shares and direct investments excluded).

Figure 6: Estimations of non-financial corporations' holdings of securities located abroad

In parenthesis, amounts are expressed in relation to the total of the sector's holdings in securities statistics (hence excluding direct investments and holdings of unquoted shares)



Source: Banque de France, authors' calculation

[10] Securities holdings are presumed to be participating interests if they represent more than 10 % of the shares of the invested entity.

2. Holdings by households

Concerning households, Banque de France's estimates also use the SHSDB as a source to cover assets located in the Euro Area. Regarding investments in custody outside the Euro Area, the approach applied is close to the one described by Henry (2012)[11]. The idea is to extrapolate to securities the dynamics of French households' deposits abroad. This extrapolation relies on the BIS detailed Locational Banking Statistics on French deposits in foreign banks, and data on securities custody for non-resident customers published by the Swiss National Bank (SNB).

Several contributing countries provide the amount of deposits held by French households in their local banks to the BIS. Deposits, however, are only a minor part of offshore financial wealth. Zucman (2013) estimates that globally, the amount of offshore securities portfolios is 3 to 4 times bigger, while Henry (2012) considers (based on information from wealth managers) that the ratio between liquidity assets and total assets for wealthy individuals ranges between 3 and 4.5.

To scale up offshore securities holdings from offshore deposits, statistics published by the BNS on securities custody in Swiss banks owned by non-resident households are used to calculate the ratio of positions in securities compared to positions in deposits.

Applying this ratio as a scaling factor to available data on French households' deposits in non-Euro Area countries[12] brings a rough estimate of households' securities in third party holdings outside the Eurozone.

One caveat of this estimation is that not all countries provide detailed information on French households' deposits in their countries. To improve these estimates, ad hoc methodologies are applied for the most important ones. For example, if a country provides data on French deposits owned by non-bank entities, it is assumed (based on what is observed for countries providing the detailed decomposition of non-banks) that one third of this amount refers to households' ownership.

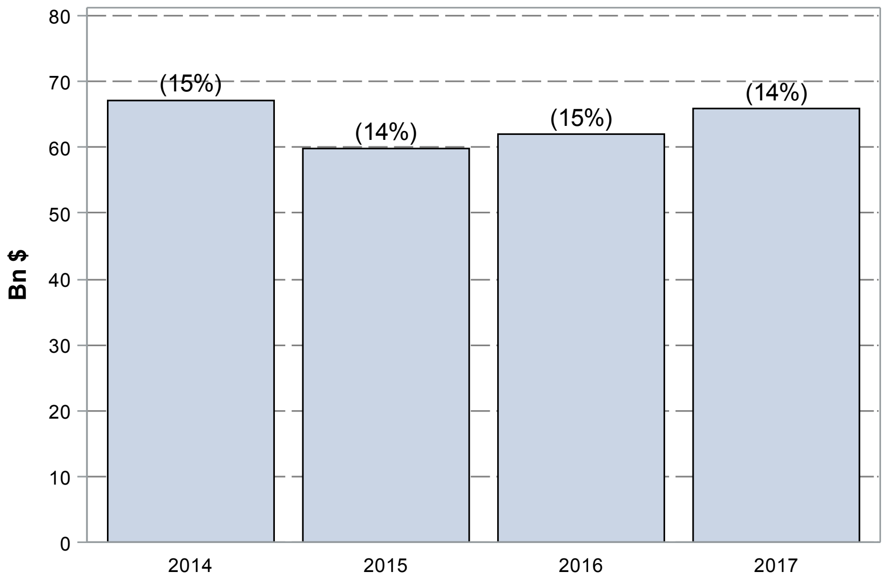
Eventually, total securities held by French households in custody abroad (in and out of the Euro Area) are estimated at around 65 Bn $ (see Figure 7).

Figure 7: Estimations of households' holdings of securities located abroad

In parenthesis, amounts are expressed in relation to the total of the sector's holdings in securities statistics (hence excluding direct investments and holdings of unquoted shares)

11 Henry (2012) uses Locational Banking Statistics and extrapolates from cross-border deposits amounts to total value of offshore wealth, assuming that deposits account for one quarter of the total.

12 French households' holdings of securities in custody in the Euro Area are covered by the mutualized Securities Holdings Statistics DataBase of the ECB.



Source: Banque de France, authors' calculation

It is worth noticing that despite the similarities between the two methodologies, Henry's (2012) estimates of global households' hidden wealth are three times higher than those of Zucman (2013) (between 20-30 Tn $ vs 8 Tn $), whereas the ones of the Banque de France are much lower than those derived for France by AJZ (2017b) (65 Bn $ vs 300 Bn $[13]). One explanation may be that Henry's (2012) estimates are based on the Locational Banking Statistics for the non-bank sector, whereas ours use detailed series on the household sector.

4. Sharing data on third party holdings would be the best way forward to measure households' hidden wealth

Any estimate of third party holdings should be considered as uncertain. This is true for both the Banque de France's estimates and the ones provided by the academic literature.

Clearly, the most solid of the methodologies presented in section 3 is the one based on French holdings collected in Euro Area partner countries, and consolidated by the ECB in the Securities Holdings DataBase. However, this database does not include those countries that are expected to manage the larger share of securities in foreign accounts (notably Switzerland, the United Kingdom, and other major financial centers).

Therefore, a more global approach is required, that could be integrated to the CPIS. In fact, this issue was raised at the very beginning of the implementation of

[13] Estimates for French households' hidden wealth in securities only. For this comparison, AJZ (2017b) original estimates referring to total financial wealth (deposits + securities) have been scaled down using securities/deposits ratio in Zucman (2013)

the CPIS by the IMF Committee on Balance Of Payments Statistics, who had set up a Working Group on Third Party Holdings (WGTPH) in 2001.

Among the conclusions in the report of the WGTPH in 2004, it is suggested that a Third Party Holdings Survey could be conducted annually. This survey:

- Would be limited to holdings of the household sector, as it is the sector for which under-coverage of third party holdings is expected to be most critical;
- Requires that each contributing country breaks down third party holdings in custody in their jurisdiction by residency of the holder and of its counterpart;
- May require that - in addition to custodians - brokers/dealers, investments companies, and private banks contribute to reporting;
- Could ensure confidentiality by trusting the IMF for receiving all national contributions and releasing only aggregated data, such that the specific amounts located in a given country would not be identifiable.

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Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

How to identify "hidden securities assets" in the Balance of Payments: methods of Bank of France[1]

Emmanuel Gervais and Pierre Bui Quang,

Bank of France

[1] This presentation was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

BANQUE DE FRANCE
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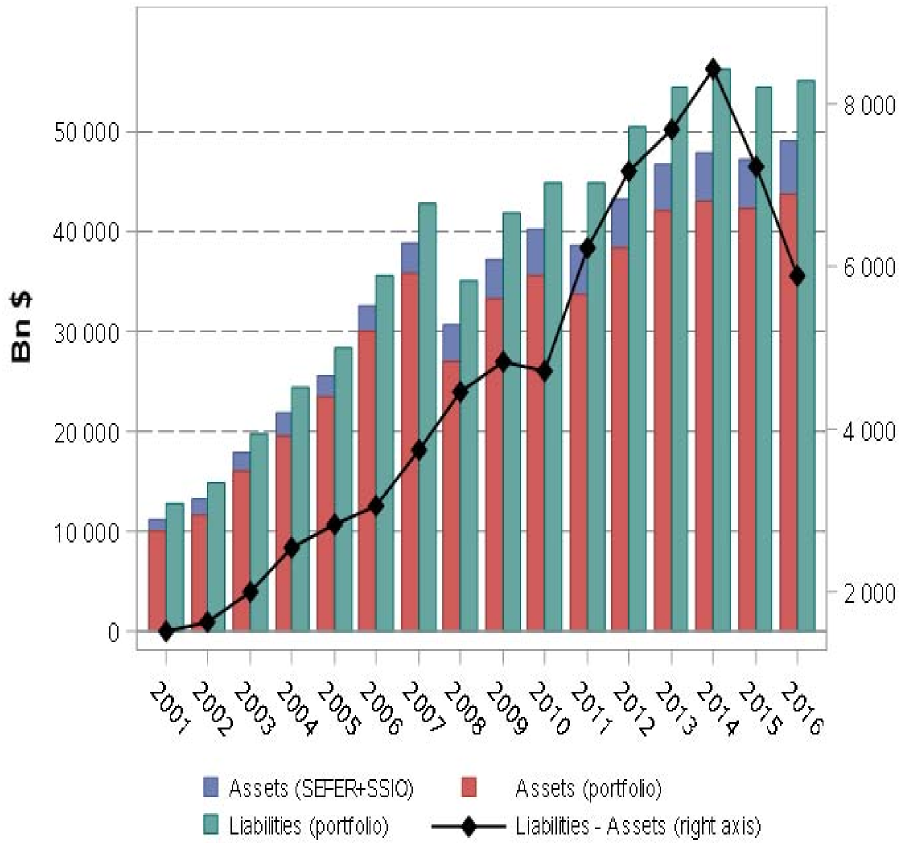
Irving Fisher Committee
30th – 31st August 2018

How to identify "hidden securities assets" in the Balance of Payments: Methods of Banque de France

Emmanuel Gervais, Pierre Bui Quang

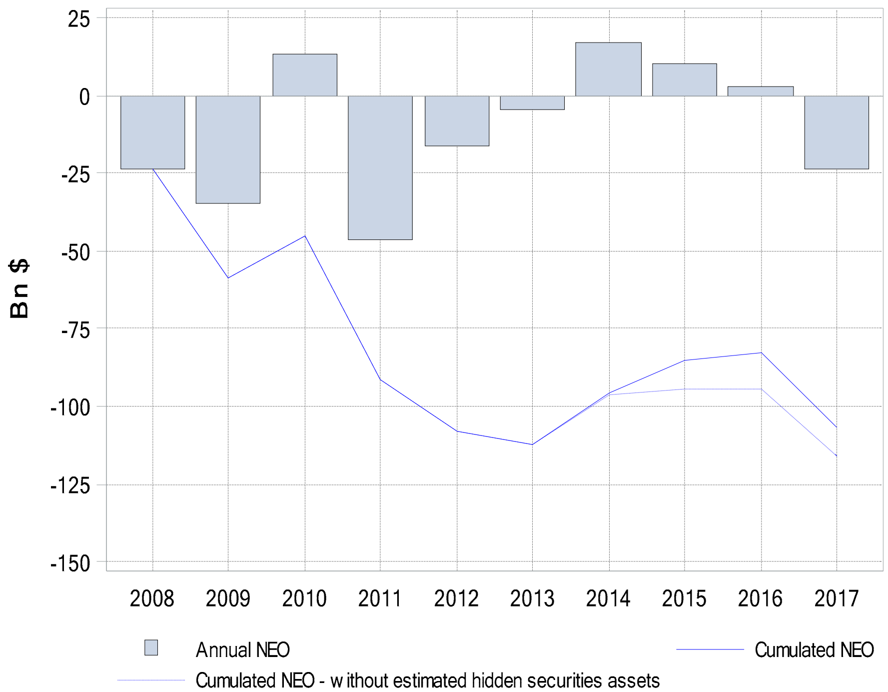
Statistical inconsistencies may be accounted for by « hidden assets »

Global portfolio positions : assets versus liabilities



Source: IMF – Authors' calculations

Errors and omissions in French BOP



Source: Banque de France

Likely impact of hidden assets on French IIP

- More on the assets side than on the liabilities side
  - Anecdotal evidence supports the idea that most of resident positions on French securities are held in France or in the Euro Area.
  - The share of liabilities calculated as a residual and thus estimated has been rather stable since 2008 (less than 10 %).
- Mainly held by households and non-financial corporations
  - In European law, financial corporations are required to report their whole portfolios whatever the « physical » location of their assets

Academic literature provides rather large estimates of unrecorded holdings attributed to French households

- Alstadsæter, Johannesen and Zucman (2017) allocate global households' "hidden wealth" across countries
  - Using Zucman (2013) estimates of global hidden wealth based on international inconsistencies
  - With BIS bilateral banking statistics and Swiss data
- For France, households' offshore financial wealth would be as large as 15 % of GDP in 2007 (vs. world average = 9.8 %)
  - ➔ Additional position in portfolio investments would amount to 300 Bn $
  - To be compared with 480 Bn $ of households' holdings of securities in BDF statistics in 2017

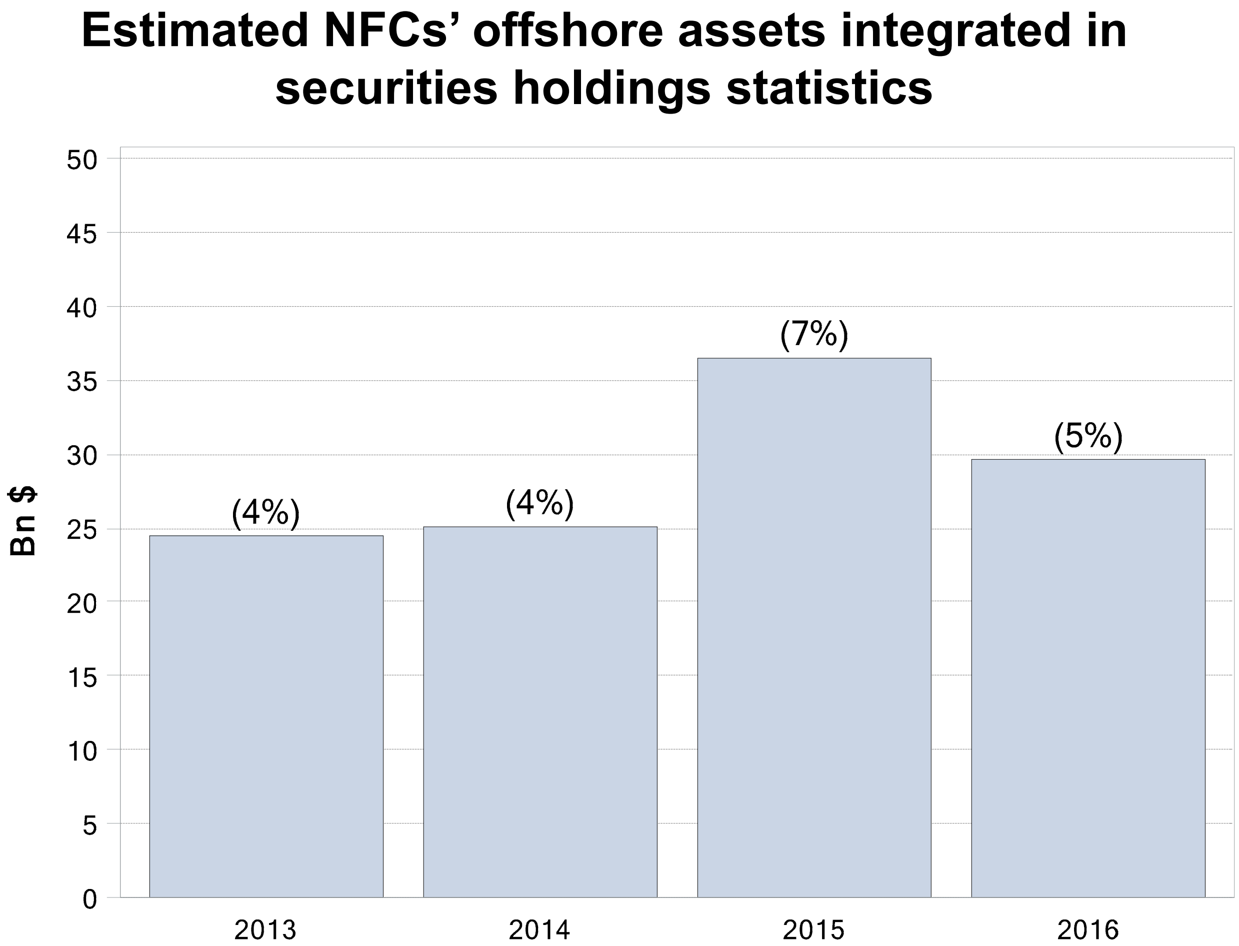
Can these estimations be used in statistics?

- They should be adjusted to statistics concepts and methodology
  - Difference between nationality and residency
  - Splitting between direct investments and portfolio investment
- Derivation of time series using these estimations would be difficult
- Non-financial corporations should also be taken into account

Estimation of non-financial corporations' offshore assets

- Regarding assets located in the Euro Area, we rely on the Eurosystem *Securities Holdings Statistics DataBase* (SHSDB)
  - SHSDB centralizes granular contributions from NCBs all compiled according to SHS Regulation
- For remaining assets, we compare the total of granular data to the aggregated portfolios of non financial corporations according to their balance sheet
  - These data come from a database maintained by the BDF
- The difference is deemed to be the assets located outside the Euro Area

Estimation of non-financial corporations' offshore assets



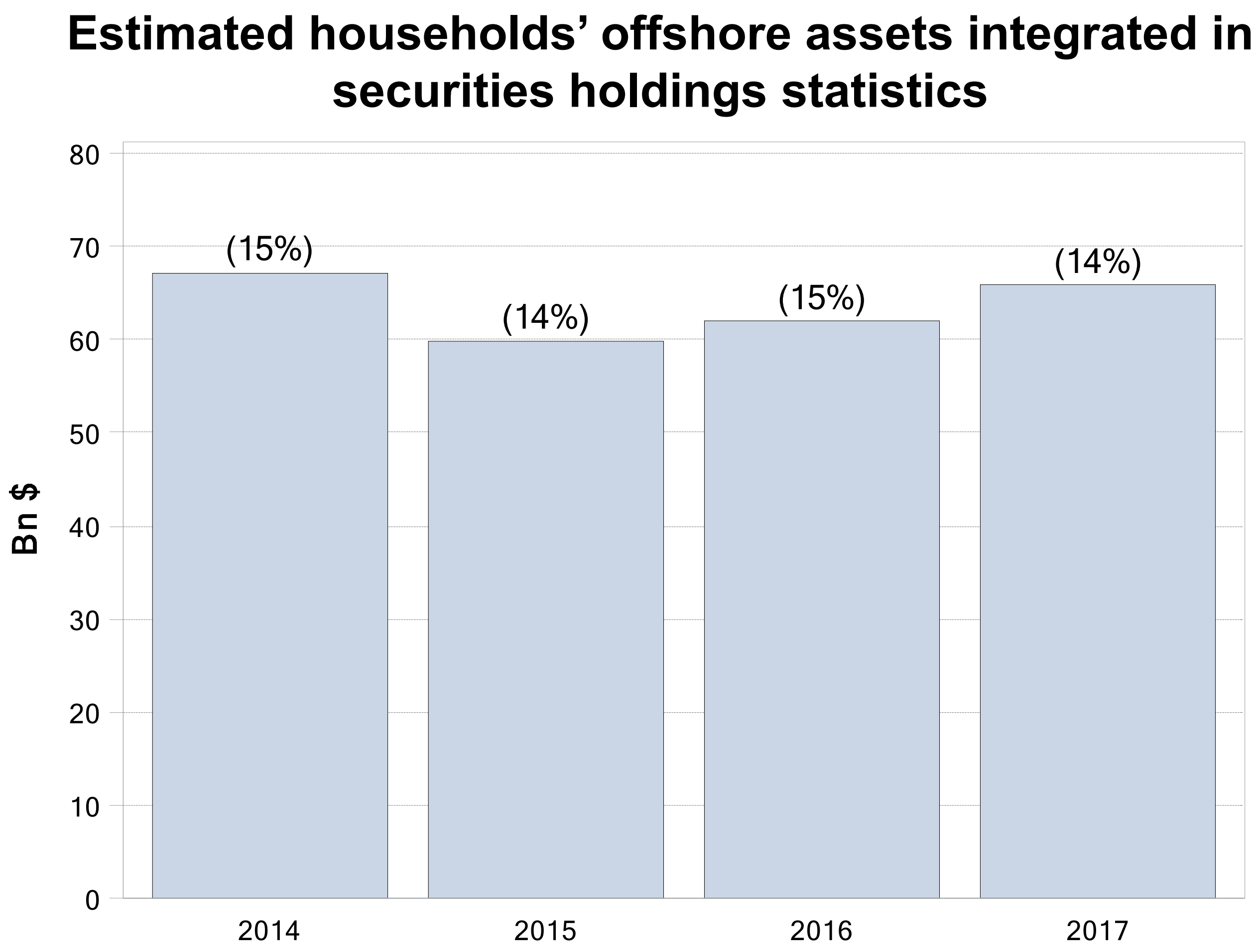
Source: Banque de France

Estimation of households' offshore assets

- Regarding assets located in the Euro Area, our source is SHSDB

- Regarding assets located outside the Euro Area, we extrapolate from French households' deposits in foreign banks
  - Based on BIS detailed Locational Banking Statistics
  - Using Swiss National Bank (SNB) published data on securities custody for non-resident customers to estimate a securities / deposits ratio for households' offshore wealth

Estimation of households' offshore assets



Source: Banque de France

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Exchange rate effects in the international investment position - methods, tools and applications for Germany[1]

Stephanus Arz, Stefan Hopp and Ulf von Kalckreuth,
Deutsche Bundesbank

1 This paper was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

Exchange Rate Effects in the International Investment Position – Methods, Tools and Applications for Germany

Stephanus Arz[1], Stefan Hopp[2] and Ulf von Kalckreuth[3]

Abstract

Exchange rate movements play an important role in explaining the dynamics of national and sectoral gross and net wealth and the rate of return on foreign investments. The German international investment position (IIP) statistics have long since provided and published data on assets and liabilities with foreign counterparties by sector and by financial instrument. For the period since 2012, all the items can additionally be broken down by seven currencies: euro and six non-euro denominations. Ex post, this allows the effect of exchange rate changes on the euro value of assets and liabilities to be calculated, enabling a wide range of analytical work. These exchange rate changes are now collected in an index of exchange rate effects in the IIP, which depicts the influence of individual exchange rate movements on all non-derivative assets and liabilities in the external position on an aggregated level as well as on various disaggregated levels. Ex ante, it is possible to conduct sensitivity analyses concerning exchange rate shocks in terms of gradients and in terms of volatility measures. The extended IIP approach can be used to indicate potential currency mismatches and imbalances and as a basis for delving deeper into sectoral currency risk exposure and vulnerabilities on the aggregate level.

Keywords: IIP, external position, currency composition, exchange rate sensitivity.

JEL classification: C43, F31, F36

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Contents

1. Introduction

International spill-overs of financial shocks can be transmitted by a variety of channels, among them direct financial interlinkages and demand effects. Since the days of Keynes and Mundell, one focus in monetary macroeconomics has been the exchange rate. The exchange rate is a summary relative price for traded goods and services as well as for real and financial assets. Thus, the exchange rate will determine the values of all of these items in terms of other currencies, steer trade and financial flows, and determine the relative wealth of people, sectors and nations, including their state of solvency. The Asian crisis started out as a series of currency devaluations that triggered stock market declines and made the foreign debt positions of a number of countries unsustainable.

The IIP is to national wealth what the current account is to GNP: national wealth is the sum of real capital plus the net foreign position of a country. Thus, in order to categorize and analyse wealth effects of exchange rate fluctuations, the IIP is the notional point of departure. Obviously, wealth effects of exchange rate movements on countries, sectors and individuals depend on their overall gross and net financial positions as well as on the currency composition of their portfolio. In terms of macroeconomic effects, these portfolio effects may even more than offset the trade channel.[4] For investors holding unhedged net positions denominated in a foreign currency, exchange rate movements will translate directly, without any further intermediation, into changes in the market value of their net wealth. This is why the new Balance of Payments and International Investment Position Manual, BPM6,[5] asks for a standardized breakdown of changes of IIP positions into transactions, revaluations – exchange rate changes among the latter – and other changes:

Beginning of period position

+ Transactions during the period

+ Revaluations during the period:

of which due to

◦ exchange rate changes

◦ other price changes

+ Other changes in volume during the period (reclassifications etc.)

= End of period position

This accounting identity for the "law of motion" holds at all levels – countries, sectors, economic agents – and for single financial instruments as well as for aggregate assets, liabilities or net positions.

To identify the effect of exchange rate changes, there needs to be a system of bookkeeping for currency denominations. For each position, each instrument of each entity that is covered, consistent and updated information on the currency

[4] Kearns and Patel (2016).

[5] International Monetary Fund (2009).

composition is required.[6] This is why the currency composition of IIP positions figures explicitly in the recommendations of the G 20 Data Gaps Initiative, Phase II.[7] The information is not easy to come by – in many instances, hard data from mandatory reports or surveys have to be complemented by reliable estimates. But once the matrix of currency compositions is in place, it is quite straightforward to use it for depicting exchange rate effects on many levels, both ex post as well as ex ante, for forecasting and policy and scenario analyses.

It is important to understand that, in principle, IIP positions are valued at market prices in the home currency, and if market prices are not available, close substitutes are used. The IIP positions are changed by flows from the current account – trade in goods and services, primary and secondary income, and by stock adjustments. Looking at the consequences of exchange rate changes for the IIP of a country, we can thus distinguish between the effects on stocks and on flows as two broad levels of analysis. Regarding stocks, there are first of all instantaneous revaluation effects given the portfolio composition and denomination structure. Gross assets and liabilities denominated in foreign currencies enter the balance sheets of individuals or sectors at a new rate of exchange. Second, depending on how economic agents respond, and with some lag, there may be portfolio rebalancing effects resulting from an attempt to restore portfolio equilibrium. These lead to direct purchases or sales of financial assets, with an effect on prices and the asset and liability structure. Concerning the current account, we can make the same distinction. The flows of trade in goods and services, of primary income from labour or as a return on assets, and of secondary income are revalued. In addition, there is an economic adjustment of quantities, as a result of re-optimisation given the new relative prices. While the effects of flows on the IIP may be important in the long run, the effects on stocks are "fast" or even instantaneous.

This paper takes a look at the instantaneous effect that revaluations have on stocks. The valuation effects are mechanical, but depending on the currency denomination of external positions, they can be very strong. The elasticity approach of Marshall, Lerner and Robinson, as it is known, looks at the conditions under which the trade balance reacts "normally" to an exchange rate movement despite the translation effects. Similarly, we may ask ourselves, with respect to the IIP, whether and when in a given situation the portfolio rebalancing effects and the effects on the current account can possibly override the immediate revaluation effects of an exchange rate change. Think, for example, of a country with a currency mismatch, where liabilities denominated in foreign currency are much larger than the corresponding assets. As usual, a devaluation of the home currency may help this country's export sector, but the valuation effect makes the foreign net position deteriorate instantaneously. Even worse, the interest or dividend payments on the liabilities denominated in foreign currency also become more of a burden.

6 See Lane and Shambough (2010), who construct a database of currency compositions for aggregate IIP positions of 127 countries. See also Bénetrix, Lane and Shambough (2015).

7 Recommendation 10 on the International Investment Position in DGI II. An overview of progress on currency breakdowns is given by IMF (2015).

This paper gives a methodological exposition with a focus on the German IIP.[8] Section 2 introduces the basic ideas. Section 3 outlines the dimensions of the set of statistical information that is available for analysing exchange rate effects for Germany. As the compilation of statistical data in Germany is guided by the methodologies set out in the IMF BPM6 directives, which apply worldwide, it can be expected that this type of analysis is feasible in many other countries. Section 4 introduces the IIE, a system of indices of exchange rate valuation effects. Section 5 investigates some measures of sensitivity and volatility with respect to exchange rate valuation effects that can be readily calculated on the basis of available information. Section 6 concludes by discussing the relationship between these sensitivity measures and currency risk exposure, taking into account the role of hedging.

2. Exchange rate effects: using stocks as a weighting matrix for relative changes

Consider any vector a_t of *K* different IIP stocks at the end of period *t* on any level of aggregation – different instruments in the balance sheet of a sector, or aggregates across multiple classes of instruments:

$$\mathrm{a}_t = \begin{pmatrix} a_t^1 \\ \vdots \\ a_t^K \end{pmatrix}.$$

Note that *K* is not fixed but depends on the analytical question at hand. There is an associated composition matrix A_t. For each entry a_t^k of the stocks vector, line *k* of the composition matrix gives the currency composition. Let *N* be the number of currency denominations and *n* a running index, with 1 indicating the home currency:

$$\mathrm{A}_t = \begin{pmatrix} a_t^{11} & \cdots & a_t^{1N} \\ \vdots & \ddots & \vdots \\ a_t^{K1} & \cdots & a_t^{KN} \end{pmatrix}, \text{ with } \sum_{n=1}^{N} a_t^{kn} = a_t^k .$$

All elements in a_t and A_t are denominated in units of home currency. Let $\hat{\mathrm{E}}_t$ be the vector of relative exchange rate changes for the *N* currencies with respect to period *t*, the first element being an entry for the home currency which is identically equal to zero. The exchange rates indices are given in price notation, i.e. in units of home currency per unit of foreign currency:

$$\hat{\mathrm{E}}_t = \begin{pmatrix} 0 \\ \Delta E_t^2 / E_{t-1}^2 \\ \vdots \\ \Delta E_t^N / E_{t-1}^N \end{pmatrix}.$$

[8] For an introduction to the new German IIP statistics, also concerning exchange rate effects, see Schipper and Jäcker (2016), as well as Deutsche Bundesbank (2018).

To indicate the exchange rate effect in the changes of positions from *t-1* to *t*, we condition on the asset structure in *t-1*. Then the *vector of exchange rate effects* for all positions in A_t is given by the matrix product

$$EE_t = \mathrm{A}_{t-1} \cdot \hat{\mathrm{E}}_t \ .$$

It is useful to rephrase this in terms of rates of change, using weights. Define a weighting matrix for the currency composition of assets, where the elements in each line add up to one:

$$\mathrm{W}_t = \begin{pmatrix} a_t^{11} / a_t^1 & \cdots & a_t^{1N} / a_t^1 \\ \vdots & \ddots & \vdots \\ a_t^{K1} / a_t^K & \cdots & a_t^{KN} / a_t^K \end{pmatrix} , \tag{1}$$

and, accordingly, a *vector of IIP weighted exchange rate changes:*

$$\eta_t = \mathrm{W}_{t-1} \cdot \hat{\mathrm{E}}_t \ .$$

The term η_t is a vector of growth rates. One can look at it in two ways. First, by weighting the exchange rate changes on the basis of IIP positions, they are "translated" into effects on wealth stocks. Second, from the perspective of these stocks, the elements of η_t denote the relative change in the positions of a_t induced by exchange rate variations. The absolute value of effects can be recovered by simply multiplying the weighted changes η_t back into the stocks a_{t-1}.

$$EE_t = \begin{pmatrix} a_{t-1}^1 \eta_t^1 \\ \vdots \\ a_{t-1}^K \eta_t^K \end{pmatrix} .$$

By suitably choosing components of interest in a_{t-1}, one can compute exchange rate effects by instrument, by sector or by any combination of the two. And obviously, the same set of computations is possible for any matrix L_t of liability positions according to currency denominations, leading to corresponding weighted exchange rate changes η_t for liabilities. Exchange rate effects are being calculated as part of the current publication programme of DG Statistics at the Deutsche Bundesbank.

At this point, an important caveat is in order. The exchange rate effects that can be computed on the basis of the currency composition of IIP positions do not necessarily translate fully into wealth effects for the respective creditor or debtor, i.e. into capital gains or losses. Economic agents may be hedged, either by holding derivatives or by currency diversification in multinational enterprises (natural hedge). Other parties may be affected. The IIP does not deliver sufficient information on these hedging activities, and, when analysing the distribution of wealth effects, this information has to be added separately. This issue will be addressed in Section 6.

3. The extended information set for Germany

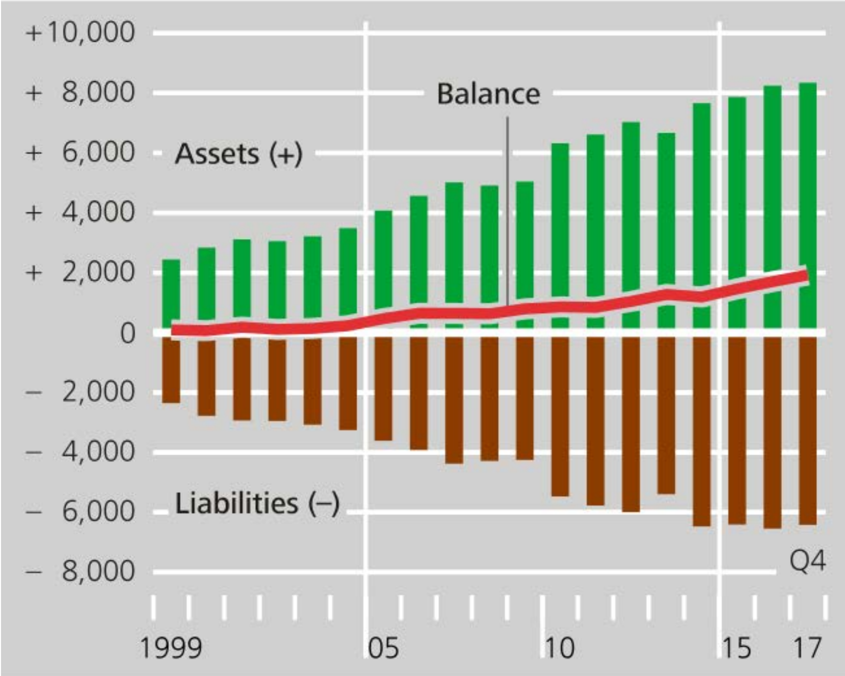
German IIP positions, including the net balances, have been increasing dramatically in recent years. Graph 1 depicts the dynamics of this development. The net external position of Germany – ie external assets minus external liabilities as a percentage of nominal GDP – has increased from almost 20% to around 60% in the eleven years between 2007 and 2017.[9] At the end of 2017, external assets reached a volume of € 8,346 bn and external liabilities amounted to € 6,417 bn. A large share of these positions is denominated in foreign currencies: 34% of all assets and 20% of all liabilities. This equates to € 1.5 trillion of net IIP at the end of Q3/2017, or around 50% of GDP. For such a portfolio, even small exchange rate changes may have a high impact.

Consider, for example, a devaluation of the euro against the other currencies. The euro value of Germany's debt positions denominated in foreign currencies will increase, as will the asset positions. The absolute value of foreign-currency-denominated positions on the asset side is larger – both the total size and the share of foreign-currency-denominated positions are larger for assets than for liabilities. Combine this with the conjecture that the currency composition of income flows from assets and liabilities will be similar to the composition of the stocks. Disregarding hedging, there will be a systematic positive effect on the IIP in home currency, also concerning income flows, at least for the aggregate economy.[10] These structural effects will be quite different from the effects that the same depreciation may have on a net debtor country with a large reliance on foreign-currency-denominated liabilities; see e.g. the analysis by the IMF Spillover Task Force (2015). The situation at the level of sectors or individuals may be rather diverse in both countries, of course, depending on the underlying financing structure. Gross positions are important, as the holders of financial liabilities will not coincide with the holders of foreign assets.

[9] See Deutsche Bundesbank (2018).

[10] Indeed, in 2017 an appreciation by the euro against the US dollar and other currencies led to a negative exchange rate effect on Germany’s net position in the order of € 123 bn, which is the balance of a decrease of the euro value of assets by € 207 bn and of liabilities by € 84 bn; see Bundesbank (2018), pp 33.

Graph 1: The international investment position of Germany.
€ bn, end of year



3.1 Institutional sectors in German IIP

Following the directives of the BPM6, German IIP statistics provide quarterly information on international investment positions for a rich set of institutional sectors and financial instruments. In this section, we show how the elements of A_t and L_t can be chosen based on the information infrastructure of German IIP statistics. The institutional classification used in German IIP statistics is given below in Table 1. Economic agents are grouped into six sectors. Compared to the earlier standard, the sector "Monetary Financial Institutions (MFIs) excluding central banks" has been split further into "Deposit taking institutions" and "Money market funds". Furthermore, "Financial corporations" have been separated out from the old residual category "Other sectors", to give a more complete picture of financial institutions.

3.2 Financial instruments in German IIP

For each of the sectors listed above, IIP statistics provide data on assets or liabilities with an external counterparty, according to a rather detailed set of 20 instruments (within functional categories) at the deepest level of disaggregation, which is listed in Table 2.

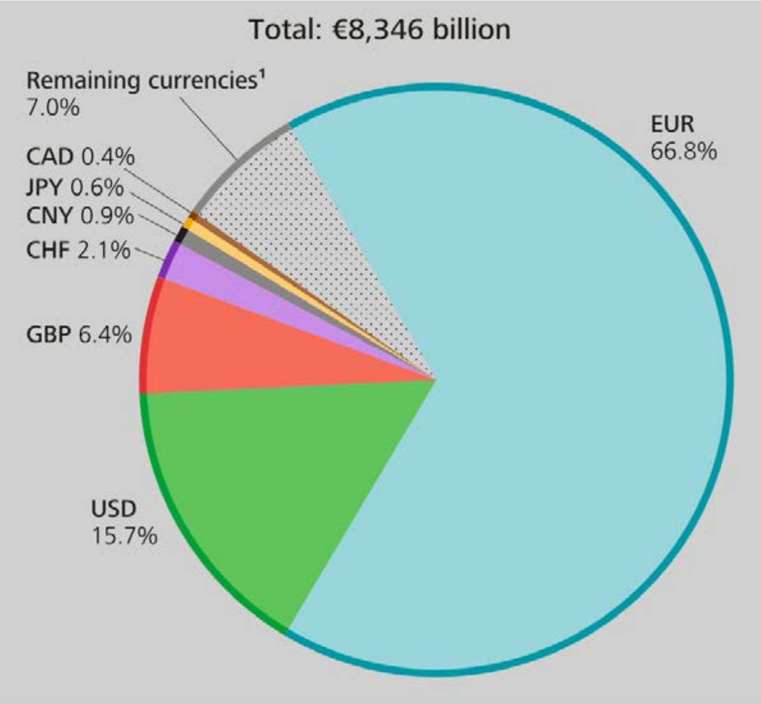
Table 2: Financial instruments in German IIP
I. Direct investment
1. Equity capital
1.1. Listed
1.2. Unlisted
1.3. Other equity
2. Debt instruments
2.1. In direct investment enterprise
2.2. In direct investor (reverse investment)
2.3. Between fellow enterprises
II. Portfolio investment
1. Shares
2. Investment fund shares
3. Short-term debt securities
4. Long-term debt securities
III. Financial derivatives and employee stock options
IV. Other investment
1. Loans
1.1. Short-term debts
1.2. Long-term debts
2. Currency and deposits
2.1. Currency and short-term deposits
2.2. Long-term deposits
3. Trade credits and advances
4. Insurance, pension and standardised guarantee schemes
5. Other equity
6. Other accounts receivable / payable
7. Special drawing rights (only liabilities)
V. Reserve assets

3.3 Currency denominations in German IIP

Combining sectors and instruments will lead to a system of balance sheets concerning external assets and liabilities, and data on currency denominations need to be produced for the respective positions. At present, this bookkeeping is being carried out for a set of six major foreign currencies (US dollar, pound sterling, Japanese yen, Swiss franc, Chinese renminbi and Canadian dollar), plus the euro, and plus gold and special drawing rights in the context of central banking. This approach will depict the currency composition of most of the assets and liabilities of German residents and their financial linkages with the outside world.

Table 3: Currency denominations in German IIP
I. Foreign currencies
- US dollar
- Pound sterling
- Japanese yen
- Swiss franc
- Chinese renminbi
- Canadian dollar
II. Special drawing rights (in the reserve position of the Deutsche Bundesbank)
III. Euro

Graph 2: IIP assets by currency in Germany
Percentage share, end of 2017



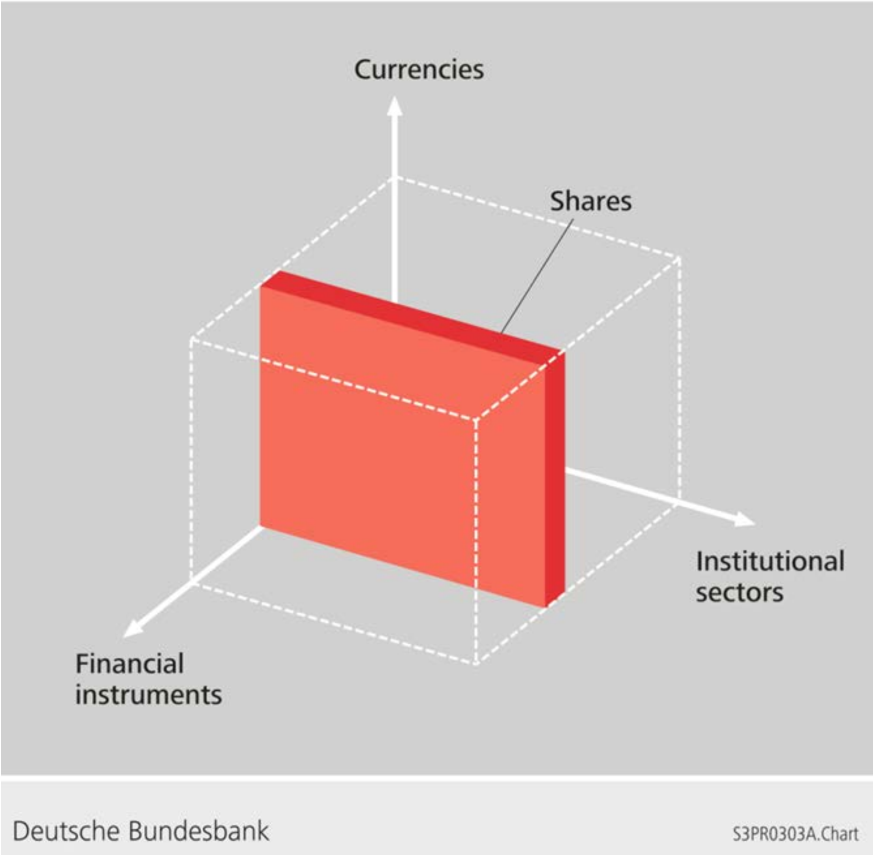
1 Including special drawing rights (XDR) and monetary gold.
Deutsche Bundesbank S3PR0326.Chart

Around 93% of assets and 96% of liabilities in Germany are being held in euro, gold or one of the six currency denominations named above; see Graph 2 above.[11] There are some more major currencies for international finance in Germany, such as the Indian rupee, the Swedish krona, the Danish krone and the Brazilian real. These

[11] In this graph, the gold reserves of the Deutsche Bundesbank are part of the external assets, and they are considered to be denominated in euro. With a view on monetary history, one might have also thought of treating gold as a currency in its own right, with the gold price serving as the exchange rate.

are almost exclusively being used in financial positions with the counterparty resident in the country where the respective currency is legal tender. At the current stage, these currencies do not enter the analysis.

Graph 3: Dimensions of analysis for exchange rate effects



3.4 The cube of statistical information for exchange rate analysis in German IIP

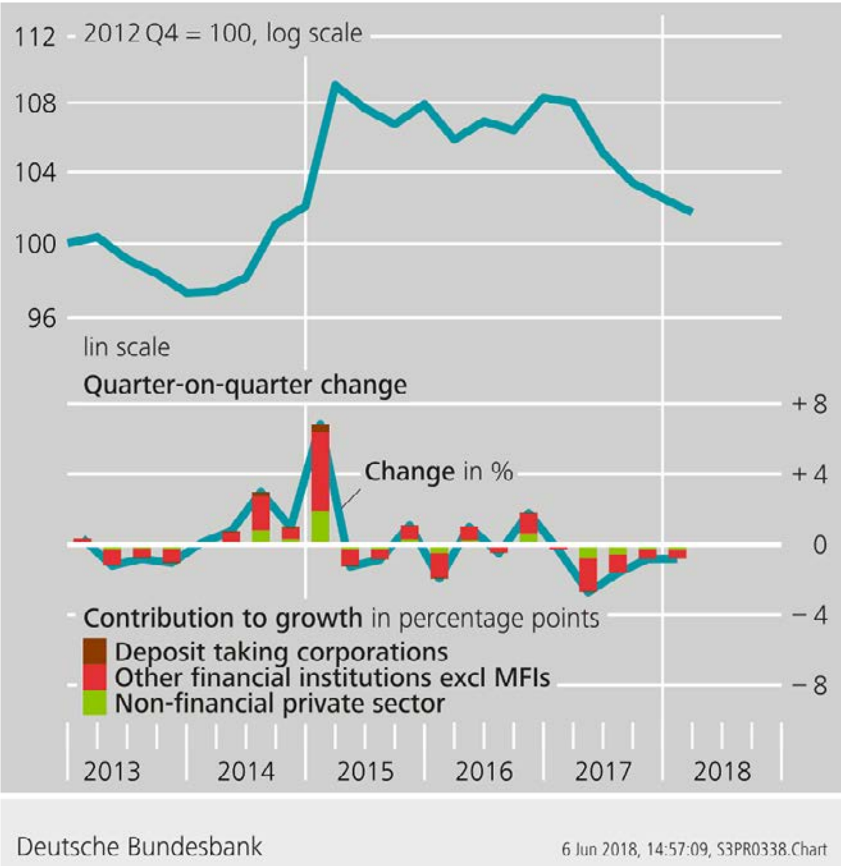
The preceding paragraph shows that the elements of the composition matrices A_t and L_t can be chosen along three dimensions: sectors, instruments, and currency denominations. At the lowest level of disaggregation, this encompasses a number of 960 elements in the composition matrices, both for assets and for liabilities, each of which will yield separate low-level exchange rate effects. Not all the combinations are filled, though. Households do not issue currency and deposits. There are assets denominated in special drawing rights only for the Deutsche Bundesbank. On the other hand, the Deutsche Bundesbank does not hold any foreign direct investments. Of course, all sorts of aggregations are also possible and meaningful. Statisticians are accustomed to visualizing this type of information structure in terms of a cube; see Graph 3 above.

4. An index of IIP-weighted exchange rate effects

Given a time series of η_t^k for any asset or liability position, it is straightforward to construct Laspeyres-type indices of exchange rate effects, upon which analytical work can be based. Chain-linking the growth factors associated with η_t^k while setting some base period equal to 100 yields an index for the capital gains and losses caused by exchange rate changes in the respective IIP positions. For any asset or liability position *k*, we obtain IIE_t^k, the **I**ndex of **I**IP-weighted **E**xchange rate effects:

$$IIE_t^k = 100 \cdot \left(1+\eta_1^k\right) \cdot \left(1+\eta_2^k\right) \cdot \ldots \cdot \left(1+\eta_t^k\right) = IIE_{t-1}^k \cdot \left(1+\eta_t^k\right) .$$

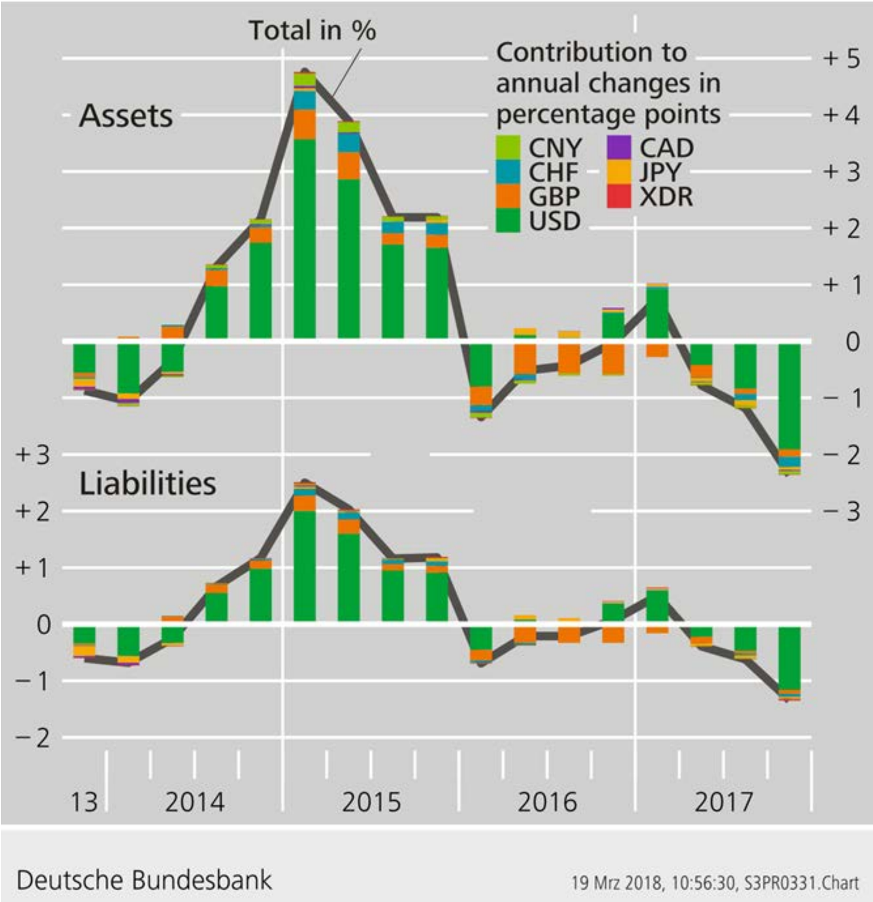
Graph 4: IIE for shares in portfolio investment (asset side)



For aggregate gross positions, IIP-weighted effective exchange rates have been proposed and evaluated, in slightly different ways, by Lane and Shambough (2010) and Patel and Kearns (2016). At the Deutsche Bundesbank, in a joint effort by the General Statistics and External Statistics divisions, the IIE are being computed and stored, item by item, for the baseline combinations of sectors, instruments and currency denominations, as well as for many meaningful aggregates, ready for analytical use.

As an example, Graph 4 shows how the index of IIP-weighted exchange rate effects on the value of foreign shareholdings has evolved in both aggregated terms and disaggregated by sector. The top panel shows the IIE for aggregate holdings, the panel below, the associated quarter-on-quarter changes by sector. One can readily observe the depressing effects of the euro appreciation in 2013 and the strong positive effect that the depreciation in 2014 had on the euro value of foreign shareholdings, and the deflating effect of the re-appreciation in 2017. The panel below shows that the brunt of the effects is borne not by MFIs but by other financial institutions and, to a lesser degree, by private households as well. This sort of information, facilitated by the breakdown of positions by currency and the calculations of exchange rate effects, can be of high analytical value for financial stability analysis.

Graph 5: Currency decomposition of IIE changes in percentage points
Total assets and liabilities



Graph 5 above decomposes the annual percentage change of IIE by currency, in percentage points. For liabilities, the total effects are clearly smaller, due to a lower share of positions denominated in foreign currencies, compared to assets. Concerning magnitudes, the dynamics are clearly dominated by the US dollar – the percentage change of the dollar's exchange rate is highly indicative of the total exchange rate effect.

It is instructive to see the absolute values behind this decomposition. The IIE year-on-year change of -2.4% on the asset side in Q4/2017 corresponds to an absolute decrease of € 207 bn, whereas the decrease of 1.3% on the liability side translates into € 84 bn in absolute terms!

5. Sensitivity and volatility of aggregates and specific positions

For financial stability purposes, it can be useful to calculate the sensitivity of aggregates or sub-categories to exchange rate changes.

5.1. Sensitivity-related results

As a starting point for quantitative analysis, we may be interested in the partial revaluation effect of a one-percentage-point change of a given currency, eg the US dollar, on the value of some or all asset or liability positions. This is the kind of question which proved to be highly relevant in the Latin American debt crisis of the early eighties or the Asian Crisis in the late nineties. For currency *n*, for example, the effect on η_t in percentage points is simply given by the vector w_{t-1}^{n} of weights for currency *n*, i.e. column *n* of the weighting matrix W_{t-1} in (1). As a sensitivity measure in absolute terms, we obtain – as a gradient with respect to relative changes in the rate of currency *n* – the *n*'th column of the composition matrix A_{t-1}:

$$\frac{\mathrm{da}}{\mathrm{d}\hat{E}_t^n} = \begin{pmatrix} a_{t-1}^{1} \cdot w_{t-1}^{1n} \\ \vdots \\ a_{t-1}^{K} \cdot w_{t-1}^{Kn} \end{pmatrix} = \begin{pmatrix} a_{t-1}^{1n} \\ \vdots \\ a_{t-1}^{Kn} \end{pmatrix} = \mathrm{a}_{t-1}^{n} \ .$$

There is an interesting extension to this exercise. Exchange rate changes often do not happen in isolation. Changes for different currencies are typically highly correlated – for an illustration of this, see Graph 5. If one considers a hypothetical change of exchange rate *n* as a structural stochastic shock, one might be interested in how the values of IIP positions respond to an increase of exchange rate *n* by one standard deviation, additionally taking into account the correlation structure regarding the other currencies. Let Ω be the covariance matrix of the exchange rates of our analytical system – including the euro, entering with zeroes for the variance and all covariances:

$$\Omega = \operatorname{cov} \hat{\mathrm{E}}_t = \begin{pmatrix} 0 & 0 & \dots & 0 \\ 0 & \operatorname{var} \hat{E}_t^2 & \dots & \operatorname{cov}\left(\hat{E}_t^2, \hat{E}_t^K\right) \\ \vdots & \vdots & \ddots & \vdots \\ 0 & \operatorname{cov}\left(\hat{E}_t^2, \hat{E}_t^K\right) & \dots & \operatorname{var} \hat{E}_t^K \end{pmatrix} .$$

The estimated effect of a *one-standard-deviation shock* to currency *n* on the asset positions a_t in absolute values, taking into account the correlation structure, will then be:

$$\mathrm{s}\left(\mathrm{a}_{t-1}, E_t^n\right)_\Omega = \sqrt{\mathrm{a}_{t-1}^{n} \cdot \Omega \cdot 1(\mathrm{n})} \ ,$$

where $1(\mathrm{n})$ is a column vector that has 1 as its *n*'th element and zeroes elsewhere.

5.2. Volatility aspects

To understand the volatility induced in the IIP by exchange rate movements, it is straightforward to first consider the historical/ex post volatility of the IIE. Table 4 shows the volatility of portfolio investment assets, computed on the basis of Q4/2012 to Q4/2017 data.

Table 4: Std dev of portfolio investment assets: quarter-on-quarter changes of IIE

	All sectors	Banks	MM funds	Fin. corp. w/o MFIs	Gov	Others*
All instruments	0.6	0.9	0.1	0.8	1.7	0.4
Long-term debt securities	0.6	0.3	0.0	0.6	1.5	0.3
Short-term debt securities	0.8	1.2	3.3	0.8	0.0	0.6
Shares	2.0	1.5	0.0	2.0	0.0	2.4
Investment fund shares	0.6	0.9	0.1	0.8	1.7	0.4

*Non-financial corporations, households and non-profit institutions serving households

This volatility measure implicitly comprises the historic volatility both of exchange rates and the currency composition of assets. In a forward-looking type of analysis, it may be more interesting to consider the volatility of *IIP*, given the current structure of assets and liabilities. Consider any asset or liability position a_t^k. Let the row vector $g_t^k{}'$ be the currency weights for this position – row *k* in the general weighting matrix in equation (1) – and η_t^k be the associated weighted exchange rate change. Then

$$\mathrm{std}\left(\eta_t^k\right) = \sqrt{\mathrm{var}\left(g_{t-1}^k{}' \cdot \hat{E}_t\right)} = \sqrt{g_{t-1}^k{}' \cdot \Omega \cdot g_{t-1}^k}$$

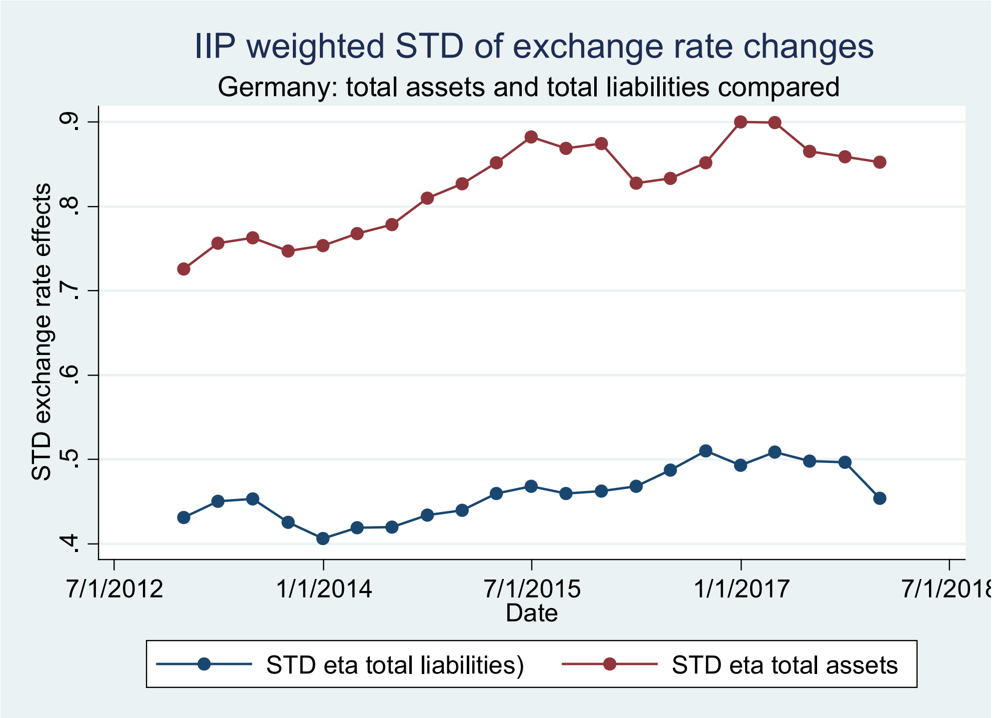
is the standard deviation of *IIE* for a_t^k on the basis of the current exchange rate composition and the correlation structure for exchange rates. The elements of Ω can be estimated on the basis of time series observation.

To also take into account the absolute value of the position, which may change quite strongly over time, we can instead consider the exchange-rate-induced standard deviation of position a_t^k:

$$\mathrm{std}\left(a_t^k \eta_t^k\right) = a_t^k \,\mathrm{std}\left(\eta_t^k\right) = a_t^k \sqrt{g_{t-1}^k{}' \cdot \Omega \cdot g_{t-1}^k} \qquad (2)$$

For the overall exchange-rate-induced variance in the German IIP, the massive increase in assets and – to a lesser degree – in liabilities denominated in foreign currencies will be an important driver.

Graph 6: Standard deviations of exchange-rate effects in percentage points. Total assets and total liabilities in Germany

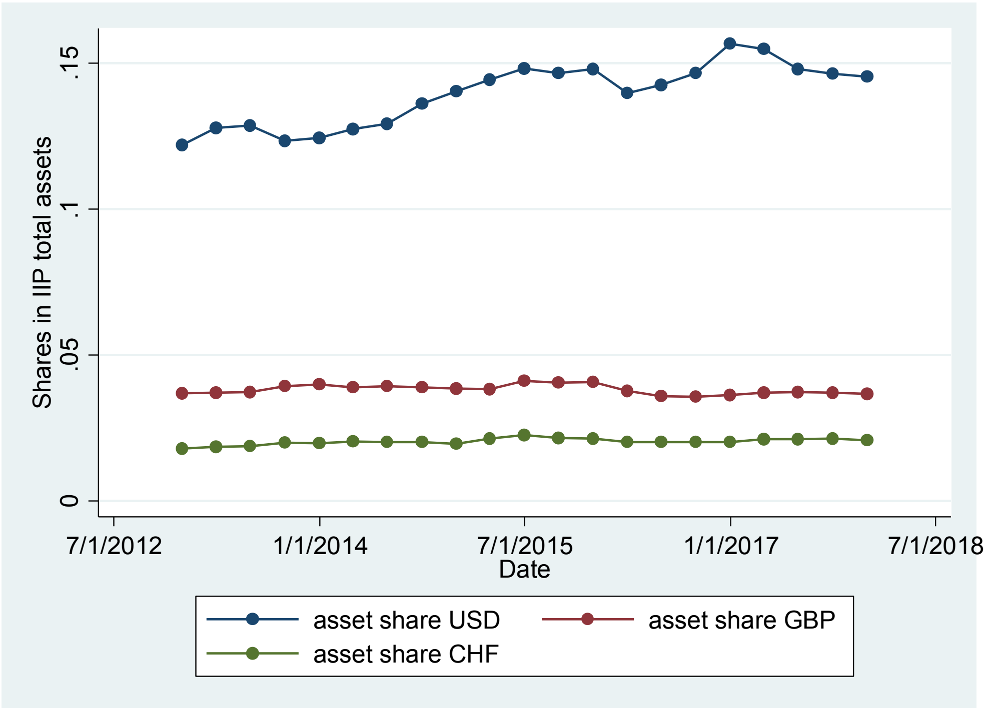


Let us now consider, as an example, the standard deviations for the η_t^k concerning total assets and liabilities. Graph 6 plots the standard deviations in percentage points for the five years between Q4/2012 and Q4/2017. The standard deviations have been calculated using the covariance matrix generated from the deviations of exchange rate indices in the time between Q4/2012 and Q1/2018. The value is given in percentage points: i.e. the quarterly standard deviation of total assets in Germany in Q4/2017 was 0.85 percentage point of its absolute value. Whereas the standard deviation for assets has increased noticeably, the standard deviation for total liabilities is lower and rather stationary.

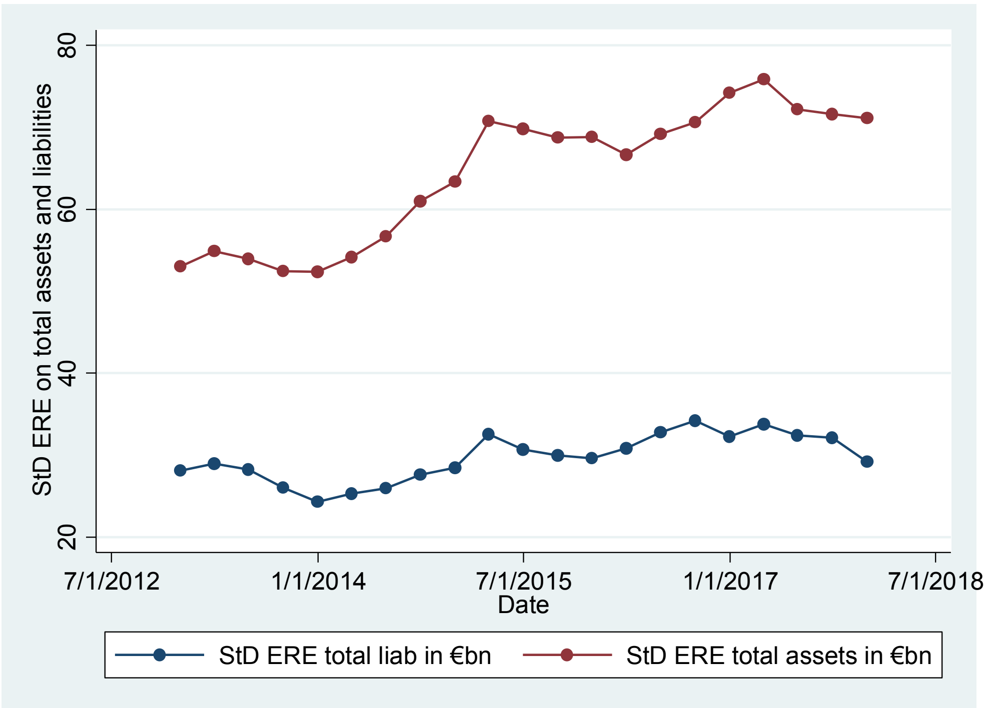
Graph 7 gives an explanation of why the standard deviation of assets has grown: the share of dollar assets increased over that time. While the standard deviation of exchange-rate-induced valuation changes does not seem to be impressive, Graph 8 shows how this translates into absolute values. The units are now shown in billions of euro. As both assets and liabilities have been increasing over this time, the rise in the standard deviations of absolute values is steeper than the increase of their etas.

Although these numbers are large in absolute terms, they are a more or less mechanical outcome for a large economy that is closely integrated into the worldwide financial system, both on the asset and the liability side. Of course, the standard deviation of Germany's net position (not shown) is much lower, and – as has already pointed out – we are not yet in a position to trace the important consequences of hedging activities.

Graph 7: Exchange rate weights in total assets in Germany.
The largest three: USD, GBP and CHF



Graph 8: Standard deviations of exchange rate effects for totals
Total assets and total liabilities in Germany



6. An outlook: IIP information and currency risk exposure

So far, we have been careful to avoid using the words "risk" and "exposure". The exchange rate effects η_t^k and the associated indices IIE^k are the result of a mechanical decomposition of the corresponding changes in IIP positions. By itself, they are not necessarily informative about the ultimate distribution of capital gains and losses.[12] The economic agents may be hedged (although this may be costly or incomplete), either by forward markets or derivatives or by holding natural hedges, such as FX gains from export business or being part of a multinational enterprise group. Derivatives are reported at market values among the IIP securities where they constitute a relationship with the outside world, but even then there is no additional information on whether the items are hedging exchange rate risk or something quite different, or whether they are in fact being used as speculative instruments to take on currency risk.

Thus, in order to construct indicators for currency risk exposure, one has to combine the information from the IIP with information on hedging activity. Let $g*_t^k$ be the currency shares with respect to the unhedged portions of position a_t^k, not summing up to 1 but to the total unhedged position as a fraction of a_t^k. Corresponding to (2), a macro-statistical indicator for the wealth risk from currency exposure concerning IIP item a_t^k may be given by:

$$WR\left(a_t^k\right)\big|_{FX} = a_t^k \sqrt{g*_t^{k\,\prime} \cdot \Omega \cdot g*_t^k} \quad .$$

Finding useful representations of $g*_t^k$ is easy in some cases. Households do not usually hold derivatives to hedge their currency risks. In this case, one may safely assume $g*_t^k = g_t^k$. Regarding direct investment activity, the currency risk activities could be hedged using revolving derivatives positions, but this is expensive, and given the many other sources of risk in direct investment, it is not likely to happen. Deposit taking institutions usually do not hold open foreign currency positions concerning their short-run credit or portfolio investment. In terms of statistical aggregates, these positions could be regarded as mostly hedged, and $g*_t^k = 0$.

For other combinations of sectors, functional categories and instruments, the relationship between wealth effects and exchange rate changes is less clear-cut. In these cases, one may interpret the $\mathrm{std}\left(a_t^k \eta_t^k\right)$ in (2) as being indicators for the need to hedge. Specific research is needed on the unhedged portion of the IIP position in question and, if possible, its currency composition. Two caveats are in order. First, the results will typically involve an element of educated guessing.[13] Second, if currency-related derivatives are traded between domestic residents, the aggregate

12 Information on the currency composition of assets and liabilities has been repeatedly used to compute the "balance sheet effects" of exchange rate changes for a cross-section of countries, e.g. IMF Spillover Group (2015), Lane and Shambough (2010), and Bénetrix, Lane and Shambough (2015). This is perfectly legitimate and informative as long as one keeps in mind that an interpretation in terms of wealth effects and currency risk exposure needs additional information and assumptions regarding hedging activities.

13 When considering the FX exposure of the corporate sector in emerging market economies and developing countries, the IMF Spillover Group summarily assumes that half of FX liabilities are hedged.

exposure will not change, though the resulting systemic risk may well diminish if the currency risk of diverse agents is netted out or the residual risk is borne by agents better able to deal with it. And derivatives contracts between residents and non-residents may both increase and diminish aggregate exposure.

A better understanding of the relationship between the exchange rate effects and sensitivity measures in the IIP on the one hand, and revaluation-induced wealth effects on the other, is the subject of ongoing research.

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Exchange rate effects in the international investment position - methods, tools and applications for Germany[1]

Stephanus Arz, Stefan Hopp and Ulf von Kalckreuth,
Deutsche Bundesbank

[1] This presentation was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

Exchange Rate Effects in the IIP

Methods, Tools and Applications for Germany

Ulf von Kalckreuth, Principal Economist-Statistician, DG Statistics, Deutsche Bundesbank*

9th biennial IFC Conference "Are post-crisis statistical initiatives completed?"
BIS, Basel, 30-31 August 2018

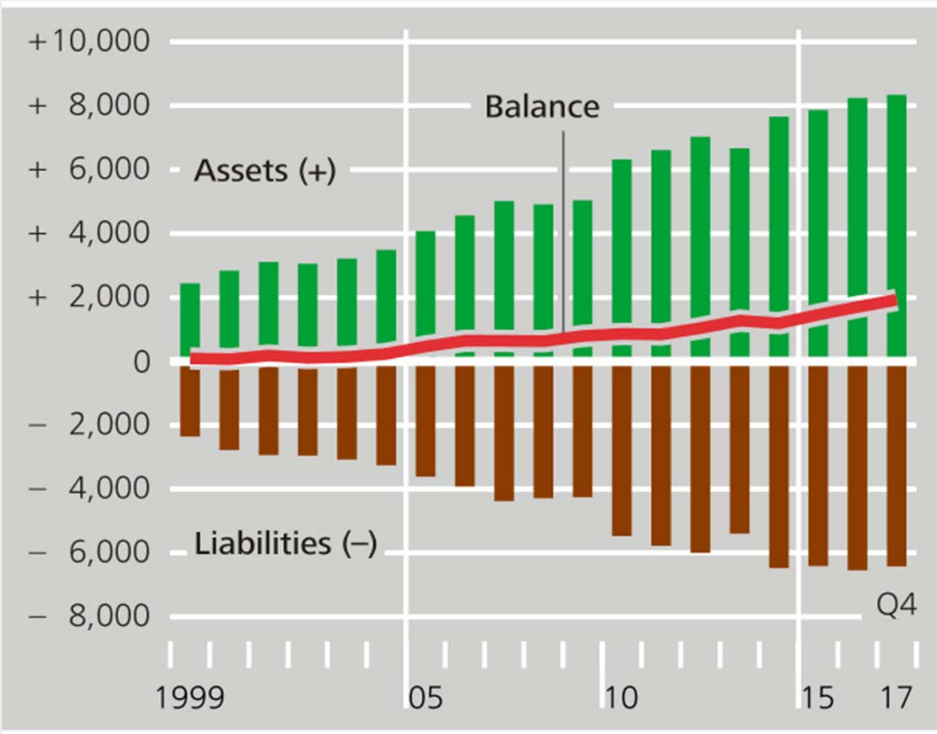
*The paper is joint work with Stephanus Arz and Stefan Hopp. It represents the authors' personal opinion and does not necessarily reflect the views of the Deutsche Bundesbank or the Eurosystem..

Outline

- Introduction: The significance of exchange rate fluctuations on the IIP for wealth and financial stability
- Basic concepts: the matrix of currency compositions
- An index of IIP weighted exchange-rate effects
- Sensitivity analysis
- Outlook: taking hedging into account

Introduction

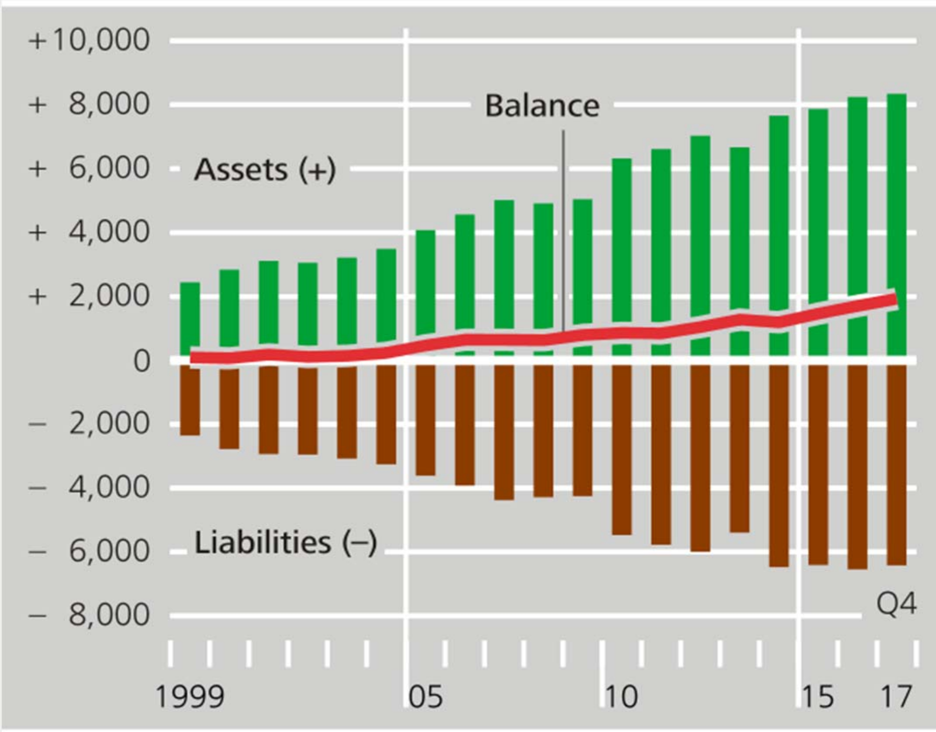
German IIP, all sectors, 1999 to end of 2017



The net external position of Germany has **increased from almost 20% to around 60% of GDP** in the years between 2007 and 2017. At the end of 2017, **external assets have reached a volume of € 8,346 bn** € and **external liabilities amount to € 6,417 bn €.**

Introduction

German IIP, all sectors, 1999 to end of 2017



A large share of IIP is denominated in foreign currencies: 34% of all assets and 20% of all liabilities – **net exposure is equivalent to € 1.5 trillion**, around 50% of GDP. For such a portfolio, even small exchange rate changes may have a high impact.

Introduction

- **National wealth** is **sum of real capital** plus **net foreign position**
- For wealth effects of exchange rate changes, IIP is the point of departure.
- Wealth effects on countries, sectors and individuals **depend on the currency composition of their portfolio**
- For investors holding **unhedged net positions** in a foreign currency, **exchange rate changes will directly affect net wealth.**
- **BPM6** asks for **breakdown** of changes of IIP positions into **transactions, revaluations** – exchange rate changes among them – and **other changes.**

- To identify effects of exchange rate changes, a **system of bookkeeping for currency denominations is needed** -- for each position, each instrument of each entity!

→ **Matrix of currency compositions needed!**

Basic concepts

Euro value of *N* currency positions in IIP stock *k*, the first being €

Exchange rate change for home currency, identically = 0

$$\mathrm{a}_t = \begin{pmatrix} a_t^1 \\ \vdots \\ a_t^K \end{pmatrix} \qquad \mathrm{A}_t = \begin{pmatrix} a_t^{11} & \cdots & a_t^{1N} \\ \vdots & \ddots & \vdots \\ a_t^{K1} & \cdots & a_t^{KN} \end{pmatrix} \qquad \hat{\mathrm{E}}_t = \begin{pmatrix} 0 \\ \Delta E_t^2 / E_{t-1}^2 \\ \vdots \\ \Delta E_t^N / E_{t-1}^N \end{pmatrix}$$

Vector of *K* different IIP stocks, in €

Matrix of currency compositions of stocks in a_t

Vector of exchange rate changes w.r.t. to €, for currencies 1 to *N*

Basic concepts

The **vector of exchange rate effects** is given by:

$$EE_t = \mathrm{A}_{t-1} \cdot \hat{\mathrm{E}}_t$$

Share of currency *N* in the Euro value of item 1

Consider the matrix of weights

$$\mathrm{G}_t = \begin{pmatrix} a_t^{11} / a_t^1 & \cdots & a_t^{1N} / a_t^1 \\ \vdots & \ddots & \vdots \\ a_t^{K1} / a_t^K & \cdots & a_t^{KN} / a_t^K \end{pmatrix}$$

and accordingly a **vector of IIP weighted exchange rate changes:**

$$\eta_t = \mathrm{G}_{t-1} \cdot \hat{\mathrm{E}}_t$$

Basic concepts

Formally, η_t is a **vector of growth rates.** One can look at it in two ways:

- By **weighting the exchange rate changes on the basis of IIP positions**, η_t "translates" these changes into effects on wealth stocks.
- Regarding the stocks, the elements of η_t denote the **relative changes of IIP positions** induced by exchange rate variations.

Absolute value of exchange rate effects can be **recovered** by simply **multiplying the weighted changes back into the stocks.**

An index of IIP weighted exchange rate effects

Chain-linking the growth factors associated with asset *k* while setting some base period equal to 100 yields an index for the capital gains and losses due to exchange rate changes in the respective IIP positions.

For any asset or liability position *k*, we obtain the **I**ndex of **I**IP-weighted **E**xchange rate effects:

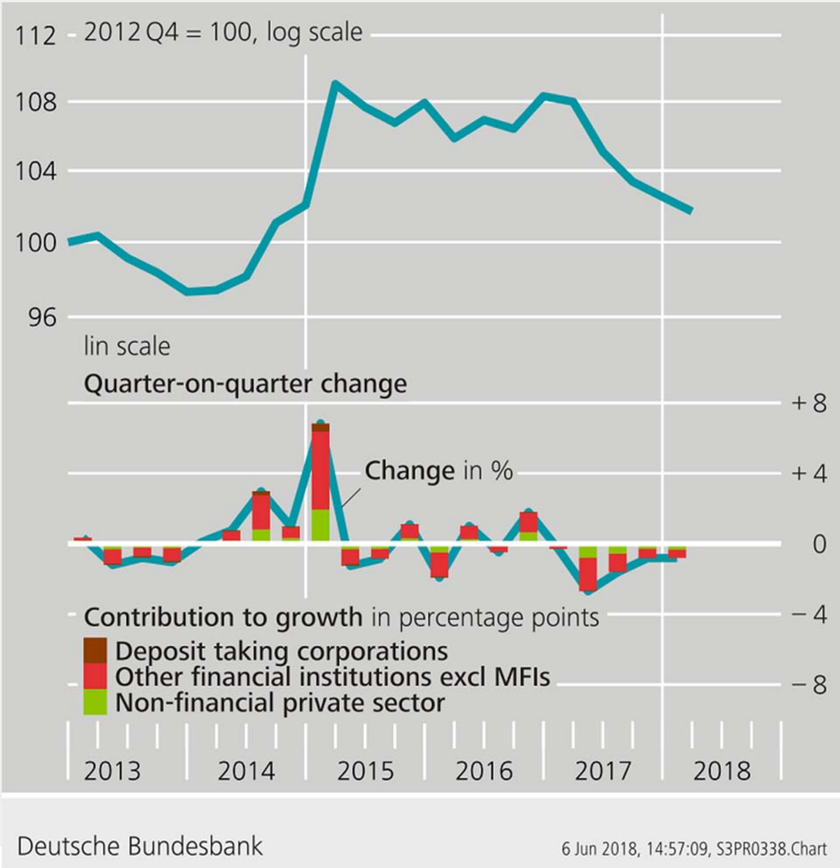
$$IIE_t^k = 100 \cdot \left(1+\eta_1^k\right) \cdot \left(1+\eta_2^k\right) \cdot \ldots \cdot \left(1+\eta_t^k\right) = IIE_{t-1}^k \cdot \left(1+\eta_t^k\right)$$

See Lane and Shambough (2010), Bénétrix, Lane and Shambough (2015) and Kearns and Patel (2016) for similarly constructed aggregate indices!

At the Bundesbank, as a service to analysts, the *IIE* are being computed and stored **for the baseline combinations of sectors, instruments and currency denominations, as well as for many meaningful aggregates!**

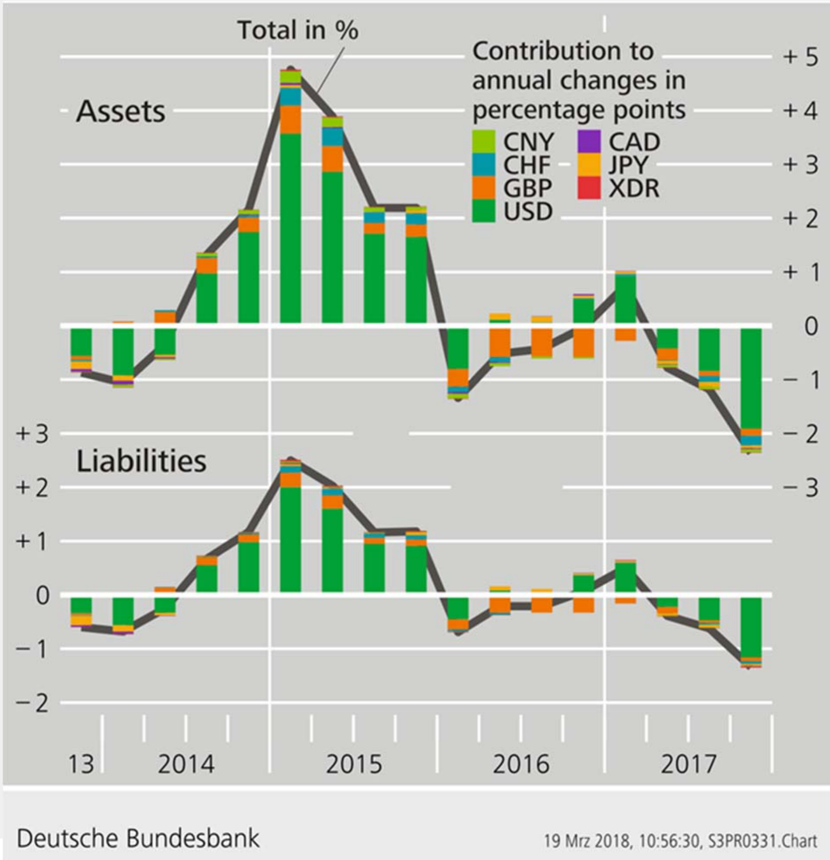
An index of IIP weighted exchange rate effects

IIE for shares in portfolio investment (asset side)



An index of IIP weighted exchange rate effects

Currency decomposition of IIE changes in percentage points
Total assets and liabilities



Sensitivity: ex post analysis

We may start by looking at time series **variability of IIP weighted exchange rate changes**, for certain asset positions or an aggregate portfolio, using historic currency compositions and ER-changes.

Std dev of portfolio inv. assets: q-on-q changes of IIE

	All sectors	Banks	MM funds	Fin. corp. w/o MFIs	Gov	Others*
All instruments	0.6	0.9	0.1	0.8	1.7	0.4
Long term debt securities	0.6	0.3	0.0	0.6	1.5	0.3
Short term debt securities	0.8	1.2	3.3	0.8	0.0	0.6
Shares	2.0	1.5	0.0	2.0	0.0	2.4
Investment fund shares	0.6	0.9	0.1	0.8	1.7	0.4

However, the currency compositions of asset or liability positions evolve over time, as does the covariance structure of exchange rate volatility.

Sensitivity: the effect of a 1 pp exchange-rate change

More informative to study **current IIP and currency composition.**

The effect of an isolated 1 percentage point change in currency *n*…

$$\frac{\mathrm{da}}{\mathrm{d}\hat{E}_t^n} = \begin{pmatrix} a_{t-1}^1 \cdot g_{t-1}^{1n} \\ \vdots \\ a_{t-1}^K \cdot g_{t-1}^{Kn} \end{pmatrix} = \begin{pmatrix} a_{t-1}^{1n} \\ \vdots \\ a_{t-1}^{Kn} \end{pmatrix} = \mathrm{a}_{t-1}^n$$

… is given by the respective **column of the currency composition matrix**

Sensitivity: considering correlation

However, exchange rate changes **do not happen in isolation.**

Covariance matrix of exchange-rate fluctuations:

Exchange rate change for home currency identically 0

$$\Omega = \operatorname{cov}\hat{\mathrm{E}}_t = \begin{pmatrix} 0 & 0 & \cdots & 0 \\ 0 & \operatorname{var}\hat{E}_t^2 & \cdots & \operatorname{cov}\left(\hat{E}_t^2, \hat{E}_t^K\right) \\ \vdots & \vdots & \ddots & \vdots \\ 0 & \operatorname{cov}\left(\hat{E}_t^2, \hat{E}_t^K\right) & \cdots & \operatorname{var}\hat{E}_t^K \end{pmatrix}$$

We obtain

$$\left.\frac{\mathrm{da}}{\mathrm{d}\hat{E}_t^n}\right|_{\Omega} = \sqrt{\mathrm{a}_{t-1}^n \cdot \Omega \cdot 1(\mathrm{n})}$$

as the effect of a one standard deviations shock to currency n on the asset positions in absolute values, taking into account the correlation structure.

Sensitivity: standard deviation for rates of change

Total volatility given **current currency composition** and **current covariance structure** of exchange rate changes

Std. dev. of asset or liability position *k* resulting from ER volatility:

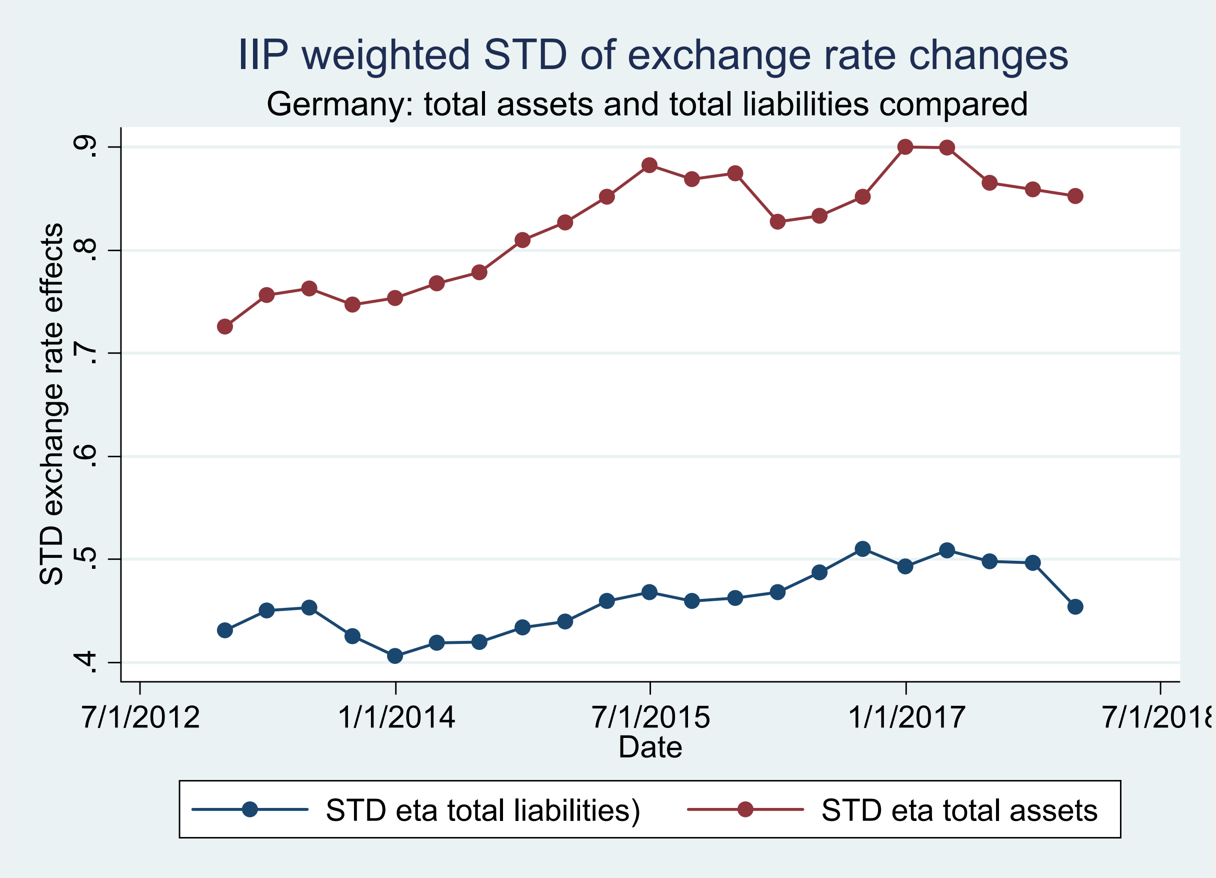
$$\operatorname{std}\left(\eta_t^k\right) = \sqrt{\operatorname{var}\left(g_t^k{}' \cdot \hat{E}_t\right)} = \sqrt{g_t^k{}' \cdot \Omega \cdot g_t^k}$$

Exchange-rate induced r.o.c. in IIP position *k*

Currency weights for IIP position *k*

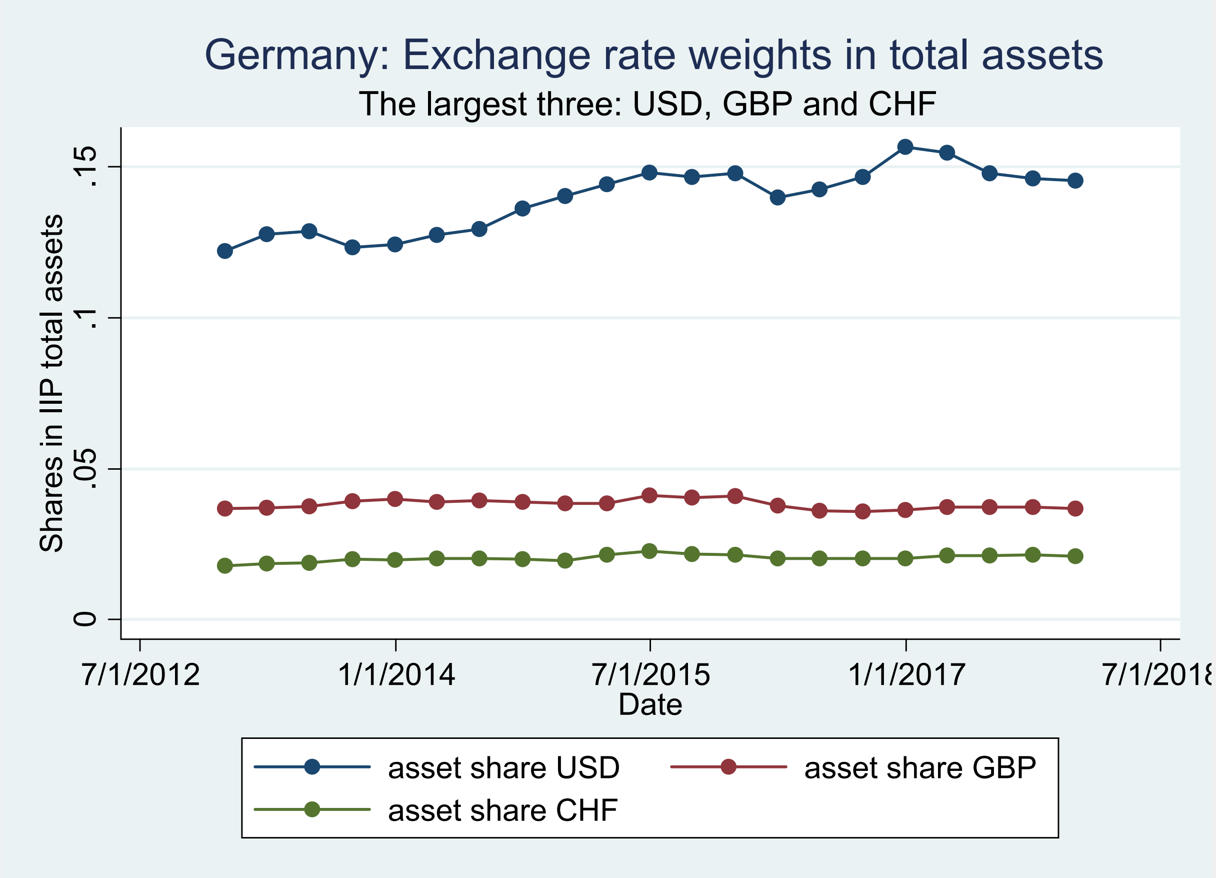
Sensitivity: standard deviation for rates of change

Growing exchange rate sensitivity of total assets…



Sensitivity: standard deviation for rates of change

… due to rising share of US Dollar



Sensitivity: standard deviation for absolute changes

Looking at absolute values

The **absolute value** of position *k* may be changing quite strongly over time.
→ look at the **scaled standard deviation:**

$$\mathrm{std}\left(a_t^k \eta_t^k\right) = a_t^k \,\mathrm{std}\left(\eta_t^k\right) = a_t^k \sqrt{g_t^k{}' \cdot \Omega \cdot g_t^k}$$

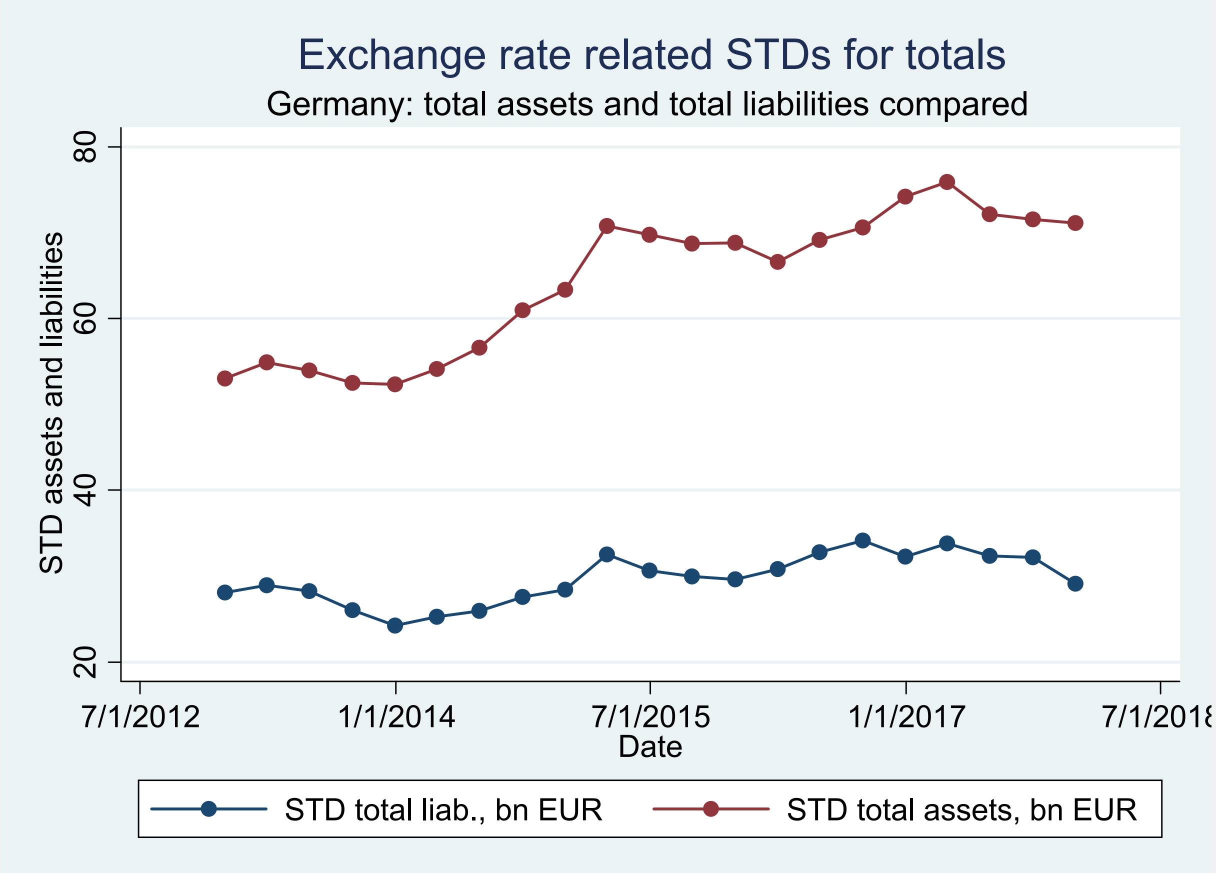
Absolute value of
change in IIP position *k*

Currency weights for
IIP position *k*

This is a **measure for potential currency risk** in position *k*

Sensitivity: standard deviation for absolute changes

Strongly increasing volatility of total assets



Outlook: taking hedging into account

Taking hedging into account – a way towards useful macro-statistical risk measures?

Part of IIP positions are hedged (forward contracts, derivatives or holding counter positions within the group). No direct information in IIP!

If there is exogenous information on hedging, we may construct **modified weights g*** to be used instead of g**:**

$$WR\left(a_t^k\right)\Big|_{FX} = a_t^k \sqrt{g*_t^{k}{}'\cdot\Omega\cdot g*_t^k}$$

Std dev of exchange rate induced changes in unhedged part of IIP position *k*

Currency weights of **unhedged assets or liabilities** in IIP position *k*

Outlook: taking hedging into account

This may **delineate the path** towards **operational macro-statistical risk measures** of foreign currency exposure associated with IIP.

But:

- Empirical values for g* are not to be had without estimates and approximations.
- Derivative contracts between agents that are both domestic residents will not reduce the aggregate exposure of the country – although it can still reduce systemic risk if currency risk in different positions is annihilated or ultimately rests with agents that are able to deal with it.
- Trading in derivatives with non-residents may increase or reduce aggregate open positions, thereby affecting aggregate exposure outside the IIP.

A better understanding of sectoral hedging activities is needed.

This is the end…

Thank you!

Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

Going further than ITRS to draw up the French BOP: three tailor-made surveys[1]

Cécile Golfier,
Bank of France

[1] This paper was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

Going further than ITRS to draw up the French BOP

Three tailor-made surveys

Cécile Golfier[1], Banque de France

Abstract

The 2008 financial crisis broke out against a backdrop of corporate globalisation and financial innovation. Two decades after financial liberalisation and given that further globalisation is a milestone towards firms' recovery, the measure of international transactions and positions is crucial for guaranteeing financial stability. This monitoring contributes to the overall prevention of disequilibria in the private sector.

In France, the measure based on the International Transactions Reporting System (ITRS) became irrelevant when foreign exchange controls were abolished in 1989. In 2011, three surveys were launched to continue capturing firms' involvement in the global economy. All three of them are integrated into the national survey system. The direct questioning of firms provides richer and more precise information for the Balance of Payments (BOP) and the International Investment Position (IIP) than the ITRS. The new instruments gave the opportunity to improve the quality of data, because they are fitted to their purposes.

While all largest contributors must report, the other firms are covered by random surveys, with a lower frequency and, for one survey, fewer details.

For international trade in services, the breakdown of the collected transactions complies with the Sixth Edition of the IMF's Balance of Payments and International Investment Position Manual (BPM6). For the survey, the selection of firms is based on Customs data in order to focus on firms that actually buy or sell services to European counterparts.

As regards commercial and financial assets and liabilities, two tailor-made surveys capture the components of the IIP and measure the interest paid on intra-group financial loans. They were recently reviewed to improve the precision of the assessment of financial stocks, while slightly decreasing firms' reporting burden.

Keywords: balance of payments, international investment position, trade in services, international assets and liabilities, corporate globalisation

[1] With the help of Martial Ranvier and Hadrien Caradant.

JEL classification:

C81 Methodology for Collecting, Estimating, and Organizing Microeconomic Data • Data Access

C83: Survey Methods • Sampling Method

F23: Multinational firms • international business

L80 Industry studies: services/ general

Contents

1. Three post-ITRS surveys for the BoP and the IIP

In France, under the foreign exchange control regime, the International Transactions Reporting System (ITRS) was used to compile data on trade in services for the Balance of Payments (BoP), as well as the financial and commercial loans entering the financial account and the International Investment Position (IIP).

The end of foreign exchange controls in 1989 led to a sharp decrease in ITRS reporting. The 2008 financial crisis highlighted the need to monitor firms' activity and financial structure. In 2011, the Banque de France set up a new measurement framework that would sidestep the ITRS shortcomings.

1.1. France has adopted a dual system to collect firms' data

In 1990, the Banque de France brought about a major change in its statistical system: it ended the indirect measure *via* the banking system of international trade in services and positions, and engaged in a direct relationship with firms. The new system addresses the intrinsic shortcomings of ITRS when used for measuring services and positions:

- no possibility for BOP compilers to check data through a direct contact with firms;
- incomplete data:
- – the reporting threshold was biased as regards trade in services, because it was calculated on goods and services; furthermore, it stood at a high level (initially set at EUR 12,500, it has gradually been raised to EUR 50,000);
- – there was no information on intra-group transactions without payment;
- – settlements involving non-resident banks were not taken into account;
- heavy reporting burden for banks.

A two-fold system was set up to face the challenge, with clear benefits in terms of data quality and reporting burden. From 1990, non-financial corporations and insurance companies trading for more than EUR 30 million or with revenues above this threshold were classified in the so-called "Full Direct Reporters" (FDRs) category. The system was refined in 2003. All FDRs must report for the three new questionnaires that are for this population "censuses". The other firms are covered by surveys.

As regards trade in services, FDRs have been monitored since 1990 using a specific monthly questionnaire [Economic Transactions Reporting – "*Relevé de Transactions Économiques*" (RTE)]. Transactions are broken down by category, in line with the Sixth edition of the IMF's Balance of Payments and International Investment Position Manual (BPM6) requirements, and by counterparty country. For the rest of the economy, the reporting burden is smaller: the Complementary survey on international trade in services ["Enquête complémentaire sur les échanges internationaux de services" (ECEIS)] is an annual random survey conducted using a sample of 5,500 firms (1% of the survey scope) and with fewer questions and details than in RTE.

As regards international assets and liabilities, two surveys – one for commercial outstandings, the other for financial outstandings– are the same for FDRs and other firms. The frequency is the only difference: quarterly for all FDRs, quarterly or annual for the others. For non FDR firms, the sample has 1,600 firms for commercial outstandings (0.2%) and 2,000 firms for financial outstandings (2%).

For the three surveys, data are collected via a secure website, OneGate. This IT platform was designed and used to be maintained in cooperation with the National Bank of Belgium. Firms have the choice between entering data online and uploading a file.

Box 1

A largely integrated survey system for BOP and IIP

The three surveys in the French legal and statistical environment

The surveys on international trade in services (ECEIS) and on assets and liabilities (ECO and EFI) are fully integrated into the French legal and statistical environment.

The general framework is defined by regulation (EC) No. 184/2005 of the European Parliament and of the Council of 12 January 2005 on Community statistics concerning balance of payments, international trade in services and foreign direct investment. At the national level, the Monetary and Financial Code (Article 141-6.2) provides, under the Statutes of the Banque de France, that the Banque de France "shall establish the balance of payments and the external position of France. It shall contribute to the establishment of the balance of payments and to the overall external position of the euro area in the framework of its membership in the European System of Central Banks as well as to the establishment of the statistics of the European Union in the area of balance of payments, international trade in services and foreign direct investments".

For the three surveys, the reference population is based on the French Statistical Business Register SIRUS (Identification System to Statistical Units Register – Système d'identification au repertoire des unités statistiques) produced by INSEE, the French National Statistical Institute. It contains eight million firms.

The surveys for non FDRs are authorised by the National Council for Statistical Information ["Conseil national de l'information statistique" (CNIS)]. ①

① The survey of FDRs is set out in decision 2007-01 of the Banque de France; FDRs have the obligation to report their trade in services and their international assets and liabilities.

Nowadays, the key points for the quality of data are the response rate and the accuracy of the answers. In that view, a modernising of the statistical portal and a clarification in the methodological documents have been conducted.

However, as globalisation is still underway, the current system will also certainly need to be adjusted in the future. Indeed, the surveys currently used all deal with legal units. The next step will probably be to address the structure of multinationals by considering the "enterprise" as defined by Council regulation (EEC) No. 696/93.

1.2. A 360° delineation of the survey frames

1.2.1. A multi-criteria selection for the services survey frame

Under the ITRS system, some information on international trade in services was found in the Payments report ("Compte rendu de paiements" – CRP).

ECEIS survey went to live in 2011. Its population of 6 million firms covers all industries except public administrations, financial and insurance activities and extraterritorial activities. These industries are identified with the French APE code in SIRUS (the French code in line with the International Standard Industrial Classification of All Economic Activities (ISIC rev.4).

Within the population, the survey scope covers firms that are engaged in international trade in services. For that purpose, two administrative sources are used depending on the counterparty area:

- for transactions within the European Union: the Customs database is used [European Declaration of Services – "Déclaration européenne de services" (DES)] – compiled by the Directorate General of Customs and Indirect Taxes ["Direction générale des douanes et droits indirects" (DGDDI)];
- for extra-EU transactions, an ITRS report collecting transactions in services with countries located outside the Single Euro Payments Area (SEPA), known as Customer Payment Report ("Relevé de Paiement Clientèle" (RPC)], provides the best estimate.

In order to define the survey scope, export and import proxies (i.e. rough estimates) are calculated for each firm. For the year 2017, 400,000 firms were identified as players in the international trade in services.

The definition of the survey frame is operated in two phases. In a first step, the main survey frame is composed of two building blocks:

- a primary main survey frame is set up with firms whose trade in services is presumed higher than EUR 200,000 of exports and/or EUR 75,000 of imports[2]. An additional selection is made on proxies obtained from the accounting database ESANE[3] (produced by INSEE), which contains annual tax declarations (structural business statistics). There were roughly 48,500 firms in the main survey frame for the reference year 2017; they accounted for more than 95% of French international trade in services not measured by RTE;
- a "safety net" is then added to the primary component; it is made up with 1,500 firms: on the one hand, firms with a turnover above EUR 100 million according to their tax declaration; on the other, firms that belong to an international group (the information on Financial links is found in LIFI, produced by INSEE) and have a "high turnover" relative to the rest of their industry.

In a second step, all the remaining firms are considered as part of the supplementary survey frame. This component allows enlarging the sample to all the scope, with a very low survey rate. This gives a chance to pick up some firms with trade in services but not selected in the main survey frame.

[2] Many firms import services to conduct their activity; the amount is one component of their purchases among others; it is proportional to their inclusion in the global value chain. Fewer firms export services; it is then one element of the turnover and the value is in most of the case higher than the value of import.

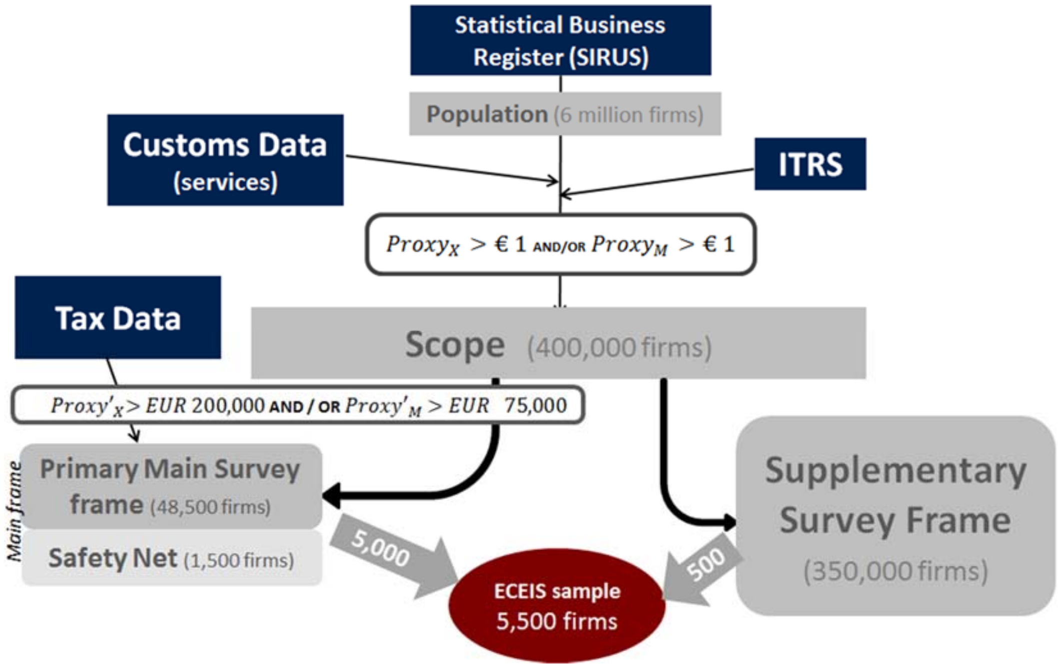
[3] ESANE provides tax data reported by firms to the French National Tax Office ["Direction générale des impôts" (DGI)] and completed by the Annual Sectoral Survey ["Enquête sectorielle annuelle" (ESA)].

Main and supplementary survey frames are stratified by industry (seven categories) crossed, for the main survey frame, with turnover. The latter is obtained from the Banque de France's FIBEN company database ("Fichier Bancaire des ENtreprises")[4]. When it is not available in FIBEN, turnover is picked up from INSEE's ESANE database.

On that basis, the survey sample is randomly selected as follows:

- 5,000 firms from the main survey frame;
- 500 firms from the supplementary survey frame. (Chart 1)

Chart 1 ECEIS sample definition



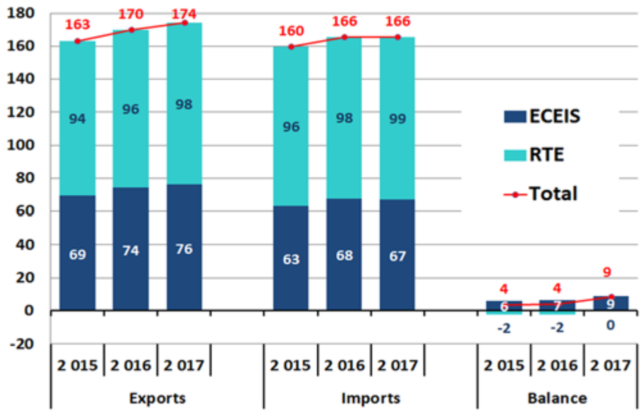
Source: Banque de France

Reporting firms break down all their data on trade in services by category of services, in line with the classification of the BPM6. For each category of services bought or sold, reporting firms must detail the transactions with the top three counterpart countries (name of the country and amount paid or received). If there are any other counterpart countries, firms report their number and the relevant global amount (sum of exports or imports with the set of non-individualised countries).

ECEIS accounts for 40% of the international trade in services measured by both services surveys (Chart 2).

[4] The FIBEN company database contains detailed information on 250,000 firms, which are selected according to at least one of the two following criteria: a turnover of at least EUR 0.75 million or bank loans disclosed to the Banque de France's central credit register of at least EUR 0.38 million.

Chart 2 International trade in services excluding travel measured by RTE and ECEIS for the French BOP euro billion



Note: Trade in services measured by RTE and ECEIS do not include travel, financial intermediation services indirectly measured (FISIM) and the price of transport included in goods prices ("fobisation").

Source: Banque de France

1.2.2. Twin surveys to complement an FDI questionnaire

Data on foreign direct investment (FDI) in equity and real estate are collected separately as soon as a transaction reaches EUR 15 million or the FDI holding in a firm reaches EUR 5 million (Box 2).

Box2

The FDI specific collection process

The FDI basic collection process covers non-financial and financial corporates.

Stocks have to be declared as soon as the FDI holding in a firm reaches EUR 5 million or the total FDI assets of a firm reaches EUR 10 million.

The main channel to collect FDI transactions is a questionnaire, for all transactions above EUR 15 million. For the year 2017, 1,450 transactions out of the 1,800 transactions recorded have been collected via this questionnaire (of which 1,100 have been filled by FDRs).

It relates both inwards and outwards FDI, for investments as well as divestments. It covers FDI in equity and in real estate. It has to be sent to the Banque de France within 20 days after the transaction.

Some other transactions are identified:

- at the end of each year when compiling stocks, reconciling FDI stocks and flows points to some additional flows; for the year 2017, 300 transactions have been identified likewise;
- the financial market regulator ["Autorité des marchés financiers" (AMF)] releases information when the participation in listed companies crosses thresholds; for the year 2017, 50 transactions have been added.

1,800 individual FDI transactions recorded in 2017

- **FDI questionnaire: 1,450 transactions**
  - Full direct reporters (FDRs) : 1,100 transactions
  - Non FDRs firms : 350 transactions
- **Yearly stocks compiling : 300 transactions**
- **Financial market regulator: 50 transactions**

The FDI statistics have recently been expanded with the identification of the Ultimate Investing Country (UIC), thanks to the use of LIFI, the financial links database produced by INSEE. The Banque de France has also been testing a breakdown of the FDI by purpose, in order to distinguish between greenfield investment (creation from scratch), brownfield investment (extension), mergers and acquisitions and financial restructuring.

For investments not covered by the FDI-specific collection process, two surveys have been set up: the ECO survey covers commercial assets and liabilities vis-à-vis non-residents and the EFI survey deals with financial assets and liabilities vis-à-vis non-residents. All FDRs are surveyed on a quarterly basis for both of them; for the other non-financial corporations, the reporting frequency depends on the expected amount: the most globalised firms report on a quarterly basis; the others on an annual basis. For ECO and EFI, the questions are the same for both populations (FDRs and other firms).

When the reported value relates to an affiliated entity, it is recorded as a "direct investment" in the financial account of the balance of payments and in the measurement of the international investment position. If the counterparty is not an affiliate, the reported value is recorded under "other investment".

The ECO and EFI surveys are derived from questionnaires respectively known as "E84" and "E90", which used to prevail under the ITRS system. These questionnaires were aimed at collecting stocks to complement the information on transactions collected through the ITRS system.

1.2.2.1 ECO for Commercial assets and liabilities

The ECO survey provides a measure of outstanding amounts of trade receivables and payables of resident non-financial corporations vis-à-vis non-residents.

For firms that are not FDRs, the survey sample is generated on the basis of auxiliary information contained in administrative and accounting databases, i.e.:

- SIRUS (see box 1 above);
- Customs data, used to define the sampling frame and stratify the annual component of it;
- FIBEN, used for a consistency check of the Customs data and as auxiliary information to calculate proxies for assets and liabilities;
- LIFI (see box 2 above), used to stratify the annual sampling frame based on international group membership.

Firstly, the survey population is comprised of resident non-financial corporations, identified by their SIREN identification number, which are not engaged in financial activities, life insurance, reinsurance, pension funds, activities operated by households as employers and extraterritorial activities. The industry is identified by the APE code in SIRUS. The population contains 6 million firms.

Secondly, those that are also in the Customs database are selected for the survey scope; they are firms that engage in international trade in goods and services. In 2017, they amounted to 700,000.

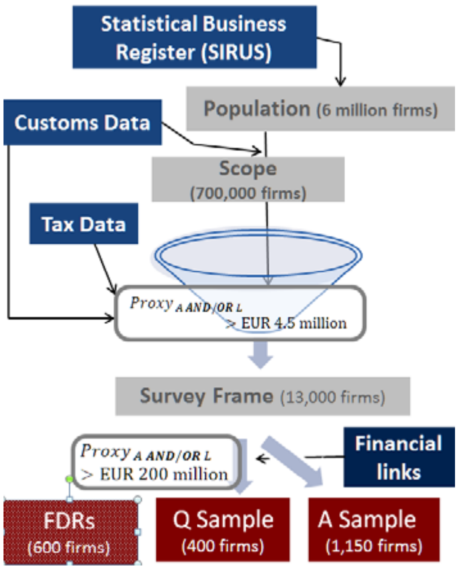
Thirdly, companies with annual imports or exports that exceed EUR 4.5 million are selected for the survey frame (13,000 firms). To achieve this, Customs data are benchmarked with tax data collected in FIBEN, if available (profit and loss accounts items):

- if imports in the Customs database are higher than total purchases in FIBEN, the latter are considered as the import value;
- exports are capped by the turnover in FIBEN.

Fourthly, a proxy for international commercial assets or liabilities firms is calculated on the basis of Customs data and auxiliary information contained in FIBEN. Firms with a proxy higher than EUR 200 million are included in the quarterly sample; these are exhaustively surveyed. For the year 2017, they totalled 400.

Lastly, firms are randomly drawn to be put into the annual sample according to a stratified sampling design, out of the remaining component of the sampling frame (stratification according to whether or not they belong to an international group, cross-referenced with the past two-year average proxy for international assets and liabilities). For the 2017 annual sample, 1,150 firms were drawn out of 13,000 firms. One quarter of it is renewed each year. (Chart 3)

Chart 3 ECO sample definition



Source: Banque de France

The positions to be declared are found in four specific items of the balance sheet:

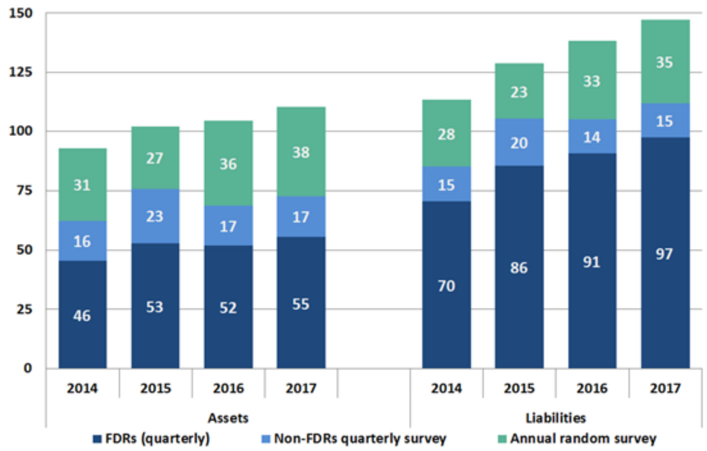
- trade receivables;
- trade payables;
- advances and down-payments paid;
- advances and down-payments received.

This information must be broken down by currency of denomination, by country of residence of the counterparty and by nature of the relationship with the counterparty (affiliated or not).

As expected, commercial assets and liabilities mostly stem from the quarterly component of the ECO sample (Chart 4).

Chart 4 International assets and liabilities measured by ECO

Yearly average, euro billion



Source: Banque de France

1.2.2.2 EFI for Financial assets and liabilities

The EFI survey provides an assessment of outstanding amounts of financial assets and liabilities of resident non-financial corporations vis-à-vis non-residents.

For firms not covered by FDR rules, the survey sampling frame is constructed on the basis of administrative and accounting information:

- SIRUS (INSEE): the statistical business register is used to identify companies;
- LIFI (INSEE): the financial links database is used to identify international groups;
- FIBEN (Banque de France) and ESANE (INSEE): tax data are used to identify the relevant firms and to stratify the sampling frame[5].

Firstly, the survey population is comprised of resident non-financial corporations, identified in the SIRUS statistical business register by their SIREN identification number, which are not engaged in pension funds and extraterritorial activities. The industry is identified by the APE code in SIRUS. The population comprises 6 million legal units.

They are put into the survey scope if they are identified in LIFI as members of multinational groups. A few other firms are added on the basis of information obtained via the FDI collection process, or because previous year's EFI captured international assets or liabilities. There are 94,000 firms in the scope.

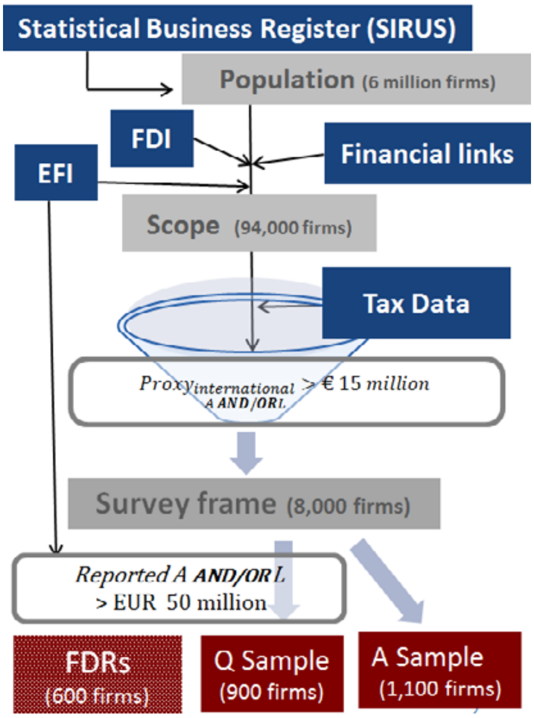
Only those with financial assets or liabilities above EUR 15 million according to the FIBEN or ESANE databases are kept for the survey frame. For the year 2017, the latter contained 8,000 firms.

[5] ESANE contains information on all firms, but aggregates certain tax data (that is not the case in FIBEN), and the publication lag is longer than for FIBEN.

Firms that declared financial assets or liabilities of more than EUR 50 million in the previous year's EFI survey are included in the quarterly sample. They are exhaustively surveyed. So are the firms identified via the FDI collection process. If necessary, the quarterly sample is completed in order to reach 900 firms by selecting firms on the decreasing value of their proxy for international assets and liabilities.

The firms in the annual sample are drawn randomly according to a stratified sampling design from the remaining component of the sampling frame (stratification according to whether or not the firms belong to a French or foreign international group, cross-referenced with the total value of the proxy for outstanding assets and liabilities). For the year 2017, the annual sample contained 1,100 firms. One quarter of it is renewed each year. (Chart 5)

Chart 5 EFI sample definition



Source: Banque de France

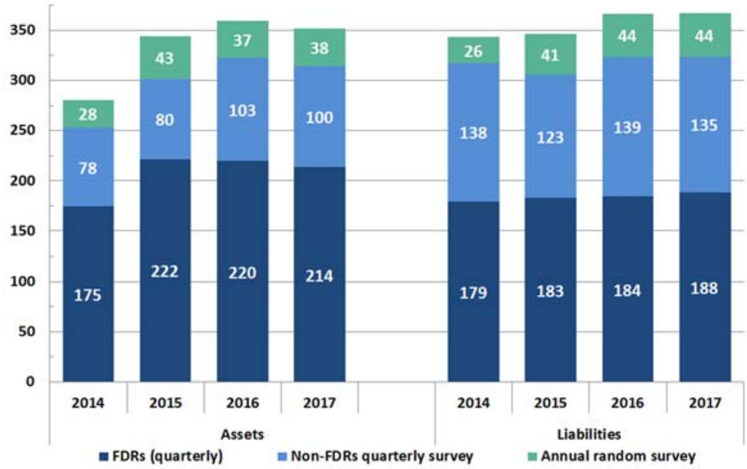
The breakdown of values is the same as for the ECO survey: the information must be broken down by currency of denomination, by country of residence of the counterparty and by nature of the relationship with the counterparty (affiliated or not).

In addition to positions, interest received from or paid to affiliates is requested. This information is used to compile the "interest" sub-heading of "direct investment income" under "primary income" of the balance of payments.

As for the ECO survey, financial assets and liabilities are mostly measured on a quarterly basis, but with outstanding amounts two to three times higher than for ECO (Chart 6).

Chart 6 International assets and liabilities measured by EFI

Yearly average, euro billion



Source: Banque de France

2. Fine-tuning the measure of financial assets and liabilities measure

The financial assets and liabilities compiled through the EFI survey are larger than those compiled through the ECO survey, while the hierarchy of sample sizes used to be the reverse. Furthermore, the variability was higher for EFI than for ECO. The measurement system was therefore adjusted in 2017.

2.1 The need to adjust the ECO/EFI system

The structure of the figures produced by the ECO and EFI surveys highlighted the need to adjust the framework.

In line with the assigned objective, both surveys provided larger values for "direct investment" than for "other investment". For the year 2014, the values were respectively EUR 650 billion and EUR 185 billion.

As expected, the main contributions to the international investment position stem from the quarterly components of both surveys. For instance, in the foreign direct investment data compiled for the year 2014, 74% of the value came from the quarterly component of EFI, whereas only 11% came from its annual component; similarly, the FDI data obtained through ECO mostly came from its quarterly component (12%, compared to 3% for the annual component).

However, the contributions of the different components were not optimal in terms of the total amounts measured. The positions collected through the EFI survey accounted for 85% of FDI measured by ECO and EFI surveys (EUR 550 billion out of EUR 650 billion). Yet, the contribution to total FDI of EFI annual sample was equivalent to that of ECO quarterly sample (respectively 11% and 12% as commented above). There was clearly a need to rebalance the contributions from quarterly ECO to EFI. (Table 1)

International investment positions measured by ECO and EFI for 2014

Sum of assets and liabilities — Table 1

	Amount					Share				
	Quarterly		Sub-	Annual	Total	Quarterly			Annual	Total
	FDRs	Others	total			FDRs	Others	Total		
Direct investment	375	185	559	92	651	58	28	86	14	100
of which EFI	320	164	484	70	554	49	25	74	11	85
of which ECO	54	21	75	22	97	8	3	12	3	15
Other investment	104	47	151	35	185	56	25	81	19	100
of which EFI	37	24	61	9	70	20	13	33	5	38
of which ECO	67	23	90	25	115	36	12.5	48.5	13.5	62

Source: Banque de France

The time required for compiling data was another reason for reviewing the frequency structure of the surveys: the initial structure induced relatively large revisions once a year, when the annual figures were produced.

Indeed, when the figures are compiled at the very beginning of year N+1 for the annual report covering year N, only the quarterly data are available for year N. Including annual data implies carrying out revisions one year later, at the beginning of year N+2.

As regards the EFI survey, the data contained in the first publication were too much based on estimated annual data. For FDI data measured by EFI, the revision was close to EUR 30 billion for 2012 and 2013 data (but below EUR 10 billion for 2014). (Table 2)

ECO and EFI Revision from estimation to collected data

Table 2

	2012		2013		2014	
	EUR billion	%	EUR billion	%	EUR billion	%
Direct investment	26	28	27.5	28	10.5	11
of which EFI	28	39	29	38	8.5	12
of which ECO	-2	-10	-1.5	-8	2	8
Other investment	-11	25	-3	-7.5	-1.5	-4
of which EFI	-14	80	-2	-10.5	-3.5	-36
of which ECO	3	13	-1	-5	2	8

Source: Banque de France

2.2 Rebalancing the samples towards the financial FDI measure

The rebalancing of the survey schemes to improve the financial FDI measure was carried out under the dual objective of increasing the global precision of the IIP measure and reducing the firms' reporting burden.

It was designed with the objective of keeping the number of firms surveyed unchanged or reducing it. Indeed, there is a general commitment in France to simplifying firms' administrative environment of firms. When authorising a survey, the CNIS makes sure that the reporting burden is reasonable for firms. At the same time, the Banque de France has been engaged in a large simplification process. In particular, it has been paying special attention to its bilateral relationships with firms.

Simulations were made under the hypothesis of a reduction in the ECO quarterly sample from 871 to 375 and an increase in the EFI quarterly sample from 574 to 864. The new scheme reduces the ECO survey rate by 3 points, to 17%, and increases that of the EFI survey by 4 points, to 38%. (Table 3)

Changes in ECO and EFI sampling frames as planned in 2016 Table3

		Current frame		Simulated frame	
		Sample	Survey rate	Sample	Survey rate
ECO	FDRs	615	*100%*	615	*100%*
	Quarterly	871	*100%*	375	*100%*
	Annual	970	*9%*	1,170	*10%*
	Total	2,456	*20%*	2,160	*17%*
EFI	FDRs	615	*100%*	615	*100%*
	Quarterly	574	*100%*	864	*100%*
	Annual	1,110	*20%*	1,116	*21%*
	Total	2,299	*34%*	2,595	*38%*
ECO + EFI	FDRs	615	*100%*	615	*100%*
	Quarterly	1,445	*100%*	1,239	*100%*
	Annual	2,080	*12%*	2,286	*14%*
	Total	4,140	*22%*	4,140	*22%*

Source: Banque de France

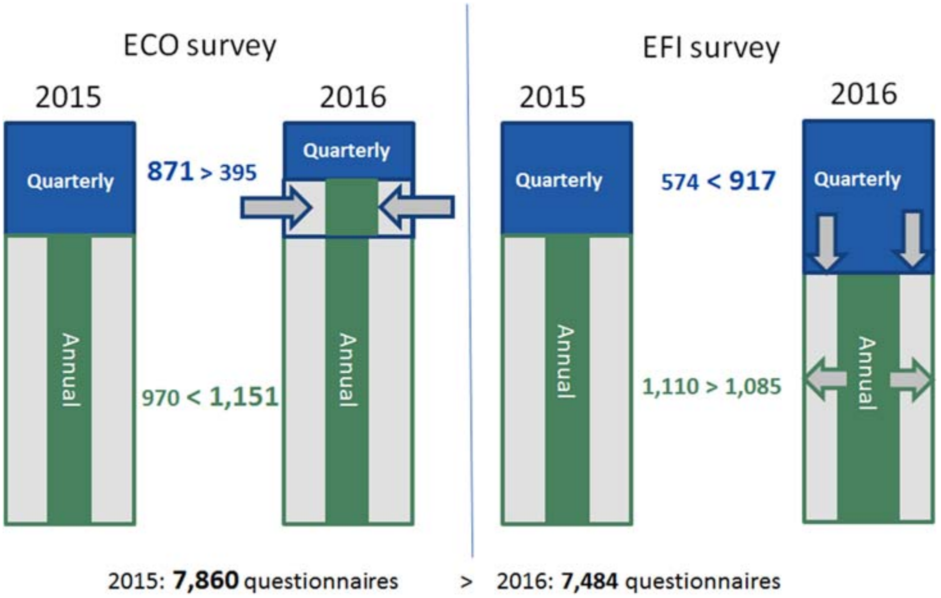
The assessment of the reform's impact on the reporting burden must take into account the time spent answering the respective questionnaires. The average reported time spent answering the survey is lower for EFI than for ECO, because in general a firm has relationships with more countries for its providers and customers (relevant for ECO) than for its affiliates (mainly relevant for EFI). The annual median durations (including the gathering of information) are:

- for ECO, 135 minutes for a quarterly questionnaire, 95 minutes for an annual questionnaire;
- for EFI, 35 minutes for a quarterly questionnaire, 20 minutes for an annual questionnaire[6].

In the end, the reform alleviates the reporting burden. The simulation points to an 8% decrease in the number of questionnaires and a resulting about 30% decline in the median time spent by the whole community of firms.

In practice, there were some small differences with the planned revision of the samples. The total number of firms surveyed by both surveys decreased, but the size of the EFI sample increased slightly more than initially planned. The number of questionnaires was reduced by 5% and the time spent by the whole community of firms by about 30% as planned. (Chart 7)

Chart 7: The rebalancing of ECO and EFI samples carried out in 2017



Source: Banque de France

2.3 Stabilising the quarterly and annual samples

For the ECO and EFI surveys, the collection process was each year pretty much impacted by shifts of firms from the quarterly component of the sample to the annual component and conversely. The result was an artificial increase in the variability of the compiled data. In addition, firms face an undesirable cost when overhauling their IT system in order to change the frequency of the reporting.

[6] Quarterly surveys are filled by the largest contributors. These latter report in most of the cases assets and liabilities vis-à-vis a higher number of counterpart countries than firms which report on an annual basis.

There are two reasons for the numerous changes in frequency: the volatility of the proxies and, for ECO, the concentration of firms in the neighbourhood of the threshold delineating quarterly and annual samples. One specific solution was designed for each survey to reduce the impact of these elements.

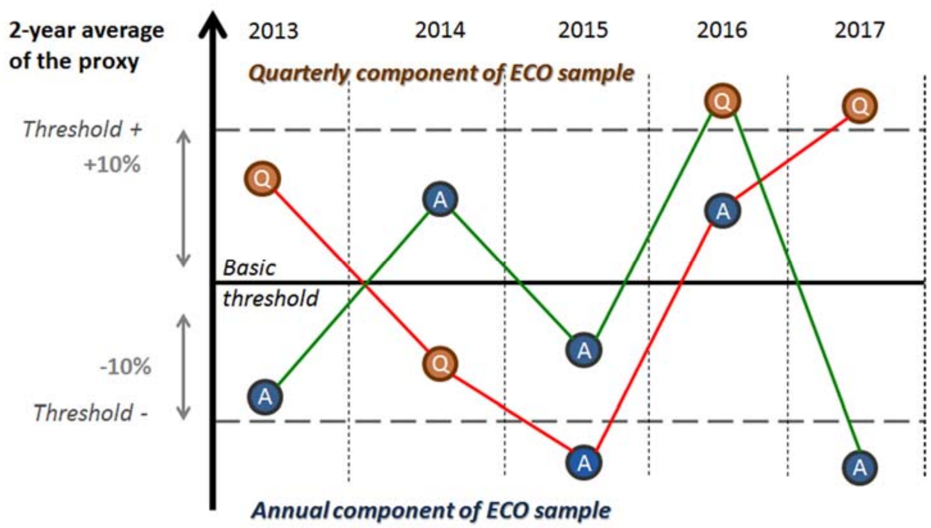
2.3.1 A “no-man’s land” for ECO

As regards ECO, the solution implemented as of 2017 data is twofold:

- the information used to review the frequency qualification is now a two-year average, instead of the last year value;
- the threshold for a change in the frequency depends on the current frequency, through a “no-man’s land” mechanism.

Henceforth, a firm shall change frequency only if the two-year average of the proxy crosses the “no-man’s land” threshold, i.e. only if the two-year averaged proxy deviates by more than 10% from the basic threshold. (Chart 7)

Chart 7: ECO sampling scheme stabilisation system: a “no-man’s land”



Key: The red and green lines show the respective paths followed by two different firms. The firm tracked by the red line is surveyed on a quarterly basis for the year 2013. In 2014, the 2-year average of the proxy falls below the basic threshold but is still above the lower limit of the “no-man’s land”; thus the firm remains in the quarterly sample. By contrast, in 2015, the 2-year average of the proxy falls below the lower limit of the “no-man’s land”; in these conditions, there is a change in the frequency for the 2015 survey. After that, the value of the 2-year average of the proxy increases for two years. The firm returns to the quarterly sample only for the 2017 survey, when the proxy exceeds the upper limit of the “no-man’s land”.

Source: Banque de France

The ex-post simulation of the “no man’s land” indicates a reduction in the number of frequency changes ranging from 50 between 2012 and 2013 to 90 between 2011 and 2012. The average reduction represents 45% of the number of changes in the frequency. (Table 4)

Annual frequency shifts for ECO

Number of firms which change frequency between two successive years — Table 4

Nature of the shift	2011 →2012	2012 →2013	2013 →2014	2014 →2015	Total
Actual methodology until 2016					
Quarterly to annual	51	62	60	97	270
Annual to quarterly	99	94	103	81	377
Total (A)	150	156	163	178	647
Ex-post simulation of the "no-man's land"					
Quarterly to annual	27	42	46	41	156
Annual to quarterly	31	65	50	56	202
Total (B)	58	107	96	97	358
Variation in % (B/A)	-61	-31	-41	-46	-45

Key: When the 2013 sample was designed, the "waiting room" would have reduced from 94 to 65 the number of firms shifted from the annual sample to the quarterly one.

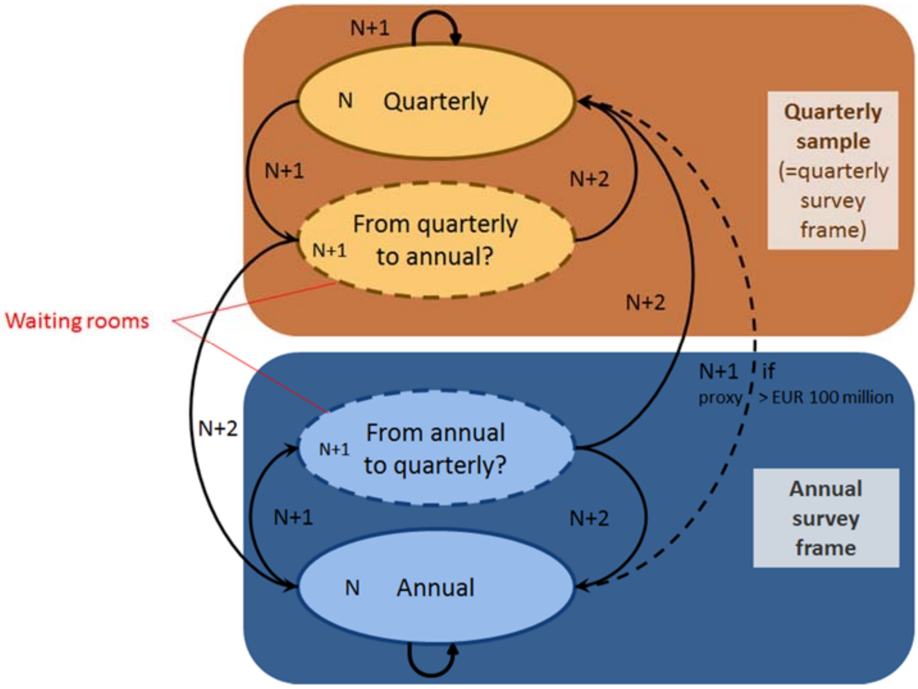
Source: Banque de France

2.3.2 "Waiting rooms" for EFI

The solution engineered for ECO would not have been relevant for EFI because the variations in the values are too large. More precisely, given the proportion of firms displaying a null proxy one year and breaking twice the threshold the following year, too many firms would have been shifted to the quarterly sample in the long run. In addition, a simulation showed that, due to the low concentration of firms in the neighbourhood of the EFI threshold, the ECO method would not have significantly reduced the number of shifts from one sample to the other.

As regards EFI, "waiting rooms" were created: one "observation" year was introduced in order to wait for confirmation of the need to shift the firm to the other frequency. The exception is firms with a reported value higher than EUR 100 million; the shift to the quarterly sample then occurs immediately. (Chart 8)

Chart 8: EFI sampling scheme stabilisation system: two "waiting rooms"



Source: Banque de France

The impact of this method is that only two firms out of three that would have been put in the "waiting room" in 2014 would have changed frequency in 2015. The new method would have postponed by one year the "upgrading" of 24 firms from annual to quarterly frequency and the "downgrading" of 31 firms from quarterly to annual frequency.

Indeed, the simulated general impact of the "waiting rooms" is a reduction in the number of changes. The ex-post simulation points to a 20% average reduction in the number of frequency changes. (Table 5)

Annual frequency shifts for EFI

Number of firms which change frequency between two successive years — Table 5

Nature of the shift	2011 →2012	2011 →2013	2013 →2014	2014 →2015	Total
Actual methodology until 2016					
Quarterly to annual	85	57	36	50	178
Annual to quarterly	100	84	92	79	276
Total (A)	185	141	128	129	454
Ex-post simulation of the "waiting-room"					
Quarterly to annual	-	69	43	31	143
Annual to quarterly	69	74	71	77	222
Total (B)	69	143	114	108	365
Variation in % (B/A)	-63	1	-11	-16	-20

Source: Banque de France

Key: When the 2015 sample was designed, the "waiting room" would have reduced from 50 to 31 the number of firms shifted from the quarterly sample to the annual one.

Irving Fisher Committee on
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BANK FOR INTERNATIONAL SETTLEMENTS

Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

Going further than ITRS to draw up the French BOP: three tailor-made surveys[1]

Cécile Golfier,

Bank of France

[1] This presentation was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

BANQUE DE FRANCE
EUROSYSTÈME

GOING FURTHER THAN ITRS TO DRAW UP THE FRENCH BOP: THREE SURVEYS

Irving Fisher Committee on Central Bank Statistics
Are post-crisis statistical initiatives completed?

CÉCILE GOLFIER
FDI AND CROSS-BORDER TRADE IN SERVICES UNIT

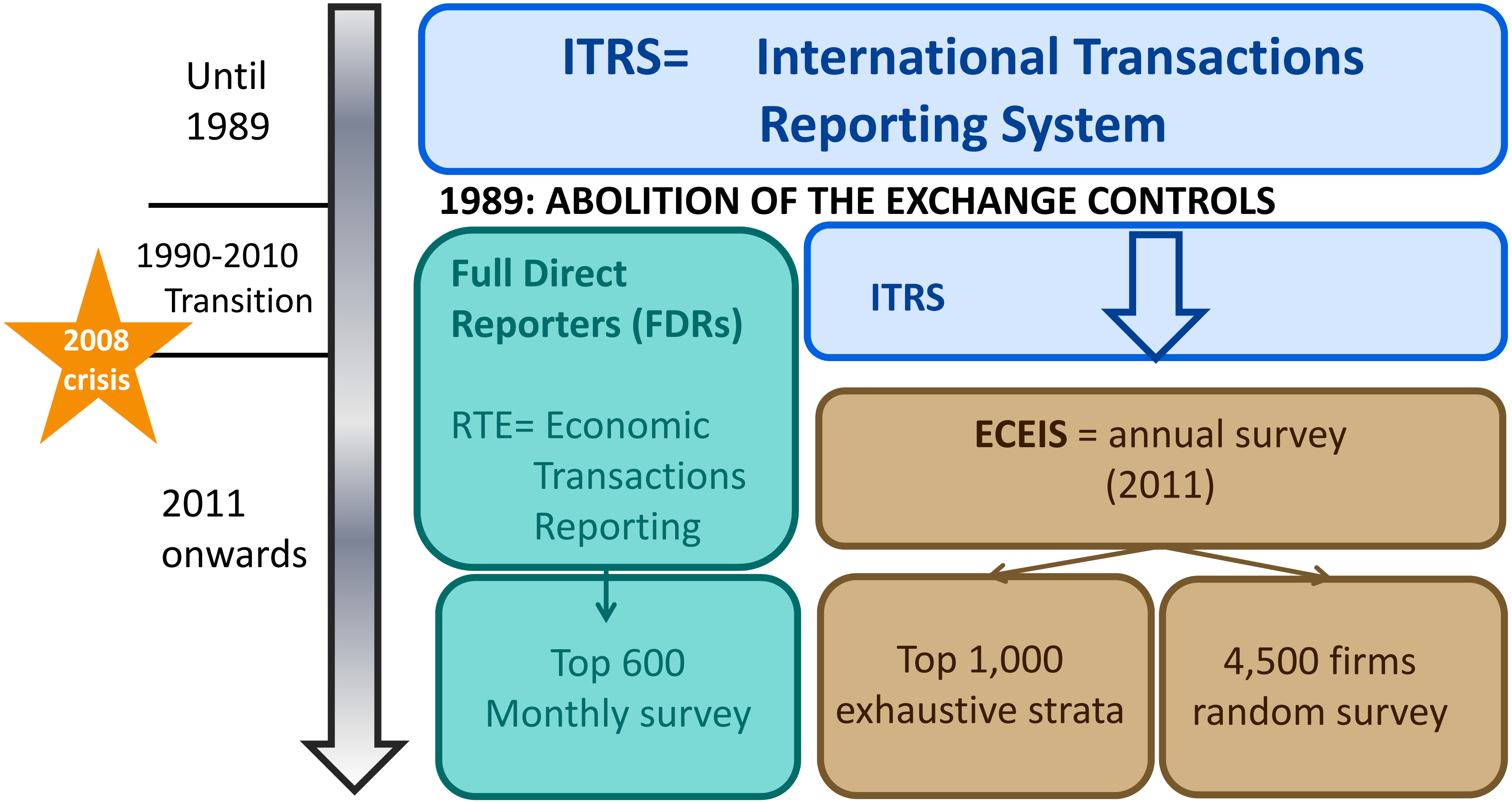
30 AUGUST 2018

1. The inception of a direct relationship with firms

2. Customised survey frames

3. Recent reengineering of the surveys used for the IIP

FRANCE HAS ADOPTED A DUAL SYSTEM TO COLLECT FIRMS' INTERNATIONAL TRADE IN SERVICES DATA



BANQUE DE FRANCE
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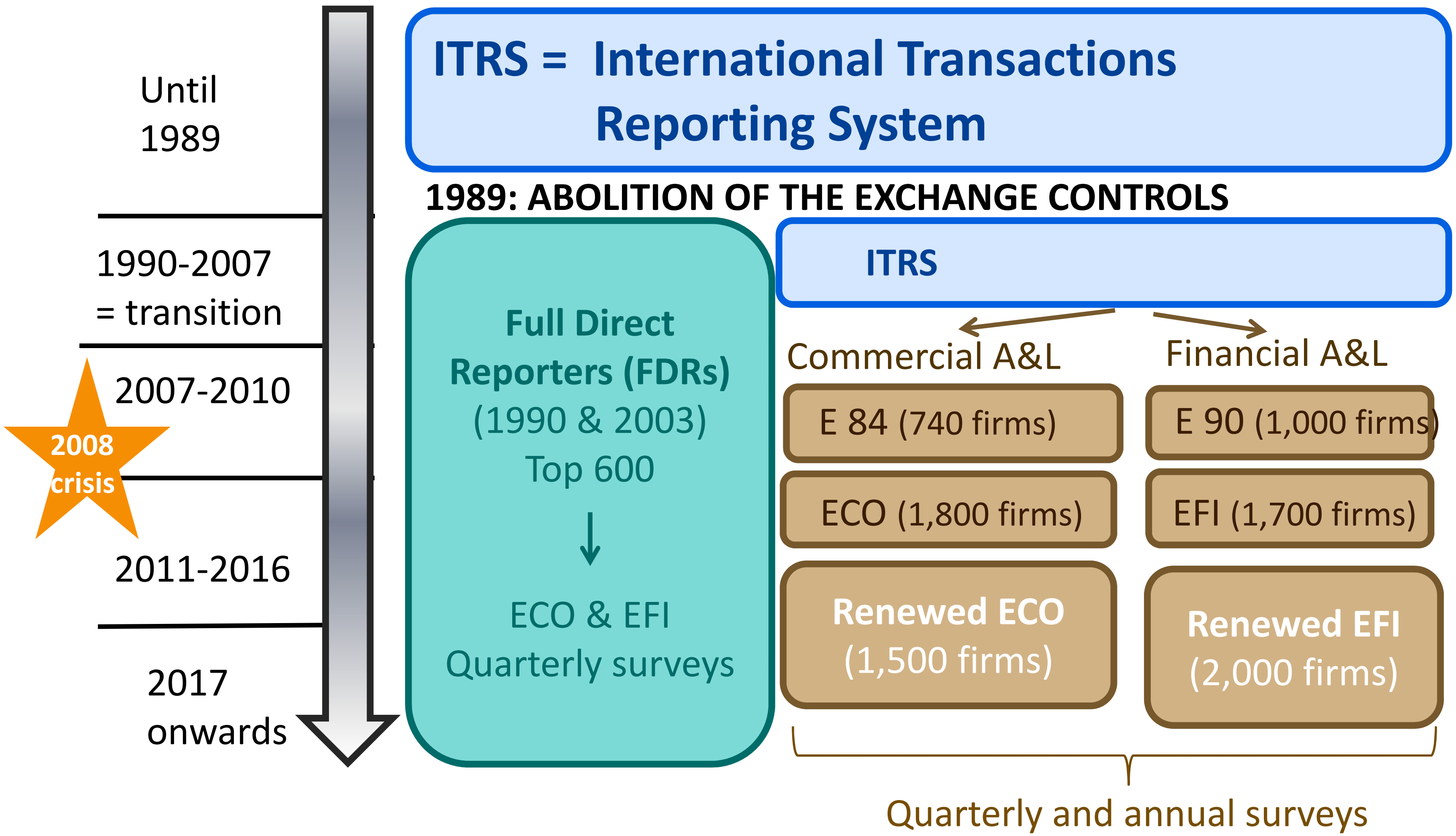
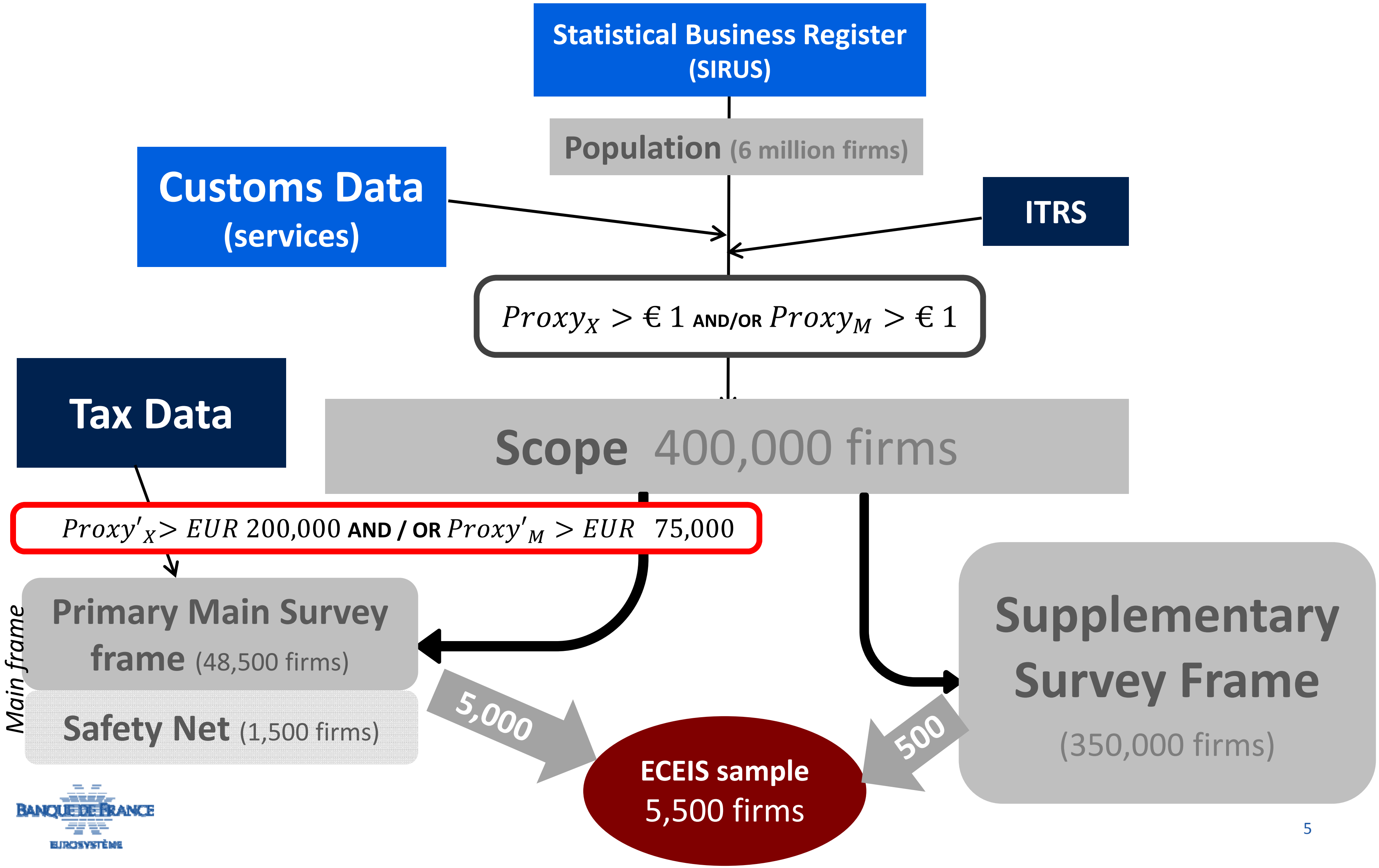
ECO AND EFI SURVEYS TO MEASURE FIRMS' INTERNATIONAL ASSETS AND LIABILITIES

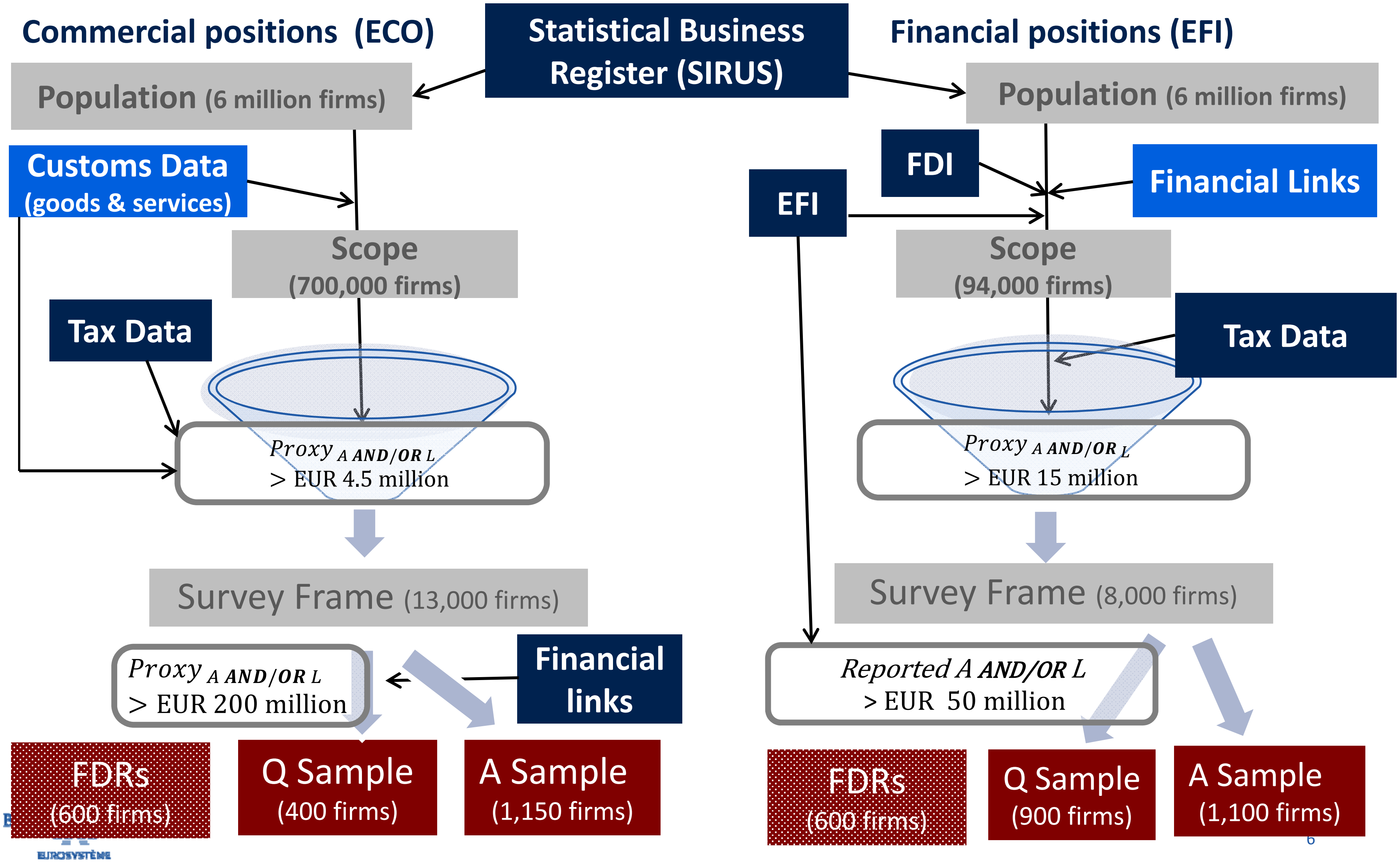


=> "Direct investment" and "other investment" in the BOP

A MULTI-CRITERIA SELECTION FOR THE SERVICES SURVEY FRAME



TAILOR-MADE SURVEYS FOR INTERNATIONAL INVESTMENT



TWO REFINEMENTS IN THE ECO/EFI SCHEMES IN 2017

- Rebalancing the survey schemes to improve the FDI measure
  - enhancement of the overall accuracy (EFI + ECO): an improvement in EFI (financial assets and liabilities) that outweighs a slight deterioration in ECO (commercial assets and liabilities)
  - combined with a small decrease in the firms' reporting burden

- Stabilising the frequency (A/Q) within the samples of each survey
  - "no-man's land" for ECO: shift to the other frequency sample only if the two-year averaged proxy deviates by more than 10% from the threshold
  - "waiting-rooms" for EFI: one "observation" year to wait for confirmation of the need to change the frequency of the firm

    (exception: immediate shift towards the quarterly sample if the last reported value is higher than EUR 100 million)

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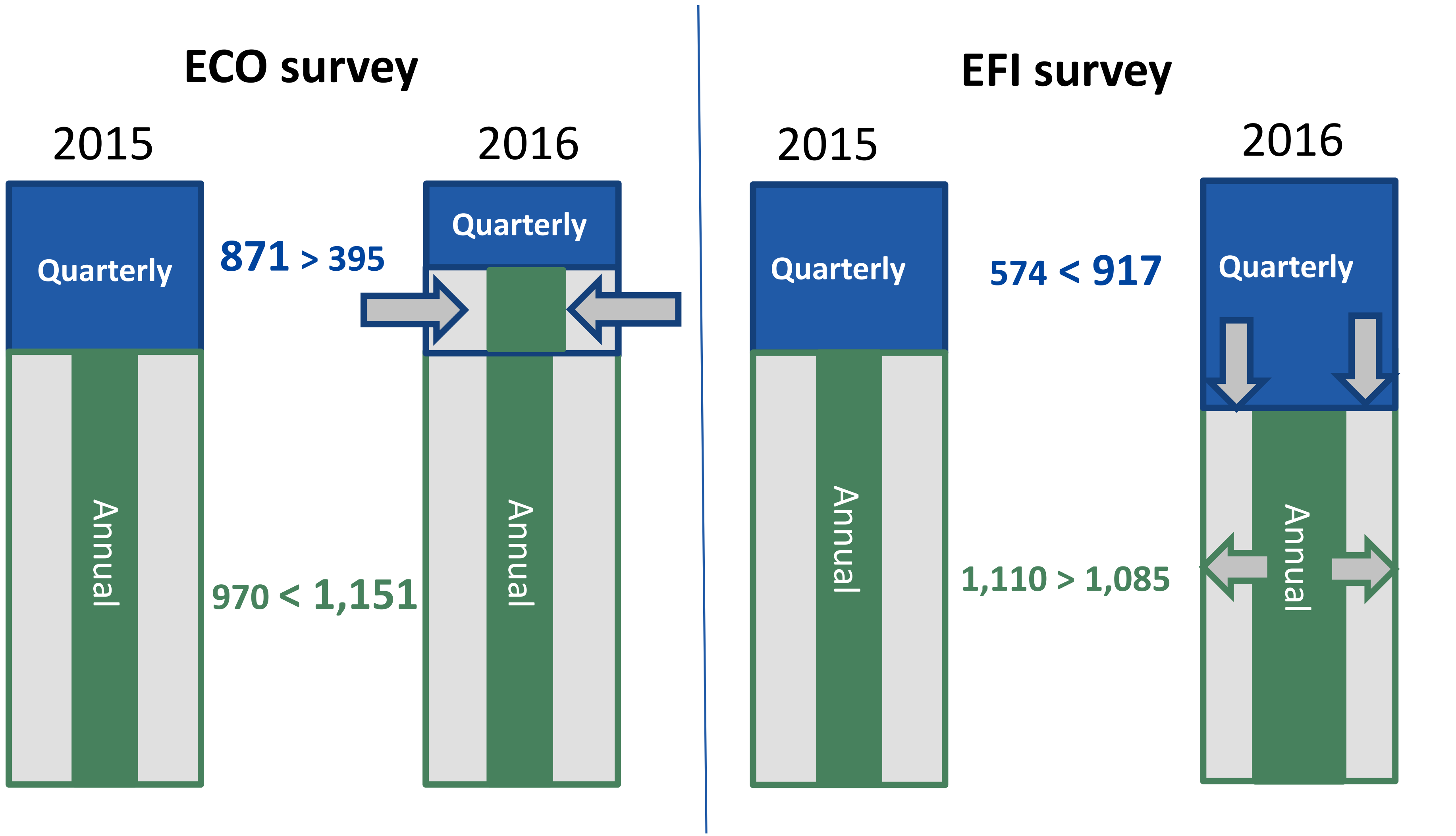
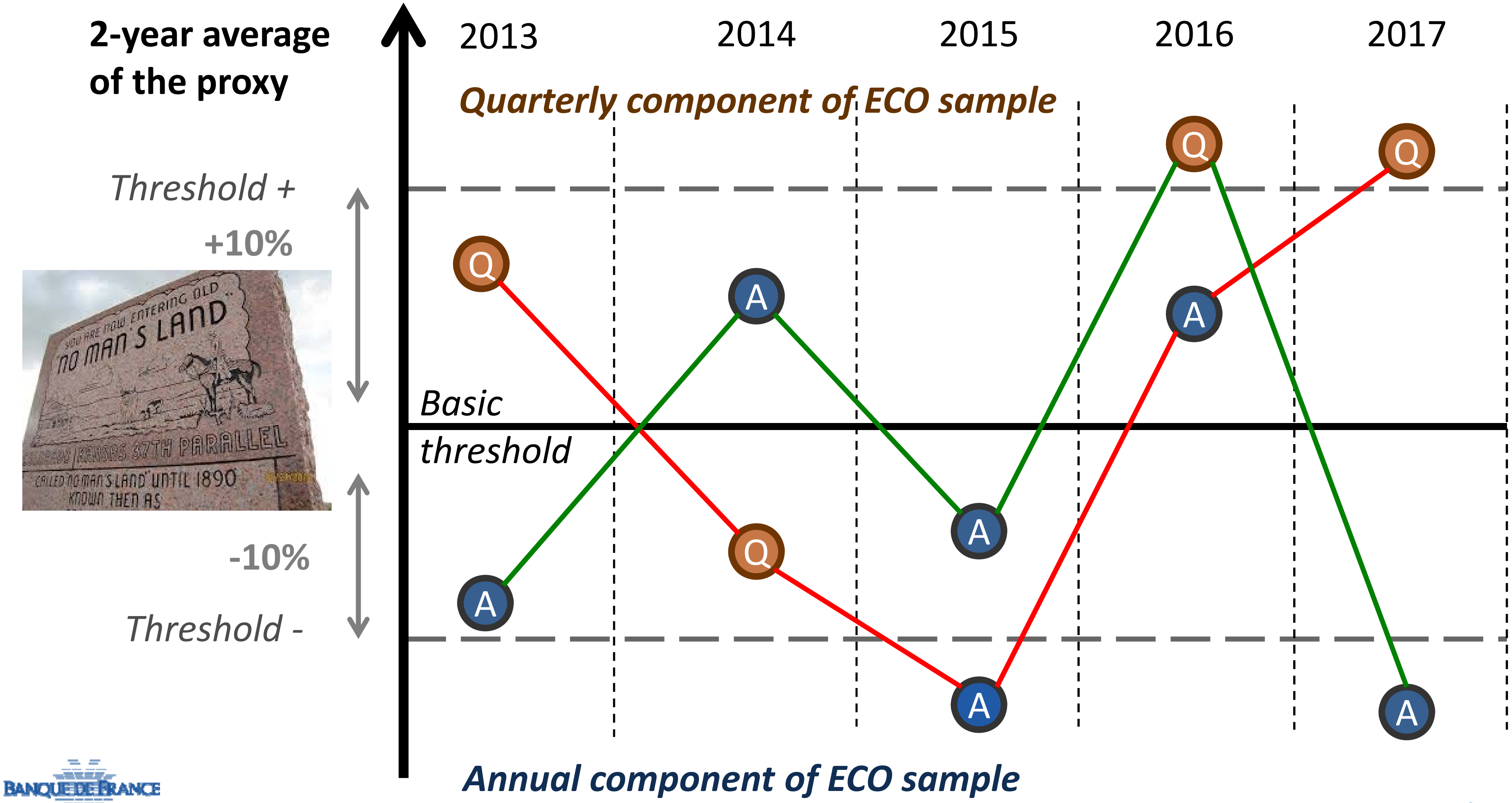
IMPROVING EFI PRECISION BY REBALANCING THE SAMPLES, WITH A SLIGHT DECREASE IN THE REPORTING BURDEN



2015: **7,860** questionnaires > 2016: **7,484** questionnaires

A "NO-MAN'S LAND" TO STABILISE THE ECO SAMPLE

ECO: the "*no-man's land*"



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The IMF balance sheet approach: towards from-whom-to-whom information on cross-border portfolio securities[1]

Artak Harutyunyan and Carlos Sánchez Muñoz,
International Monetary Fund

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[1] This paper was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

The IMF Balance Sheet Approach: towards from-whom-to-whom information on cross-border portfolio securities

Artak Harutyunyan and Carlos Sánchez Muñoz[1]

Abstract

This paper proposes an international exchange of information on issuers of securities and their institutional sector. This exchange would contribute substantially to breaking down portfolio positions by country and sector of both holders and issuers and thus to uncovering the financial interconnections between sectors and countries at the global level.

The paper first discusses how the Balance Sheet Approach is constructed and how it contributes to major activities carried out at the IMF. It then explains areas for future development towards the longer-term goal of compiling a Global Flow of Funds matrix. Such a matrix would require breaking down all financial positions by counterpart country and sector.

To compile from-whom-to-whom information for portfolio securities, the paper describes an ongoing project of the IMF Statistics Department in coordination with the IMF Committee on Balance of Payments Statistics. The project consists of setting up a centralized database to store information about securities issuers and their institutional sector. By putting this information at the disposal of the IMF Coordinated Portfolio Investment Survey reporters (more than 80 economies), the database would permit breaking down cross-border portfolio securities by country and sector of holders and issuers with a view to compiling from-whom-to-whom portfolio information.

Keywords: Balance Sheet Approach, global flow of funds, financial crisis, IMF surveillance, from-whom-to-whom, portfolio investment, securities, Coordinated Portfolio Investment Survey

JEL classification: F21 International Investment • Long-Term Capital Movements

[1] International Monetary Fund, Balance of Payments Division. We are grateful to Thomas Alexander, Marco Espinosa and Giovanni Ugazio for useful comments on the paper. The views expressed in this paper are entirely our own and do not necessarily reflect those of the International Monetary Fund, its Executive Board, or its management.

Contents

Introduction

Ever-increasing global financial interlinkages among different sectors and economies require that, besides monitoring transactions, analysts and policy makers pay increasing attention to positions. In a globalized world with complex financial inter-linkages, drawing a global financial network between different economies and sectors requires sufficiently detailed sectoral financial balance sheets. Sectoral balance sheets (financial assets and liabilities) broken down by counterpart country and sector may facilitate early detection of potential vulnerabilities and risks of spillovers from individual sectors and countries to the rest of the global economy.

Developing a global flow of funds — expanding the traditional single-economy flow of funds — has been identified by the IMF as a longer-term goal that can fundamentally change the IMF bilateral and multilateral surveillance work. Given the complexity of building such a global flow of funds for both positions and transactions covering all sectors and instruments, a step-by-step approach is needed. In the last years, two data collection frameworks managed by the IMF — the Coordinated Direct Investment Survey (CDIS) and the Coordinated Portfolio Investment Survey (CPIS) — have helped compilers address bilateral asymmetries.

This paper describes how an international exchange of information could substantially help CPIS reporters compile from-whom-to-whom information on cross-border portfolio securities. Section 1 describes the importance of the Balance Sheet Approach (BSA); how to compile it; how the IMF uses it for surveillance; and how it can be further developed. Section 2 focuses on how exchanging information internationally could help break down portfolio investment positions by counterpart country and sector, a step towards the longer-term goal of a Global Flow of Funds matrix.

1. The Balance Sheet Approach

1.1 What is the Balance Sheet Approach? Why is it important?

The BSA pulls together the assets and liabilities of each sector within a country, i.e. its aggregate (including cross-border) positions/balance sheet. Such sectoral balance sheets convey important information on risks and vulnerabilities to policies and shocks, as well as on the interlinkages and exposures between the different sectors of an economy and vis-à-vis the rest of the world.

Renewed interest on balance sheets arose from the 2007-2008 Global Financial Crisis.[2] An important trigger of the crisis was the inability of some sectors in certain countries to service their excessive debt, which generated global spillover effects. Increasingly interconnected financial markets require close examination of an economy's sectoral balance sheets for complementing the traditional flow-based analysis.[3] This analysis allows exploring the buildup of balance sheet interlinkages and how they make a sector or an economy vulnerable to shocks.

Policy makers need to detect balance sheet risks and vulnerabilities early enough to be able to apply timely policy responses. Balance sheet interlinkages and networks also inform the analysis of

2 This is reflected in the IMF's 2014 Triennial Surveillance Review, which advocates the development of a global flow of funds "to build on the national balance sheet approach to better analyze cross-border linkages."

3 Allen et al. (2002)

potential shock propagations from one sector to another, permitting policy makers to take timely preventive measures.

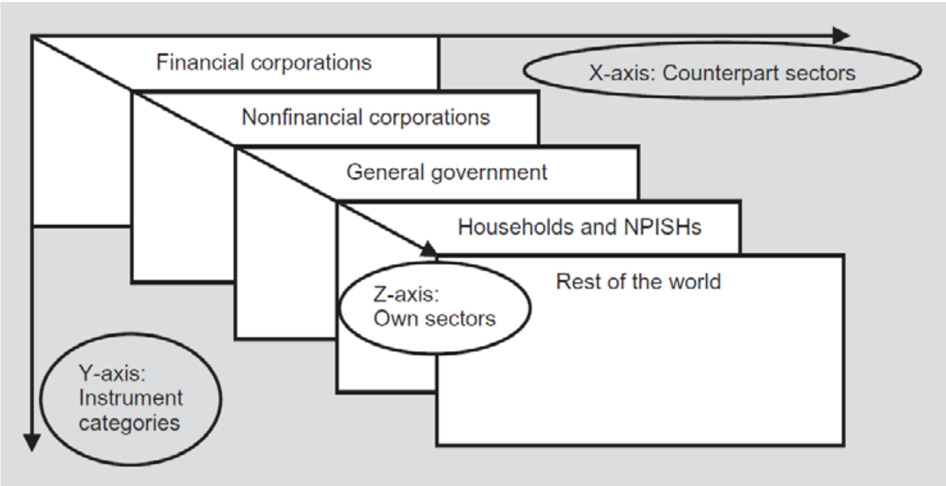
Analyzing balance sheets allows exploring key macroprudential questions. Examples of such questions are: how healthy is the aggregate balance sheet of each sector and the external (international investment) position of the economy as a whole; what the potential risks associated to balance sheet vulnerabilities over time are; how such vulnerabilities amplify and propagate the impact of external shocks; and whether there are potential channels of shock propagation among different sectors of the economy.

1.2 How to compile and analyze the Balance Sheet Approach

Financial balance sheets can be compiled at two-dimensional and three-dimensional levels. [4] The two-dimensional financial balance sheets present, for each sector, financial assets and liabilities without identifying the counterpart sectors.[5] The three-dimensional balance sheets, in addition to the two-dimensional approach contain from-whom-to-whom information, where financial assets and liabilities are broken down by sector and by counterpart sector (Figure 1), thus allowing to draw the financial network between different sectors of the economy and the rest of the world.

The three-dimensional approach is most suitable for the type of analysis discussed in Subsection 1.1, with interconnectedness being at the core of the analysis. The data requirements for the three-dimensional presentation are much more demanding though. Figure 2 below shows an integrated system of financial balance sheets of key sectors and identifies possible data sources for each cell.

Figure 1: Concept of three-dimensional balance sheets



Source: MFSMCG Figure 8.2.

Mirror data from counterpart sectors can be used to populate those cells of the matrix for which obtaining source data is difficult. For example, asset side loan data from the banking sector can be used to populate loan liabilities of the household sector instead of obtaining these data from households, resulting in cost efficiency and better quality of data.

4 See the IMF's Monetary and Financial Statistics Manual and Compilation Guide (MFSMCG)

5 As in the balance sheets of the *System of National Accounts 2008* (*2008 SNA*)

The analysis of from-whom-to-whom financial balance sheets focuses on three intra-sector and inter-sectoral macroeconomic vulnerabilities: maturity, currency, and capital structure mismatches. To analyze such mismatches, three key indicators are compiled and analyzed: net short-term position (short-term assets *less* short-term liabilities); net foreign currency position (foreign currency assets *less* foreign currency liabilities); and net financial position (financial assets *less* liabilities).

Maturity mismatches arise when assets are longer-term, mainly illiquid, while liabilities are short-term. Maturity mismatches can arise in both domestic and foreign currency, creating rollover risk, interest rate risk for the debtor, and reinvestment risk for the creditor.

Currency mismatches arise when assets and liabilities are denominated in different currencies. This mismatch creates exchange rate risk. For example, if assets are held in domestic currency but liabilities are denominated in foreign currency, substantial losses may result if the domestic currency depreciates sharply.

Capital structure mismatches result from excessive reliance on debt financing instead of equity. The absence of an equity buffer can lead to solvency issues when a sector encounters a shock.

Solvency or credit risk emerges when a sector's financial assets no longer cover its financial liabilities. Solvency risk is closely linked to maturity mismatch risk, currency mismatch risk, and capital structure mismatch risk.

Figure 2. The Balance Sheet Approach and data sources

Issuer of liability (debtor) \ Holder of liability (creditor)	Central bank	General government	Other depository corporations	Other financial corporations	Nonfinancial corporations	Other resident sectors	Nonresidents
Central bank		1. SRF 1SR (Liabilities)	1. SRF 1SR (Liabilities) 2. SRF 2SR (Assets)	1. SRF 1SR (Liabilities)	1. SRF 1SR (Liabilities)	1. SRF 1SR (Liabilities)	1. SRF 1SR (Liabilities) 2. IIP 3. JEDH
General government	1. SRF 1SR (Assets)		1. SRF 2SR (Assets)	1. SRF 4SR (Assets)	n.a. 1/	n.a. 1/	1. IIP 2. QEDS
Other depository corporations	1. SRF 1SR (Assets) 2. SRF 2SR (Liabilities)	1. SRF 2SR (Liabilities)		1. SRF 2SR (Liabilities)	1. SRF 2SR (Liabilities)	1. SRF 2SR (Liabilities)	1. SRF 2SR (Liabilities) 2. IIP 3. QEDS
Other financial corporations	1. SRF 1SR (Assets)	1. SRF 4SR (Liabilities)	1. SRF 2SR (Assets)		1. SRF 4SR (Liabilities)	1. SRF 4SR (Liabilities)	1. SRF 4SR (Liabilities) 2. IIP 3. QEDS
Nonfinancial corporations	1. SRF 1SR (Assets)	GFS	1. SRF 2SR (Assets)	1. SRF 4SR (Assets)		n.a.	1. IIP 2. QEDS 3. JEDH
Other resident sectors	1. SRF 1SR (Assets)	GFS	1. SRF 2SR (Assets)	1. SRF 4SR (Assets)	n.a.		1. IIP 2. CPIS 2/
Nonresidents	1. SRF 1SR (Assets) 2. IIP 3. CPIS	1. IIP 2. CPIS	1. SRF 2SR (Assets) 2. IIP 3. CPIS	1. SRF 4SR (Assets) 2. IIP 3. CPIS	1. IIP 2. CPIS	1. IIP 2. CPIS	

1/ This data gap can in the future be filled with data from the public debt data template (which also covers assets) which is being piloted in some countries.
2/ CPIS data can be used to derive other resident sector's claims as residual.

Source: IMF training materials.
Notes: SRF=standardized report form for monetary statistics, GFS=government finance statistics, QEDS=Quarterly External Debt Statistics, JEDH=Joint External Debt Hub

Detection and analysis of the above risks in an integrated from-whom-to-whom balance sheet framework is an essential input for taking macroeconomic policy decisions. For example, when balance sheet risks are observed, policy makers may implement policies that reduce sectoral vulnerabilities by focusing on changes in key financial variables like exchange and/or interest rates. Furthermore, network-based analysis permits policy makers to evaluate the impact and trade-offs between different policy measures and objectives, and to assess the systemic impact on the financial and the real economy.

The expansion of the financial balance sheet analysis to cover cross-border bilateral positions by country and sector would strengthen the analysis of interconnectedness across borders. The primary goal would be to construct a global flow of funds matrix mapping domestic and external financial positions that can be broken down bilaterally by countries/regions and ideally also by counterpart sectors. An even longer-term objective would be to extend the analysis to identify flows for regular monitoring of bilateral cross-border financial flows.[6]

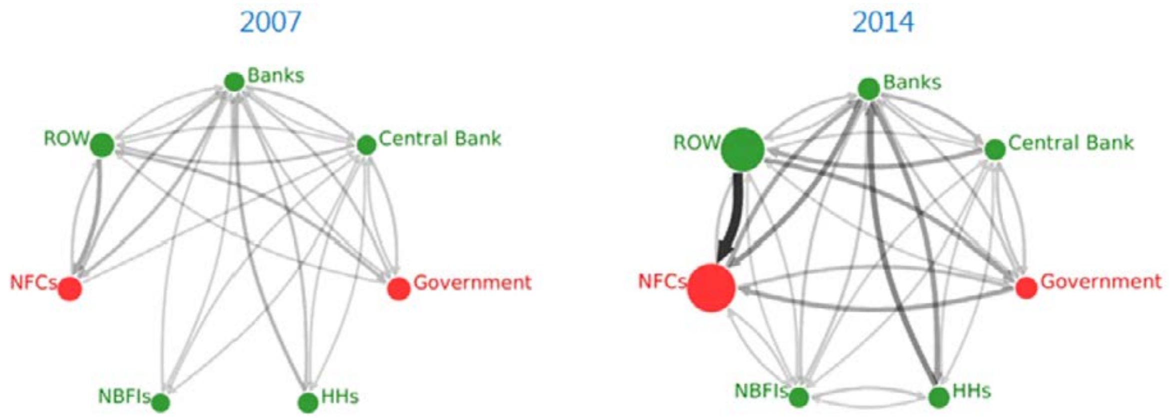
1.3 Using the Balance Sheet Approach at the IMF

The Fund BSA is the analysis of financial balance sheets on a from-whom-to-whom basis. While Fund staff developed the framework in the early 2000s, only recently has it been mainstreamed into Fund surveillance.

The 2014 Triennial Surveillance Review (TSR) called for incorporating macro-financial analysis and the BSA into the regular Fund surveillance, with the Statistics Department of the IMF (STA) stepping up its role.[7] STA supports Fund surveillance by preparing the relevant matrices and supporting analytical work. Following two rounds of Fund-wide pilots on mainstreaming macro-financial surveillance, where BSA was one of the themes, STA has developed a new automated BSA tool using in-house IMF data. The tool guides Fund users in the construction of the BSA matrix for about 120 countries. Certain analytical features are also embedded in the tool; for instance, following an exchange rate depreciation/appreciation shock of a designated magnitude the tool automatically calculates balance sheet positions.

As an example, the Selected Issues Paper for the 2016 Article IV staff report for Indonesia features the analytical potential of the BSA. Figure 3 presents the balance sheet interconnectedness network for Indonesia in 2007 and 2014. The evolution of the Indonesian BSA between these two years suggests two areas of vulnerability: first, the increasing reliance of non-financial corporations (NFCs) on cross-border funding; and second, the banking sector increasing exposure to NFCs. Such spillover risks demonstrate the analytical power of the BSA, especially when monitored for multiple periods.

Figure 3. Indonesia: BSA matrix in network map form



Source: Indonesia: Selected Issues Paper, 2016, Figure 1 on page 29, IMF.
Note: The thickness of the arrow indicates the size of gross exposure, while the color of the nodes distinguishes net creditors (green) from net debtors (red).

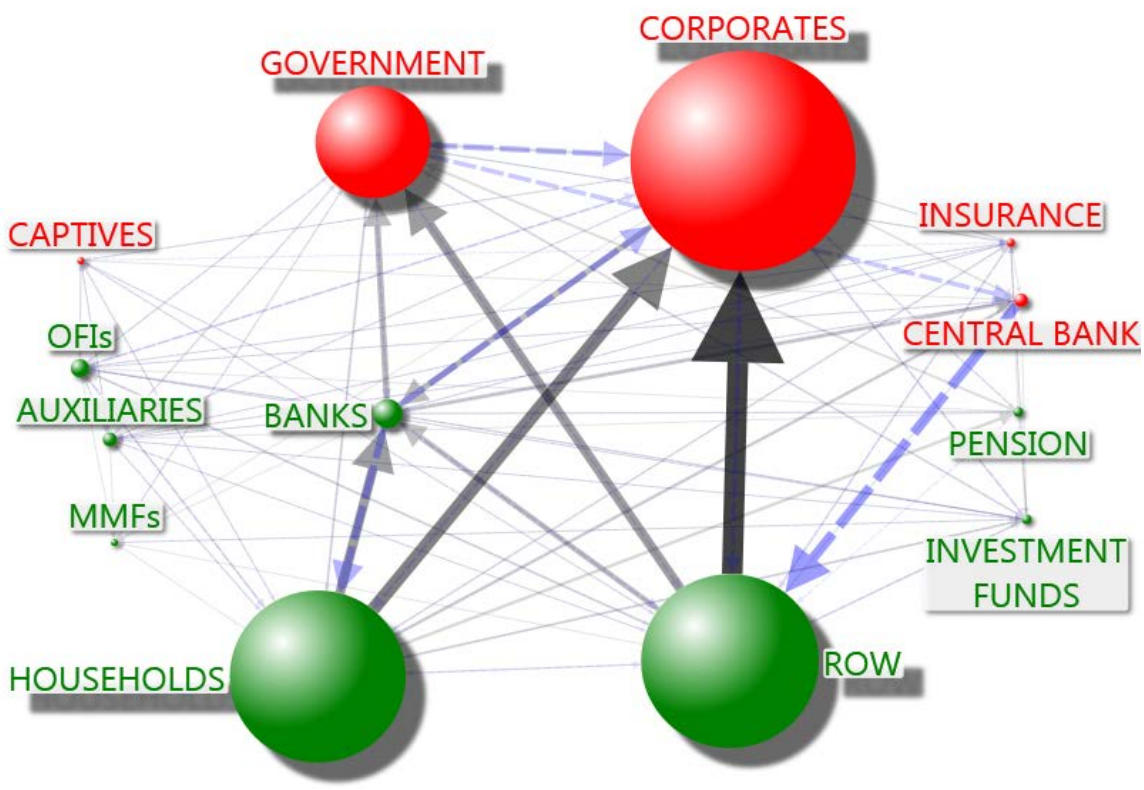
6 Errico et al. (2014), for example, present an approach to understanding the shadow banking system in the United States using a similar approach anchored on the analysis of global flow of funds.

7 The 2015 paper on *Balance Sheet Analysis in Fund Surveillance* takes detailed stock of the developments until 2015.

Abbreviations: NBFI – Non-bank Financial Intermediaries; NFCs - Non-financial corporations; HHs – Households; ROW – Rest of the World

BSA-type analysis is also gaining traction for the Fund's work on financial sector assessments. Several recent Financial Sector Assessment Programs (FSAP)[8] and Financial Sector Stability Reviews (FSSR)[9] have used BSA-type analysis in their assessments as a starting point for detecting major macroeconomic vulnerabilities that may directly or indirectly affect the financial system. The recently concluded Romania FSAP, for example, used the BSA to analyze macro-financial interlinkages, sectoral dependencies, and potential balance sheet vulnerabilities for all resident sectors (Figure 4).

Figure 4. Romania: Network of balance sheet exposures (2016)



Source: Romania: FSAP Technical Note on Balance Sheet Analysis, 2018, IMF.
Note: Red nodes represent net borrowers and green nodes net lenders. The diameter of nodes and thickness of arrows show the relative size of imbalances and exposures, respectively.

8 The FSAP is a comprehensive and in-depth analysis of a country's financial sector. FSAP assessments are the joint responsibility of the IMF and World Bank in developing economies and emerging markets and of the IMF alone in advanced economies.

9 FSSRs are a new IMF technical assistance instrument providing a diagnostic upon which financial sector reform programs can be built and implemented. FSSRs provide baseline diagnostic assessments, highlight key weaknesses in financial systems and institutional capacities, and set out prioritized medium-term action plans for well-sequenced financial sector reforms, to be supported by follow-up TA from the IMF and other sources.

Abbreviations: OFIs – Other Financial Intermediaries; MMFs – Money Markey Funds; ROW: Rest of the World

1.4 Areas for future development

Mainstreaming BSA-type analysis has become possible because of the increased availability of underlying balance sheet data thanks to the IMF's and member countries' efforts. Yet, important data gaps remain. STA continues to work on the future improvements of balance sheet statistics through the Data Gaps initiative for G-20 countries[10]. STA is preparing a medium- to long-term strategy to improve the availability of balance sheets for the financial, external, fiscal, and real sectors, with a view to better supporting BSA and its use for surveillance. Capacity development in the field of BSA is also supported by one of the statistical modules of the Financial Sector Stability Fund[11].

As mentioned previously, one of the major BSA future developments is breaking down global cross-border positions by counterpart countries and sectors. The lack of information on portfolio investment assets by issuer sectors is an impediment to continue advancing this work. This is further discussed in the next section.[12]

2. A Balance Sheet Approach extension: breaking down portfolio investment positions by geography and sector

2.1 Portfolio liabilities and the Coordinated Portfolio Investment Survey

Compiling accurate statistics on portfolio investment liabilities broken down by country is a well-known statistical challenge. Domestic issuers of securities may be aware of who first acquires such securities in primary markets, but they most often cannot trace subsequent purchases and sales, nor consequently determine the residence of the final holder. When investors operate via foreign financial intermediaries, it is extremely hard for statistical compilers to find information sources that can determine who ultimately holds domestic securities.[13] This could only be possible by enquiring/surveying final investors. However, reporting requirements typically only address resident reporters, so foreign investors cannot be legally obliged to provide such statistical information.

In the late nineties, the IMF started to conduct the CPIS[14] with a view to mitigating the increasing size of global portfolio investment asymmetries. Such sizeable asymmetries had

10 See latest Progress Report of the Second Phase of the G-20 Data Gaps Initiative (DGI-2) under https://www.imf.org/external/np/g20/pdf/2017/092117.pdf. Under recommendation II.8, the DGI-2 encourages advanced economies to disseminate data on a from-whom-to-whom basis.

11 The Financial Sector Stability Fund is an IMF trust Fund that provides technical assistance and training to low- and lower-middle-income countries in support of financial sector stability, inclusion, and deepening. See https://www.imf.org/external/np/ins/english/pdf/FSSF.pdf

12 Other aspects for BSA future development include reconciliation of asymmetries between different underlying datasets; sectoral financial accounts with from-whom-to-whom counterpart detail; maturity breakdowns for all financial instruments; further breaking down the nonbank financial sector; and compiling matrices of financial flows corresponding to balance sheet positions.

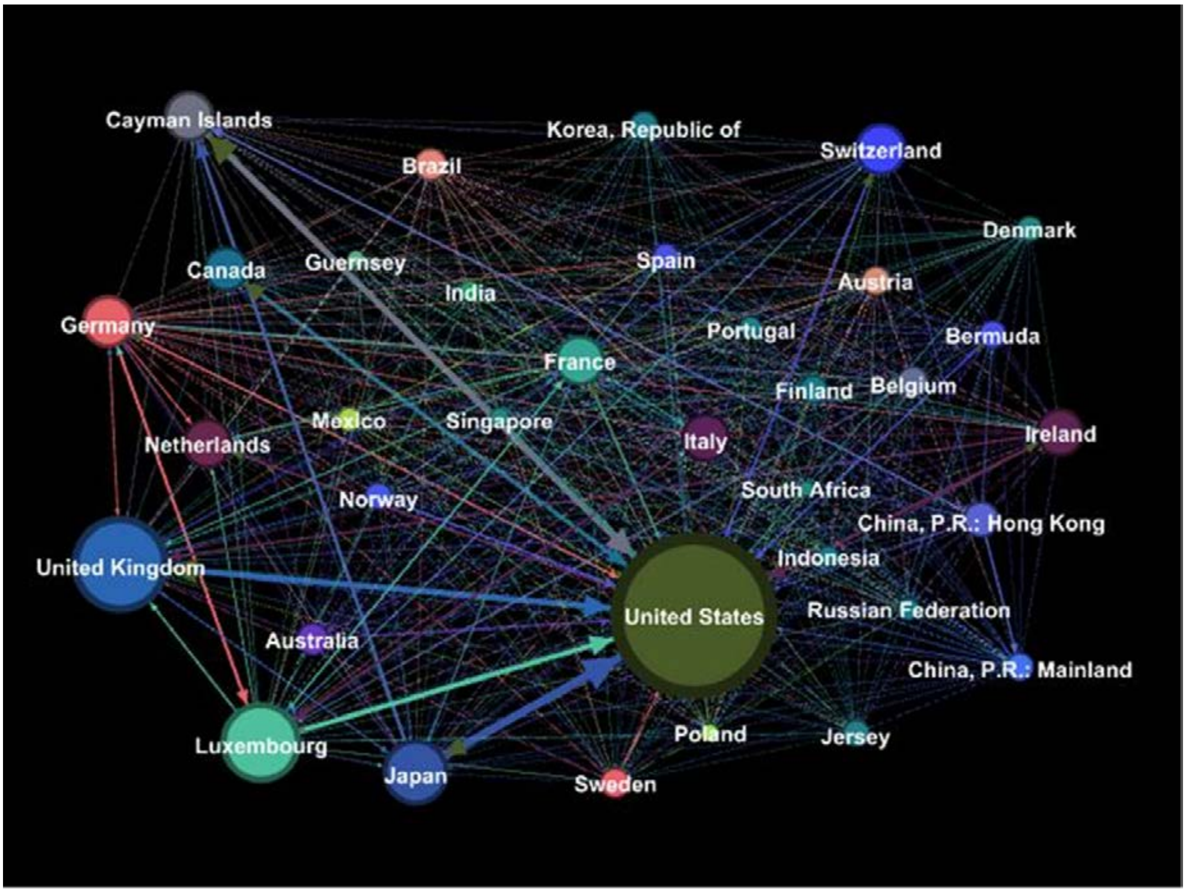
13 This is particularly true because most investors transact and keep securities in custody with financial intermediaries, often through a long chain of custodians and sub-custodians. The frequently long chains of custodians/sub-custodians/final investors usually entail cross-border relationships involving several countries.

14 http://data.imf.org/cpis

resulted from the increased liberalization of cross-border transactions and the above-described measurement issues. The CPIS is a global survey of portfolio investment stocks collecting semi-annual (end-June and end-December) information on cross border holdings of debt and equity securities.

The CPIS provides each economy with mirror statistics on its portfolio investment liabilities, coming from what every other economy reports to be holding of the securities issued by residents in that country. Compiling detailed information about cross-border portfolio investment assets (domestic holdings of foreign securities) is substantially more straightforward than compiling similar information about liabilities (domestic securities held abroad). Therefore, with the mirror information provided by the CPIS, each economy can compile the geographic distribution of its nonresident creditors. In this way, the information provided by the CPIS permits that cross-border position statistics portray complex financial interlinkages between different economies as in figure 5:

Figure 5: CPIS networking analysis

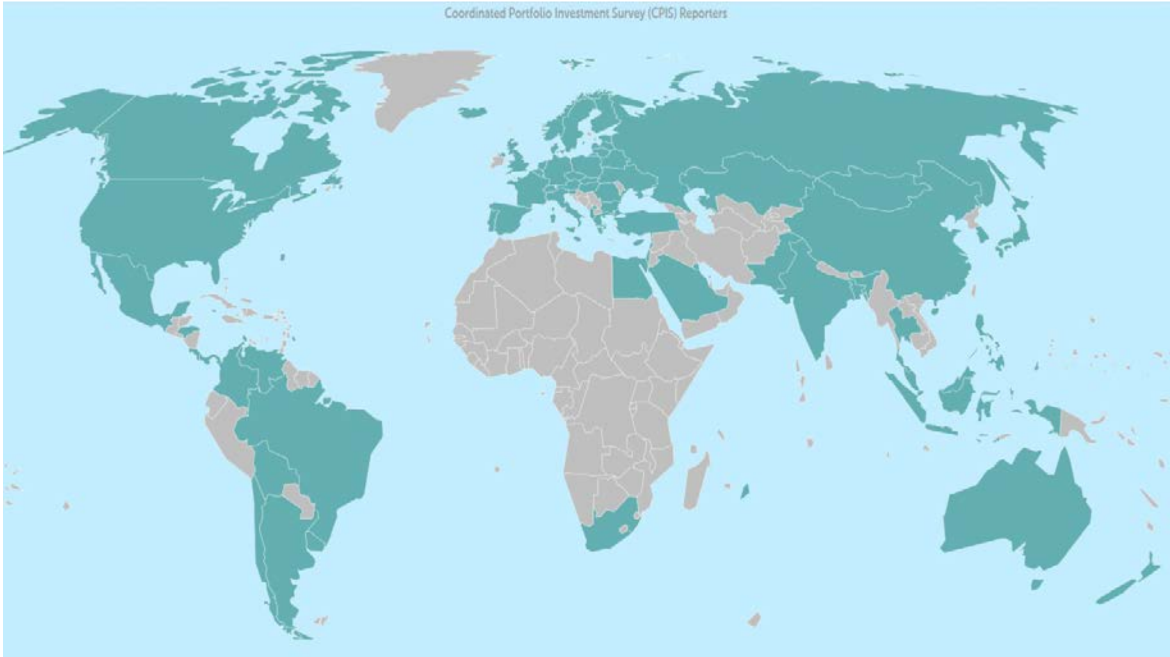


Source: End-June 2017 CPIS data
Size of circles is proportional to total cross-border issues/holdings and size and direction of arrows, to the scale and direction of the financing

More than 80 economies participate in the CPIS, including all major industrialized economies as well as most offshore financial centers and emerging markets (see figure 6).[15]

Figure 6: CPIS participating economies

[15] The list of CPIS reporters can be consulted here: http://data.imf.org/?sk=B981B4E3-4E58-467E-9B90-9DE0C3367363&sId=1481580274211



2.2 Still missing: which foreign sectors are domestic investors financing?

From-whom-to-whom portfolio information requires that cross-border securities holdings be broken down by domestic (holding) sector and by counterpart (issuing) country and sector. Ignoring the institutional sector of the foreign securities held by domestic investors (i.e. which non-resident sectors are resident sectors financing) may jeopardize financial stability. Whether domestic banks are holding foreign securities issued by foreign banks; by mutual or hedge funds; by financial vehicle corporations; by (public or private) non-financial corporations; etc. may involve substantially different risks. The lack of information on portfolio investment assets by issuer sectors impedes efforts to build up a global map of interlinkages between lenders and borrowers.

Even if information about securities holdings is available security by security, it is significantly more challenging to sectorize non-resident issuers than domestic holders. Statisticians need to sectorize domestic institutional units to compile macroeconomic statistics, so they need to have access to (or keep a record of) the institutional sector where each resident entity belongs. However, having access to similar information for non-resident units is much harder. [16]

2.3 Exchanging information internationally to close the gap

A centralized exchange of information across countries could improve the CPIS' sectorization of non-resident issuers. The Inter-Agency Group on Economic and Financial Statistics and the Financial Stability Board Secretariat recommended the IMF Committee on Balance of Payments Statistics[17] (hereinafter BOPCOM) to consider the feasibility of such an exchange. This was reflected

16 Central Banks in the European Union (EU) benefit from the information available in the so-called Centralized Securities Database (CSDB), which contains reference data for individual securities sourced from the central banks themselves and from commercial data providers. This way of exchanging information at the regional level has already proved to be successful for sectorizing non-resident issuers of the (respective) other European Union countries. However, even in the CSDB sectorizing issuers of jurisdictions beyond the European Union remains a challenge.

17 https://www.imf.org/external/bopage/bopindex.htm

in recommendation II.12 of the G-20 Data Gaps Initiative[18] and is also in line with recommendation II.20, which promotes sharing granular data to cover more comprehensively highly interconnected markets and to reduce bilateral asymmetries.

At its 2016 annual meeting, BOPCOM considered the possibility to address this gap by setting up a centralized database hosted by the IMF that would permit an international exchange of information. The IMF would receive from each CPIS reporter information on individual securities (ISIN codes[19]) and/or the IDs of the most important foreign issuers of securities held by their domestic investors. Securities/issuers IDs would be grouped according to their country of residence; duplicates be eliminated; and the resulting list of securities/issuers be sent to each country participating in the exchange for their subsequent sectorization. In this way, each economy would only sectorize its domestic issuers. The resulting information would be stored in a database hosted at the IMF and be made available to all CPIS reporters for later use to identify the issuer sector of the foreign securities held by domestic investors.

Countries usually collect portfolio investment data either on an aggregate or on a security-by-security basis. The latter countries usually collect a reduced volume of information from investors (which may be as limited as just the number and/or the nominal value of the securities they held plus the ISINs or other securities identifiers[20]), which is later combined with the reference information (e.g. mark-to-market value, currency, maturity, coupon, rating) contained in a securities database. By combining these two elements, statisticians have full flexibility to compile the aggregate statistics they need and even to review time series retroactively by adding new breakdowns without the need to request additional information from respondents. Conversely, countries that compile portfolio investment statistics on an aggregate basis need to provide instructions to reporters on how to aggregate their raw microdata according to the breakdowns they want to produce. In this case, producing new breakdowns and reviewing historical series would force compilers to come back to their reporters and request additional information.

Countries with access to information connecting individual securities (via e.g. their ISIN) with issuers (via their LEI[21] or another standard identifier) and their institutional sector could exchange information at the level of individual securities. This may not require security-by-security data collection, since the information may be available through another local database (e.g. stock exchange, public debt or other securities databases) connecting individual securities with issuers and their institutional sector.

Countries collecting only aggregate information and without access to any such database may still participate in the project by providing more limited information. They would be required to provide a list of the domestic issuers with the largest cross-border liabilities (again identified through their LEI or another standard identifier by the other CPIS reporters) and their corresponding institutional sector.

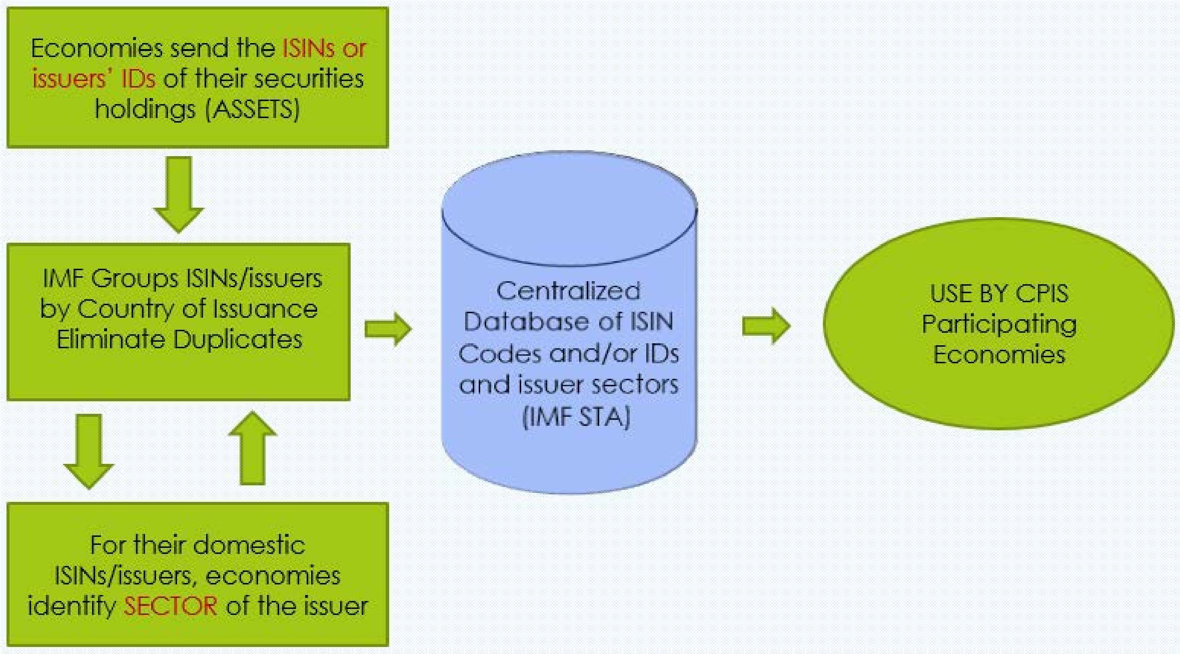
18 This recommendation monitors among others the number of G-20 economies that report the CPIS table with information by sector of issuer.

19 The International Securities Identification Number (ISIN) is a 12-character alphanumeric code that uniquely identifies a security according to ISO standard 3166.

20 CUSIP (Committee on Uniform Security Identification Procedures) number, SEDOL (Stock Exchange Daily Official List) number, etc.

21 The Legal Entity Identifier (LEI) is a 20-digit alpha-numeric code that uniquely identifies a legal entity participating in financial transactions.

Figure 7: IMF-centralized exchange of data to improve sectorization of issuers in the CPIS



No additional information (e.g., currency, type of security, original maturity, etc.) would be part of the proposed exchange. That's because any additional information could exacerbate potential copyright and confidentiality issues.

Conclusions

In a globalized world with increasingly complex cross-border linkages, sufficiently detailed sectoral balance sheet positions become fundamental in anticipating potential risks and spillovers. Whereas some progress has been made in analyzing sectoral interlinkages within individual domestic economies, much more needs to be done to extend the analysis to the global level. This can only be possible when a full matrix of cross-border positions between countries and sectors be constructed.

Constructing a full matrix of cross-border positions between countries and sectors is particularly complex when it comes to sectorizing non-resident counterparts. While statisticians usually have information to sectorize domestic institutional units, having access to similar information for non-resident units is much harder, thus why exchanging information across countries looks worth exploring. Given the high level of standardization of portfolio securities, progress in this area can proceed faster as it can benefit from a high degree of automation.

The IMF in coordination with BOPCOM is currently studying the possibility to set up a centralized database to store information about non-resident issuers of securities and their institutional sector. The information in the database would be used by the CPIS reporters to sectorize non-resident issuers and be able to compile and disseminate from-whom-to-whom information for portfolio securities.

All countries (even those which only compile aggregate information) would substantially benefit from participating in the project. Participating in the exercise and sharing their data with the other CPIS countries would bring substantial benefits to all participants, since they could use the mirror CPIS data provided by counterpart economies to compile their portfolio investment liabilities by issuer sector with a much higher degree of accuracy.

Before proceeding with the exchange, several issues need to be addressed. First, participants may need to deal with potential copyright restrictions, mostly referring to data coming from commercial data providers. Second, only a high degree of standardization would permit to reap the benefits of a largely automated process. Finally, it must be assessed whether the foreseeable benefits of the database outweigh its set up and running costs.

Annex 1: Pilot project between the European Central Bank and the US Fed

As a proof of concept, in 2017 the US Federal Reserve System (FED) and the European Central Bank (ECB) undertook a pilot exercise aimed to assess whether such an exchange of information could bear useful results. In the pilot (limited to securities with an ISIN code) the ECB provided the FED with more than 120,000 US securities from its Centralized Securities Database[22], while the Fed transmitted the ECB 45,000 securities issued by EU residents. Both institutions sectorized their respective issuers and sent back the resulting matching of security-issuer-sector to the other party.

The exercise confirmed that home-country reviewers could far more precisely assign a sector to domestic issuers (sometimes even just based on the issuer name) than what had been previously stored in each respective database. Prior to the exercise, both institutions had already assigned institutional sectors to foreign issuers in their databases. The pilot was supposed to validate the accuracy of such information, and revealed a number of errors. Typical cases were securities correctly classified as Government-issued, but to which the level of government assigned (i.e. state or local) was sometimes incorrect. Another example was that of financing arms of nonfinancial firms, which often was also erroneously considered as nonfinancial.

The pilot also showed the importance of standardization. The FED gives freedom to respondents to report using any security identifiers (ISIN, CUSIP, SEDOL, even internal codes). The pilot showed that it was much more difficult for them to be able to match EU securities (and for the ECB to do the same with US securities). Therefore, it was concluded that a high level of standardization was key for the more exhaustive tranche of the exchange (the one exchanging information by individual securities instead of by individual issuers).

Characteristics of the exchange based on the pilot conclusions

All in all, the results of the pilot suggested that the more exhaustive tranche of the exchange (based on security-issuer-sector) should be as automated as possible. This is because the volumes of information to be exchanged would be much higher than for the other tranche (only encompassing individual issuers and sectors). Therefore, the information to be exchanged should be highly standardized, i.e. using the ISIN code as the securities' identifier and the LEI as issuers' identifiers. Besides, the exhaustive tranche should only focus on securities for which cross-border holdings exceed a certain threshold (e.g., USD 1 mil.)

The alternative tranche would cover only limited information about individual issuers and their corresponding sector. This would allow additional countries to participate in the exchange by not covering any information at the level of individual securities. Only a limited number of the national issuers accounting for the largest cross-border positions liabilities above a certain threshold (still to be defined) would be covered.

Depending on the information available at national level, each CPIs reporter would decide whether they wanted to participate in the exchange via the more exhaustive (security/issuer/sector) or the more limited (only issuer/sector) tranche of the exercise. Participants in either tranche of the exchange should use a single methodology for the sector classification of issuers, namely the SNA 2008 and BPM6 methodology. Any bridging from national

[22] At the time of the exercise, the CSDB kept reference information on 2 million live securities, of which 180,000 corresponded to US issuers.

sectorization or identification codification to internationally accepted standards should take place prior to the provision of the data to the centralized database.

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Ninth IFC Conference on “Are post-crisis statistical initiatives completed?”

Basel, 30-31 August 2018

The IMF balance sheet approach: towards from-whom-to-whom information on cross-border portfolio securities[1]

Artak Harutyunyan and Carlos Sánchez Muñoz,

International Monetary Fund

[1] This presentation was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

Balance of Payments Division
IMF Statistics Department

The IMF Balance Sheet Approach: towards from-whom-to-whom Information on Cross-border Portfolio Securities

Carlos Sánchez-Muñoz

Irving Fisher Committee Conference; August, 2018

Outline

- The IMF Balance Sheet Approach
- Breaking down portfolio investment positions by geography and sector
- Exchanging information internationally to close the gap
- Conclusions

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The IMF Balance Sheet Approach

- Assets and liabilities of each sector (positions)
- Estimate inter-sectoral financial positions by instrument, maturity, and currency
- Objective: detect sector vulnerabilities / policies to reduce them

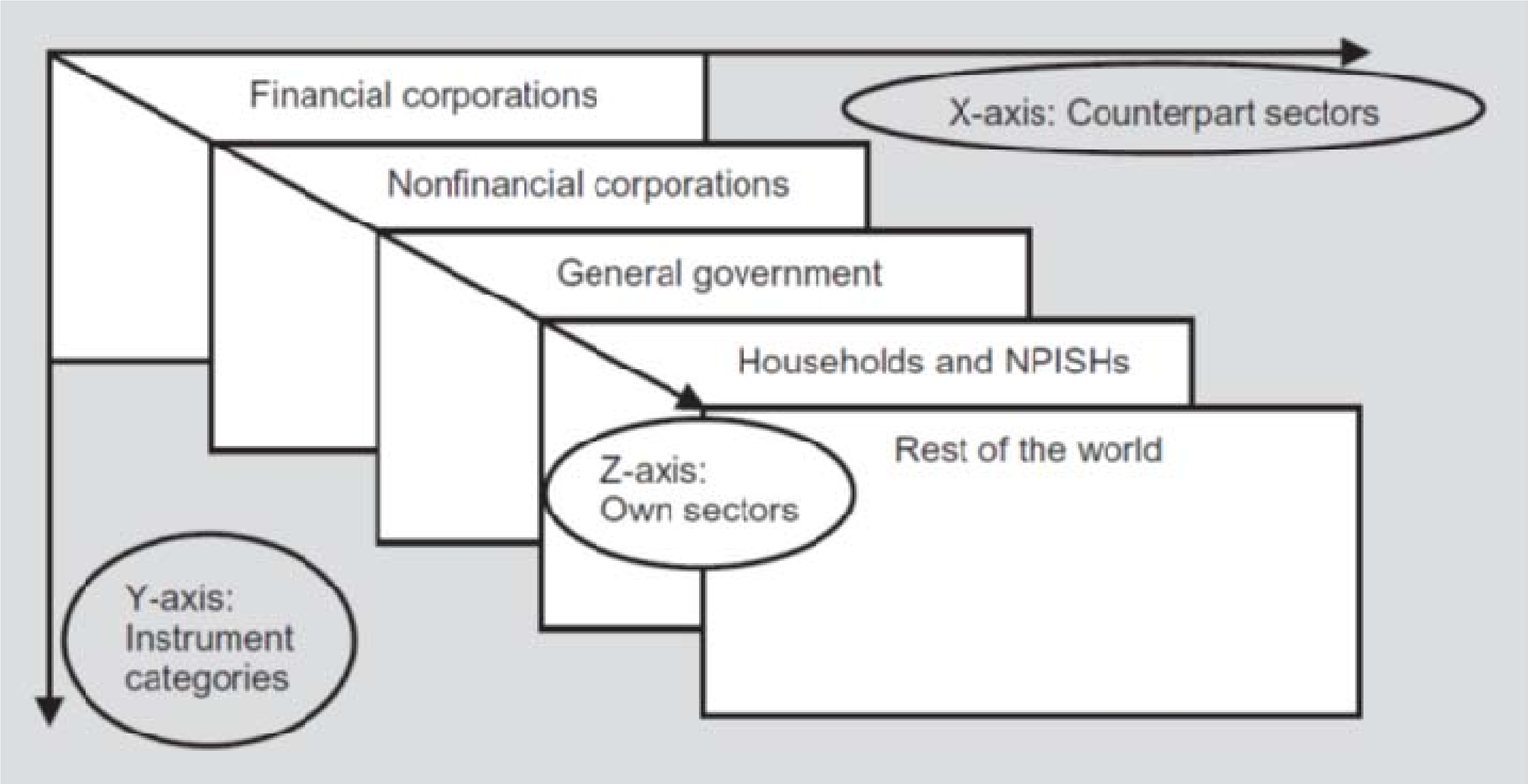
Three intra-sector mismatches:

- Maturity mismatches ➔ LT illiquid assets vs. ST liabilities
- Currency mismatches ➔ exchange rate risks
- Capital structure mismatches ➔ not enough equity

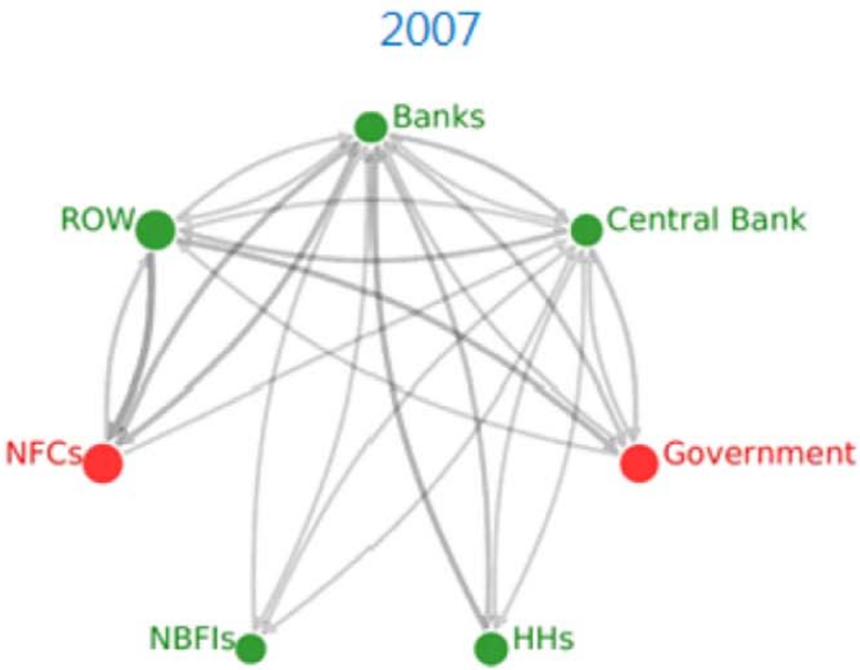
Can turn into ➔ **Solvency or credit risk** (financial assets < liabilities)

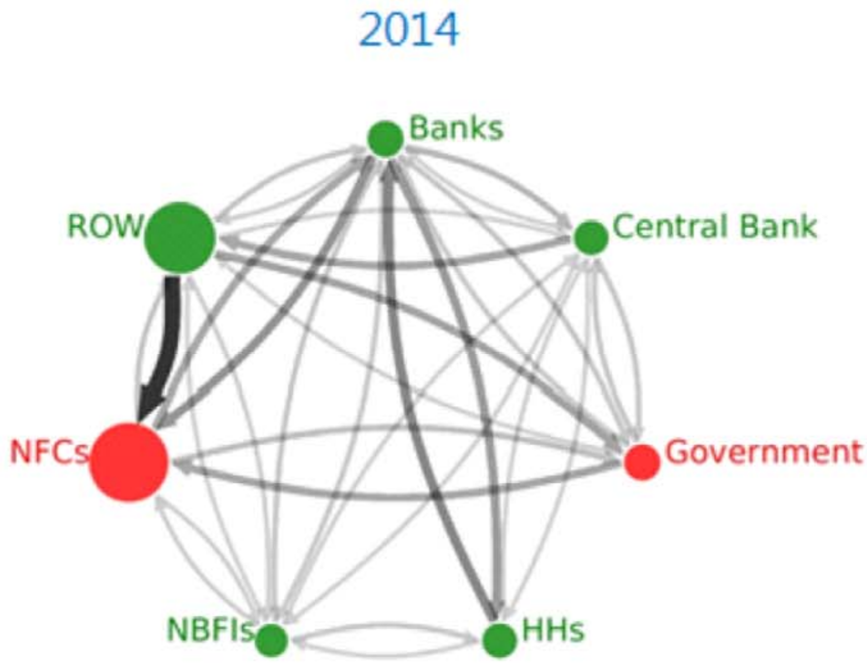
How to compile and analyze the Balance Sheet Approach

- The three-dimensional BSA provide counterpart information



Example: BSA network map for Indonesia





Source: *Indonesia: Selected Issues Paper, 2016, Figure 1 on page 29, IMF.*
Note: *The thickness of the arrow indicates the size of gross exposure, while the color of the nodes distinguishes net creditors (green) from net debtors (red).*
Abbreviations: NBFI – Non-bank Financial Intermediaries; NFCs - Non-financial corporations; HHs – Households; ROW – Rest of the World

Areas for future development

- Maturity breakdowns for all financial instruments
- Further breaking down nonbank financial sector
- Reconciliation of asymmetries
- Compiling matrices of inter-sectoral financial flows

And

Breaking down global cross-border positions with from-whom-to-whom counterpart (country and sector) detail

Outline

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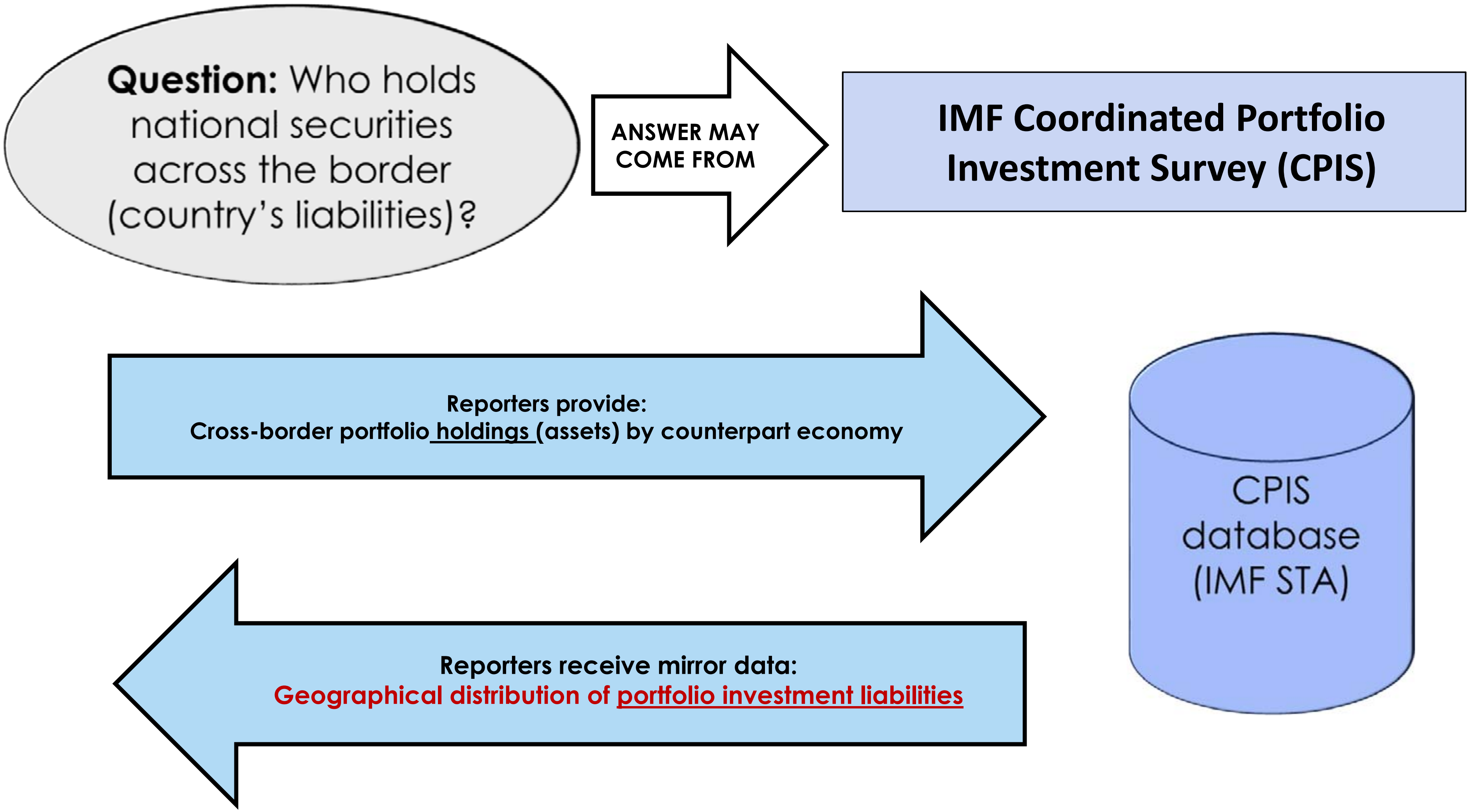
Break down by geography cross-border positions



CPIS : Participating economies

- Reporters cover:
  - All major industrialized economies
  - Most offshore financial centers
  - Most emerging markets
  - Lacking some oil-producing economies
- Results for December 2017 to be posted in September 2018

What is missing to permit identification of who (holder) finances whom (issuer)?

- We know which domestic sectors hold securities, but…
- ... don't know which non-resident sectors they are financing:

Very different risks depending on borrowing/issuing sector!

- Government (state, local)?
- Banks?
- OFIs (e.g., hedge funds, FVCs, etc.)?
- NFCs?

- But how to sectorize non-resident issuers?
- Compilers sectorize resident entities to compile macro economic statistics, so the economy where the issuer is resident could provide this service to its counterparts

Outline

- The IMF Balance Sheet Approach
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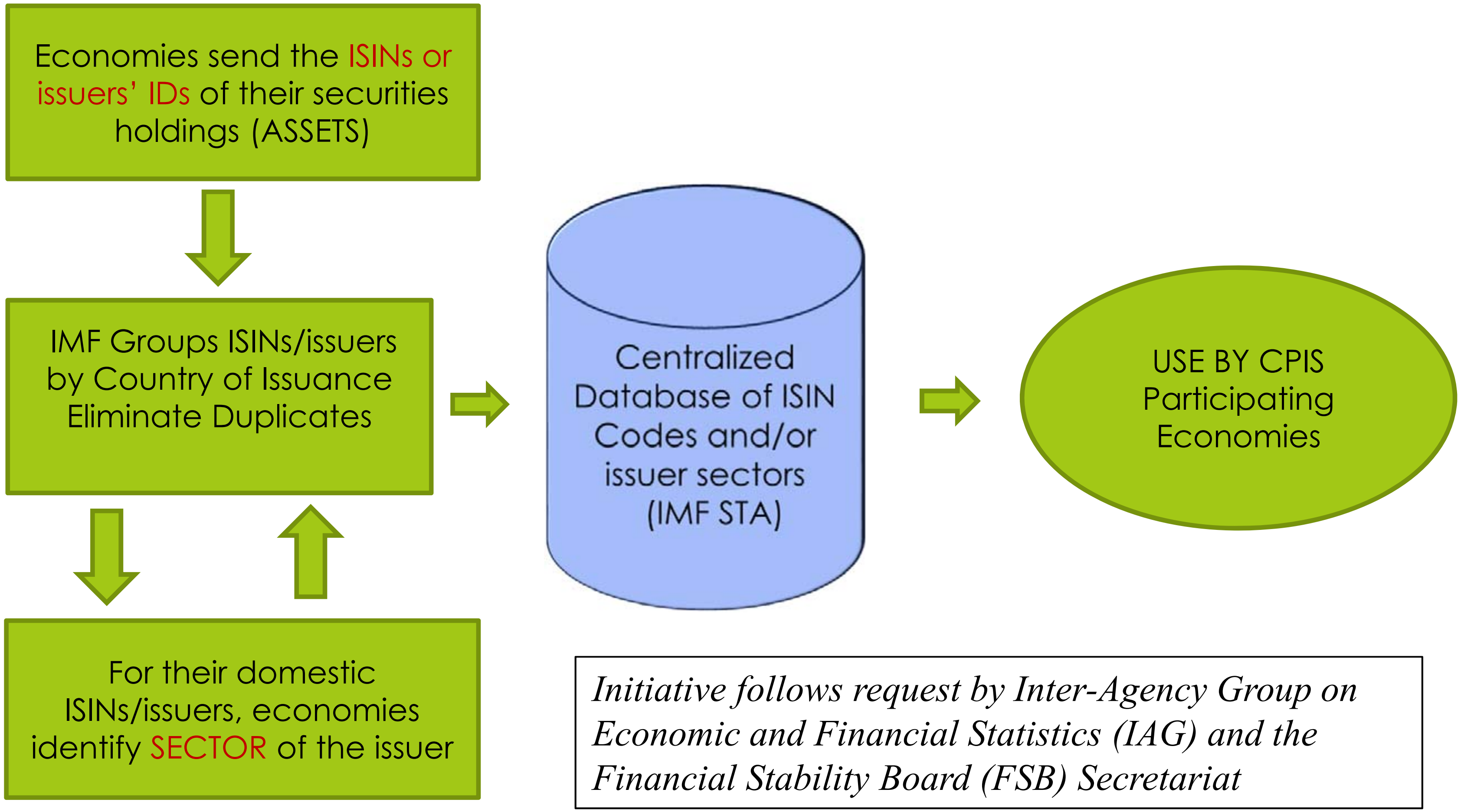
Project: centralized exchange of data to improve sectorization of issuers in the CPIS



Initiative follows request by Inter-Agency Group on Economic and Financial Statistics (IAG) and the Financial Stability Board (FSB) Secretariat

[ISIN: International Securities Identification Number]

IMF BOP Committee (Oct. 2017)

- Based on the pilot results, BOPCOM fully supported the initiative
- Underlined the importance of sectorization for IMF surveillance and to address asymmetries
- Need to address contractual issues with commercial data providers
- Automatized process requires standardization:
  - ISIN to identify securities
  - Legal Entity Identifier (LEI) to identify issuers

IMF BOP Committee (Oct. 2017)

- However:
  - Implementation of the LEI can take time
  - Around 1/3 of securities don't have an ISIN
  - Even fewer in certain parts of the world (e.g., Asia)
- Therefore, combined approach:
  - Individual securities (with ISIN) for countries collecting security-by-security data
  - Only issuer IDs (domestic issuers with largest cross-border liabilities) for countries collecting aggregate data

What comes next?

- Survey run with CPIS economies in 2018:
  - Volume of securities
  - Update frequency
  - Identifiers used (ISIN, CUSIP, SEDOL, etc.) + (LEI)
  - Confidentiality, copyright, contractual limitations to share information
- With survey results, IMF feasibility study of:
  - A centralized database hosted/managed by the IMF
  - Technical requirements
  - Associated costs
- Proposal to be presented to the IMF Committee on Balance of Payments Statistics October 2018

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Conclusions

- Detailed sectoral balance sheets fundamental to anticipate risks and spillovers
- Sectorizing non-resident counterparts necessary to achieve a full matrix of cross-border positions
- Exchanging information across countries could make it possible
- High level of standardization of portfolio securities enables automation ➔ progress could be faster

Conclusions (cont'd)

- IMF STA + BOPCOM studying the possibility to set up a centralized database of securities issuers and sectors
- Information to be used by CPIS reporters
- Sharing data with other CPIS countries would provide participants with mirror CPIS data by issuer sector to compile their portfolio investment liabilities
- Several issues to be addressed:
  - Potential copyright restrictions (commercial data providers)
  - High degree of standardization required
  - Benefits must outweigh set up and running costs

Thank you very much for your attention

Questions/comments welcome

Background Slides

Questions BSA can address

What Kind of Questions Can Balance Sheet Analysis Address?

- How healthy are the aggregate balance sheets of the household, nonfinancial corporate, bank, nonbank financial, and government sectors?
- Are there pockets of vulnerability within these sectors that are concealed by aggregate indicators?
- Is balance sheet repair constraining the transmission of macroeconomic policies to real activity?
- What balance sheet vulnerabilities could amplify and propagate the macro-financial impacts of systemic risks?
- How would these macro-financial feedback loops operate, and could they constrain the effectiveness of mitigating policies?

The Balance Sheet Approach: Analysis of Key Mismatches

Maturity mismatches: typically arise when assets are long-term, mainly illiquid, while liabilities are short-term. Maturity mismatches can arise in both domestic and foreign currency. Maturity mismatches create:

- rollover risk: the risk that it will not be possible to refinance maturing debts and that debtors will have to meet their obligations with liquid assets.
- interest rate risk for the debtor: the risk that the level and/or structure of interest rates on the outstanding debt will change.
- reinvestment risk: the risk that a creditor will not be able to reinvest a maturing claim at the previous higher interest rate.

Currency mismatches: This risk arises when assets and liabilities are denominated in different currencies. It creates:

- Exchange rate risk: If assets are held in domestic currency but liabilities are denominated in foreign currency, substantial losses may result if the domestic currency depreciates sharply in an exchange rate shock.

Capital structure mismatches: This risk results from excessive reliance on debt financing instead of equity. The absence of an equity buffer can lead to a financial crisis when a sector encounters a shock.

- Debt rather than equity risks

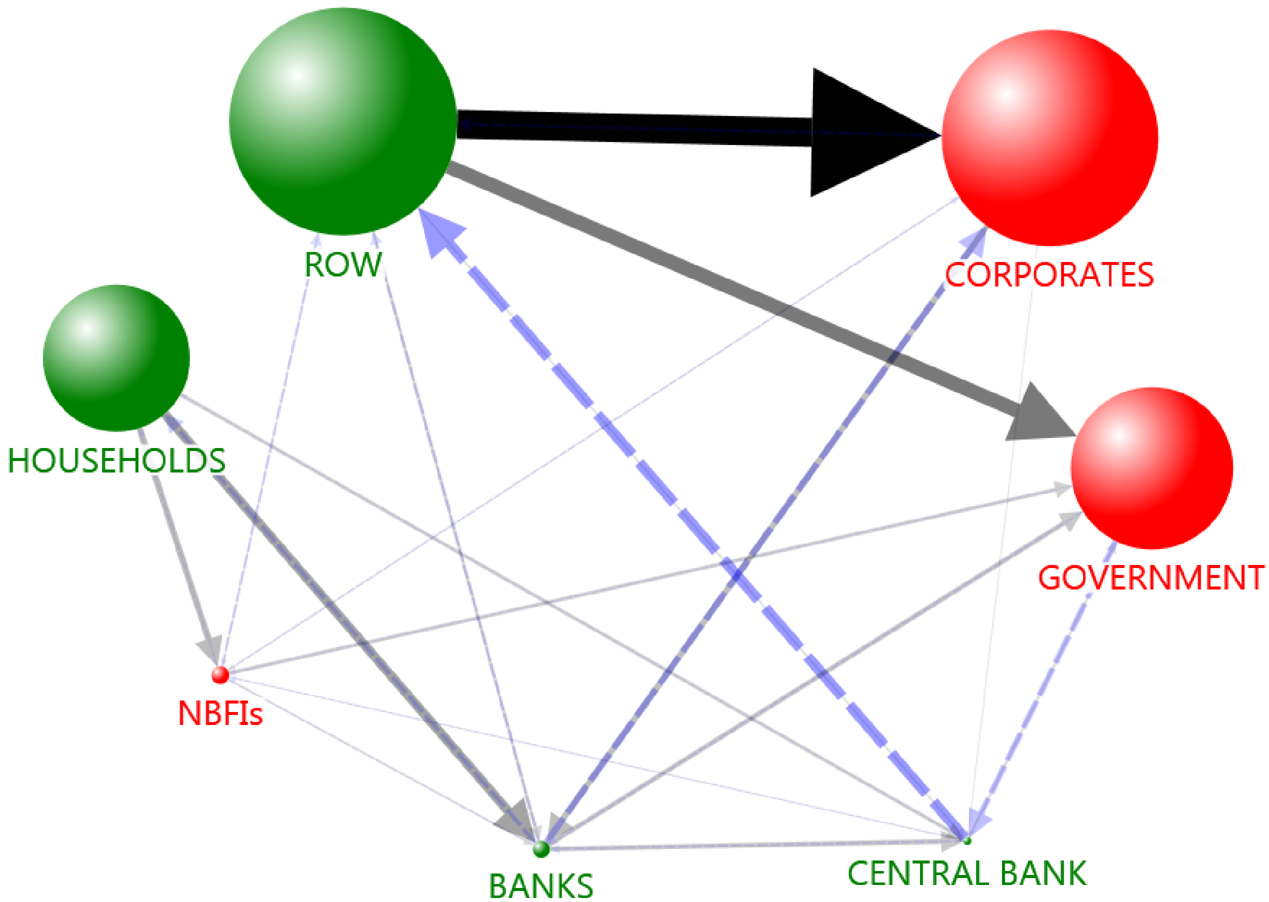
Solvency or credit risk: This risk emerges when a sector's financial assets no longer cover its financial liabilities. Solvency risk is closely linked to maturity mismatch risk, currency mismatch risk, and capital structure mismatch risk.

Source Data for the BSA Matrix

Issuer of liability (debtor) \ Holder of liability (creditor)	Central bank	General government	Other depository corporations	Other financial corporations	Nonfinancial corporations	Other resident sectors	Nonresidents
Central bank		1. SRF 1SR (Liabilities)	1. SRF 1SR (Liabilities) 2. SRF 2SR (Assets)	1. SRF 1SR (Liabilities)	1. SRF 1SR (Liabilities)	1. SRF 1SR (Liabilities)	1. SRF 1SR (Liabilities) 2. IIP 3. JEDH
General government	1. SRF 1SR (Assets)		1. SRF 2SR (Assets)	1. SRF 4SR (Assets)	n.a. 1/	n.a. 1/	1. IIP 2. QEDS
Other depository corporations	1. SRF 1SR (Assets) 2. SRF 2SR (Liabilities)	1. SRF 2SR (Liabilities)		1. SRF 2SR (Liabilities)	1. SRF 2SR (Liabilities)	1. SRF 2SR (Liabilities)	1. SRF 2SR (Liabilities) 2. IIP 3. QEDS
Other financial corporations	1. SRF 1SR (Assets)	1. SRF 4SR (Liabilities)	1. SRF 2SR (Assets)		1. SRF 4SR (Liabilities)	1. SRF 4SR (Liabilities)	1. SRF 4SR (Liabilities) 2. IIP 3. QEDS
Nonfinancial corporations	1. SRF 1SR (Assets)	GFS	1. SRF 2SR (Assets)	1. SRF 4SR (Assets)		n.a.	1. IIP 2. QEDS 3. JEDH
Other resident sectors	1. SRF 1SR (Assets)	GFS	1. SRF 2SR (Assets)	1. SRF 4SR (Assets)	n.a.		1. IIP 2. CPIS 2/
Nonresidents	1. SRF 1SR (Assets) 2. IIP 3. CPIS	1. IIP 2. CPIS	1. SRF 2SR (Assets) 2. IIP 3. CPIS	1. SRF 4SR (Assets) 2. IIP 3. CPIS	1. IIP 2. CPIS	1. IIP 2. CPIS	

1/ This data gap can in the future be filled with data from the public debt data template (which also covers assets) which is being piloted in some countries.
2/ CPIS data can be used to derive other resident sector's claims as residual.

BSA: An example of Network Representation



Capital Flight and Depreciation Simulation Results

Country Example: Net cross-sectoral exposures

	Government	Central Bank	Banks	NBFIs	NFCs	HHs	ROW
(In percent of GDP, after 25 percent depreciation shock)							
Government		-0.05%	0.11%	0.00%	0.00%	0.00%	4.46%
Central Bank	0.05%		0.44%	0.00%	0.00%	0.00%	-3.95%
Banks	-0.11%	-0.44%		-0.03%	-0.63%	0.58%	0.62%
NBFIs	0.00%	0.00%	0.03%		-0.16%	0.00%	0.23%
NFCs	0.00%	0.00%	0.63%	0.16%			14.39%
HHs	0.00%	0.00%	-0.58%	0.00%			0.00%
ROW	-4.46%	3.95%	-0.62%	-0.23%	-14.39%	0.00%	
(In percent of GDP, after combined shocks)							
Government		-0.05%	0.11%	0.00%	0.00%	0.00%	4.46%
Central Bank	0.05%		0.44%	0.00%	0.00%	0.00%	-3.95%
Banks	-0.11%	-0.44%		-0.03%	-6.90%	0.58%	0.62%
NBFIs	0.00%	0.00%	0.03%		-0.16%	0.00%	0.23%
NFCs	0.00%	0.00%	6.90%	0.16%			8.12%
HHs	0.00%	0.00%	-0.58%	0.00%			0.00%
ROW	-4.46%	3.95%	-0.62%	-0.23%	-8.12%	0.00%	

Banking system overall not very exposed to FX shocks

The depreciation increases corporate external liabilities

Liquidity withdrawal involves financial system

Source: Indonesia 2015 Article IV Consultation Selected Issues Paper.

Policy Implications

- Information in sectoral balance sheets should be timely:
  - allows policymakers to identify and correct weaknesses
- Focuses attention on policies that can reduce sectoral vulnerabilities:
  - in particular, the vulnerability to changes in key financial variables
- Allows policymakers to evaluate trade-offs between different policy objectives:
  - systemic threat to the financial and economic system
- Helps the official sector to assess the case for financial intervention:
  - to better understand the scale of official support

Pilot project: ECB and Federal Reserve

[September 2017]

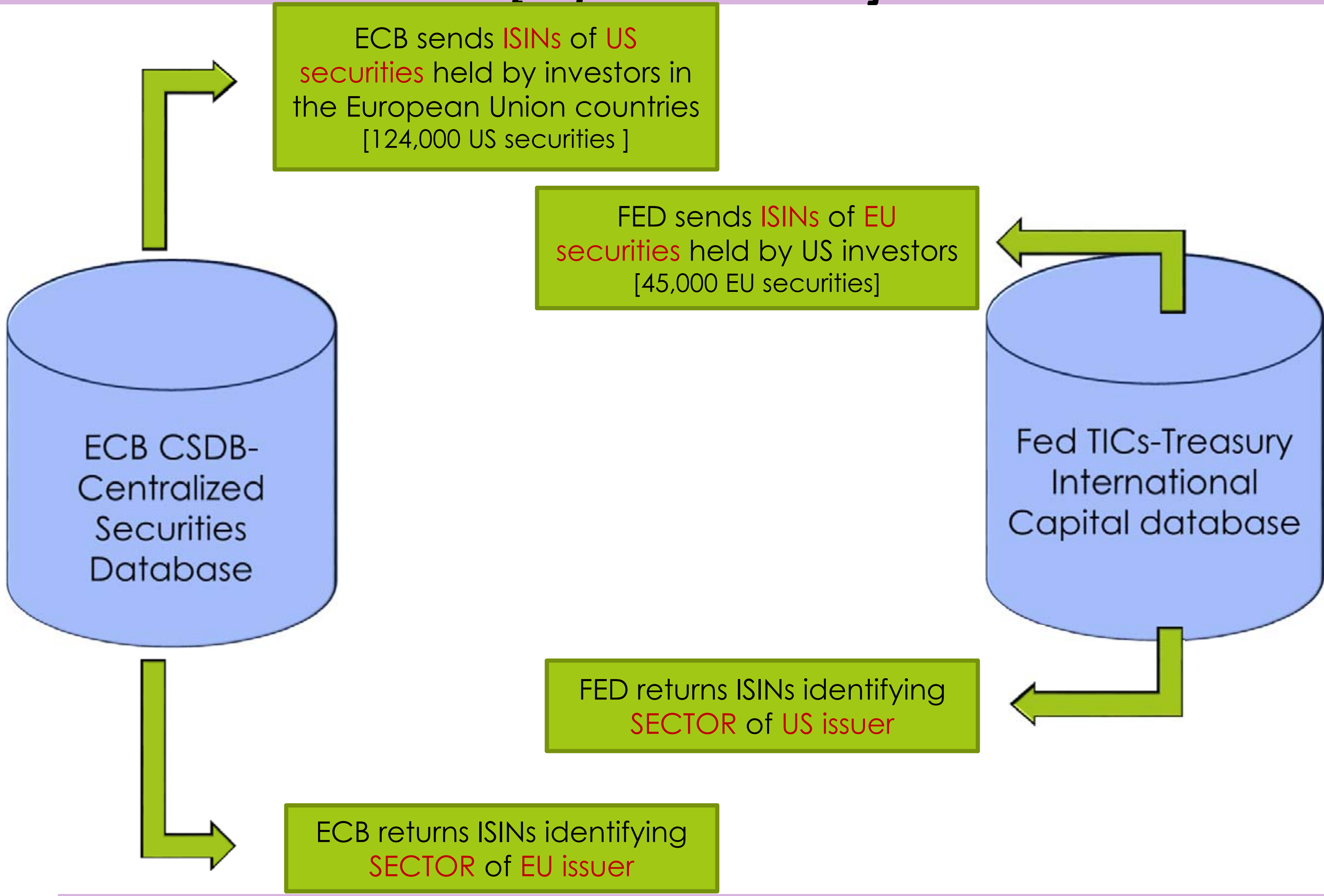
- Limited to a bilateral exchange (limitation of ECB contracts with commercial data providers) completed in September 2017

  European Central Bank ➔ Centralized Securities Database – daily updates (from which: US securities held by 27 EU countries)

  US Federal Reserve ➔ Treasury International Capital (TIC) system – annual updates (from which: EU securities held by US investors)

- ECB sent 124,000 US securities
  (alive market capitalisation > EUR 10 million)
- FED sent 45,000 EU securities (held by US residents)

Pilot project: ECB and Federal Reserve
[September 2017]



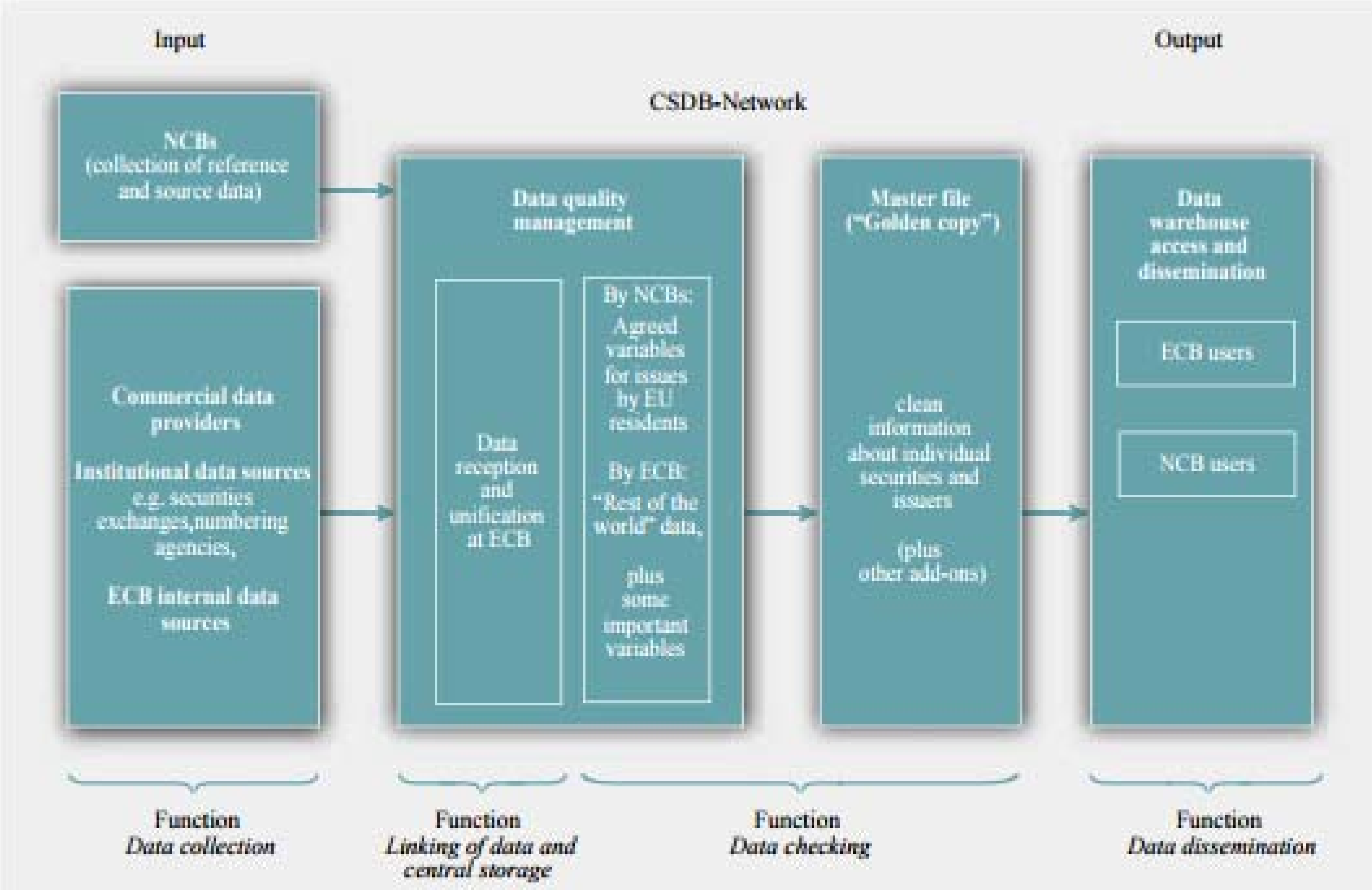
Federal Reserves data collection system

- U.S. cross-border securities dataset part of the Treasury International Capital (TIC) system
- Individual-security data collected annually: end-June (U.S. liabilities) and end-December (U.S. claims)
- Largest 125–150 reporters ➔ about 98% of market
- "Benchmark" surveys conducted once every five years covering all known reporters.

Federal Reserves data collection system

- Security characteristics: security type, currency of denomination, issue and maturity dates, issuer name, security description, etc.
- Securities characteristics are aggregated and reconciled across reporters to produce the reference security database.
- Additional securities characteristics (e.g., NAICS industry code, coupon type, dividend, coupon rates) obtained from a commercial vendor.

ECB Centralized Securities Database (CSDB)



https://www.ecb.europa.eu/pub/pdf/other/centralisedsecuritiesdatabase201002en.pdf

What did we learn from the pilot?

- Exercise confirmed that the sector assignment by home-country reviewers is easier than for external reviewers
- Examples:
  - Government securities correctly classified, but the level of government (state or local) sometimes incorrect
  - Financing arms of nonfinancial firms: can be difficult to assign correct sector
- Home country reviewers best equipped to assign right allocation (sometimes even just based on the issuer name)

What did we learn from the pilot?

- FED permits to report using any security identifiers (ISIN, CUSIP, SEDOL, even internal codes): difficulty to be able to match both US and EU securities

➔ Therefore, standardization proves key:

  - ISIN to identify securities
  - LEI to identify issuers

- Sectorization not always following common (BPM/SNA) rules ➔ common methodology necessary

- Many securities insignificant in terms of cross-border holdings ➔ focus on the most relevant in terms of outstanding amounts/market capitalization

Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

Keeping track of MNEs through business group databases: the experience of Bank of Portugal[1]

Ana Bárbara Pinto, José Alexandre Neves and Tiago Pinho Pereira,

Bank of Portugal

[1] This paper was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

Keeping track of MNEs through business group databases: The experience of Banco de Portugal

Ana Bárbara Pinto | Banco de Portugal

José Alexandre Neves | Banco de Portugal

Tiago Pinho Pereira | Banco de Portugal

Abstract

The world has gone global and statistics developed at national level will miss the global picture if we do not react accordingly. Our national economies are impacted not only by local firms but also by multinational enterprises (MNEs) which operate around the globe and organize themselves in various complex and interconnected ways hardly captured by the current statistical standards and definitions. Several statistical domains are therefore likely affected by this phenomenon, namely in the field of balance of payments and related statistics such as foreign affiliates statistics. There are already a number of ongoing initiatives lead by international organizations such as the OECD and the Eurostat and in this paper we present the contribution of Banco de Portugal in this respect. The presence of MNEs in Portugal, as well as Portuguese groups across the world, has several implications in our economy through the interlinkages they establish with the domestic agents. To address this issue, Banco de Portugal developed its own business groups' database that clearly depicts the group structure of Portuguese non-financial corporations (NFCs), showing all the relationships within the group, covering both the resident and non-resident members of the group. This paper presents the architecture and the methodology underlying the design of the database and provides some highlights about its geographical dispersion. Namely, it shows the countries of the ultimate controlling institutional units (UCIs) of multinational groups in Portugal and the host countries of Portuguese groups.

Keywords: Business statistics; database design; multinational enterprises (MNEs)

JEL classification: C80; F23; F60

Acknowledgements: We would like to thank Filipa Lima and André Cardoso Dias for their valuable comments. Ana Teresa Oliveira and all the other colleagues at the Banco de Portugal involved in the design of the business groups' database and in the quality control of data for their contributions. The views expressed are those of the authors and not those of the Banco de Portugal.

Contents

1. Introduction

The mission of central banks is not confined to the financial world. Understanding the interlinkages between financial intermediaries and the other agents of the economy is key to decide on the adequate monetary policy, macroprudencial framework and credit risk assessment. Banking supervision also benefits from a better knowledge of those dynamics.

There is then a case for central banks to have good quality data on non-financial corporations (NFCs). Sector financial accounts, Balance of Payments, International Investment Position and Foreign Affiliates' Statistics are powerful analytical tools that the Statistics Department of Banco de Portugal provides to the other Departments of the Bank so that the different dimensions of Portuguese NFCs can be assessed.

Complementarily, there is a need to move beyond the aggregates and the use of micro data is fundamental. Banco de Portugal manages the Central Balance Sheet data Office (CBSO) since 1983, with full coverage of all companies operating in Portugal since 2006. Internal and external researchers by BPLim – Microdata Research Laboratory of Banco de Portugal also benefit from this micro database.

In an increasingly global world, understanding NFCs requires also a business groups' database to keep track of Portuguese and foreign MNEs and their impact in the Portuguese economy. To get a complete picture of NFCs sector, consolidated data is also needed to complement individual accounts and business groups' structures.

Banco de Portugal participation's in the European Committee of Central Balance-Sheet Data Office (ECCBSO) promoted the exchange of experiences and encouraged the creation of a consolidated accounts database at Portuguese Central Balance Sheet data Office (CBSO). Starting with listed companies compliant with International Accounting Reporting Standards (IFRS), nowadays, consolidated accounts database has information from 2013 onwards for all companies publishing consolidated annual reports according with IFRS (listed and non-listed) and National Generally Accepted Accounting Practices (National GAAP).

This paper provides a complete overview of the business groups' database and its remainder is as follows: Section 2 shows the data source of the business groups' database, while Section 3 presents the database, namely its architecture, the functioning of the algorithm that loads the database, the visualization tool and some summary statistics that characterize the database. All Names and Tax payer identification numbers used in Sections 2 and 3 are fictional. Section 4 presents the relevance of MNEs in Portugal by comparing some of their economic and financial indicators with those of all-resident enterprise groups and non-groups. Section 5 concludes with some final remarks. Definitions are presented in the Annex.

2. Data source

The business groups' database developed by Banco de Portugal contains information on the group structure of Portuguese Non-Financial Corporations (NFCs). The main data source is the *Simplified Corporate Information* (IES, in the Portuguese acronym), a mandatory annual report through which NFCs submit their annual accounts (balance-sheet, income statement, statement of changes in equity, cash flow statement and the annex to the financial statements) simultaneously to the Tax Authority, Ministry of Justice, Banco de Portugal and Statistics Portugal. IES is reported within six and a half months after the end of the economic year, which, for most enterprises resident in Portugal, corresponds to 15th July of the year following the reference year. After the submission of IES, information is subject to quality control at the Central Balance Sheet Data Office (CBSO) of Banco de Portugal until the end of September. The results presented in this paper refer to the year 2016, the last year available at the time of writing.

The following items are required to ramp up the business groups' database:

- Tax payer identification number (Tax ID)
- Legal entity identifier (LEI) (optional)
- Name
- Country
- NACE (Statistical Classification of Economic Activities in the European Community)
- Direct participation in share capital (percentage)
- Direct participation in voting rights (percentage)
- Date of beginning and end of the participation

Tax payer identification number is mandatory for all entities (resident and non-resident). In Portugal, the Tax ID is unique and mandatory for all entities and is used as the key number in all micro data databases managed by Banco de Portugal.

The information about group structure is collected through five distinct tables. One table collects the identification of ultimate controlling institutional unit (UCI) and the ultimate controlling entity in Portugal if the UCI is non-resident. In this table only the first four above items are required. In the remaining four tables all the above items are collected according to the type of participation:

(1) Direct upward;

(2) Direct downward;

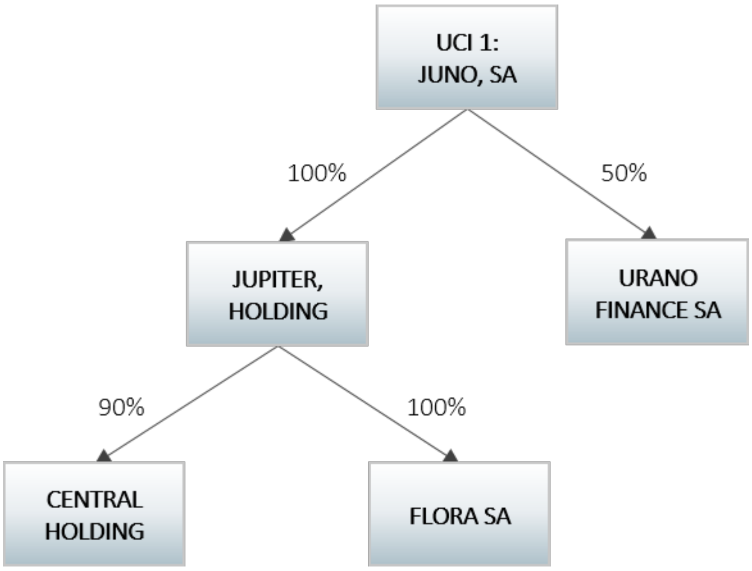
(3) Indirect upward;

(4) Indirect downward.

Direct upward participations exist when one or more companies have a participation in the share capital of the reporting entity. If there are other companies participating in the share capital of the direct upward participants then indirect upward participations occur. The same rationale applies to downward participations.

All indirect participations are reported in pairs of companies, i.e., link by link of the control chain in the group structure. For example: JUNO, SA reports a direct downward participation in JUPITER, HOLDING and an indirect downward participation of JUPITER, HOLDING in FLORA SA and other indirect downward participation of JUPITER, HOLDING in CENTRAL HOLDING (Figure 1).

Figure 1 – Report of an indirect downward equity participation



Direct participations are mandatory for all reporting entities with no minimum threshold, implying that the reporting entity has to declare all direct upward and downward participations. Instead of asking for the complete group structure to the Portuguese UCI or the ultimate controlling entity in Portugal if the UCI is non-resident, the option was to require all direct participations for all NFCs in order to reach better quality on group structure data. The assumption was that reporting companies have a better knowledge of their direct participations. This option also allowed to avoid missing data from reported companies on the top of the control chain in Portugal. The report of all direct participations will generate repeated participations in the database, which will later be deleted by the algorithm in order to build a complete and non-redundant business groups' database.

Indirect participations are mandatory only for Portuguese UCIs or for the ultimate controlling entity in Portugal if the UCI is non-resident. In the case of indirect upward participations only those from non-resident companies in the field of Balance of Payments statistics are required. The solution applied to indirect participations reduces the reporting burden on NFCs.

The structure of the tables mentioned above was adopted in 2014 when data for Balance of Payments and International Investment Position (BoP/IIP) statistics was also included in IES, namely equity, dividends and retained earnings of non-resident entities in the scope of foreign direct investment statistics, and variables for outward Foreign Affiliates Statistics (FATS) for all non-resident entities controlled by a Portuguese UCI. This change in the structure of the tables and the incorporation of information for BoP/IIP and FATS statistics was of utmost importance to improve data quality. Data collection became more user friendly and facilitated the reporting of the group structure. At the same time, the inclusion of information from BoP/IIP statistics promoted a better report of the group structure, with a complete coverage of foreign direct investment and FATS entities.

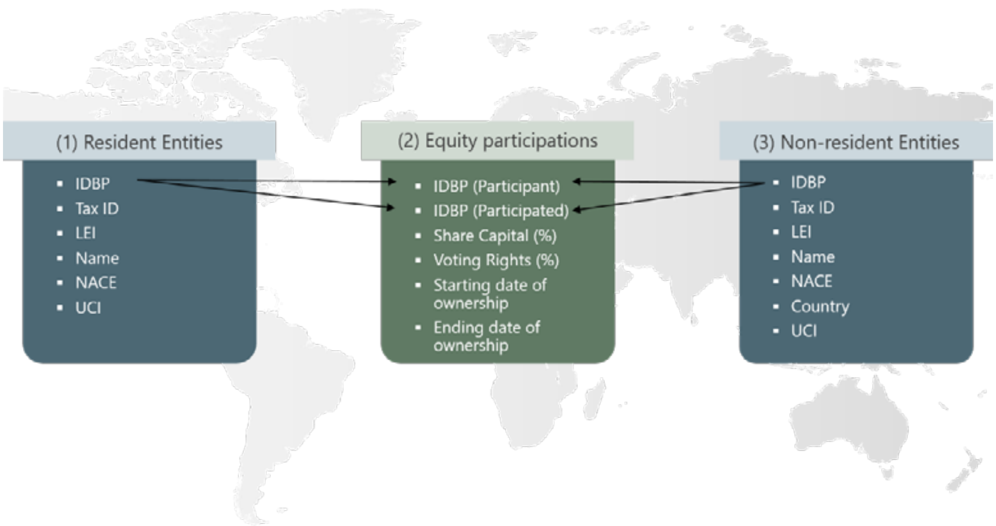
3. The business groups' database

CBSO developed an algorithm to analyse and conciliate all the information reported by companies. The algorithm eliminates repeated information, chooses the best option when the information is similar but not equal and tries to identify the correct UCI. When it is not possible to detect automatically the most accurate information, manual quality control will apply.

3.1 Architecture

The business groups' database comprises 3 tables: (1) the business register of resident entities, (2) all the equity participations between entities characterized by the percentages of participation in share capital and voting rights and (3) the business register of non-resident entities (Figure 2).

Figure 2 – Architecture of the business groups' database



3.2 Algorithm

The algorithm deals with the identification of: (1) non-resident entities; (2) equity participations and (3) UCIs. At the end, the algorithm result is uploaded in the business groups' database.

3.2.1 Non-resident entities

Non-resident entities are reported by resident NFCs and are identified by Tax ID, Name and Country.

Although the Tax ID is mandatory for all entities, a check digit validation only applies for national tax payer numbers. For non-resident entities some checks are also done, like eliminating dots and spaces and even removing the entire Tax ID if it is presumably wrong.

Also, the Name of the same non-resident entity could be reported in slightly different ways by different reporting entities. This situation requires a procedure to find out similarities on Tax IDs and Names and decide whether the entity is the same or not.

The similarity procedure on Tax IDs and Names uses the fuzzy lookup add-in for Excel which executes a matching of textual data in Excel to identify fuzzy duplicate data. Fuzzy lookup ignores dots, commas, question marks and other punctuation marks and special characters.

The algorithm compares the attributes of all non-resident entities according to the following rules:

1) If Tax ID, Name and Country are equal the entity is considered the same;

2) If Country is the same and:

   a. Tax ID is equal: Fuzzy lookup compares the Name and considers that it is the same entity when the similarity of the Name is higher than 55%;

      Example: "FLORA SA France" with Tax ID "96720542239" and "Flora SA" with the same Tax ID "96720542239" are compared as "FLORASAFRANCE" and "FLORASA" and considered the same company;

   b. Tax ID is different: Fuzzy lookup compares the binomial (Tax ID, Name) and decides that the entity is the same if the similarity (Tax ID, Name) is higher than 70%;

      Example: "Ares Corp. SA" with Tax ID "70253621" and "Ares SA" with a slightly different Tax ID "AB7025321" are compared as "70253621AresCorpSA" and "AB7025321AresSA" and considered the same company;

3) If Country is different and:

   a. The similarity of the binominal (Tax ID, Name) is higher than 70%, then those entities are selected for manual check;

      Example: "Local Company Ltd Corp" from Brazil is compared with "Local Company Ltd" from USA with the same Tax ID "850401763" and delivered for manual check;

   b. The similarity of (Tax ID, Name) is lower or equal than 70%, then those entities are considered different.

Example: “Central Holding” from Austria without Tax ID and “Central Investments Ltd” form Italy with Tax ID “456292930” are considered different companies.

At the end of this procedure the table with all non-resident entities is uploaded with an internal ID called IDBP which will be used in the following steps.

Finally, for the same non-resident entity, the algorithm compares the classification of economic activity (NACE) and LEI and if one or both are different, those cases are selected for manual quality control.

3.2.2. Equity participations

As all direct equity participations are requested, there is some overlap between information reported by different entities. Moreover the same equity participation could be reported as indirect by different entities or even reported as direct by one company and as indirect by another company.

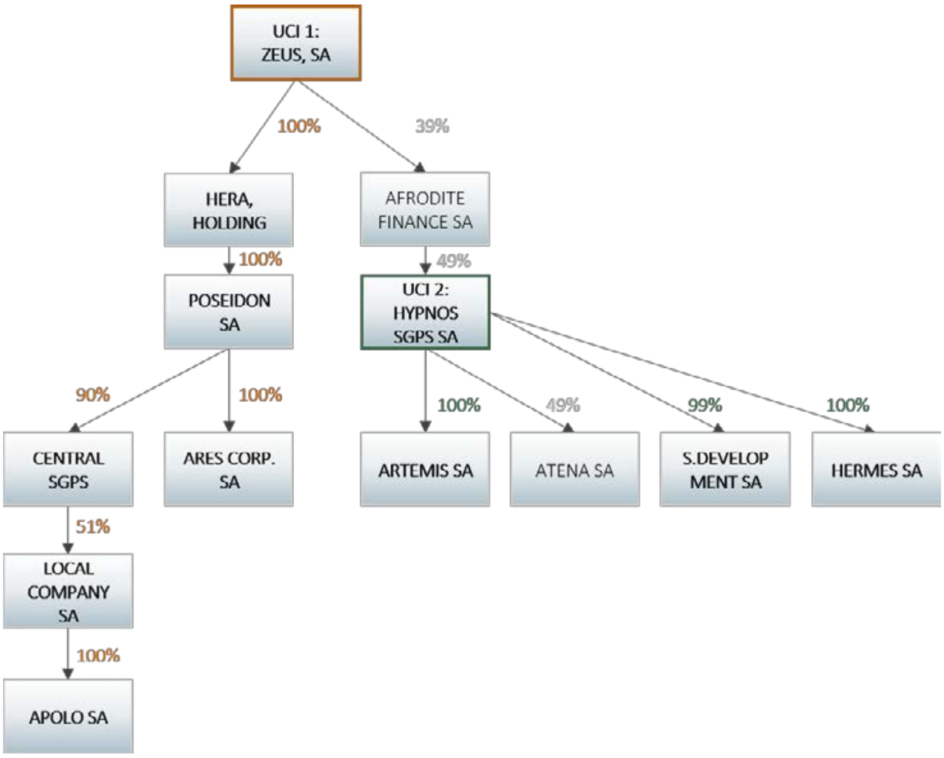
The algorithm uses the IDBP of the entity generated in the previous step to compare the percentages of equity participation and voting rights and decide if the equity participation is the same or not. The algorithm follows the following hierarchy:

- Entries reported more than once by different firms (duplications) are eliminated;
- Entries where the reporting firm reports itself as part of an indirect participation (it should only be part of direct participations) are eliminated
- Direct participations prevail over indirect participations (it is assumed that each reporting firm is more knowledgeable for its direct participations);
- Direct downward participations (firm A participates in firm B) prevail over direct upward participations (firm B is participated by firm A) (it is assumed that each reporting firm is more knowledgeable for its assets than for its liabilities).
- Mismatches between direct participations reported by different entities are selected for manual quality control.

3.2.3. Ultimate Controlling Institutional Unit (UCI)

Empirical evidence shows that companies tend to wrongly identify themselves as UCI. To attribute the correct UCI to a group of companies, the algorithm analyses the chain of voting rights higher than 50% (generally more than 50% implies control) and goes up into the group structure to find out the correct UCI. The UCI of the group will be the company on the top of the control chain. In the example of Figure 3, two different UCIs will be detected by the algorithm: UCI 1 – ZEUS, SA and UCI 2 – HYPNOS SGPS SA. Manual quality control will apply to treat unsolved situations by the algorithm.

Figure 3 – UCI detection by the algorithm



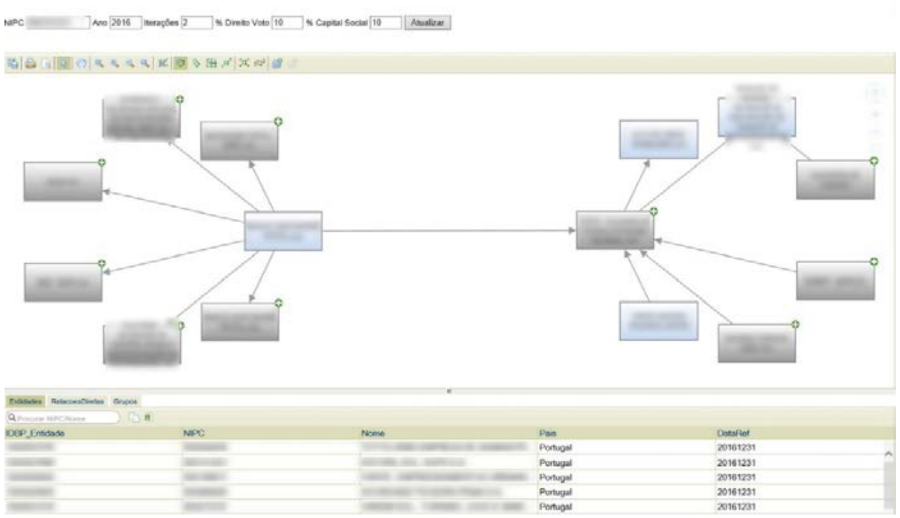
3.3 Visualization

Tom Sawyer software is used to visualize and analyse business group structures. This software allows us to use filters to visualize different perspectives of the same group: all equity participations with the same UCI or outside the scope of the group, changing the percentages of share capital or voting rights.

A company can be found by name or tax number and the group structure appears in the main screen or below in a table (Figure 4). All the information could be exported to Excel.

Tom Sawyer also shows different views besides the hierarchical layout: circular layout, orthogonal layout and symmetric layout.

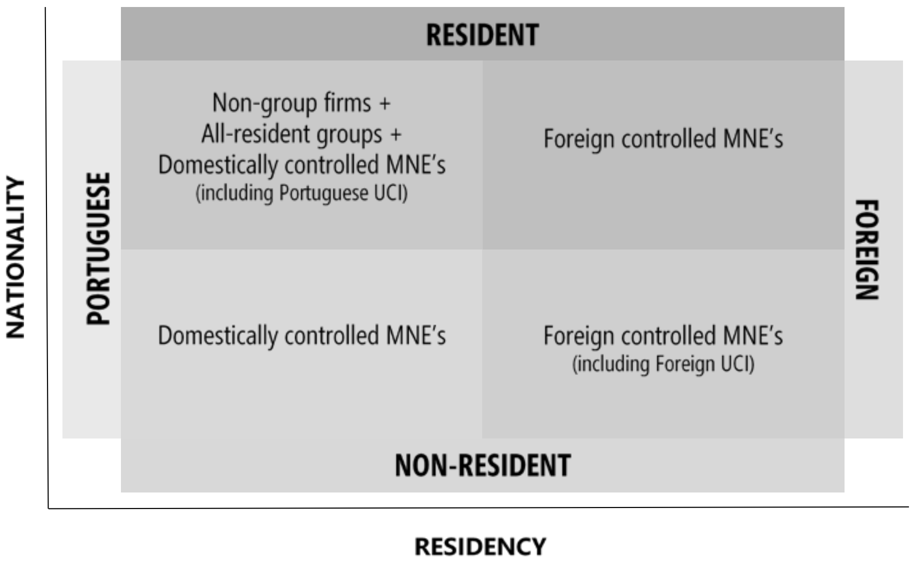
Figure 4 – Group structure visualization with Tom Sawyer software



3.4 Brief characterization of the database

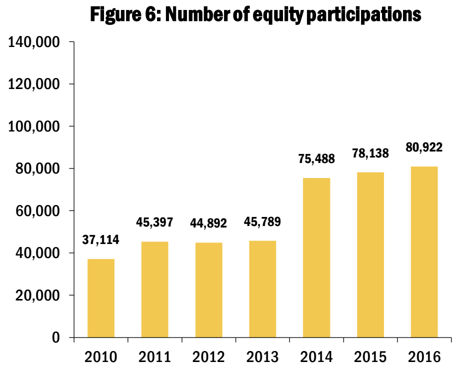
The entities in the business groups' database were classified depending on their nationality and residency as illustrated by Figure 5. Next figures will be based on different reference universes according to these concepts of nationality and residency.

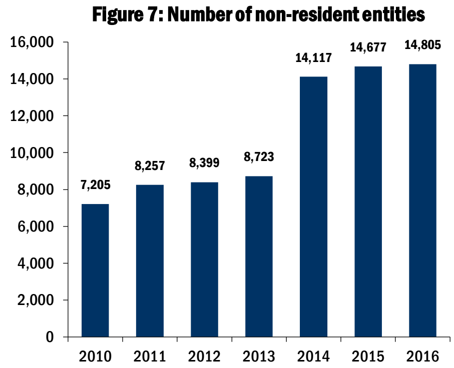
Figure 5 – Nationality vs. residency

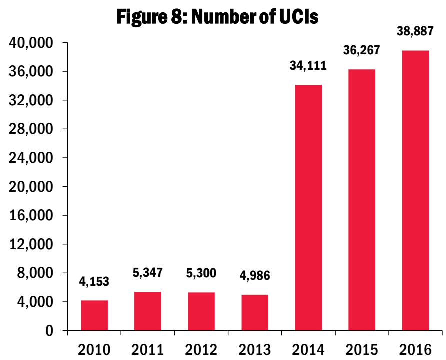


The business groups' database has information from 2010 onwards. In 2010, with the adoption of a new accounting framework in Portugal - in line with the IFRS -

information about UCI and indirect equity participations became also available, in addition to the information on direct equity participations already available in the previous National GAAP. As mentioned in section 2, in 2014 the framework changed, which resulted in an overall improvement in data quality. The impact of these changes can be seen in Figures 6 to 8.





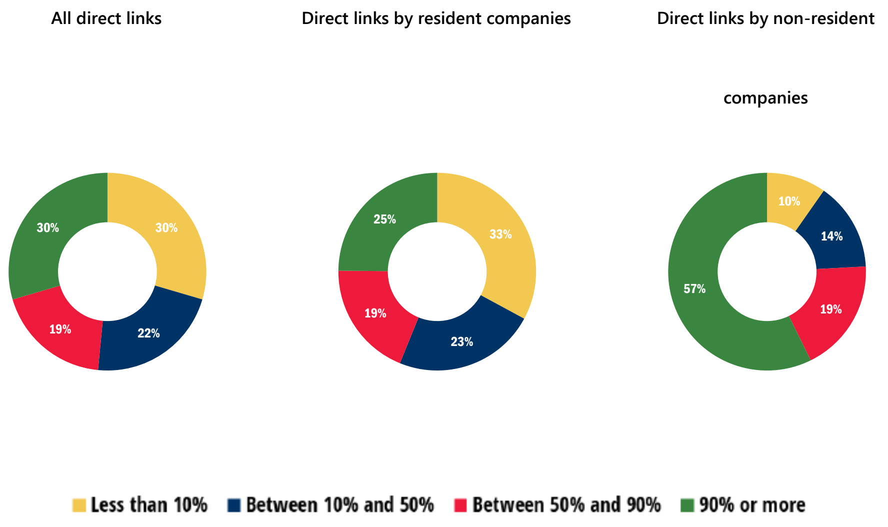


The number of equity participations and non-resident entities increased 65% and 62% in 2014, respectively. The huge increase in the number of UCIs is related to the rules applied in the new framework (Figure 8). All the reporting entities who declare the existence of, at least, one participation are obliged to identify the UCI.

Regarding the intensity of the direct shareholding link[1], 30% of the participations are below 10% (Figure 9), whereas majority equity capital stakes (more than 50%) represent 49% of the total number of equity participations. The fraction of participations in share capital above 50% are higher for non-resident rather than for resident entities (76% vs 44%). The equity participations higher than 90% represent 57% of the total equity participations held by non-resident entities, hence suggesting that non-resident entities investing in Portugal have the clear goal of controlling the management of companies.

Figure 9: Intensity of the direct shareholding link (in %, 2016)

[1] A similar analysis was performed by Heuse and Vivet (2017).



Box 1: The impact of the algorithm and the manual quality control

1. The impact of the algorithm

The reported equity participations, non-resident entities and UCIs are submitted to an algorithm developed at CBSO to build a complete and non-redundant business group database. The algorithm detects repeated equity participations and similar non-resident entities, eliminates duplicates and attributes the correct UCI.

The impact of the algorithm corresponds to deleted information shown on Figures 10 to 12. In 2016, 37% of reported equity participations, 11% of reported non-resident entities and 17% of reported UCIs were deleted.

2. The impact of manual quality control

Manual quality control will apply to treat situations not solved by the algorithm and also to complete missing information which are mainly detected through the analyses of foreign direct investment companies and consolidated annual reports. This validation procedure is based on information available in annual reports, companies' websites and through direct contacts to companies, by email or telephone and is done during the summer by 35 trainees selected from 5 universities of economics, management and accounting.

The impact of manual quality control is marginal when compared to the total reported information. Manual validation added new equity participations in an amount equivalent to 3% of the reported participations from 2014 to 2016 and changed only 0.3%. About non-resident entities, 9% of the total were added and 1% were changed. In the case of UCIs, manual quality control is residual, corresponding to 0.3% of the total.

Figure 10: Number of equity participations in IES

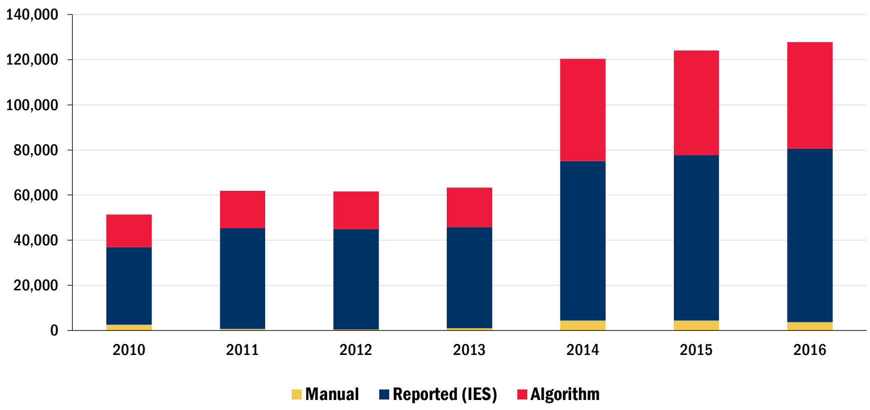


Figure 11: Number of non-resident entities in IES

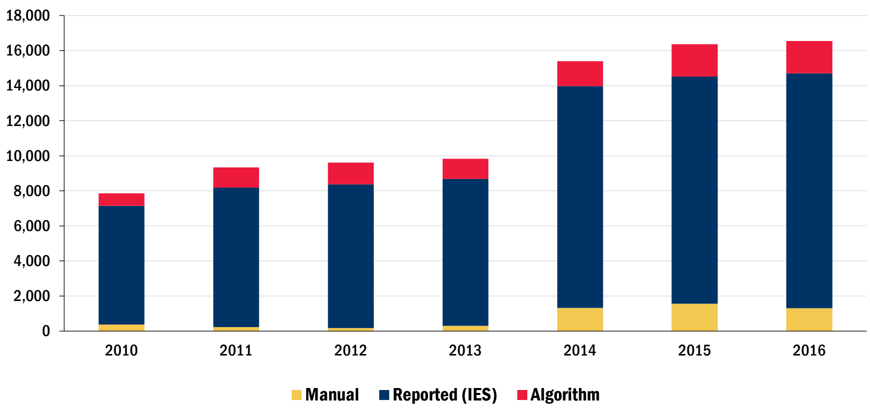
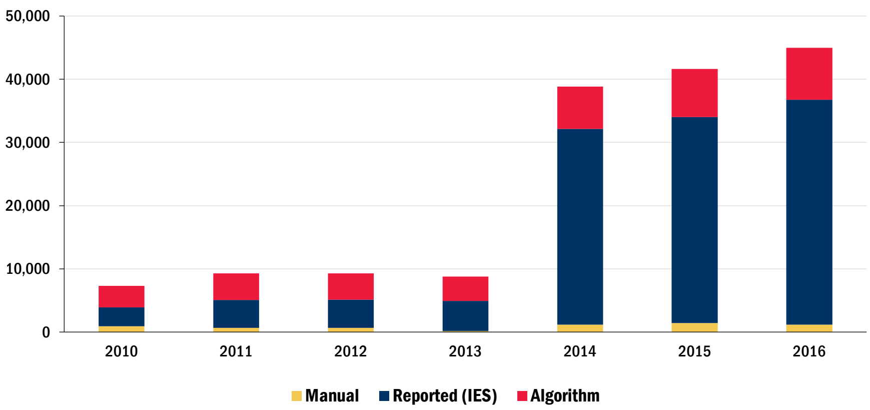


Figure 12: Number of UCIs in IES



4. Relevance of MNEs

Using the information available in the business groups' database and matching it with the information from individual accounts annual reports available at the CBSO allows us to understand the impact of MNEs in the NFCs sector (Banco de Portugal, 2018).

In this analysis, a business group is defined as a set of companies controlled, directly or indirectly, by the same UCI. The concept of control requires holding more than 50% of voting rights in another company or the existence of control due to shareholders agreements. Hence, taking the control into account, 15.182 business groups were identified in the business groups' database in 2016.

We split the business groups into three types[2]:

(1) All-resident enterprise groups: groups with resident entities only;

(2) Domestically controlled enterprise groups: groups with resident and non-resident entities, but with domestic control; and

(3) Foreign controlled enterprise groups: groups with resident and non-resident entities, but with foreign control.

Figure 13 shows the business groups entities split into resident and non-resident, by type of group. All-resident enterprise groups are, by definition, only composed by resident entities. In the MNEs, the proportion of non-resident entities is around 40%.

The number of groups by type is shown in Figure 14. In relative terms, around 50% of business groups in the database are all-resident and the other half is equally divided (25%) between domestically and foreign controlled groups.

Figure 13: Business group entities by type of group (2016)

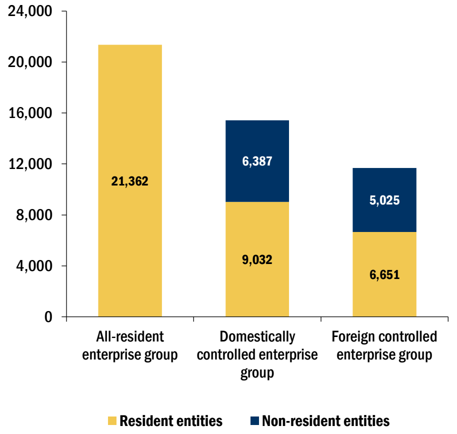
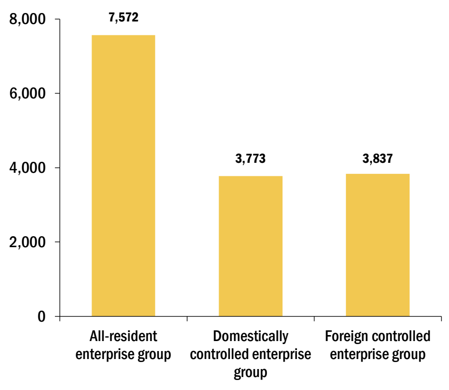


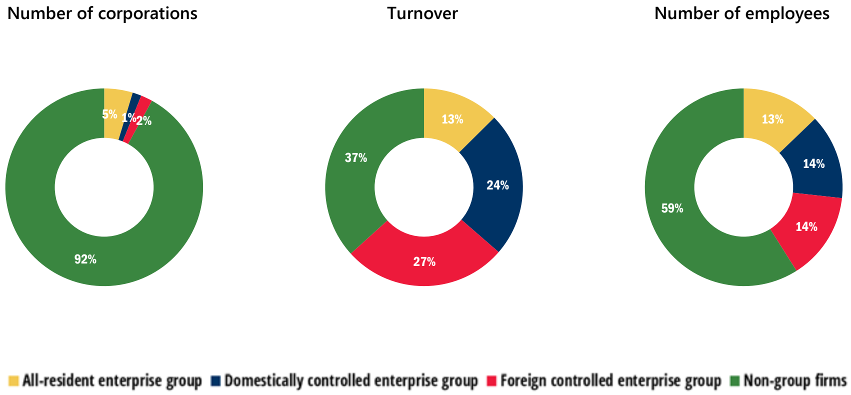
Figure 14: Number of groups by type of group (2016)



[2] These definitions and other related with MNEs are in the Annex.

The impact of MNEs in the Portuguese economy is evaluated in Figure 15 in terms of number of corporations, turnover and number of employees.

Figure 15: Resident NFCs by type of group (2016)

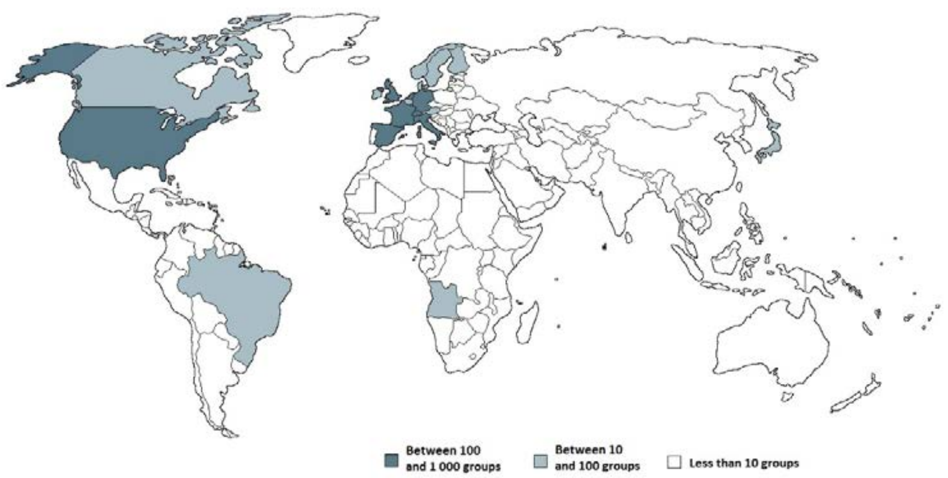


In 2016, although only 3% percent of the total NFCs are MNEs (both Portuguese or foreign controlled), they represent 51% of the turnover and 28% of the number of employees of this institutional sector, of which MNEs under foreign control respectively weighted 27 and 14 percentage points.

4.1 Foreign controlled MNEs

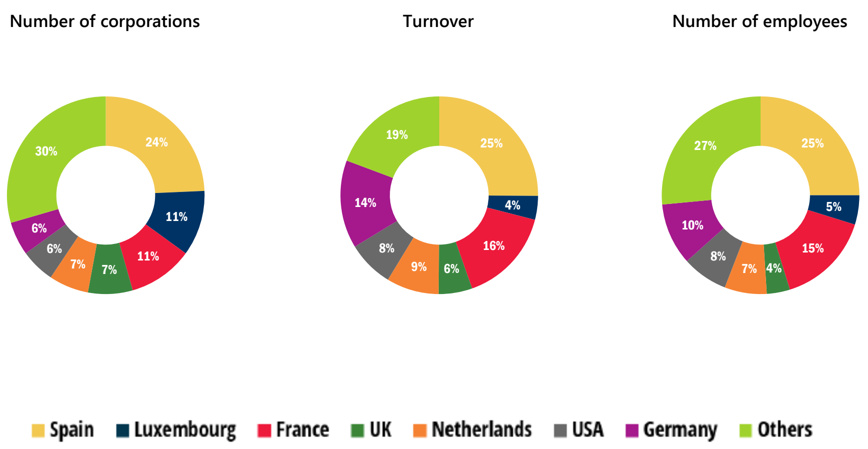
Geographical distribution of UCIs from foreign controlled MNEs shows a clear preponderance of European countries, large world economies like USA, Canada and Japan and some Portuguese speaking countries, namely Brazil and Angola (Figure 16).

Figure 16: Geographical distribution of UCIs with affiliates in Portugal



Spain appears as the most important ultimate investor in Portugal, controlling almost one quarter of resident NFCs, as well as one quarter of their turnover and employees (Figure 17). Entities from Luxembourg control 11% of companies in Portugal, but their importance in terms of the turnover and number of employees is not that significant, contrarily to what happens to entities from France and Germany, which are the ultimate investors of 17% of resident NFCs, representing 30% of the turnover and 25% of the number of employees of the NFCs sector.

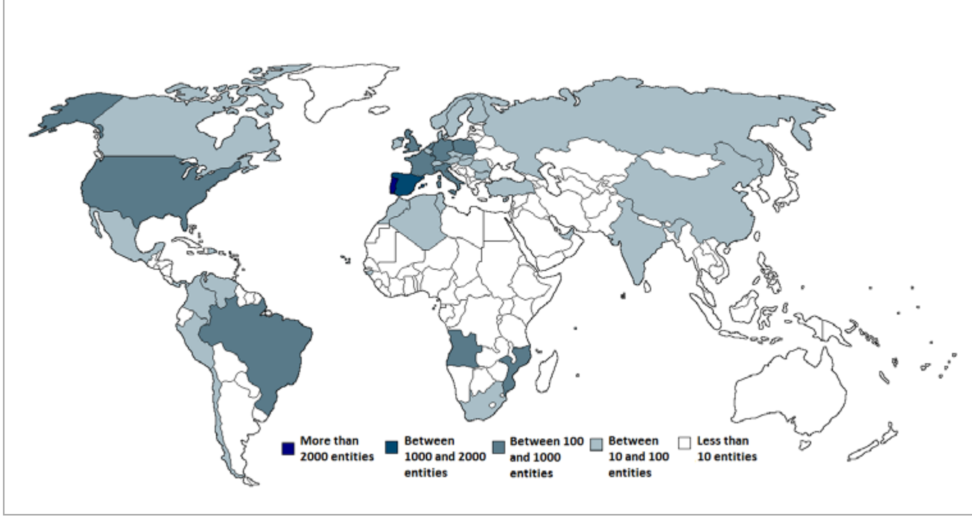
Figure 17: Foreign controlled MNEs by country of UCI (2016)



4.2 Portuguese controlled MNEs

Geographical distribution of Portuguese controlled MNEs overlap, to a certain extent, the geographical distribution of UCIs, exhibiting a strong relationship between the locations of domestically controlled MNEs and the country of the UCIs of foreign controlled groups (Figure 18).

Figure 18: Geographical distribution of Portuguese controlled MNEs



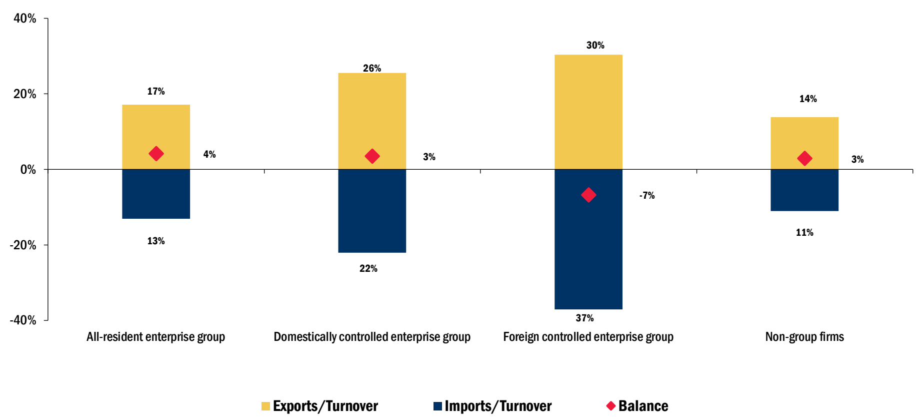
Spain is the most frequent destination of Portuguese controlled MNEs as is geographically closer for companies to start investing abroad and "benefit from corporate support functions at headquarters" (OECD, 2018). Spain is followed by other European large economies, such as France, UK and Germany. The presence of Netherlands and Luxembourg likely reflects the importance of Special Purpose Entities (SPEs) (OECD, 2018). Other large economies appear, like Russia, China, India, Latin America, North Africa regions and some Portuguese speaking countries, namely Brazil, Angola and Mozambique, with the common language leveraging foreign investment.

4.3 Economic and financial indicators

Some economic and financial indicators are presented, based on the sum of individual accounting data (non-consolidated), in order to better assess the influence of MNEs in the operating and financing activity of NFCs in Portugal (Banco de Portugal, 2018). Results for MNEs are exhibited alongside with the results for all-resident enterprise groups and non-group firms to stress the importance of MNEs.

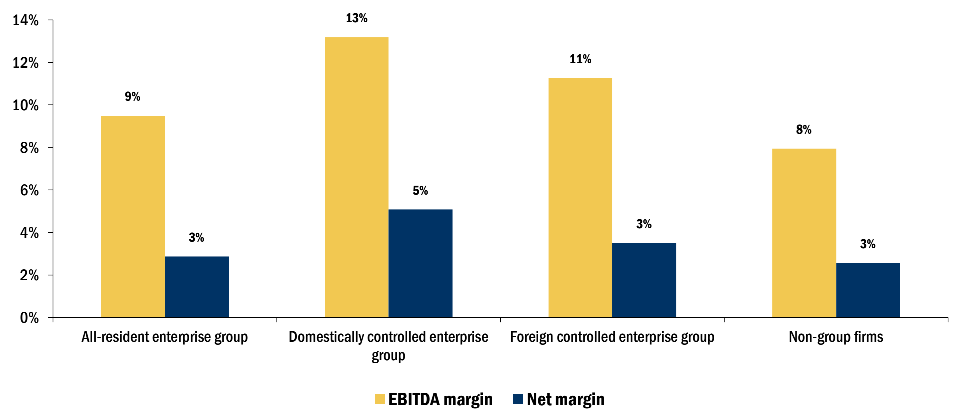
With respect to the operating activity, being part of a MNE usually implies a higher share of exports and imports in turnover. Figure 19 shows that more than 25% of the turnover generated by NFCs integrated in MNEs is exported. However, these firms also import relatively more, which leads to a negative balance (equivalent to 7% of the turnover) in the case of foreign controlled enterprises. Standalone NFCs (non-group firms) and NFCs from all-resident enterprise groups have similar structures. They export a smaller fraction of the turnover, but have positive balances.

Figure 19: Share of exports and imports in turnover (2016)



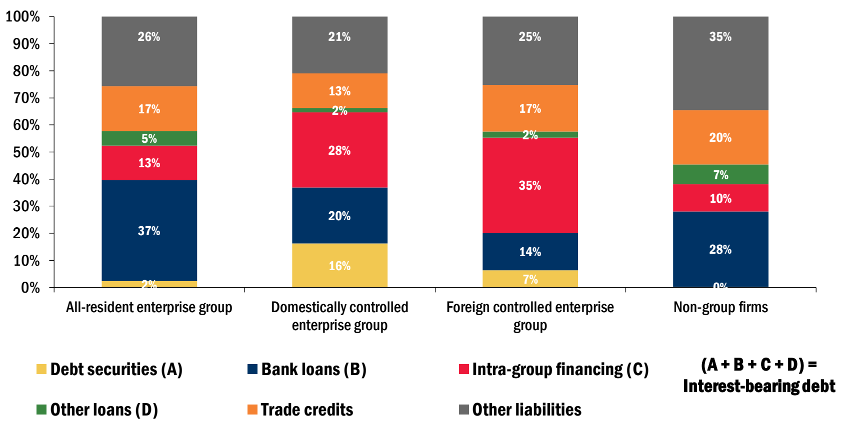
The analysis of EBITDA/Total revenues shows that MNEs are, on average, more efficient transforming revenues into operational results (Figure 20). However, there is no such a difference in the net margin, as depreciations and amortizations account for a greater percentage in total revenues of MNEs, given that they usually hold a larger amount of assets.

Figure 20: EBITDA and net margins (2016)



Another interesting distinctive feature between MNEs and all-resident and non-group firms regards the liabilities structure (Figure 21). On one hand, MNEs present a more diversified pattern of financing, in spite of the predominance of intra-group financing[3]. On the other hand, financing from debt securities is almost exclusive from MNEs. In all-resident enterprise groups and non-group firms, bank loans and other liabilities[4] prevail.

Figure 21: Liabilities structure



[3] In the context of the present analysis, group definition implies control (more than 50% of the voting rights or shareholders agreement). However, for lower voting power, intra-group financing could exist, which explains the existence of intra-group financing in non-group firms.

[4] "Other liabilities" includes income tax payable and other payables to public administrations, non-interest bearing shareholder loans, other accounts payable and other current liabilities.

5. Conclusion

This paper presents the work developed by Banco de Portugal to build a business groups' database in order to better evaluate business group relationships and understand how MNEs impact the NFCs sector and the external statistics.

The first step to successfully achieve that task was to use an administrative data source, electronic and mandatory for all NFCs. Afterwards, it was fundamental to develop an algorithm to read massive amounts of numeric and text information and implement a fuzzy matching procedure to check similarities and clearly identify and distinguish non-resident entities, equity participations and UCIs. Complementary to the automatic procedures, manual quality control is of great importance to fill in unsolved situations by the algorithm and some data gaps.

A business groups' database could be explored to perform useful analyses and studies. At the individual level, it is possible to visualize the group structure and get quick information about its entities through Tom Sawyer Software. At the aggregate level, it is also attainable to know in more detail the economic activity sectors and the world dispersion of non-resident entities belonging to Portuguese MNEs, as well as how MNEs contribute to the number of companies, turnover, employees and the results of NFCs sector. In 2016, despite accounting for only 3% of Portuguese firms, MNEs represented 51% of the turnover and 28% of the employees, thus confirming its importance in our economy.

In an increasingly globalised world MNEs will continue to expand their activities which poses a permanent challenge to high quality official statistics. Close cooperation between the statistical authorities, both domestically and internationally, is key to efficiently overcome the difficulties. It is also needed an adequate framework for the sharing of data, where the whole is greater than the sum of its parts. Complementarily, initiatives to promote the use of the Legal Entity Identifier (LEI) or even to make it mandatory should also be pursued.

The CMFB workshop on globalisation (July 2018) showed that there is already a significant number of initiatives going on but there is still work to be done. The use of blockchain for data protection, web scrapping and artificial intelligence for MNEs' profiling, the creation of a common Large Case Unit or *"an AnaCredit for MNEs"* were some of the boldest ideas that, in our opinion, could pave the way to MNE accounts.

Annex – Definitions

All-resident enterprise group

An enterprise group composed only of enterprises that are all resident in the same country (Business Registers Recommendation Manual).

Global decision centre

Institutional unit where the decisions on the global strategy of the group are taken (Business Registers Recommendation Manual).

Domestically controlled enterprise group

A multinational group where the global decision-centre is in the country compiling the business register (Business Registers Recommendation Manual).

Enterprise group

Council Regulation (EEC) No. 696/93 on Statistical Units defines the Enterprise Group as "an association of enterprises bound together by legal and/or financial links. A group of enterprises can have more than one decision-making centre, especially for policy on production, sales and profit. It may centralize certain aspects of financial management and taxation. It constitutes an economic entity which is empowered to make choices, particularly concerning the unit it comprises".

Foreign controlled enterprise group

A multinational group where the global decision-centre is outside the country compiling the business register (Business Registers Recommendation Manual).

Multinational enterprise group

The Business Register Regulation states in article 2(d) "Multinational enterprise group shall mean an enterprise group which has at least two enterprises or legal units located in different countries".

Multinational enterprise (MNE)

Multinationals usually comprise companies or other entities established in more than one country and so linked that they may co-ordinate their operations in various ways. While one or more of these entities may be able to exercise a significant influence over the activities of others, their degree of autonomy within the enterprise may vary widely from one multinational enterprise to another (OECD, 2011).

A note in the Business Registers Recommendation Manual (p. 309) refers that, although the definition is ambiguous, 'Multinational enterprise' is used in the same meaning as 'Multinational enterprise group'.

Ultimate controlling institutional unit (UCI)

The institutional unit, proceeding up in the affiliate's chain of control, which is not controlled by another institutional unit (Regulation (EC) No 716/2007). Foreign Affiliates Statistics (FATS) use the resident country of the ultimate controlling institutional unit (UCI) as global decision-centre.

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OECD Glossary of Tax Terms. Retrieved from https://www.oecd.org/ctp/glossaryoftaxterms.htm

Regulation (EC) No 716/2007 of the European Parliament and of the Council of 20 June 2007 on Community statistics on the structure and activity of foreign affiliates

Regulation (EC) No 177/2008 of the European Parliament and of the Council of 20 February 2008 establishing a common framework for business registers for statistical purposes and repealing Council Regulation (EEC) No 2186/93

Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

Keeping track of MNEs through business group databases: the experience of Bank of Portugal[1]

Ana Bárbara Pinto, José Alexandre Neves and Tiago Pinho Pereira,

Bank of Portugal

[1] This presentation was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

Keeping track of MNEs through business group databases: The experience of Banco de Portugal

Ana Bárbara Pinto • Statistics Department

9th IFC Conference on
Are post-crisis statistical initiatives completed?
30th and 31st August 2018

BANCO DE PORTUGAL
EUROSYSTEM

AGENDA

- DATA SOURCE
- THE BUSINESS GROUPS' DATABASE
- BRIEF CHARACTERIZATION OF THE DATABASE
- RELEVANCE OF MNES

1. DATA SOURCE

IES
Informação Empresarial Simplificada

Simplified Corporate Information

is the legal deposit of accounts

ANNEX A: reported by non financial companies

BANCO DE PORTUGAL
EUROSISTEMA

INSTITUTO NACIONAL DE ESTATÍSTICA
STATISTICS PORTUGAL

finanças

Annual data

(last year available: 2016)

Mandatory

100%

electronic format

More than

400.000 non-financial companies

(all)

More than

3.000 items:

Balance-sheet, income statement, statement of changes in equity, cash flow statement and the annex to the financial statements

Related parties

(1) Resident Entities

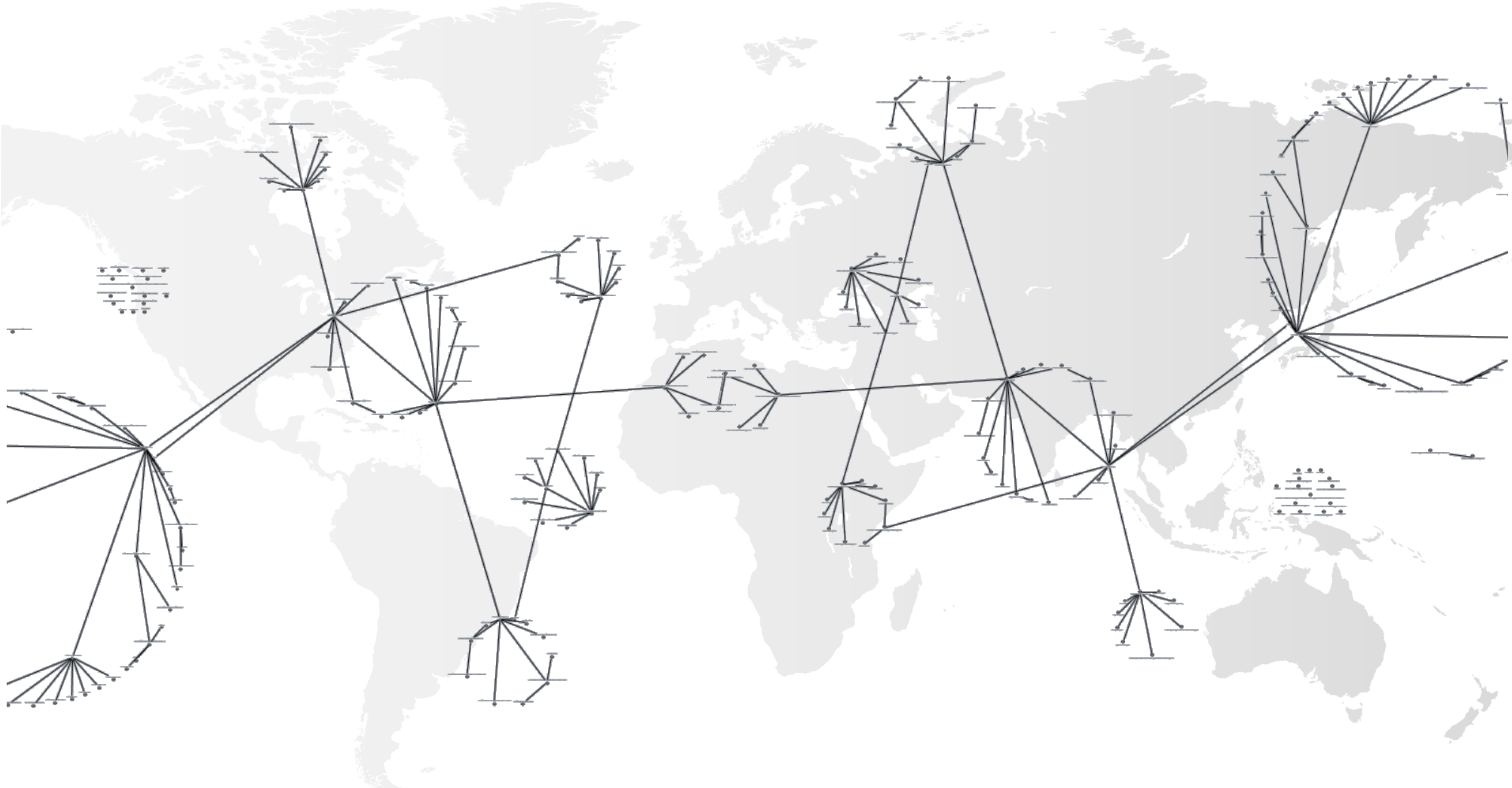
- IDBP
- Tax ID
- LEI
- Name
- NACE
- UCI

(2) Equity participations

- IDBP (Participant)
- IDBP (Participated)
- Share Capital (%)
- Voting Rights (%)
- Starting date of ownership
- Ending date of ownership

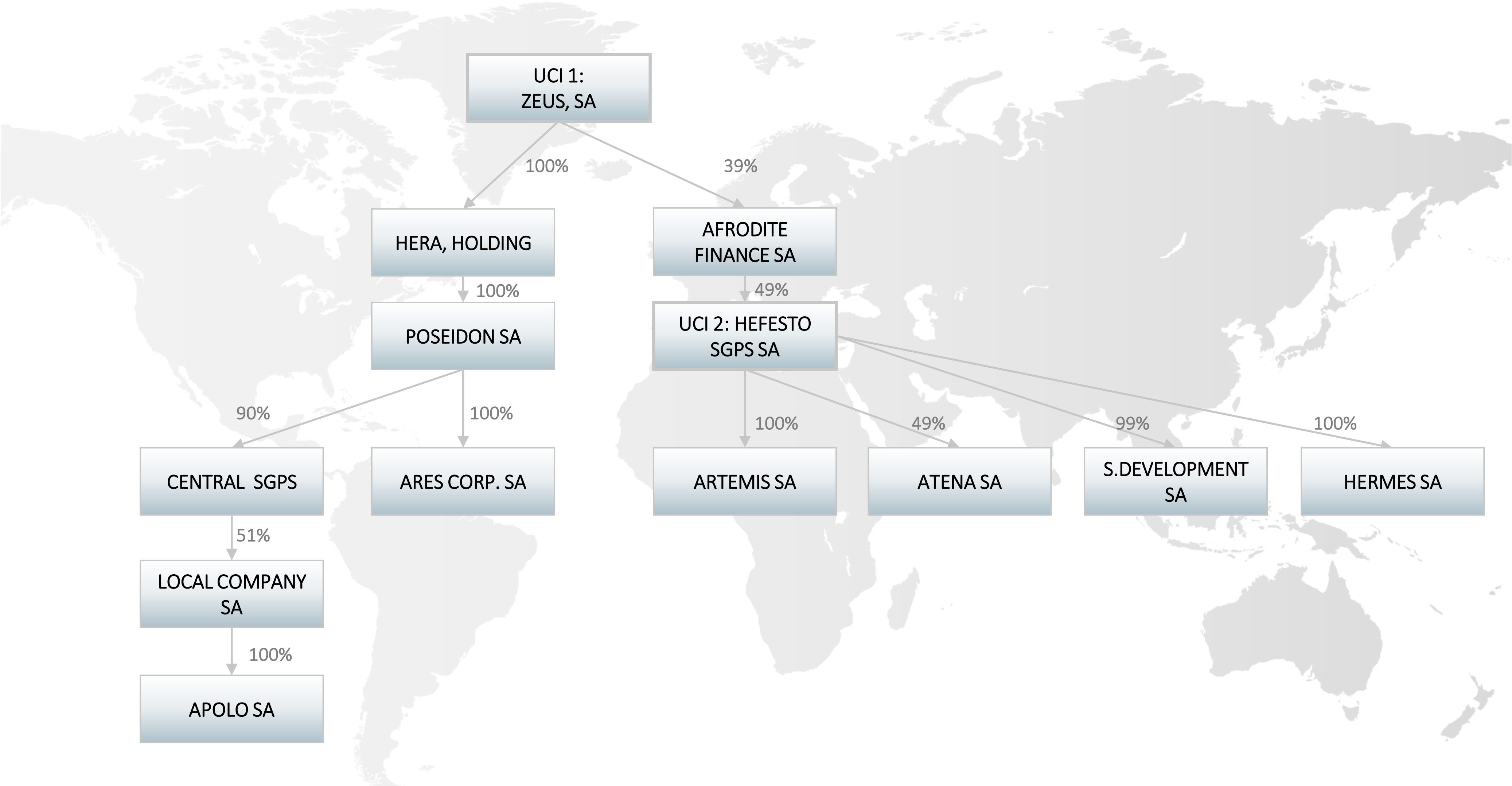
(3) Non-resident Entities

- IDBP
- Tax ID
- LEI
- Name
- NACE
- Country
- UCI



[1] **All Names and Tax IDs used are fictional and based in the Greek and Roman mythology**

2. THE BUSINESS GROUPS' DATABASE | **2.1. ARCHITECTURE AND VISUALIZATION**



[1] **All Names and Tax IDs used are fictional and based in the Greek and Roman mythology**

- The same non-resident entities is reported by different resident NFC.
- Non-resident entities are identified by Tax payer identification number (Tax ID), Name and Country.
- A check digit validation only applies for national tax payer numbers.

If it is not possible to unequivocally identify a non-resident entity, **manual quality control will apply**.

The algorithm compares the attributes of all non-resident entities and if[1]:

Situation 1
Tax ID, Name and Country are equal

The entity is considered the same

[1] All Names and Tax IDs used are fictional and based in the Greek and Roman mythology

- The same non-resident entities is reported by different resident NFC.
- Non-resident entities are identified by Tax payer identification number (Tax ID), Name and Country.
- A check digit validation only applies for national tax payer numbers.

If it is not possible to unequivocally identify a non-resident entity, **manual quality control will apply**.

The algorithm compares the attributes of all non-resident entities and if[1]:

Situation 2

Country is the same & Tax ID is **equal**

Fuzzy lookup compares the name -> the same entity when similarity > than 55%;

EXAMPLE!

Name: FLORA SA France
Tax ID: 96720542239

Name: FLORA SA
Tax ID: 96720542239

Are compared as “**FLORASAFRANCE**” and “**FLORASA**” and considered the same company;

[1] All Names and Tax IDs used are fictional and based in the Greek and Roman mythology

- The same non-resident entities is reported by different resident NFC.
- Non-resident entities are identified by Tax payer identification number (Tax ID), Name and Country.
- A check digit validation only applies for national tax payer numbers.

If it is not possible to unequivocally identify a non-resident entity, **manual quality control will apply**.

The algorithm compares the attributes of all non-resident entities and if[1]:

Situation 2

Country is the same & Tax ID is **different**

Fuzzy lookup compares the tax payer identification number and the name (Tax ID, Name) -> similarity > than 70%;

EXAMPLE!

Name: Ares Corp. SA
Tax ID: 70253621

Name: Ares SA
Tax ID: AB7025321 (slightly different)

Are compared as "**70253621AresCorpSA**" and "**AB7025321AresSA**" are considered the same company;

[1] All Names and Tax IDs used are fictional and based in the Greek and Roman mythology

2. THE BUSINESS GROUPS' DATABASE | **2.2.1. ALGORITHM - NON-RESIDENT ENTITIES**

- The same non-resident entities is reported by different resident NFC.
- Non-resident entities are identified by Tax payer identification number (Tax ID), Name and Country.
- A check digit validation only applies for national tax payer numbers.

If it is not possible to unequivocally identify a non-resident entity, **manual quality control will apply**.

The algorithm compares the attributes of all non-resident entities and if[1]:

Situation 3

Country is different

Similarity of (Tax ID, Name)

> than 70%

Entities are selected for manual check

< than 70%

Entities are considered different

[1] All Names and Tax IDs used are fictional and based in the Greek and Roman mythology

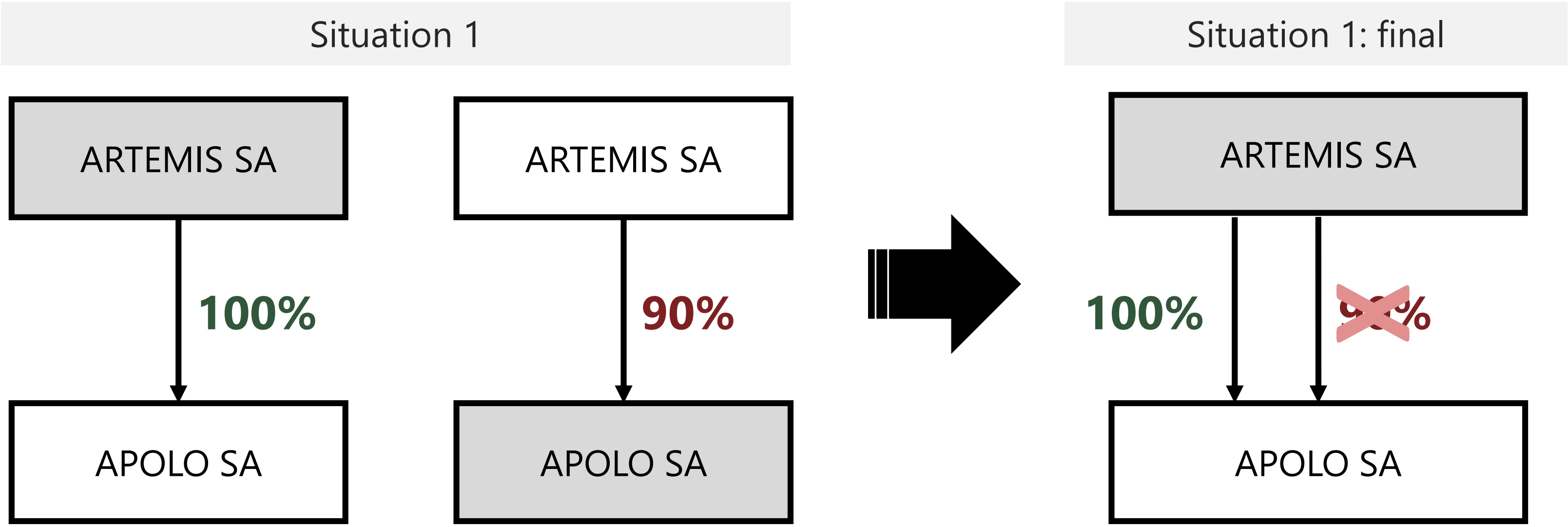
The same participation reported by different resident companies

Participation involving reporting entity filed as indirect

If it is not possible to unequivocally identify a participation, **manual quality control will apply**.

The algorithm establishes the following hierarchy:

- Repeated participations are deleted
- Indirect participations where the reporting entity is identified are deleted
- Direct participations prevail over indirect participations
- Direct downward participations prevail over direct upward participations



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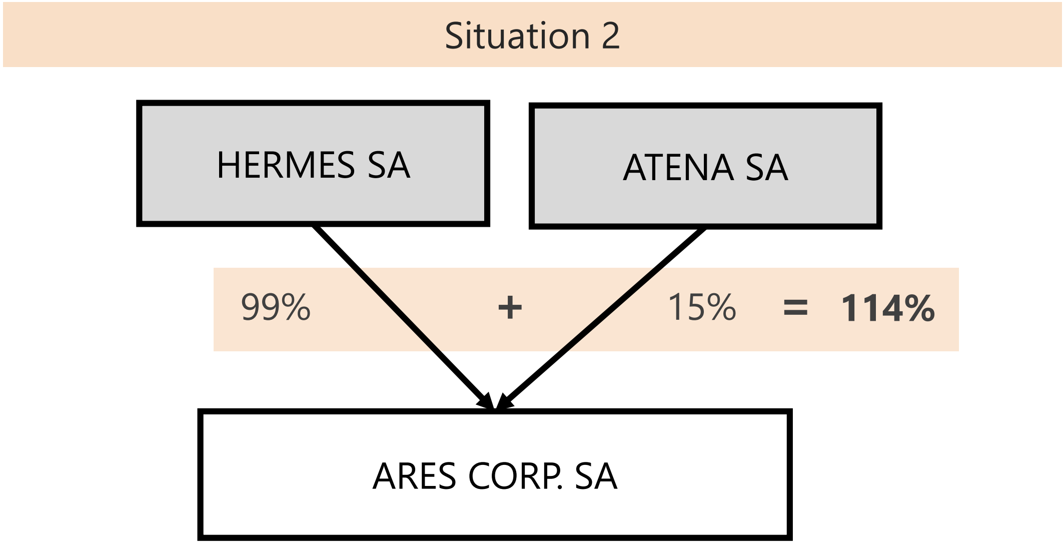
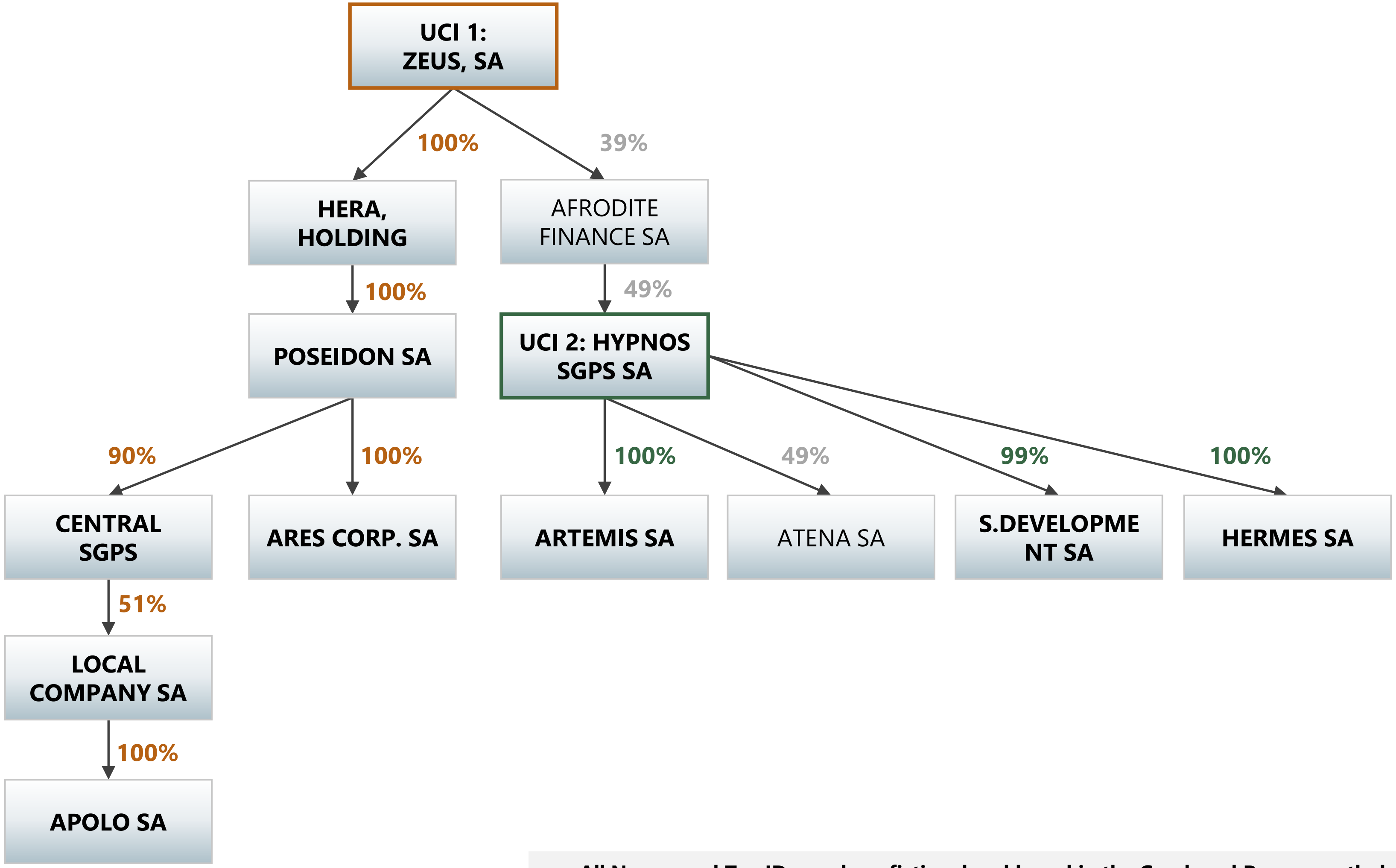


! UCI inconsistencies - companies tend to wrongly identify themselves as UCI

The **algorithm analyse** the chain of voting rights higher than 50% and go up into the group structure to find out the correct UCI

The UCI of the group will be **the company on the top of the control chain**

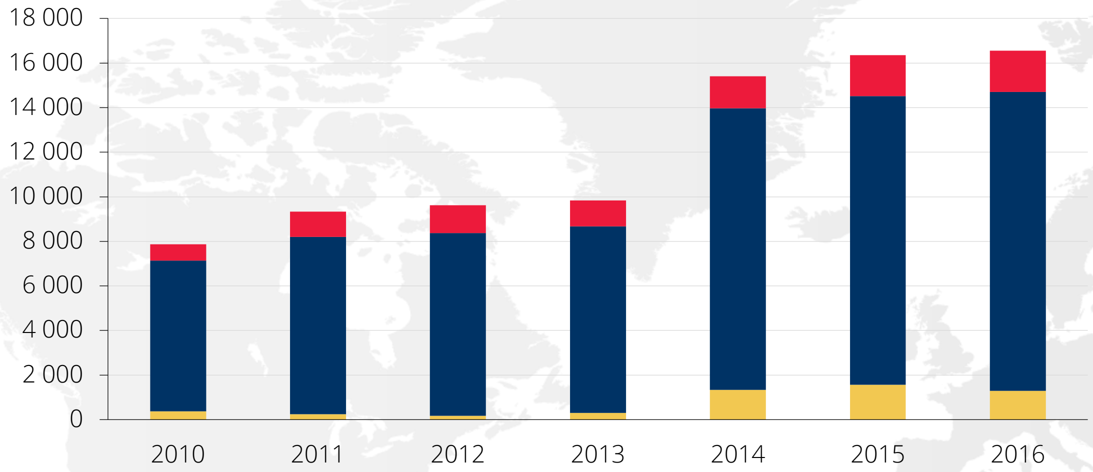
If it is not possible to unequivocally identify a UCI, **manual quality control will apply**.

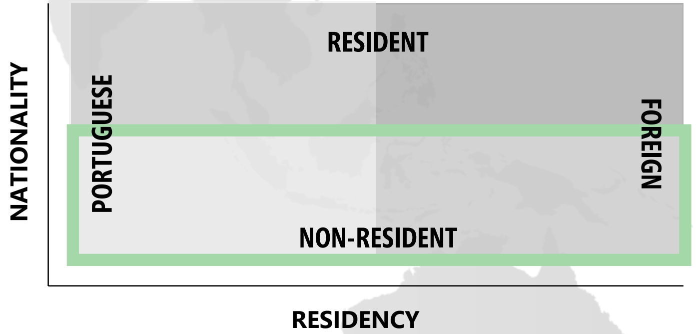


All Names and Tax IDs used are fictional and based in the Greek and Roman mythology

2.3. THE IMPACT OF THE ALGORITHM AND THE MANUAL QUALITY CONTROL

Number of non-resident entities in IES

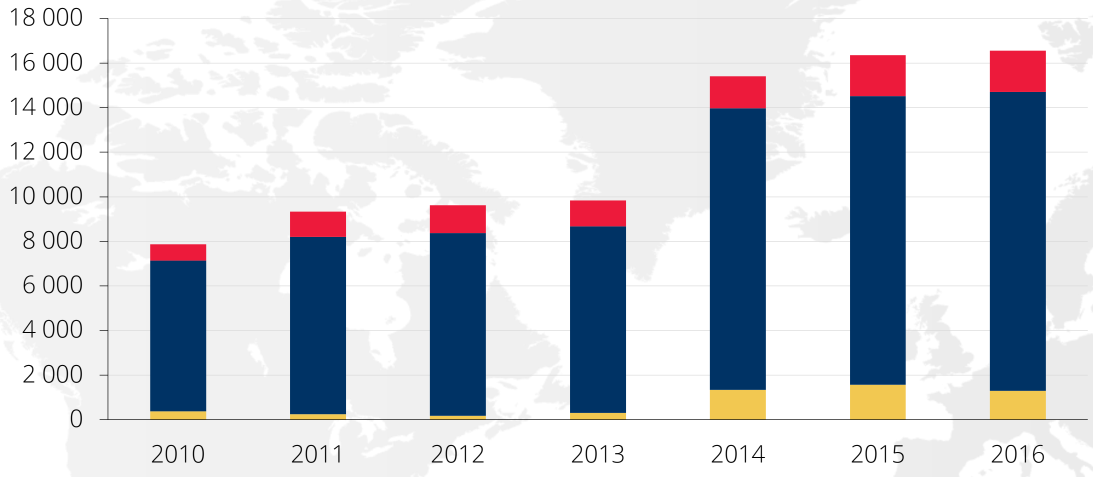




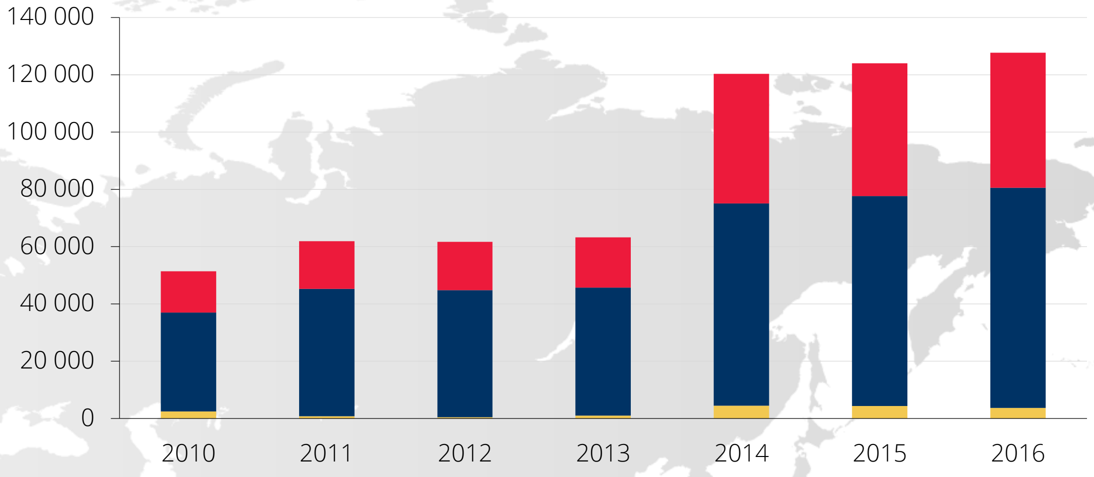
Manual Reported (IES) Algorithm

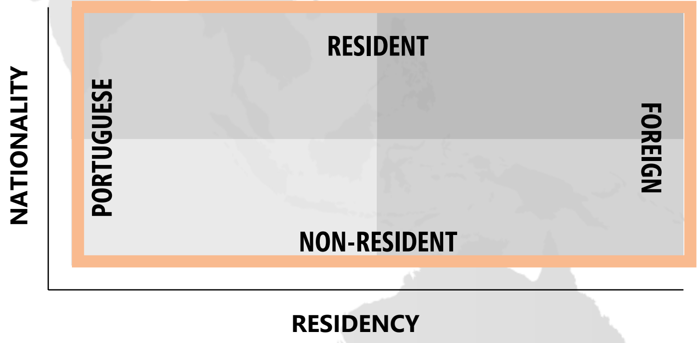
2.3. THE IMPACT OF THE ALGORITHM AND THE MANUAL QUALITY CONTROL

Number of non-resident entities in IES



Number of participations in IES





Manual Reported (IES) Algorithm

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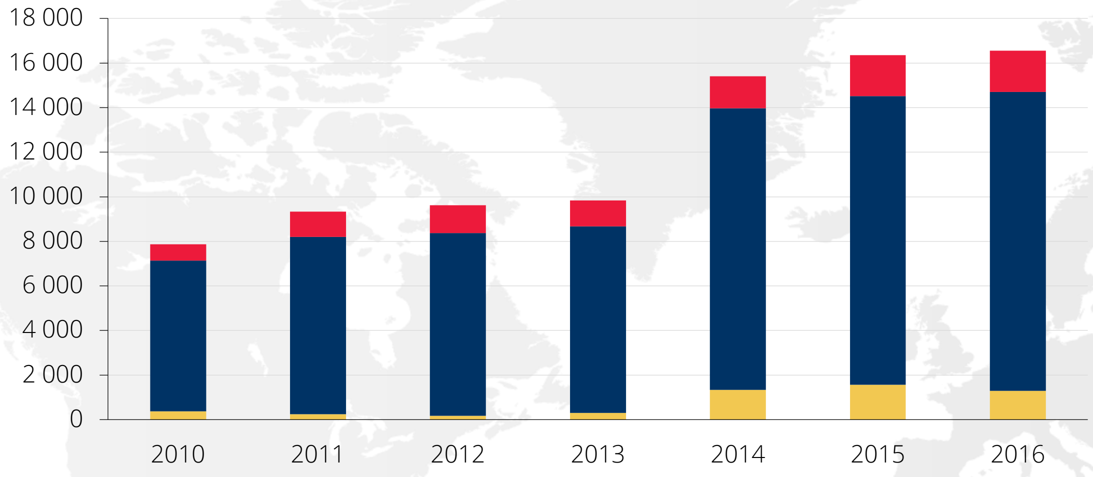
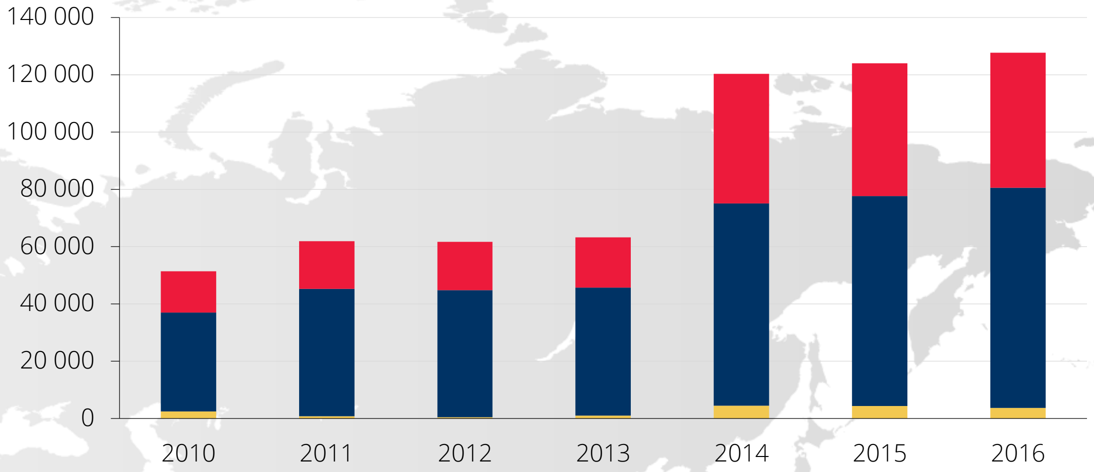
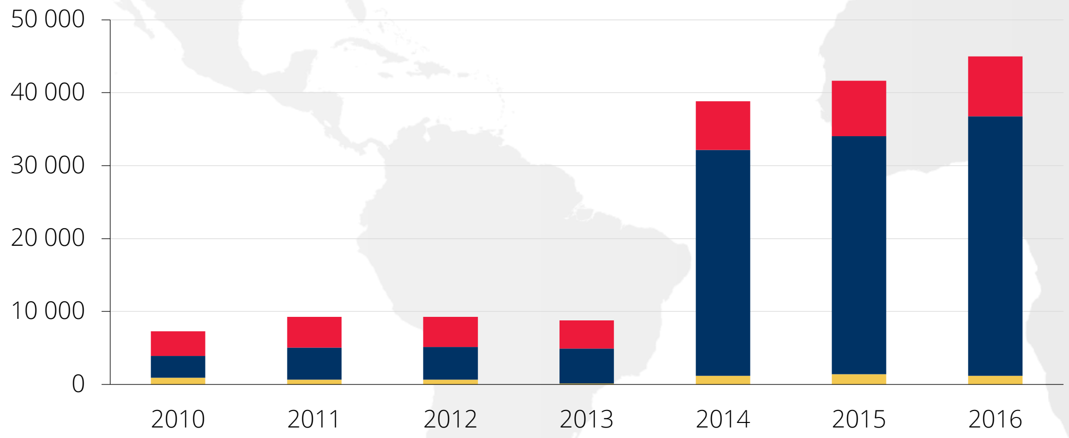
Number of non-resident entities in IES

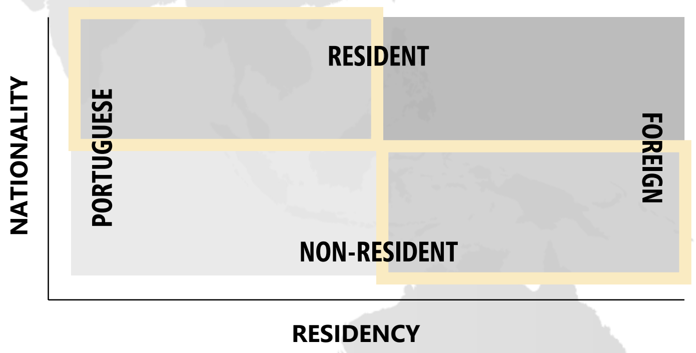


Number of participations in IES



Number of UCIs in IES

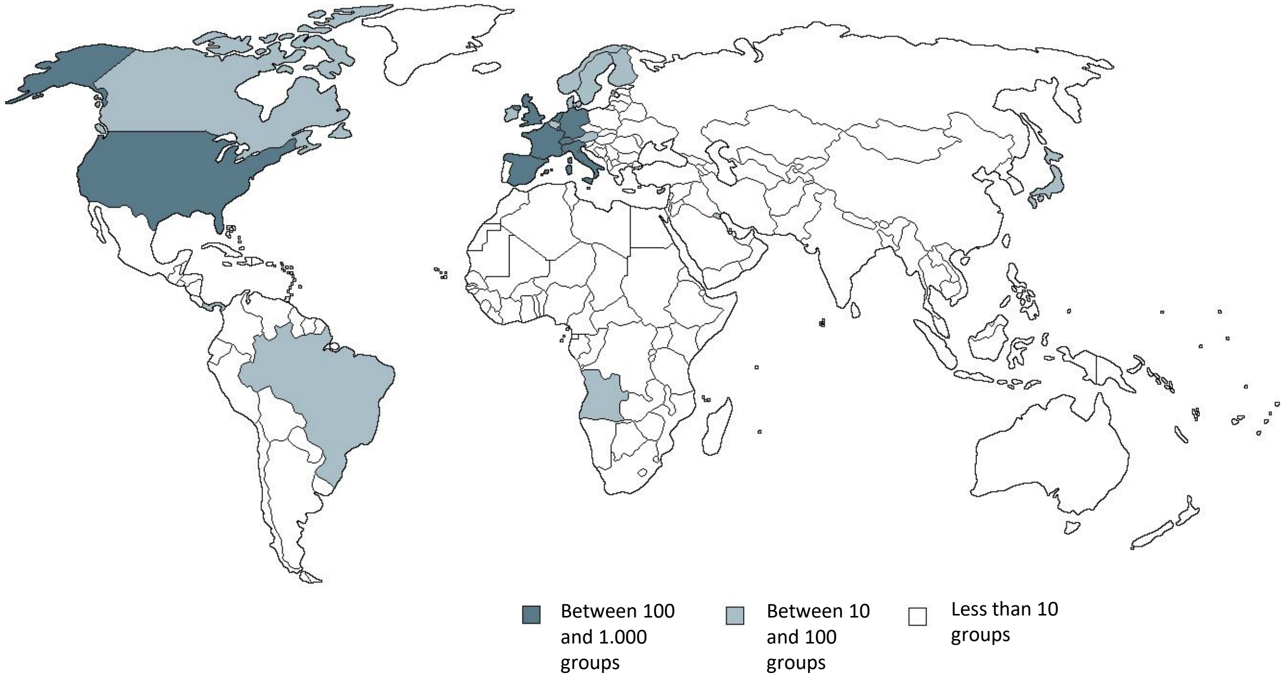




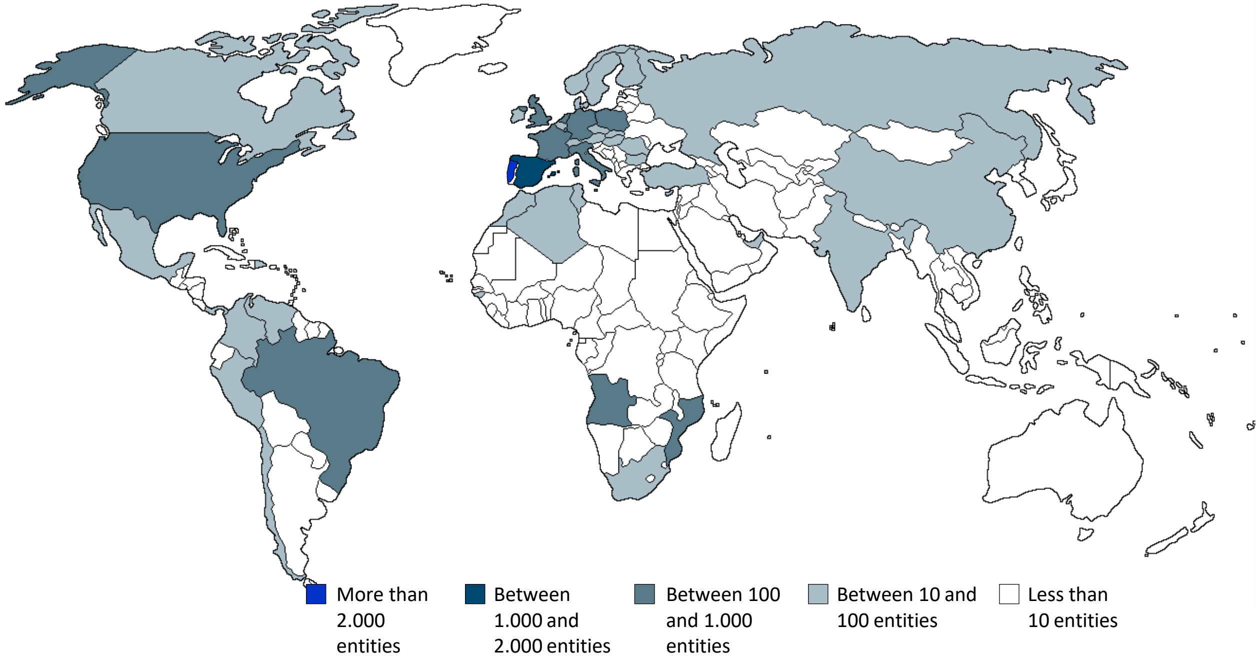
Manual ■ Reported (IES) ■ Algorithm

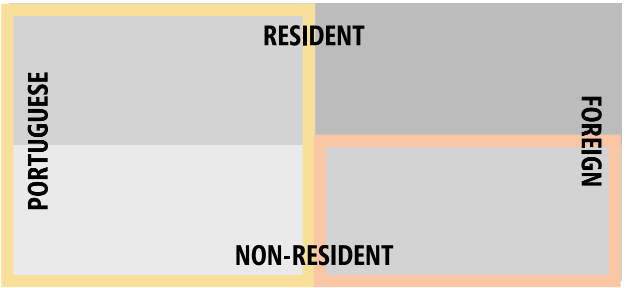
3. BRIEF CHARACTERIZATION OF THE DATABASE: SOME FIGURES (2016)

Geographical distribution of UCI with affiliates in Portugal



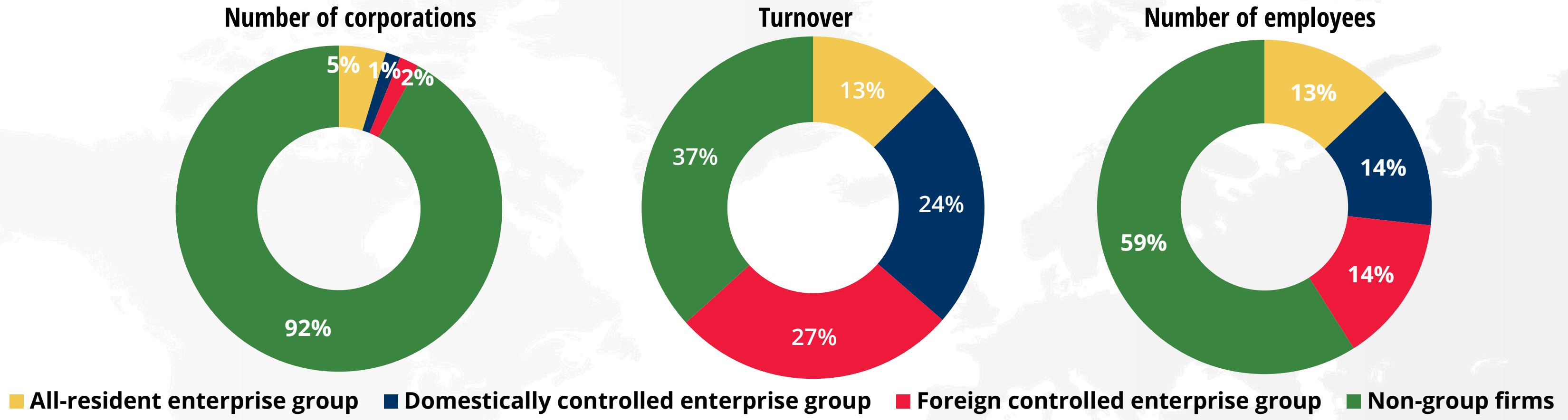
Geographical distribution of Portuguese controlled MNEs

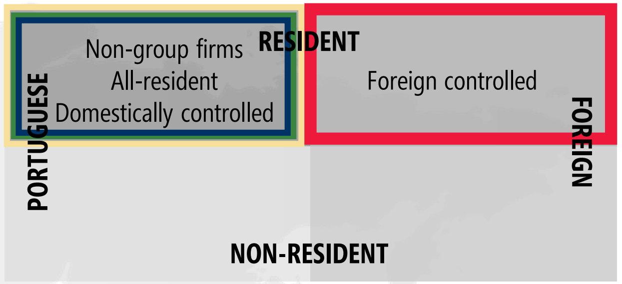




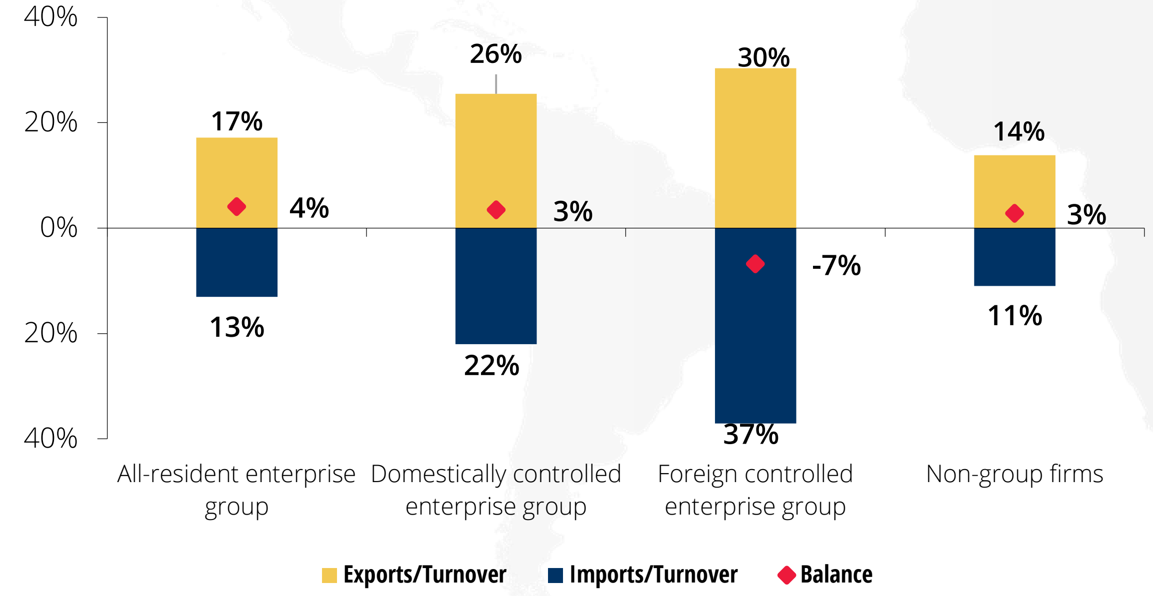
4. RELEVANCE OF MNES (2016)

Resident NFCs by type of group

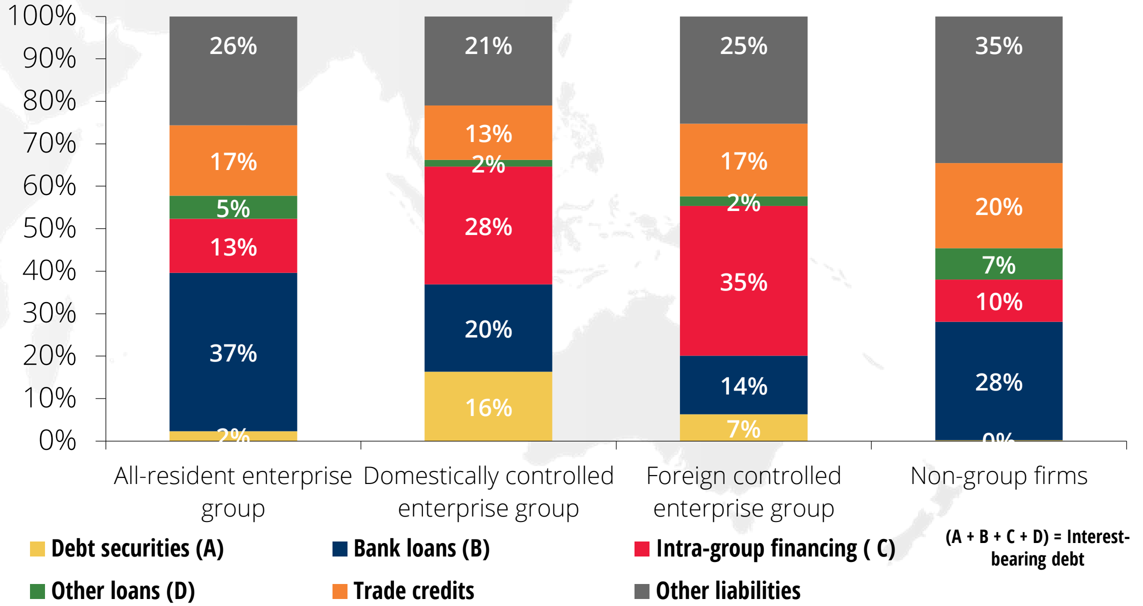




Share of exports and imports in turnover



Liabilities structure



CONCLUDING REMARKS

Improving the quality of business groups' data

- Close cooperation between statistical authorities at a national and international level
- Establishment of an effective framework to interchange data
- LEI mandatory for all entities operating in international markets (used as a key to identify non-resident entities)

THANK YOU FOR YOU ATTENTION

Ana Bárbara Pinto ● Statistics Department

Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

Cross-country bank-firm lending relationships: How can the Legal Entity Identifier help?[1]

Jose Maria Serena Garralda,

Bank for International Settlements

[1] This paper was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

Cross-country bank-firm lending relationships: How can the Legal Entity Identifier help?

Jose Maria Serena Garralda

Abstract

Bank-firm lending relationships are often constructed combining loan, firm, and bank data from commercial providers. In this paper we emphasize that datasets are best combined using borrowers and lenders' global identifiers. The three advantages are: flexibility to define relationships on a solo or a consolidated basis; efficiency to mobilise data without ad-hoc cross-checks; and relevance, since exposures reflect the actual legal arrangements in loan contracts. The Legal Entity Identifier system is theoretically well-suited for this purpose: it uniquely identifies legal entities engaged in financial transactions, provides entity-parent hierarchies, and certifies quality. However it is still incomplete. Thus we use the parallel systems of global identifiers developed by the financial industry. To illustrate the advantages of our approach, we examine the credit risks in banks' loans portfolios using borrowers' debt to EBITDA.

Keywords: bank-firm exposures, syndicated loans, matching datasets, Legal Entity Identifier.

JEL classification: C80, C81, F36, G15

Contents

1. Introduction

The Great Financial Crisis (GFC) was a major banking crisis impacting in the world economy through a contraction in bank lending. In its aftermath the lack of data on cross-country bank-firm exposures was perceived as a major gap. Data availability has increased, partly as a result of the Data Gaps Initiative (DGI) and data collected by the International Data Hub (IDH) of the BIS.

Cross-country bank-firm exposures can also be constructed combining three commercial datasets: syndicated loans, firm, and bank-level datasets. This requires firstly matching syndicated loan borrowers and lenders to, respectively, firm and bank-level datasets. Second estimating the outstanding credit of a bank to a firm using loans' issuance and original maturity dates.

The main challenge of the exercise is to match borrowers / lenders to firm / bank-level datasets. So far this is done comparing their names. Names have been traditionally compared manually -ie judging ad-hoc if they are similar enough. More recently name comparison is conducted using fuzzy matching: an algorithm computes a string similarity metric (eg Levenshtein distance), to evaluate if two names are similar enough -ie if the metric is below a threshold.

Fuzzy matching is fast but has some drawbacks. First, name similarity does not guarantee accuracy –eg two different companies could have the same name. Second, results need not be consistent with the complex arrangements between borrowers and lenders. For instance a firm might borrow through an affiliate, and the loan contract make explicit that the ultimate exposure corresponds to the parent. If the borrower name is unrelated to the parent name, name comparison is misleading. Third, matches are not flexible: researchers may be *alternatively* interested in measuring exposures on a consolidated, or an entity-level basis.

To address these problems we propose combining loan, firm, and bank through entities' global identifiers. This is feasible, since loans are legal contracts, unambiguously expliciting which entities are borrowing and lending. The Legal Entity Identifier (LEI) system is theoretically well-suited for this exercise, as was introduced precisely to accurately identify legal entities involved in financial transactions; provides entity-parent hierarchies, and the quality of LEIs is regularly checked. The main drawback of the LEI system is the lack of coverage among non-financial corporates, implying that many borrowers have not issued an LEI. As an alternative we use the system of global identifiers developed by the financial industry (Thompson Reuters permanent ID). They identify entities across datasets, and provide (static) entity-parent links. Our proposal is thus related with efforts to improve combination techniques using information on hierarhichal relationships (Cohen et al., 2018).

The dataset we construct is useful for a variety of purposes. We highlight the advantages examining credit risks in banks' loans portfolios. Credit risks can be assessed analysing borrower's financial health (debt to EBITDA ratio), for the outstanding loans of each bank. The data are useful for a variety of additional purposes. For instance, it can help to evaluate the impact of reforms on banks' lending to firms, and their activity. Some aspects of the dataset can be improved looking ahead –in particular the size of credit exposures. The actual size might depart from our estimations, since we do not adjust for risk transfers after the origination of the loan. This assumption is restrictive, since banks might buy CDS to gain protection; sale the loan; or change the terms and conditions after its inception.

The remainder of the paper is structured as follows. Section 2 reviews previous work constructing bank-firm relationships using commercial data. Section 3 presents our methodology, emphasizing the importance of using global identifiers; and the actual limitations to the use of the LEI, due to lack of coverage among loan borrowers. Section 4 summarises the data we use. Section 5 presents the main results. Section 6 concludes.

2. Literature review

The literature has explored two alternative ways of gauging cross-country bank-firm lending relationships using commercial data.

The first one consists in using data on bank-firm relationships, as collected by a data provider -for instance Kompass. Such data are ultimately obtained from chambers of commerce, firm registries, and phone interviews (Kalemli-Ozcan, Laeven, and Moreno, 2018). Survey data has drawbacks since ensuring responses are consistent on the cross-section and over time issue is challenging. Besides survey data does not provide information on the type of relationship (eg type of loan, currency, remaining maturity, and so on).

The second, more popular alternative consists in constructing lending relationships from loan data, gathered by commercial data providers. Loan data are reported by banks, which have the incentives to disclose deals to signal their market share. Loan data includes syndicated loans, but also some smaller deals (bilateral and club deals). Previous literature, focused on the US, has constructed bank-firm lending relationships comparing the names of borrowers (lenders) to the names of firms (banks) in their corresponding datasets. For instance, Chava-Roberts (2008) estimated borrower-firm links comparing the names of borrowers in Dealscan to the names of firms in Compustat.[1] Name comparison is also used to construct lender-bank links (Schwert, 2018a).

Name comparison is now automatized through probabilistic techniques (fuzzy matching) which estimate the similarity between names (eg Levenshtein distance, Jaro-Winkler); and use a threshold to evaluate if names are similar enough. Recent research has concluded that the results obtained using these techniques are enhanced using corporates hierarchical information (Cohen et al., 2018). Adjustments on entity-parent links through mergers and acqusitions (Schwert, 2018b) have also been used to define lender-bank links (Schwert, 2018b).

3. Methodology

3.1. Benefits and limits of identifiers

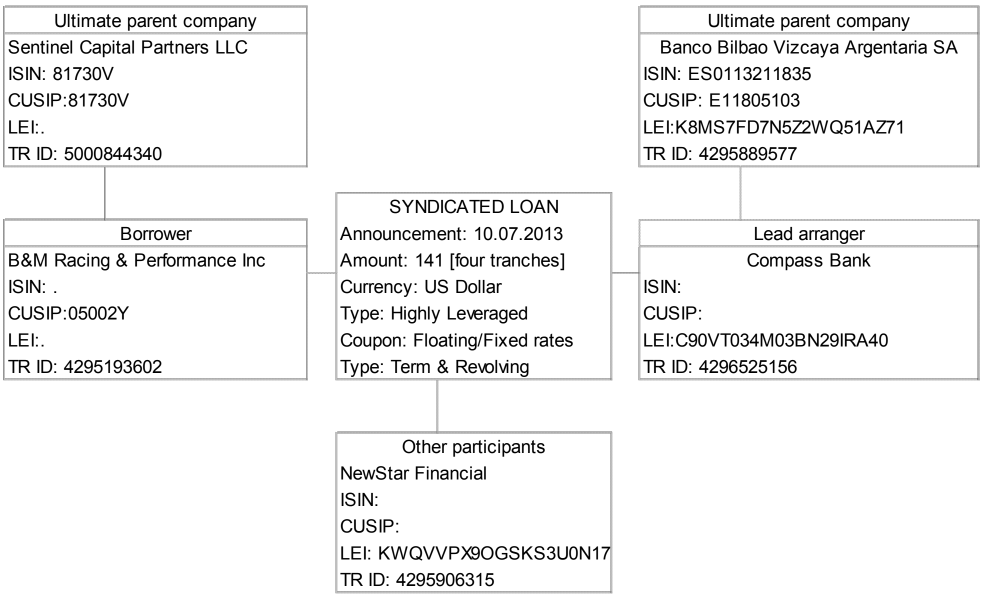
We argue that matching datasets using plain name comparison has three problems: name comparison is not accurate (Mehrhoff, 2018), the links may lack economic

[1] Chava-Roberts links are widely used in economic research to investigate bank-firm relationships (eg Acharya et al., 2018).

meaning, and they lack flexibility. These problems simultaneously appear, for instance, when firms use special purpose vehicles (SPVs) to raise funds. SPVs names can be loosely related to the ultimate borrower name, raising doubts on the relevance of the matches; and matches are likely inaccurate (thus requiring ad-hoc cross-checks).[2] Concerning flexibility: researchers need to simultaneously know the direct borrower, its immediate and ultimate parent. Reserchers may be interested in the direct borrower, if they seek to understand location; or in the parent entity, if the interest is on credit risk.

We argue that these problems can be tackled using a system of global identifiers. Diagram 1 sketches how bank-firm exposures can be estimated using global identifiers. Loans are complex legal contracts, and the terms and conditions are discussed and agreed on by parties. Among other aspects loans make explicit the legal entities acquiring the credit and the liability. Financial data providers identify each party by an (several) alphanumeric code(s): LEI, Thompson Reuters permanent ID, ISIN, or SDC CUSIP. Besides within their systems each entity related to its parent (if any).

Diagram 1. Bank-firm exposures using global identifiers



Source: TR Eikon, own elaboration.

Using global identifiers for statistical, large-scale production has some problems: some identifiers are not always available (eg the LEI), or can change over time (eg CUSIP). The financial industry has produced systems of global identifiers (FIGI, Thompson Reuters ID) which address some of these problems: each legal entity receives a unique alphanumeric code, stable over time. Still, these systems are not designed for economic research, and have some limits. The lack of historical information on entity-parent links is a major problem, which requires mobilising mergers and acquisitions data.

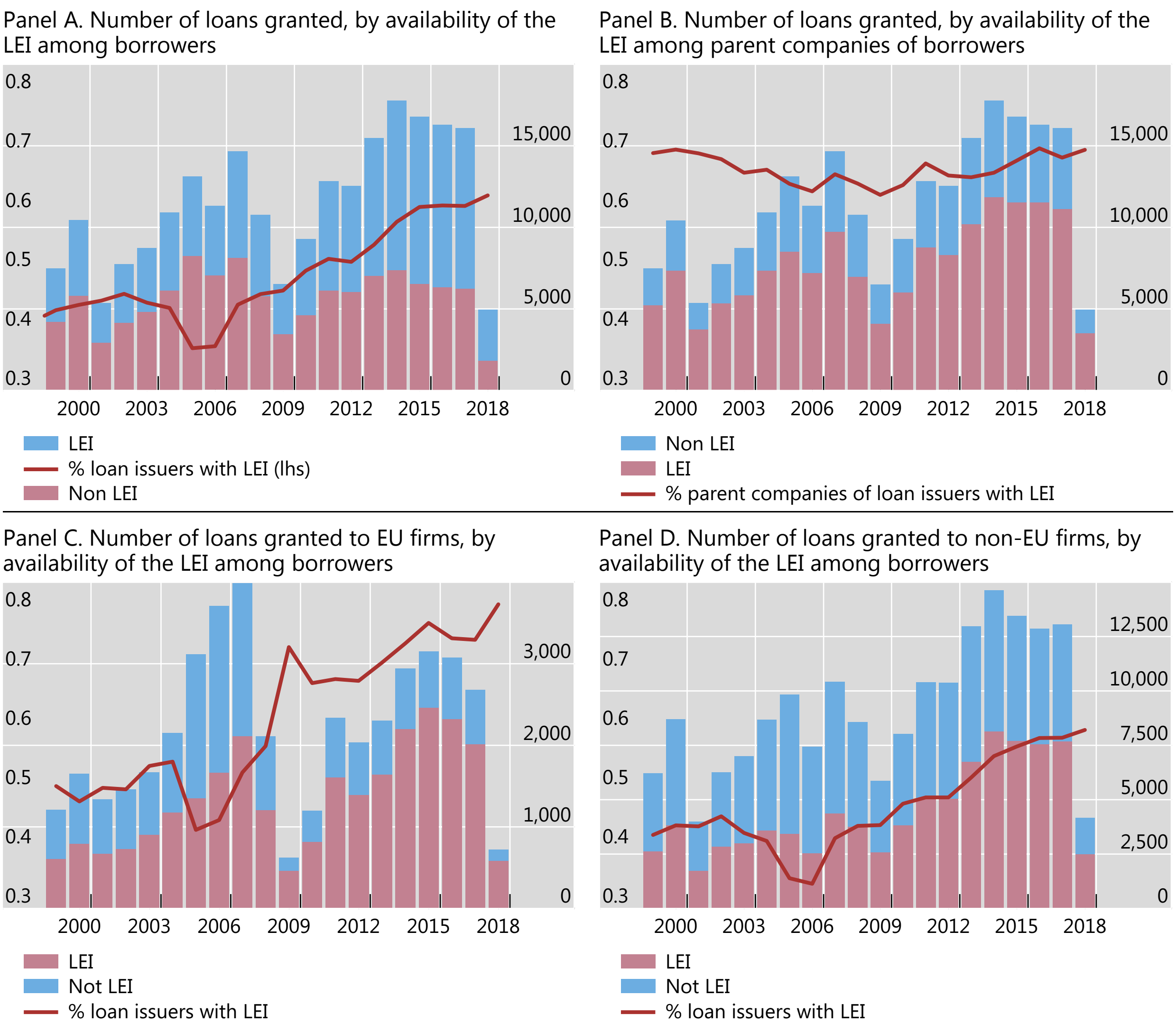
[2] See Cohen (2018) for a careful exposition of the limits of matching datasets using plain name comparison, and avenues to enhance matches using data cleaning and entity-parent links.

3.2. Loan contracts and the Legal Entity Identifier

In the aftermath of the GFC the Financial Stability Board (FSB) Plenary supported the development and implementation of a global identifier (FSB (2012)) precisely to uniquely identifying these legal entities involved in financial transactions (eg syndicated loans). The LEI system design was well-suited for large-scale statistical management: the LEI is a unique alphanumeric code assigned to a single entity; the system has entity-parent links (ie an entity LEI is associated to the LEI of the parent); and the quality is certified.

Loan borrowing in global markets. Availability of Legal Entity Identifiers

Graph 1



Sources: DealScan; authors' calculations.

The use of the LEI system for statistical production has some drawbacks: it lacks universal coverage, in particular among borrowers. As of today, in half of the loans (149,359) the LEI of the borrower is missing; the LEI of the borrower ultimate parent company is more broadly available, but it is still missing in one-third of the loans (in 90,337 instances). Panels A and B in Graph 1 represent this pattern. On the other hand the LEIs are becoming more broadly available in the in the last years. In 2017 73% of the loan borrowers had issued a LEI. Besides the number of LEIs is uneven across regions, and more often available in the EU. This likely reflects that the EU regulation has required entities active in capital markets to issue a LEI (Panels C and D).[3] Finally, statistical production requires historical information (eg LEIs for inactive companies).

3.3. Lending relationships and credit exposures

To construct exposures we retrieve the Thompson Reuters permanent ID of the borrower and lender, and their immediate and ultimate parent. For each of these entities we obtain the sector, country and incorporation, type of organisation, year of incorporation (in some instances these fields are missing).

We define the actual borrowers / lenders in a loan contract as follows. On the borrower side we consolidate at the ultimate parent level non-bank financials owned by non-financial corporation (we consolidated into the immediate parent if the ultimate parent is the government). On the lender side we consolidate always, unless the entity is as independent subsidiary.

Using these borrower-lender links we compute the amount lent by a bank to a firm in a given year; for this we use the original maturity to estimate redemptions. A bank claim on a firm is the difference between cumulated issuances and redemptions (by construction, claims have a lower bound at zero).

We assume that a lending relationship exists if this claim is positive. Further we estimate the credit exposure, which is given by the size of the claim. To estimate credit exposures we use solely term loans, since we do not have information on the amount drawn from credit lines.

Our estimations of credit exposures have limitations, since we are not adjusting for risk transfers after the origination of the loan. There are many potential risk transfers: banks can sale loans, and actually there is an active secondary market (Ivashina and Scharfstein, 2010); they can renegotiate terms, including cancelling them before the original maturity date; they may buy CDS protection against the borrower. There are other important biases in the credit exposures we estimate: we are not using all loans, as trade finance or smaller loans not recorded in Eikon; we do not have information on corporate deposits on banks, which might decrease net exposures.

Some of these problems could be adjusted using additional data sources; in particular loan sales in secondary markets or renegotiations of terms and conditions. Others problems are more structural, and constitute a limit of this approach. In particular, it seems unlikely to obtain data on corporate deposits, credit derivative markets, or small loans from banks.

Overall these caveats suggests that lending relationships derived from term loans are the most reliable part of our results. Lack of information on risk transfers casts important doubts on credit exposure estimations. However as long as banks retain a

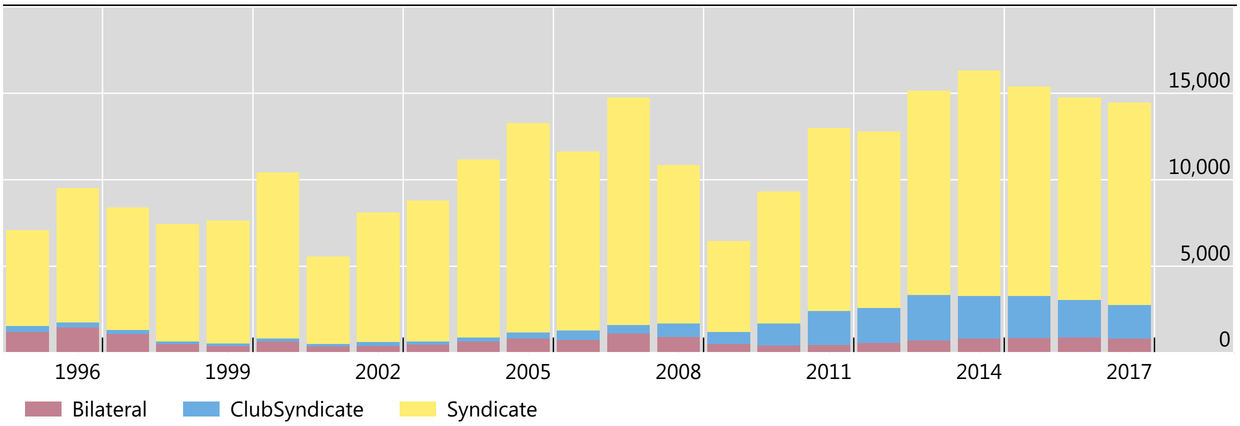
[3] It is instructive to compare the evolution of the number of ISINs and LEIs. The ISIN of an entity is sometimes used as a global ID. Its coverage in the full sample is similar to the LEI (it is available in half of the instances); however its coverage has remained constant over time.

fraction of the loans they originate, or do not fully hedge their exposures, lending relationships would still be valid. Similarly, we are not able to assess if banks draw credit lines, which suggests focusing on term loans.

4. Data

We use data on all loans to non-financial corporations, provided by Thompson Reuters Eikon. As in previous research our unit of observation are tranches. The features of the data are well know: the total number of all loans (tranches) in Eikon is over 300,000, of which 256,000 are to non-financial firms (ie excluding loans to the government and financial companies). The time span covers 1983 to 2018. The number of deals peaks in 2014, and the market was already active in the 1990s.

Number of loans to NFC. Breakdown by type[1] Graph 2



[1] For firms with an outstanding loan as of Dec 2017.

Sources: Eikon; authors' calculations.

Most of the loans in the dataset are syndicated (233,403), but there are also bilateral bank loans (18,026), and club syndicate loans (23,681); the latter are smaller deals, and typically cannot be sold in secondary markets. The dataset includes both term loans and credit lines; more specifically there are 141,478 term loans, and 117,514 credit lines. The remaining are bridge loans, which we leave aside. We do not know if credit lines are used, or the portion drawn, so we restrict the estimation of credit exposures to term loans. Graph 2 depicts some patterns in loan issuance.

There are 62,605 loan borrowers. We consolidate financial vehicles, resulting in 50,179 firms. These firms are incorporated in 144 countries. The countries with more borrowers are the US (17,117), Japan (6,085), United Kingdom 2,309), China (1,424), and Canada (1,331).

We treat banks on a (partially) consolidated basis, treating listed subsidiaries as independent banks. There are 27,849 different lenders, with different roles in the loan (eg lead arrangers, other participants). We focus on the lenders which account for 75% of the deals, and consolidate them into their 265 parent institutions. These institutions might be listed subsidiaries of another bank (eg Santander UK is treated in our sample as a separate entity from Santander).

5. Main results

5.1 Lending relationships

We assume that a bank-firm lending relationship exist when there is an outstanding loan from the bank to the firm. Table 1 describes the evolution of lending relationships over time, for the main lenders. The number of relationships has grown over time. The number of relationships by bank tends to increase, and is above 600 in 2016. The number of firms with an outstanding loan also grows, and hovers around 7,000 in 2016. The number of lenders per firm remains broadly constant, fluctuating around 10. This seems a high number, but reflects that most loans in our sample are syndicated (and thus many parties are involved).

Lending relationships based on syndicated loans data Table 1

	Bank*Firm	# Banks	Av.# firms per Bank	# Firms	Av. # banks per firm
2000	12,863	53	243	2,155	10
2004	18,524	58	319	3,532	10
2008	24,327	58	419	4,939	13
2012	29,951	58	516	5,721	11
2016	35,925	58	619	6,975	10

[1] Lending relationships defined treating banks on a consolidated basis; for firms we just consolidate financial vehicles.

Sources: own elaboration, Eikon, Thompson Reuters.

Cross-border lending relationships based on syndicated loans data Table 2

	Bank*Firm	# Banks	Av.# firms per Bank	# Firms	Av. # banks per firm
2000	9,359	51	184	1,767	10
2004	11,491	58	198	2,220	9
2008	14,426	58	249	2,949	12
2012	17,304	58	298	3,586	12
2016	20,440	58	352	4,281	10

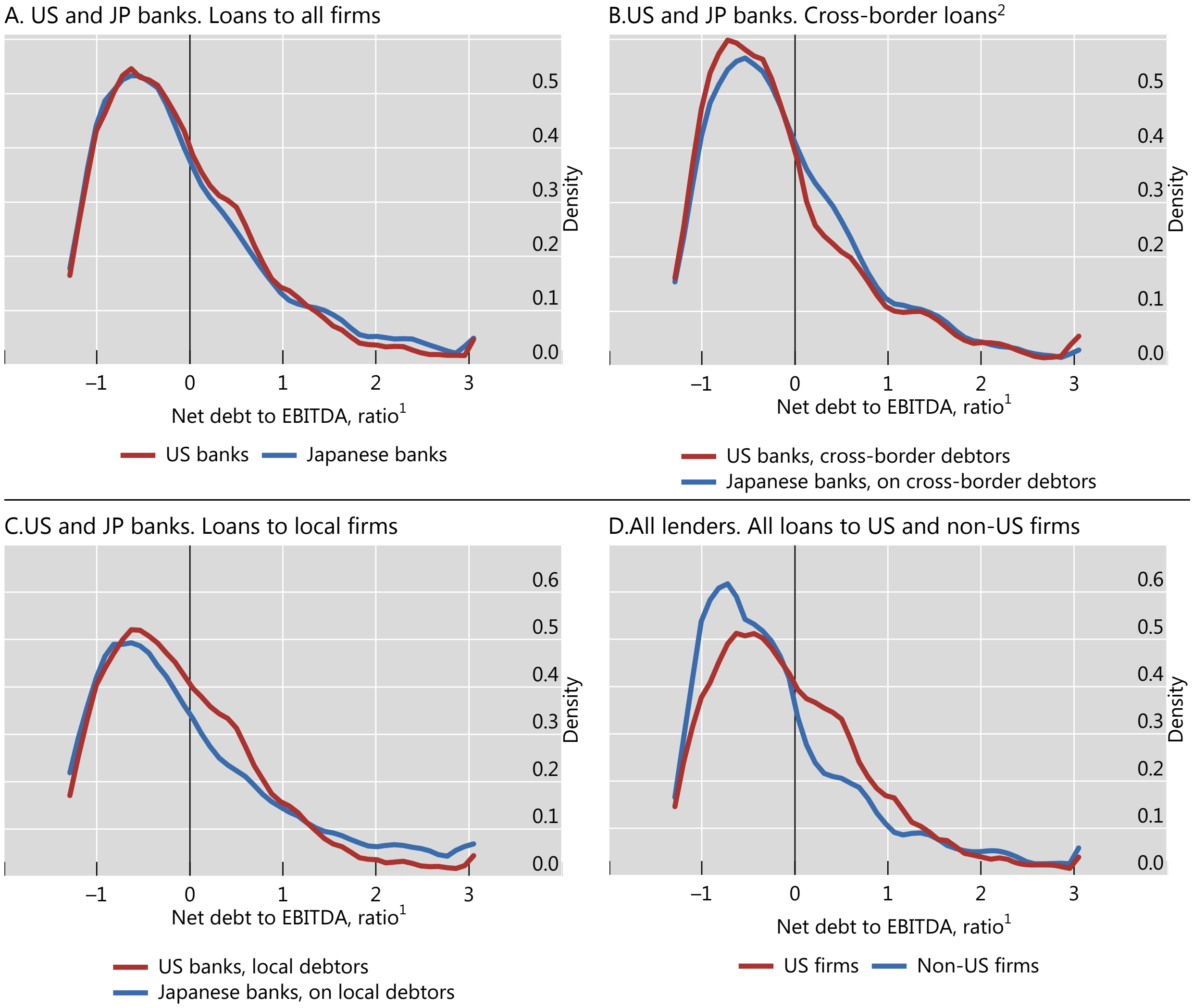
[1] Lending relationships defined treating banks on a partially consolidated basis; for firms we just consolidate financial vehicles.

Sources: own elaboration, Eikon, Thompson Reuters.

Since we have information on the country of incorporation of banks and firms we can examine bank-firm lending relationships when banks and firms are incorporated in different countries. It is important to note that we are not treating banks and firms on a solo basis, so these are not cross-border lending relationships at an entity level.[4] Table 2 shows that many of these relationships are between banks and firms incorporated in different countries.

Credit risk; portfolio of loans to NFC[1]

Outstanding loans as of Dec 2017 — Graph 3



[1] Credit risks measured with firms' net debt to EBITDA ratio. Borrowers with an outstanding loan as of Dec 2017. .

Sources: Eikon; Thompson Reuters; authors' calculations.

Bank-firm relationships might be useful to conduct cross-country comparisons of banks' loans portfolios. Panel A in Graph 3 plots the distribution of the net debt to EBITDA ratio of firms with an outstanding loan from US and Japanese banks (as of Dec 2017). Assuming that higher levels of net debt to EBITDA signal higher credit risk, US banks have riskier balance-sheets. This patterns reflects the higher risks of local debtors (Panel B), and actually the distribution of cross-border loans of Japanese banks is riskier (Panel C). In other words, the higher risk of US banks' portfolio reflects

[4] This definition of "cross-border claims" differs from the BIS International Banking Statistics definition https://www.bis.org/statistics/bankstatsguide_glossary.pdf.

the higher net debt to EBITDA ratios of US borrowers (Panel D). We remind that this exercise is for illustration purposes, and the purpose is not to extract conclusions about banks' credit risks.

5.2 Credit exposures

A bank credit exposure to a firm is the estimated amount of the outstanding loans. Our estimations of credit exposures are subject to the many limitations discussed above; in particular we are not adjusting for risk transfers after origination (eg loan sales or financial hedge). The biases are likely stronger at a granular level (ie for some bank-firm pairs). The aggregate results in Table 3 have to be taken with caution, but overall suggest there has been an increase in the size of the exposures over time.

Credit exposures based on syndicated loans data

Table 3

	Bank*Firm	# Banks	# Firms	Total exposures
2000	12,863	53	2,155	995
2004	18,524	58	3,532	1,844
2008	24,327	58	4,939	3,726
2012	29,951	58	5,721	4,508
2016	35,925	58	6,975	6,711

[1] Lending relationships defined treating banks on a partially consolidated basis; for firms we just consolidate financial vehicles.

Sources: own elaboration, Eikon, Thompson Reuters.

6. Conclusions

We construct bank-firm lending relationships matching loan-level data from commercial data providers to firm and bank-level information. Our key contribution is to match datasets using the global identifiers of borrowers and lenders. This has three advantages: it is accurate, consistent with the terms agreed on the loan contract, and flexible. Leveraging on this flexibility we consolidate borrowing by non-bank financials. On the lender side: we partially consolidate banks, treating listed subsidiaries as independent banks

We illustrate how the data is useful to define bank-firm lending relationships, and eventually conduct cross-country analyses of credit risks in banks' loans portfolios. There are several ways to improve these estimations. On the one hand some work can be done to adjust data from risk transfers: banks' loan holdings can be adjusted using data on loan sales; further, data on loan amendments after origination can be used to check if loan terms have been renegotiated (including cancelled earlier than originally agreed).

Finally, we argue that the LEI system is well-suited and could support this statistical work: the LEI is a unique identifier, has entity-parent links, and the quality is certified. Its main drawback is the coverage: it is good on the lender side, but there are gaps on the borrower side. An improvement on the LEI coverage would be of great help for statistical purposes.

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Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

Cross-country bank-firm exposures: what can we learn from public data?[1]

Jose Maria Serena Garralda,

Bank for International Settlements

[1] This presentation was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

CROSS-COUNTRY FIRM-BANK EXPOSURES: WHAT CAN WE LEARN FROM PUBLIC DATA?

Jose Maria Serena Garralda*

9th Biennial IFC Conference “Are post-crisis statistical initiatives completed?“

Bank for International Settlements

The views expressed are those of the author and do not necessarily reflect those of the BIS or the IFC.

INTRODUCTION. POST-GFC DATA NEEDS

- Post-GFC data needs on bank-firm interlinkages -the GFC was a major banking crisis transmitted worldwide.
- Data availability has improved thanks to DGI: IDH –top 30 banks, highly confidential, credit and liability exposures, I-A.
- Besides central banks have mobilized their country-level data; limits to data sharing often prevent pooling them
- However some data needs persist: cross-country (I-I) bank-firm exposures, needed for policy evaluation/risk assessment.

INTRODUCTION. POST-GFC DATA NEEDS

- Research question: can we define (I-I) bank-firm exposures from public loan data (ie large loans reported by banks, and disseminated by commercial data providers)?

- Our paper: use lenders and borrowers' common identifiers to match loans to firm/bank-level datasets ; use maturity date to define:
  - Lending-relationships: exist if there is an outstanding loan
  - Credit exposures: size of the exposure (US mn)

- Main conclusion: bank-firm lending relationships seem reliable; credit exposures require further adjustments –work ahead.

OUTLINE

1. Introduction
2. Measuring cross-country firm-bank exposures
3. Data
4. Main results
5. Conclusions

MEASURING CROSS-COUNTRY FIRM-BANK EXPOSURES.

- **Key figures**: 282,912 loans (not only syndicated), 1983-2018:
  - Average loan is 300 USD mn (median 50 USD mn); USD loans account for 60% of the total
  - Type liability: 50% are term loans; 40% are credit lines; the remaining are project finance, bridge loans.

- **Borrowers**: 78,443 issuers, with significant dispersion; 60,020 at consolidated level, based in 119 countries; top 5 are US, JP, UK, CA, AU (44%, 13%, 7%, 3%, 2%). Focus on NFC.

- **Lenders**: 16,107 lenders (any role in the deal), with remarkable concentration among banks; 549 account for 75% of all deals, ie 1,3 mn lending relationships.

MEASURING CROSS-COUNTRY FIRM-BANK EXPOSURES.

- **What we do?** We compute outstanding loans of bank i to firm j at time t, using the original maturity of the loan; then we define:
  - Lending relationships: exists if there is an outstanding loan.
  - Credit exposures: size of the exposure (US mn).

- **How we do it?** We match borrowers/lenders to firm/bank level data using their common identifiers (eg LEI); this has benefits:
  - Efficient
  - Credible
  - Economic meaning
  - Cross-border

MEASURING CROSS-COUNTRY FIRM-BANK EXPOSURES. LIMITATIONS

1. No liability-side exposures (eg corporate deposits on banks);

2. No information on important asset classes, such as small loans, trade finance, derivatives, guarantees.

3. Sample of firms is biased towards large companies.

4. We do not adjust for secondary market transactions; we assume a bullet payment, and no amendments. No information on credit hedges.

Bottom-line: public data will never be as good as supervisory data; but allows measuring cross-country, cross-border, exposures

MAIN RESULTS

1. **Lending relationships**
   - Bank*Firm relationships over time
   - Loan portfolio risk analysis

2. **Credit exposures, term loans:**
   - Top 10 bank-firm exposures, end-2017
   - Banks' exposures to distressed firms –eg Toys "R" Us '17

MAIN RESULTS (I). LENDING RELATIONSHIPS

- A lending relationship from bank i to firm j at year t exists when there is an outstanding loan.

Lending relationships based on syndicated loans data — Table 1

	Bank*Firm	# Banks	Av.# firms per Bank	# Firms	Av. # banks per firm
2000	12,634	55	230	2158	10
2004	18,476	61	303	3533	10
2008	24,468	63	388	4956	13
2012	30,153	63	479	5750	12
2016	36,811	63	584	7031	10

[1] Lending relationships defined treating banks/firms on a consolidated basis.

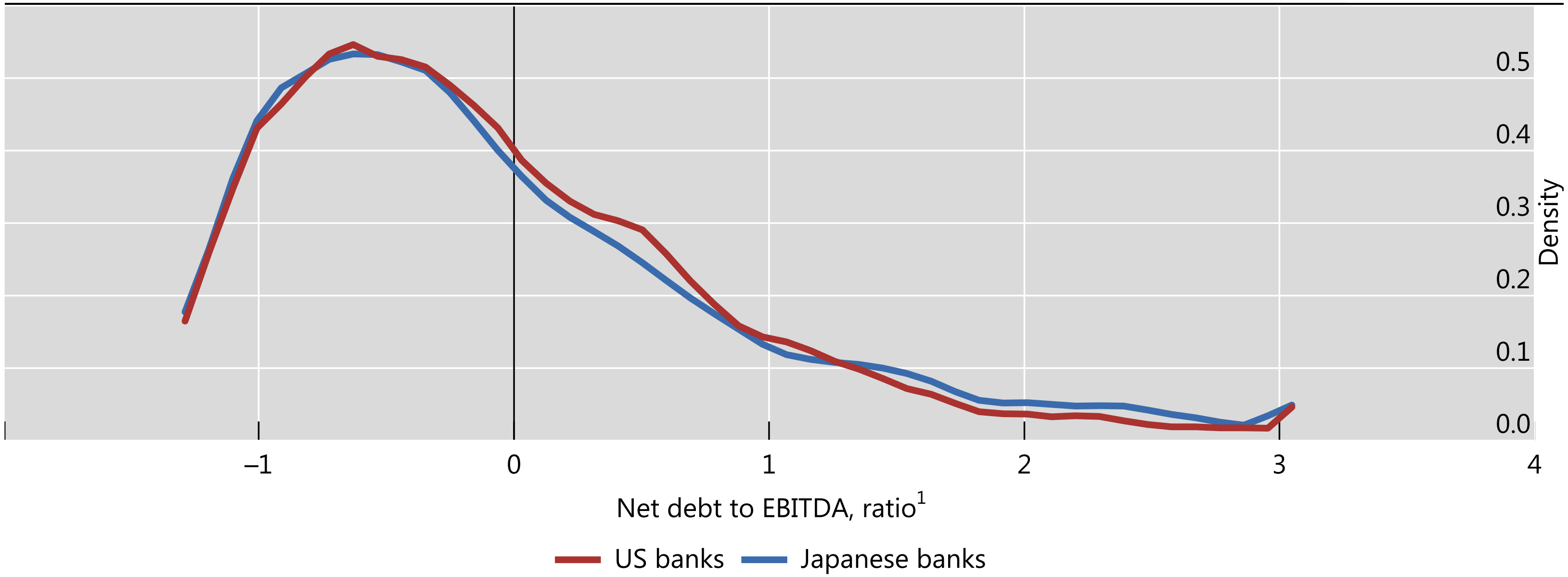
Sources: own elaboration, DealScan, Thompson Reuters.

- Exposures of top 100 banks according to total assets sep-18. Some might be large subsidiaries. Large number of lenders per firm (reflecting loans are syndicated).

MAIN RESULTS (I). LENDING RELATIONSHIPS. LOAN PORTFOLIO RISK ANALYSIS. US vs JAPANESE BANKS

- Loan portfolio US banks: 8 banks have 10,493 loans to 3,534 firms. US banks seem to have riskier portfolio -measured with firms' net debt to EBITDA.

Credit risk of US and JP banks; portfolio of loans to NFC[1] Graph 1



[1] For firms with an outstanding loan as of Dec 2017.

Sources: DealScan; authors' calculations.

MAIN RESULTS (II). CREDIT EXPOSURES. TOP 10 IN 2017, TERM LOANS.

- Credit exposures: size of bank i exposure to firm j at time t; as before we can analyse cross-border credit exposures

Credit exposures based on syndicated loans data — Table 3 A

	Bank*Firm	# Banks	# Firms	Total exposures, US bn
2000	12,863	53	2,155	995
2004	18,524	58	3,532	1,844
2008	24,327	58	4,939	3,726
2012	29,951	58	5,721	4,508
2016	35,925	58	6,975	6,711

[1] Lending relationships defined treating banks/firms on a consolidated basis.

Sources: own elaboration, DealScan, Thompson Reuters.

Cross-border credit exposures based on syndicated loans data — Table 3 B

	Bank*Firm	# Banks	# Firms	Total exposures, US bn
2000	9,359	51	1,767	634
2004	11,491	58	2,220	1,088
2008	14,426	58	2,949	2,279
2012	17,304	58	3,586	2,294
2016	20,440	58	4,281	3,103

[1] Lending relationships defined treating banks/firms on a consolidated basis.

Sources: own elaboration, DealScan, Thompson Reuters.

MAIN RESULTS (II). DRILLING DOWN INTO CREDIT EXPOSURES. BANKS' EXPOSURES TO DISTRESSED FIRMS

- Toys "R" Us filed for bankruptcy in sep 17, owned by private equity firms (Bain-KKR-Vornado). Top 10 exposures:

Top creditors of Toys R US Inc -September 2017. All loans

Table 5

Bank	Exposure	Country	LEI	Tier1 Capital Pct	Net Loans YoY %	Assets
Bank of America Corp	1,405	US	9DJT3UXIJIZJI4WXO774	13.2	2.40	22,812
JPMorgan Chase & Co	1,402	US	8I5DZWZKVSZI1NUHU748	14.4	4.16	25,336
Goldman Sachs Group Inc	792	US	784F5XWPLTWKTBV3E584	12.7	.	9,168
Citigroup Inc	728	US	6SHGI4ZSSLCXXQSBB395	14.5	6.92	18,425
Deutsche Bank AG	449	DE	7LTWFZYICNSX8D621K86	15.4	-1.76	17,691
Barclays PLC	415	UK	213800LBQA1Y9L22JB70	13.3	-6.93	15,313
Wells Fargo & Co	237	US	PBLD0EJDB5FWOLXP3B76	14.1	-1.09	19,518
HSBC Holdings PLC	76	UK	MLU0ZO3ML4LN2LL2TL39	17.3	11.78	25,218
U.S. Bancorp	62	US	N1GZ7BBF3NP8GI976H15	10.8	2.64	4,620
Toronto-Dominion Bank	62	CA	PT3QB789TSUIDF371261	12.3	4.60	9,927

- However: banks might have renegotiated debt/sold them (Irani, Iyer, Meisenzahl and Peydro, 2018).

CONCLUSIONS

- We construct (I-I) bank-firm exposures using public loan data: lending relationships and credit exposures.
- Our main contribution is to use lenders/borrowers common identifiers; we gain accuracy and do not loss data.
- Not easy to check the quality of results. Our guess is that:
  - Results on lending relationships are good enough for economic analysis.
  - The assumptions required to estimate credit exposures are too strong (ie no risk transfers/risk mitigation).
- Potential work ahead: further refine credit exposures adjusting for secondary market sales or loan contract amendments.

THANK YOU FOR YOUR ATTENTION

MEASURING CROSS-COUNTRY FIRM-BANK EXPOSURES. RELATED WORK (I)

- Gadanecz, B, and K. von Kleist (2002), “Do syndicated credits anticipate BIS consolidated banking data?” *BIS Quarterly Review, March 2002* [Loan data vs BIS IBS]

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MEASURING CROSS-COUNTRY FIRM-BANK EXPOSURES. RELATED WORK MATCHING LOAN-FIRM DATA (II)

- Kalemli-Ozcan, S., L. Laeven, and D. Moreno (2018), "Debt overhang, rollover risks, and corporate investment: Evidence from the European Crisis", *NBER WP 24555 April 2018*

- Gropp, H., T. Mosk, S. Ongena, and C. Wix (2018), "Bank Response to Higher Capital Requirements: Evidence from a Quasi-Natural Experiment", *forthcoming Review of Financial Studies*

- Hale, G., T. Kapan, and C. Minoiu (2016). "Shock transmission through cross-border bank lending: credit and real effect" *Working Paper Series 2016-1, Federal Reserve Bank of San Francisco.*

- Ivashina, V. and D. Scharfstein (2010), "Loan Syndication and Credit Cycles" *American Economic Review: P & P 100 May 2010*

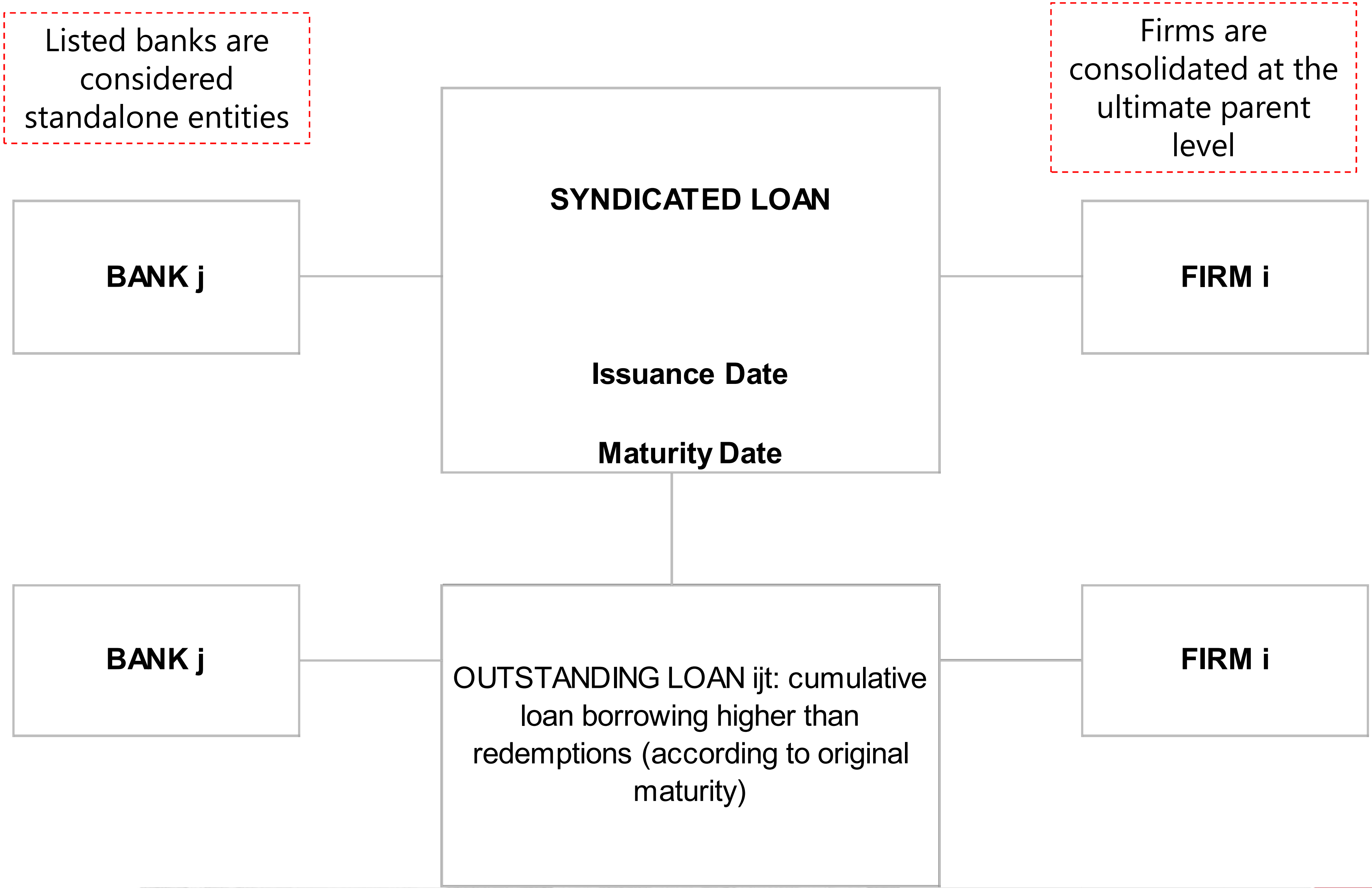
MEASURING CROSS-COUNTRY FIRM-BANK EXPOSURES. RELATED WORK ON COMMON IDENTIFIERS (III)

- Buch, C. (2017), "Keynote Speech. Data needs and statistics compilation for macroprudential analysis" in I*CF Bulletin No 46*

- GLEI-SWIFT (2018), "BIC to LEI mapping table. Factsheet"

- IAG (2017), "Update on the Data Gaps Initiative and the Outcome of the Workshop on Data Sharing" *March 2017*

MEASURING CROSS-COUNTRY FIRM-BANK EXPOSURES. ESTIMATE POSITIONS USING ORIGINAL MATURITY



How we do it? Matching loans to firm-level data using borrowers' names is costly, inaccurate, and not meaningful.

Ultimate parent company
Wilmar International Ltd
ISIN: SG1T56930848
SEDOL: B17KC69
LEI: 549300H2EAI4YRLWBB20

Borrower
Wii Pte Ltd
ISIN: .
SEDOL:.
LEI:549300ZZI8LH8D8RPL28

SYNDICATED LOAN
Announcement: 10.07.2013
Amount: 365
Currency: US Dollar
Type: Near Investment

Syndicate
National Australia Bank
Westpac Banking
Hang Seng Bank Ltd (Hong Kong)
National Bank of Kuwait (Sing)
Bank of China Ltd
First Commercial Bank (Taiwan)
Agricultural Bank of China(SG)
Bank of East Asia (Singapore)
JA Mitsui Leasing Ltd
Sumitomo Mitsui Trust Bank Ltd
Land Bank of Taiwan
Metropolitan Bank & Trust
Mega Intl Coml Bank Co Ltd
Commonwealth Bank of Australia
Hongkong & Shanghai Bank (HK)
United Overseas Bank Ltd
DBS Bank Ltd
Bank of Tokyo-Mitsubishi UFJ
CIMB Bank Bhd
Bank of Philippine Islands
Bank of Communications Co Ltd
Aozora Bank Ltd
Sumitomo Mitsui Banking Corp
Hua Nan Financial Holdings
ABN AMRO Bank
Industrial & Comm Bank China
Habib Bank Ltd
Taiwan Cooperative Bank
E Sun Commercial Bank Ltd
Banco De Oro Unibank Inc

MEASURING CROSS-COUNTRY FIRM-BANK EXPOSURES. METHODOLOGICAL CHOICES

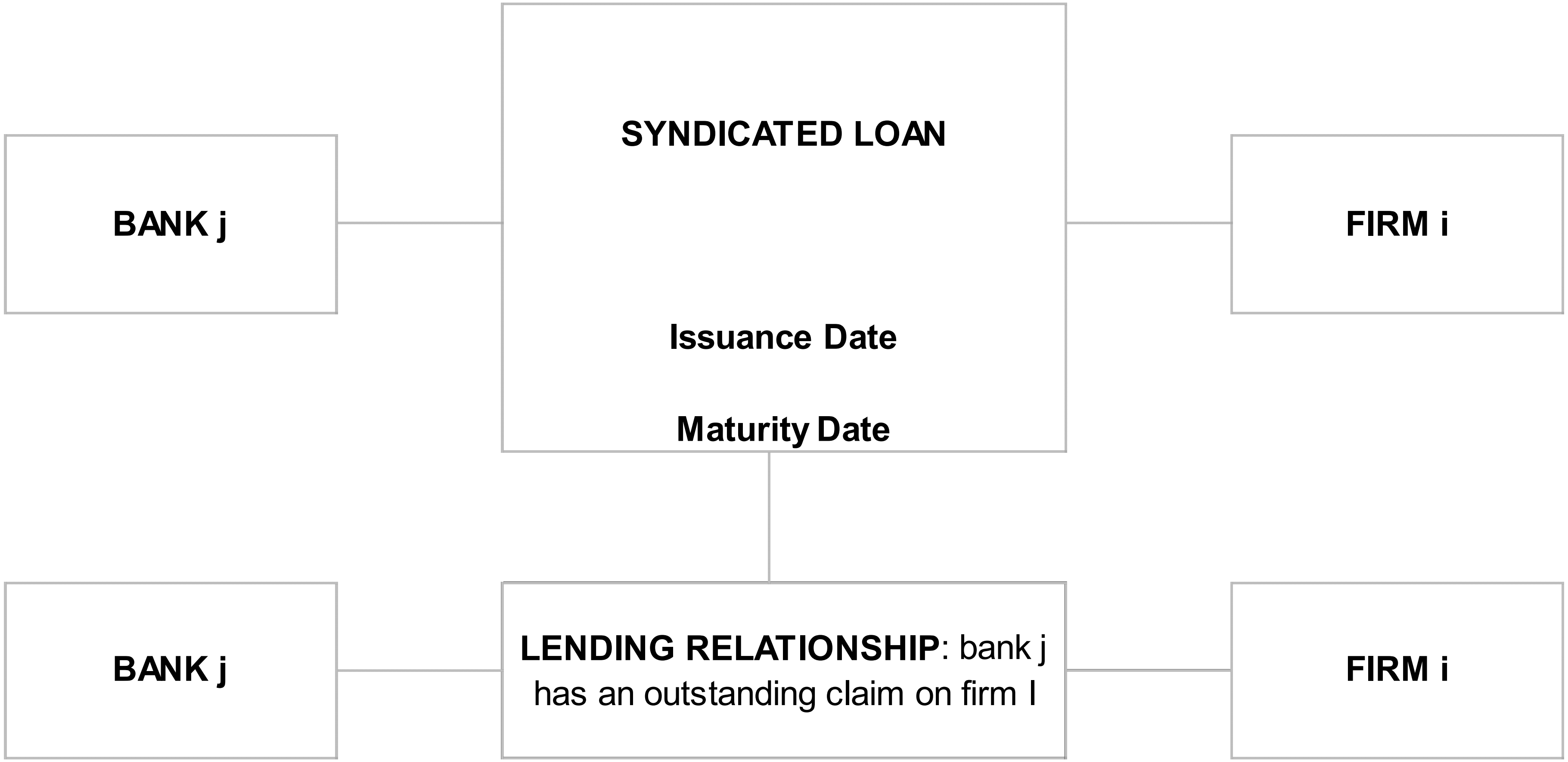
1. Borrowers are consolidated at the ultimate parent level [as long it is a non-financial firm]: consolidation of SPVs is not controversial; but some affiliates could be financially independent.

2. Lenders are consolidated up to the level of the first listed entity: since we assume that listed banks are standalone.

3. The definition of a "cross-border exposure" differs from BIS IBS (which is based on issuers/lenders location) as a result of [1] and [2] .

4. Loan allocation rule between arrangers and others is ad-hoc and reflects lack of data. Further work could be done.

MAIN RESULTS (I). LENDING RELATIONSHIPS

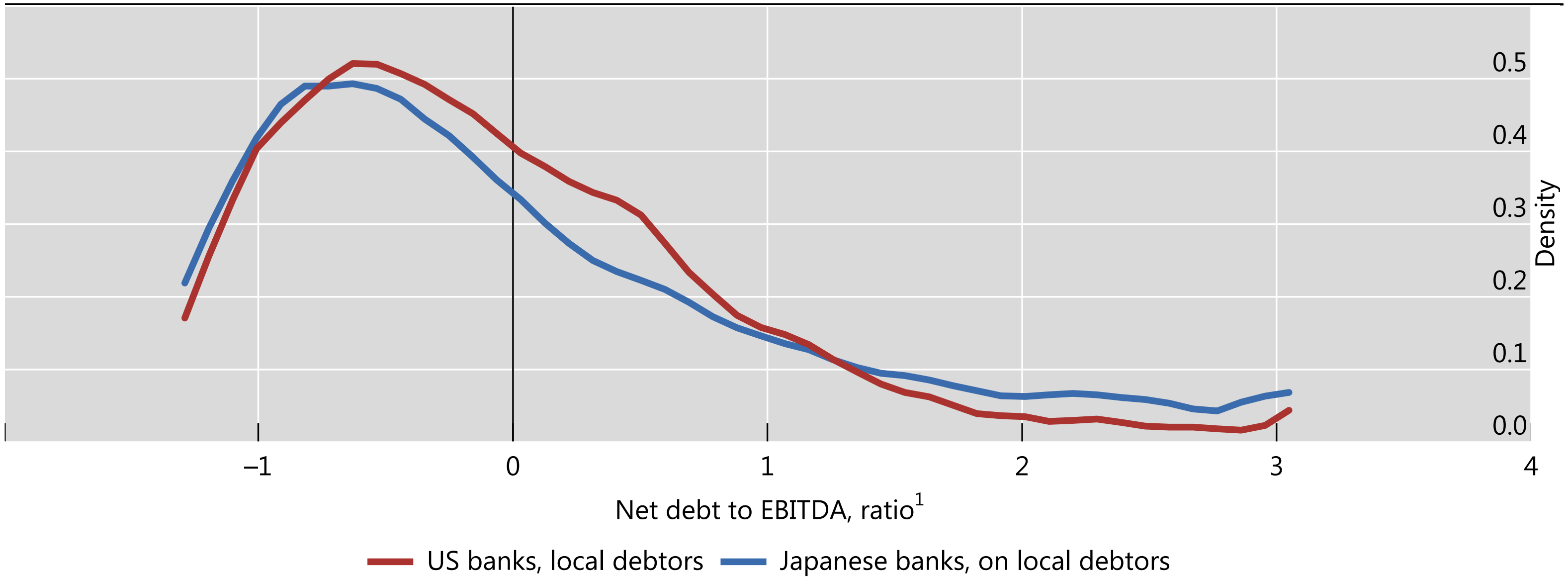


MAIN RESULTS (I). LENDING RELATIONSHIPS. LOAN PORTFOLIO RISK ANALYSIS. US vs JAPANESE BANKS

- Domestic loan portfolio US banks: US safer than Japanese banks' portfolio.

Credit risk of US and Japanese banks' portfolio of local loans to NFC[1]

Graph 3



[1] For firms with an outstanding loan vs US and Japanese banks as of Dec 2017.

Sources: DealScan; authors' calculations.

MAIN RESULTS (I). CREDIT EXPOSURES. TOP 10 IN 2017, TERM LOANS.

- Top 10 credit exposures, term loans: 4 out the 10 top 10 credit exposures are cross-border; in three instances European banks.

Credit exposures as of end-2017, term loans

Table 4

Bank	Firm	Exposure	Bank country	Firm country	Firm assets
Bank of America Corp	Broadcom Inc	11,940	US	US	544,180
Societe Generale SA	Cheniere Energy Inc	10,985	FR	US	279,060
Bank of America Corp	Charter Communications Inc	9,201	US	US	1,466,230
JPMorgan Chase & Co	Western Digital Corp	9,141	US	US	298,600
Bank of America Corp	Royalty Pharma AG in Liquidation	8,948	US	CH	.
Mitsubishi UFJ Group	SoftBank Group Corp	8,805	JP	JP	2,211,727
Deutsche Bank AG	Hilton Worldwide Holdings Inc	7,392	DE	US	142,280
Credit Agricole SA	SoftBank Group Corp	7,137	FR	JP	2,211,727
Bank of America Corp	HCA Healthcare Inc	7,081	US	US	365,930
Bank of America Corp	Level 3 Communications Inc	6,579	US	US	331,350

MAIN RESULTS (II). DRILLING DOWN INTO CREDIT EXPOSURES. BANKS' EXPOSURES TO DISTRESSED FIRMS

- Toys "R" Us filed for bankruptcy in sep 17, owned by private equity firms (Bain-KKR-Vornado). Top 10 exposures:

Top creditors of Toys R US Inc -September 2017. All loans

Table 6

Bank	Exposure	Country	LEI	Tier1 Capital Pct	Net Loans YoY %	Assets
Bank of America Corp	1,405	US	9DJT3UXIJIZJI4WXO774	13.2	2.40	22,812
JPMorgan Chase & Co	1,402	US	8I5DZWZKVSZI1NUHU748	14.4	4.16	25,336
Goldman Sachs Group Inc	792	US	784F5XWPLTWKTBV3E584	12.7	.	9,168
Citigroup Inc	728	US	6SHGI4ZSSLCXXQSBB395	14.5	6.92	18,425
Deutsche Bank AG	449	DE	7LTWFZYICNSX8D621K86	15.4	-1.76	17,691
Barclays PLC	415	UK	213800LBQA1Y9L22JB70	13.3	-6.93	15,313
Wells Fargo & Co	237	US	PBLD0EJDB5FWOLXP3B76	14.1	-1.09	19,518
HSBC Holdings PLC	76	UK	MLU0ZO3ML4LN2LL2TL39	17.3	11.78	25,218
U.S. Bancorp	62	US	N1GZ7BBF3NP8GI976H15	10.8	2.64	4,620
Toronto-Dominion Bank	62	CA	PT3QB789TSUIDF371261	12.3	4.60	9,927

- Not easy to check the quality of results, since banks might have renegotiated debt; and some loans matured in 2018.

MAIN RESULTS (II). DRILLING DOWN INTO CREDIT EXPOSURES. FIRMS' EXPOSURES TO DISTRESSED BANKS

- Firms can lose access to credit when banks default. We compute top 10 exposures to Lehman Brothers, 2008:

Top outstanding corporate loans of Lehman Brothers -September 2008 Table 7

A. Term loans			B. Credit lines		
Firm	Exposure	Country	Firm	Exposure	Country
Suitcase One Ltd	3,154	UK	Pfizer Inc	1,500	US
Vale SA	2,778	BR	Imperial Brands PLC	1,264	UK
Riverdeep Group Plc	1,088	US	AT&T Inc	1,000	US
Las Vegas Sands Corp	1,053	US	America Movil SAB de CV	1,000	MX
America Movil SAB de CV	1,000	MX	Cox Enterprises Inc	917	US
Fidelity National Information Services Inc	875	US	Kimberly-Clark Corp	844	US
Prysmian SpA	823	IT	HP Inc	750	US
Imperial Brands PLC	711	UK	Encana Corp	600	CA
Zimmer Biomet Holdings Inc	629	US	Nextera Energy Inc	500	US
NXP Semiconductors NV	542	NE	Walmart Inc	495	US

- Subject to the important caveats mentioned: implicit assumption of no risk transfers after origination; lending is often and "original-to-distribute" business (Ivashina and Scharfstein, 2010).

MEASURING CROSS-COUNTRY FIRM-BANK EXPOSURES. RELATED WORK

- **Methodological contributions**: comparison with aggregate data, Gadanecz and von Kleist (2002); loan retention shares, Gadanecz, Tsatsaronis and Y. Altunbaş (2006), and Bruche, Malherbe, and Meisenzahl (2017).

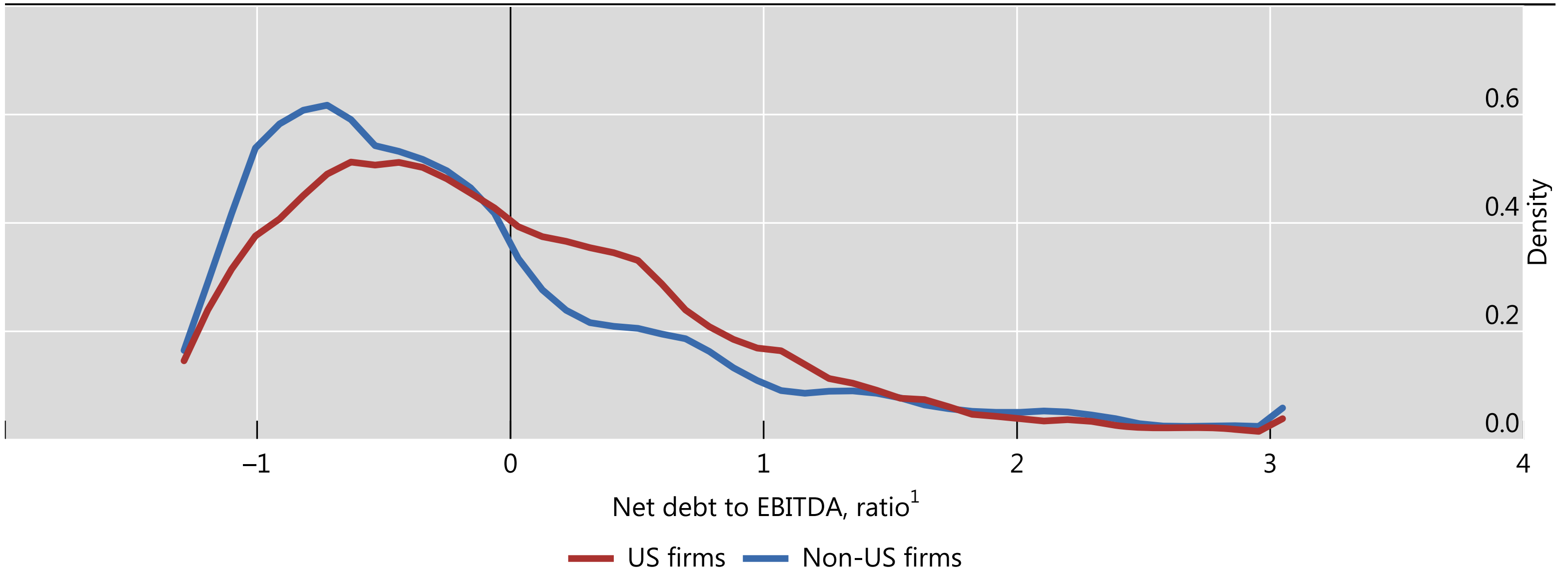
- **Construction bank-firm exposures**: Kalemli-Ozcan, Laeven, and Moreno (2018); Gropp, Mosk, Ongena, and Wix (2018); Hale, Kapan, and Minoiu (2016); Ivashina and Scharfstein (2010),

- **Discussion common identifiers**: Buch. (2017), GLEI-SWIFT (2018), IAG (2017)

MAIN RESULTS (I). LENDING RELATIONSHIPS. LOAN PORTFOLIO RISK ANALYSIS. US vs JAPANESE BANKS

- US borrowers have higher net debt to EBITDA ratios. This explains the riskiness of US banks loan portfolio.

Credit risk of US and non-US firms with outstanding loans as of Dec 2017[1] Graph 4



[1] For firms with an outstanding loan as of Dec 2017. All lenders.

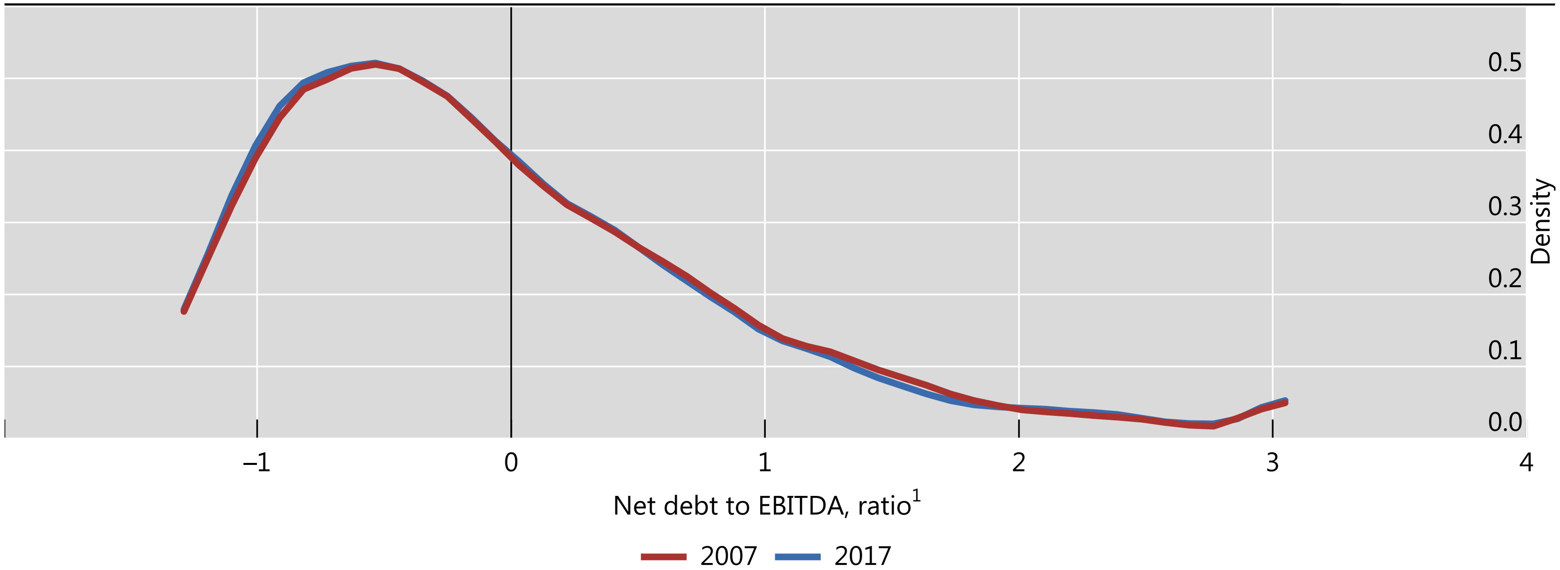
Sources: DealScan; authors' calculations.

MAIN RESULTS (I). LENDING RELATIONSHIPS, AT BANK-LEVEL: BANK OF AMERICA DISTRIBUTION

- We could further drill down into the loan portfolio: Bank of America has 2,119 lending relationships in 2017; 1,396 in 2007.

Credit risk of Bank of America, portfolio of loans to NFC - Historical evolution[1]

Graph 5



[1] For firms with an outstanding loan as of Dec 2017.

Sources: DealScan; authors' calculations.

- Up to now we have not looked at the size of the exposure.

MEASURING CROSS-COUNTRY FIRM-BANK EXPOSURES. ESTIMATE POSITIONS USING ORIGINAL MATURITY

Listed banks are considered standalone entities

Firms are consolidated at the ultimate parent level

BANK j

SYNDICATED LOAN

Issuance Date

Maturity Date

FIRM i

BANK j

LENDING RELATIONSHIP: bank j has an outstanding claim on firm i

CREDIT EXPOSURE: bank j has an outstanding claim of x US bn on firm i

FIRM i

- Data gaps in loan allocation across lenders: half for lead arrangers (pro-rata) and half for rest of the members of the syndicate (pro-rata).

How we do it? Instead we retrieve the common identifiers of the ultimate parent of the borrower/lender (eg LEI).

Ultimate parent company
Wilmar International Ltd
ISIN: SG1T56930848
SEDOL: B17KC69
LEI: 549300H2EAI4YRLWBB20
Headquarters: Singapore

Borrower
Wii Pte Ltd
ISIN: .
SEDOL:.
LEI:549300ZZI8LH8D8RPL28
Headquarters: Singapore

SYNDICATED LOAN
Announcement: 10.07.2013
Amount: 365
Currency: US Dollar
Type: Near Investment

Syndicate	
National Australia Bank	F8SB4JFBSYQFRQEH3Z21
Westpac Banking	EN5TNI6CI43VEPAMHL14
Hang Seng Bank Ltd (Hong Kong)	5493009Z5F07LWZYMK62
National Bank of Kuwait (Sing)	549300NB7FE83IH6BW96
Bank of China Ltd	54930053HGCFWVHYZX42
First Commercial Bank (Taiwan)	.
Agricultural Bank of China(SG)	549300E7TSGLCOVSY746
Bank of East Asia (Singapore)	CO6GC26LCGGRTUESIP55
JA Mitsui Leasing Ltd	
Sumitomo Mitsui Trust Bank Ltd	.
Land Bank of Taiwan	
Metropolitan Bank & Trust	549300SQYI82RVWFN715
Mega Intl Coml Bank Co Ltd	
Commonwealth Bank of Australia	MSFSBD3QN1GSN7Q6C537
Hongkong & Shanghai Bank (HK)	.
United Overseas Bank Ltd	IO66REGK3RCBAMA8HR66
DBS Bank Ltd	
Bank of Tokyo-Mitsubishi UFJ	353800V2V8PUY9TK3E06
CIMB Bank Bhd	549300FYDN5UD7USZW18
Bank of Philippine Islands	549300UW4UH6XT2X8C50
Bank of Communications Co Ltd	549300AX1UM10U30HK09
Aozora Bank Ltd	X0XUGKC9FD2CYUQNC010
Sumitomo Mitsui Banking Corp	35380028MYWPB6AUO129
Hua Nan Financial Holdings	.
ABN AMRO Bank	724500DWE10NNL1AXZ52
Industrial & Comm Bank China	5493002ERZU2K9PZDL40
Habib Bank Ltd	549300N63RJKPUYAY631
Taiwan Cooperative Bank	.
E Sun Commercial Bank Ltd	.
Banco De Oro Unibank Inc	.

MAIN RESULTS (I). LENDING RELATIONSHIPS. CROSS-BORDER

- Cross-border lending relationships: if bank i and firm j are headquartered in different countries.

Cross-border lending relationships based on syndicated loans data — Table 2

	Bank*Firm	# Banks	Av.# firms per Bank	# Firms	Av. # banks per firm
2000	9,359	51	184	1,767	10
2004	11,491	58	198	2,220	9
2008	14,426	58	249	2,949	12
2012	17,304	58	298	3,586	12
2016	20,440	58	352	4,281	10

[1] Lending relationships defined treating banks/firms on a consolidated basis.

Sources: own elaboration, DealScan, Thompson Reuters.

- Country of headquarters: for banks we use its country of incorporation (not the ultimate parent); for firms the country of incorporation of the ultimate parent.

MAIN RESULTS (II). CREDIT EXPOSURES. TOP 10 IN 2017, TERM LOANS.

- Top 10 credit exposures, term loans: numbers are not implausible, eg as of Aug 18 Broadcom Inc reports 40 US bn outstanding loans; Cheniere Energy Inc. reports 33 US bn.

Credit exposures as of end-2017, term loans

Table 4

Bank	Firm	Exposure	Bank country	Firm country	Firm assets
Bank of America Corp	Broadcom Inc	11,940	US	US	544,180
Societe Generale SA	Cheniere Energy Inc	10,985	FR	US	279,060
Bank of America Corp	Charter Communications Inc	9,201	US	US	1,466,230
JPMorgan Chase & Co	Western Digital Corp	9,141	US	US	298,600
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Mitsubishi UFJ Group	SoftBank Group Corp	8,805	JP	JP	2,211,727
Deutsche Bank AG	Hilton Worldwide Holdings Inc	7,392	DE	US	142,280
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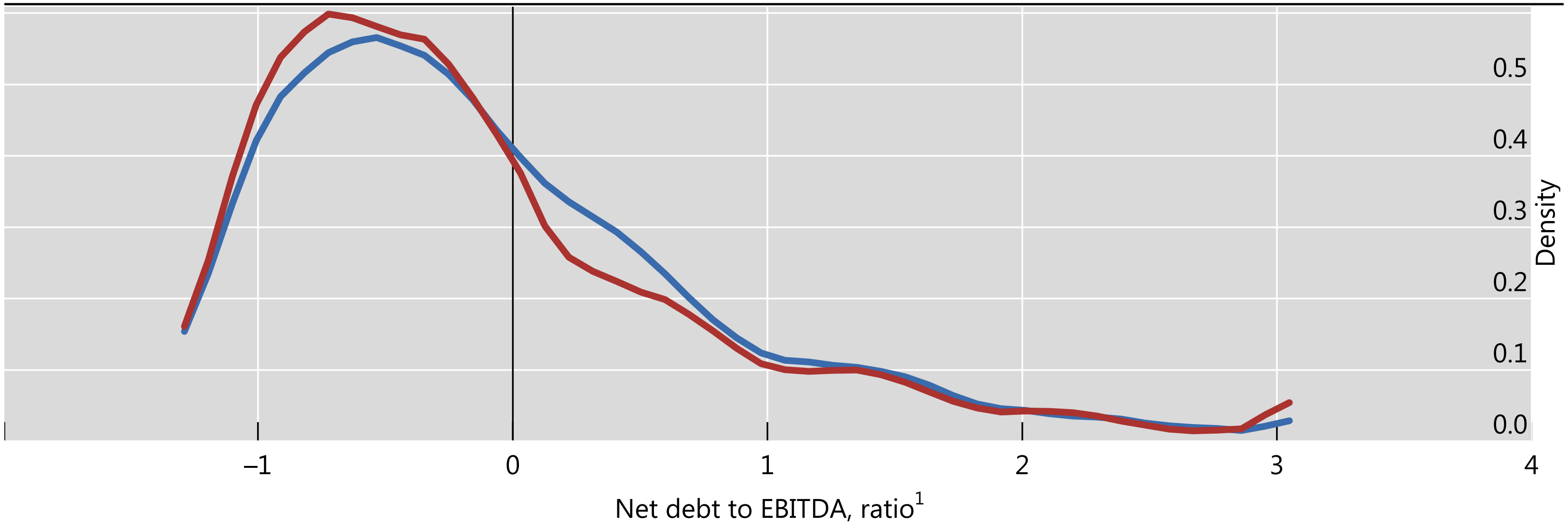
Bank of America Corp	Level 3 Communications Inc	6,579	US	US	331,350

- Cross-border exposures: 4 out the 10 top 10 credit exposures are cross-border; in three instances European banks

MAIN RESULTS (I). LENDING RELATIONSHIPS. LOAN PORTFOLIO RISK ANALYSIS. US vs JAPANESE BANKS

- Cross-border loan portfolio US banks: Japanese banks' cross-border loan portfolio are riskier.

Credit risk of US and JP portfolio of cross-border loans to NFC[1] Graph 2



[1] For firms with an outstanding loan vs US and Japanese banks as of Dec 2017.

Sources: DealScan; authors' calculations.

Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

Building a multilayer macro-network for the Netherlands: A new way of looking at financial accounts and international investment position data[1]

Melle Bijlsma, Malka de Castro Campos, Raymond Chaudron
and David-Jan Jansen,

Netherlands Bank

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[1] This paper was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

Building a Multilayer Macro-Network for the Netherlands: A New Way of Looking at Financial Accounts and International Investment Position Data

Melle Bijlsma[a], Malka de Castro Campos[a], Raymond Chaudron[a] and David-Jan Jansen[a,*]

[a]De Nederlandsche Bank, Amsterdam, The Netherlands

31 July 2018

Abstract

We argue that who-to-whom data from financial accounts can be fruitfully combined with information on the international investment position to study interconnectedness within the financial system. We illustrate this point using detailed information for the Netherlands over the year 2016. In doing so, we contribute to recent work that uses network analysis to study financial interconnectedness at the macro level. We also discuss potential further applications, such as using these network representations for financial stability analyses.

Keywords: Network analysis, financial accounts, international investment position, interconnectedness.

JEL codes: C82, G20, L14

* The views expressed in this paper are those of the authors and do not necessarily reflect official positions of De Nederlandsche Bank. Corresponding author: M. de Castro Campos, De Nederlandsche Bank, Statistics Division, P.O. Box 98, 1000 AB Amsterdam, The Netherlands. E-mail: m.de.castro.campos@dnb.nl.

1. Introduction

The financial crisis of 2007-2009 made clear that interconnectedness within the financial system can be a key driver of financial instability. Issues concerning liquidity or solvability could quickly spread across the financial system through the linkages between financial institutions. More broadly, it became apparent how instability in the financial sector could quickly affect the real economy. Since the crisis, a lot of effort has been put into better understanding interconnectedness, both within and outside the financial system. To a large extent, especially for international linkages, even the basic steps of collecting and organizing the appropriate data have shown important challenges.

This paper contributes to further understanding interconnectedness by using so-called from-whom-to-whom accounts. Exploiting the granular information about the linkages between individual sectors allows us to construct, for the first time, a detailed network representation for the Netherlands. Importantly, in addition to charting domestic linkages using financial accounts, we also take into account data from the international investment position (IIP) to enhance the available information on the 'rest of the world' sector. This allows us to study linkages with the most important counterparts in terms of geographical regions and foreign sectors. Additionally, we investigate the connections of the Dutch financial sectors with sectors from abroad. In doing so, we contribute to the debate on analysing interconnectedness at the international level. We discuss the benefits of our approach and outline a number of challenges. Having done so, we turn to a description of the network, mainly by giving various visualisations of the underlying data.

Our main conclusion is that the nature of interlinkages can differ considerably across the financial system, and are to a large extent dependent on the sectors involved. These different types of interlinkages can react differently to shocks and periods of stress. This underlines the benefits of looking at interlinkages and capital flows on a sectoral basis rather than in aggregate for the full economy.

In terms of methodology, this paper builds on recent work applying network analysis to data sets that measure financial linkages across various sectors of the economy. A closely-related paper is by Castrén and Rancan (2014), who construct a so-called macro-network for the euro area by combining flow-of-funds statistics for 11 countries with data on balance-sheet items of the MFI sector. One drawback is that they do not directly observe the bilateral links between economic sectors, which is why they have to estimate these links using entropy methods. In contrast, given the availability of from-whom-to-whom accounts for the Netherlands, we are able to construct a direct network representation.

The remainder of this paper is structured as follows. Section 2 discusses related papers that use network analysis as tools for financial stability analyses. Section 3 presents details on how we use from-whom-to-whom accounts to construct a macro-network for the Netherlands. Section 4 present various visualisations of the network that we construct. Section 5 concludes and charts paths for future analyses.

2. Related literature on network analysis

Network analysis is an intuitive tool to analyse financial interconnectedness, and the existing literature on the subject already provides a range of useful insights. An important question is at what level the network should be defined. One option is to construct a network using data on linkages between individual financial institutions. A comprehensive analysis along these lines is given in Anand et al. (2017), who focus on networks in 13 jurisdictions across 25 financial markets, with the aim of analysing the performance of different network reconstruction methods. In an analysis using data for Mexico between 2007 and 2013, Poledna et al. (2015) quantify the contributions to systemic risk from four layers of the banking system. They then assign these systemic risk levels to individual banks. They conclude that market-based systemic risk indicators underestimate expected systemic losses. Cerutti and Zhou (2017) apply network analysis to BIS data on cross-border bank lending. They find that some parts of the network are currently more interlinked regionally than before the crisis, while being less dependent on major global lenders.

Increasingly, network analysis is also applied to macro-level data. Chinazzi et al. (2013) use the IMF Coordinated Portfolio Investment Survey (CPIS) to investigate debtor/creditor relations between countries. They find that the 2008 financial crisis led to a significant change in the network properties. They also conclude that being central in the network may make countries more vulnerable in times of crisis when they are not member of a financial hub of rich countries. Castrèn and Rancan (2014) combine data from euro area flow-of-funds statistics with data from balances sheets of MFIs. This approach allows them to construct a euro area macro-network to analyse contagion and shock propagation. They conclude, inter alia, that network properties and propagation losses are highly time-dependent. They also find that network statistics (such as degree, betweenness, or closeness) can be useful to predict how shock propagate in the financial system. Building on this study, Peltonen et al. (2015) show that a more central position of the banking sector in a macro-network increases the likelihood of a banking crisis. They also find that interconnected measures can be useful additions to early-warning models for banking crises.

To our knowledge, there is little empirical work on network linkages using macroeconomic data where the different sectors of the economy, including the sector rest of the world, are integrated. From-whom-to-whom matrices based on national financial accounts data form a solid basis for such research. These matrices are a relatively recent addition to the macroeconomic datasets available to users, and are made available by more and more national statistical agencies worldwide.[†] In this paper we contribute to the literature by augmenting data from these matrices with IIP data, to provide a more granular view of international exposures. By detailing the Dutch economic network and providing a first set of analytical results, we highlight the importance of network analysis to evaluate the degree of interconnectedness among different economies and the contagion effects between them.

3. Constructing a macro-network for the Netherlands

Our empirical analysis is based on annual data for 2016[‡] for the Netherlands at market prices. As the first step in our data preparation, we obtain the financial accounts matrix of from-whom-to-whom data from Statistics Netherlands (CBS)[§]. These data are derived from the national accounts and comprise the details of exposures between sectors within the Dutch economy, and between these sectors and the rest of the world. Financial accounts data is the most comprehensive dataset about financial relationships between the sectors of an economy and has the advantage of being internally consistent, in the sense that the assets in a particular instrument of one sector vis-à-vis another sector equal the liabilities of the latter sector vis-à-vis the former. A limitation is that non-financial assets, such as housing wealth, are not included even though they form a large part of the net worth of certain sectors.

From-whom-to-whom data is available at the level of ESA2010 (sub-)sectors and details several financial instruments. For the purposes of our analysis, we define the following sectoral combinations in our dataset: non-financial corporations (abbreviated as NFC, corresponding to sector S.11 in ESA terms), monetary financial institutions or banks (MFI = S.122), investment funds (IF = S.124), other financial corporations (OFC = S.125 + S.126), special purpose entities (SPE = S.127), insurance companies (IC = S.128), pension funds (PF = S.129), government (GOV = S.13), households (HH = S.14 + S.15) and the 'rest of the world' (S.2). For each link between these sectors, the dataset discerns various types of instruments: namely exposures in savings and deposits (AF.2), bonds (AF.3), loans (AF.4), equity (AF.5) and technical reserves (AF.6).

[†] Publishing such matrices is a recommendation of the G-20 Data Gaps Initiative, which seeks to address data gaps in the measurement macrofinancial risks and vulnerabilities. For more information, see Heath and Bese Goksu (2016).

[‡] Our dataset in fact contains annual data between 2010 and 2016. Exploiting this time series dimension is left for future work.

[§] Fassler *et al* (2012) and Tissot (2016) provide background information on the compilation of the sectoral financial positions on a from-whom-to-whom basis.

Note that this from-whom-to-whom dataset does not provide any additional geographical breakdown of exposures vis-à-vis economic actors in foreign countries; all international exposures are simply assigned to the rest of the world account (S.2). As the second step of our data preparation, we therefore include a geographical breakdown of international exposures to our dataset. We do this by obtaining the IIP data compiled by De Nederlandsche Bank, which provide exposure positions of sectors of the Dutch economy vis-à-vis foreign sectors at the country and instrument level. Note that historically these statistics are not fully consistent with the figures on the rest of the world sector in the from-whom-to-whom matrix, as a result of differences in observation and compilation strategy between the National Accounts and the External Statistics frameworks.[**] We therefore scale the exposure levels in the IIP dataset to make their total consistent with the rest of the world account. For exposures of Dutch sector X on sector Y in foreign country C, for instrument i:

$$Exposure_i(X, C_y) = RoW_X\left(\frac{IIP_{i,C_y}}{\sum_c IIP_i}\right)$$

Per year the original from-whom-to-whom data has about 325 observations, including the 10 sectors mentioned above. Once the data is enriched with the countries and the foreign sectors under S.2 using the IIP data, the dataset jumps to 6,700 observations per year divided over 250 countries and the same 5 instruments. Figure 3.1 shows schematically how we have augmented the data of the national accounts. The original who-to-whom matrix is shown in the top left corner. The blue arrows indicate the steps that use IIP data to expand the international exposures.

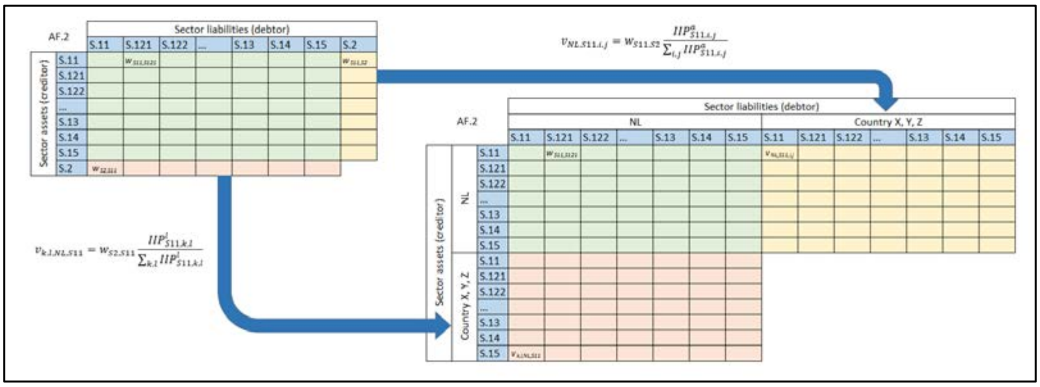


Figure 3.1: Example of constructing exposures related to the foreign counterparts using IIP data.

In the following table we show the summary statistics comparing the from-whom-to-whom data before and after including the IIP information for the year 2016. We specifically show the information for the Dutch sectors with the foreign counterparts. The observations 'original' refer to the summary statistics as in the from-whom-to-whom data when foreign counterparties were integrated into the rest of the world sector. The observations 'Inc. IIP' reflect the results after the calculations as described in Figure 3.1 aggregated over all instruments. We can see that the mean decreases as to reflect the great increase of new information to further detail the sector S.2.

Table 3.1: Descriptive statistics of counterparts in 'rest of the world' sector(s) before and after the addition of IIP data (in billions of Euro's)

Variable	Obs	Mean	Std. Dev.	Min	Max
Original	9	1043.4	1079.1	21.4	3156.4
Inc. IIP	3,242	2.8	13.6	0.0	280.9

[**] Note that for the Netherlands, due to the recent integration of the observation and compilation practices, these figures are now fully consistent from 2015 onwards.

The resulting matrix details the relationship of all Dutch sectors with each other but also with all counterpart sectors from other countries around the world. This particular combination is relatively complete – both domestic and foreign exposures are well-observed – and thus powerful for analysing interconnectedness. For the assets-side of the Dutch balance sheet the matrix is quite accurate. However, for the liabilities side the accuracy of the holder's information is lower specifically for the instruments AF.3 and AF.5. This is the case as these instrument categories can contain large volumes of tradeable securities from whom the ultimate holder is unknown; the statistical framework typically attributes these liabilities to the resident country of the security custodian.[††]

Another important issue is that at the current state of the network, the counterparts of the foreign countries are not linked to each other. Even though this paper combines statistical frameworks to provide more completeness, our resulting analysis is in this sense still partial. In an ideal world, one would run this exercise for countries worldwide and combine them to better understand global interconnectedness.

4. Visualising the macro-network

Next we visualize the networks we have created in our data compilation process.[‡‡] As an agnostic first step, we simply visualize the full exposure network including country level information for equity exposures (AF.5). Figure 4.1 shows the result. We can see that visualizing the full network is not very helpful, the output is too granular to be useful. As we focus on visualizations in this paper, we proceed to improve readability through aggregation and selection of specific sectors. It goes without saying, though, that the dataset could still be analysed to great effect at the detailed level through econometric and data-science techniques – this is an obvious avenue for follow-up work.

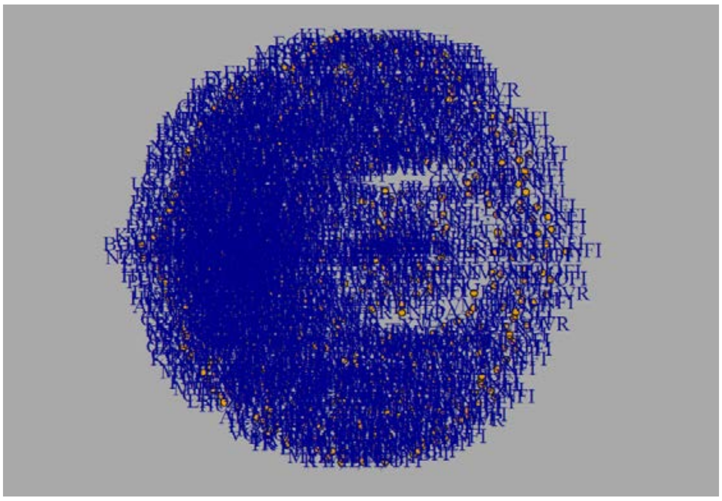


Figure 4.1: Visualisation of all equity exposures grouped by country for 2016

We aggregate data by constructing country groups instead of mapping exposures to individual countries. The country groups that comprise the rest of the world sector are Europe (=EU), North America (=US), Asia (=AZ) and other countries (OC). Each country group is further categorised into the sectors equal to the sectors for the Netherlands. Additionally, we look at all instruments aggregated. For our selection of financial sectors to analyse, we proceed to focus on the largest sectors in terms of

[††] A potential avenue for quality improvement could be to utilize mirror data from e.g. the CPIS database maintained by the IMF. Implementing such an improvement is beyond the scope of this paper.

[‡‡] We use the R-package *igraph* for this purpose.

balance sheet size; as visualized in Figure 4.2. It shows that special purpose vehicles are the largest sector in the Dutch financial system, with a balance sheet amounting to 552% gdp.§§ The next largest sector is the MFI sector, totalling 305% gdp. The third largest sector is the pension fund sector with a combined balance sheet of 171% gdp.

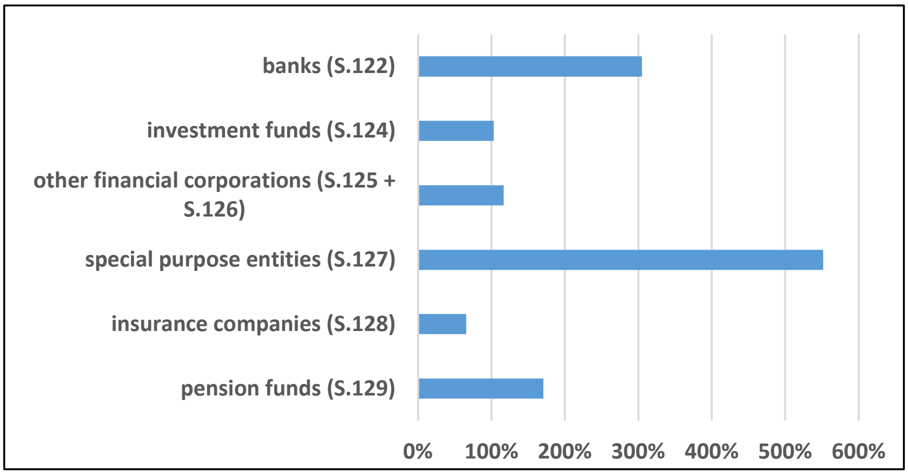


Figure 4.2: Size of the Dutch financial (sub)sectors, 2016, in % of nominal GDP

Focusing on the SPE sector, we visualize both its total assets and liabilities. Figures 4.3 and 4.4 show the results of this exercise. The figures clearly show that for this sector, international exposures dominate national exposures for both assets and liabilities. Furthermore, exposures are concentrated vis-à-vis specific sectors. Dutch SPEs main asset side exposures are to non-financial institutions and other financial institutions in the EU, Rest of the World, and to a lesser extent North America and Asia. The picture is similar on the liability side, with exposures to US non-financial and other financial institutions being more pronounced. In terms of instruments, equities (AF.5) are the dominant exposure class. Note that the in the IIP data the sector SPE is unavailable as counterpart sector. Instead, this sector is grouped with the other financial corporations (OFC) sector. Interlinkages with counterpart OFC could therefore also represent SPEs in countries other than the Netherlands. Exposures to other Dutch domestic sectors are negligible except for asset side exposures to Dutch non-financial institutions, which represents the SPE institutions with economically active sister companies in the Netherlands.

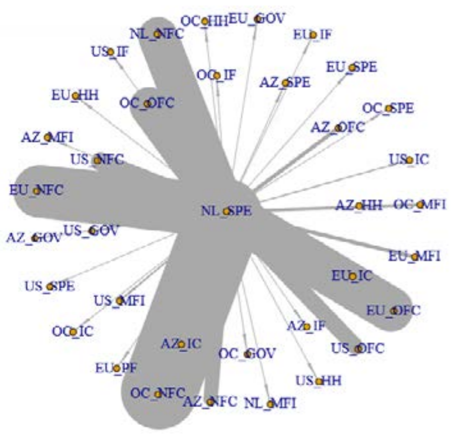


Figure 4.3: assets for the sector S.127

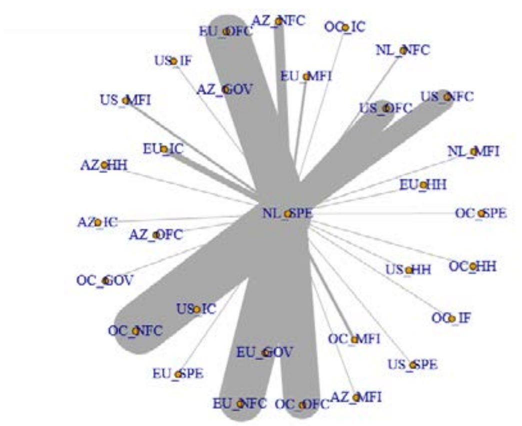
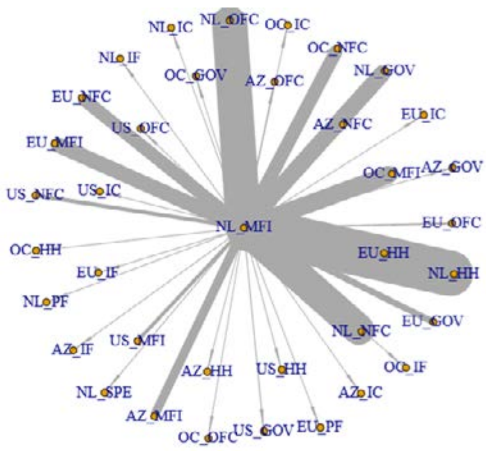


Figure 4.4: liabilities for the sector S.127

§§ Eggelte, Bijlsma & Carlier (2016) provides a more detailed description of the Dutch SPE sector and the associated statistical issues.

In contrast to the networks of the SPE, domestic exposures dominate both the assets and liabilities of Dutch banks.*** Figure 4.5 shows the sector's assets and illustrates that exposures consist largely of loans (AF.4) to Dutch households (mortgages) and non-financial corporations. The same holds for the liability side (Figure 4.6), where banks mostly hold deposits (AF.2) from the same sectors. Thus, the network of Dutch banks show the classical intermediation role in the real economy, providing the link between investors and investees. However, on both the asset and liability side some additional exposures are visible such as interbank loans to banks and exposures to other financial corporations – both in the Netherlands and abroad.



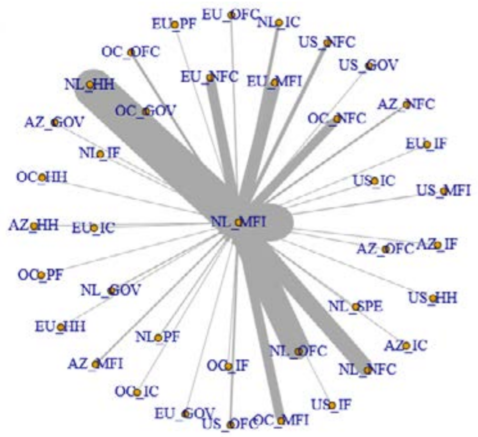
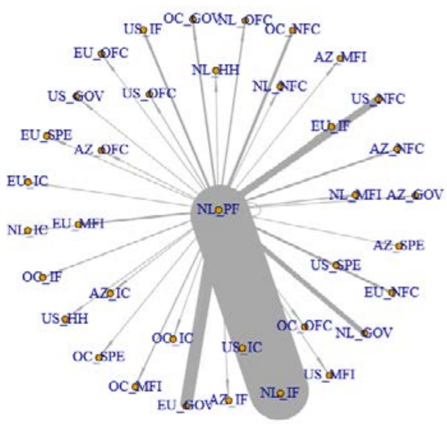


Figure 4.5: assets for the sector S.122

Figure 4.6: liabilities for the sector S.122

Finally, we visualize the exposures of the pension funds sector. Figure 4.7 and 4.8 show their asset and liabilities respectively. On the asset side, pension funds have concentrated exposures to Dutch investment funds (AF.5), while also maintaining a smaller diversified international exposure position mainly through bonds (AF.3). On the liability side, the sector's exposure is almost exclusively domestic: namely pension claims from Dutch households (AF.6).



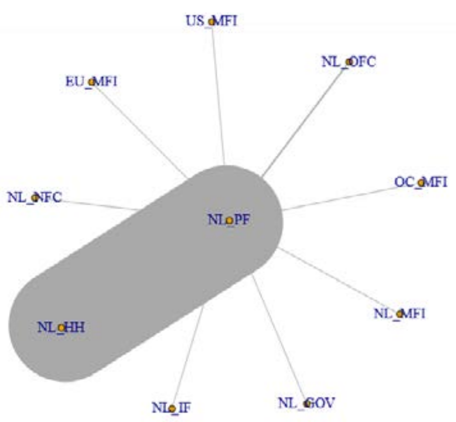


Figure 4.7: assets for the sector S.129

Figure 4.8: liabilities for the sector S.129

*** Note that we analyse MFI data according to statistical definitions, which encompass resident entities rather than full consolidated banking groups (such as in e.g. the BIS international banking statistics)

The concentrated exposures to Dutch investment funds is interesting to investigate further. Thus, we follow the financial intermediation chain and visualize assets and liabilities for the investment funds sector. Figure 4.9 shows that asset side exposures and illustrates that investment funds manage a geographically diversified, mostly international set of assets. Stocks of North American non-financial corporations and European government bonds form substantial investment categories. Figure 4.10 shows the sector’s liabilities and confirms that these are mostly related to Dutch pension funds, and to a lesser extent other Dutch institutional investors. From these figures we see clearly that investment funds are investment vehicles of Dutch institutional investors to manage their pool of assets. There is little direct participation of the Dutch real economy in this link of the intermediation chain, except for small direct holdings by Dutch households. The network analysis helps us to pinpoint this mechanism in a relatively simple way. Note that this example also illustrates how an increase in the length of the financial intermediation chain increases financial sector asset as measured in statistical frameworks. *In extremis*, if Dutch pension funds would completely invest directly instead of through investment funds, the Dutch financial sector would be 100% of GDP smaller than it is today.

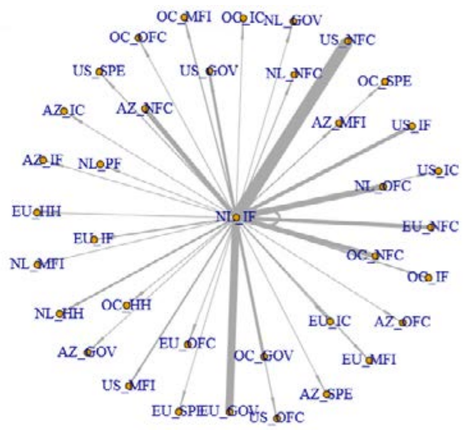


Figure 4.9: assets for the sector S.124

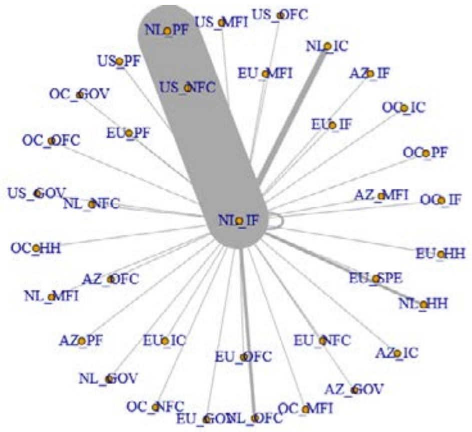


Figure 4.10: liabilities for the sector S.124

Based on the evaluation of the dynamics per financial sector in the Netherlands it is possible to conclude that the capital flows through Dutch financial sectors can have greatly varying characteristics, in terms of counterpart sectors and countries, and in terms of instruments. Several segments of interconnected sectors can be identified. SPEs generally have very little domestic exposures and are mostly exposed – through equity – to non-financial corporations, other financial institutions and SPEs abroad. MFIs generally have domestic exposures to real sectors – households and corporates – in loans and deposits. Finally, the liabilities of Dutch pension funds are (ultimately) to domestic households, and they invest in a diverse set of international assets – mostly equities and bonds – through an intermediation chain involving investment funds. The network analyses of these sectors provide a simple visualisation of these linkages and can also be used to test dynamic shocks in the economy, taking into account possible financial intermediation chains between the different sectors across multiple economies.

5. Conclusion

This paper has argued that from-whom-to-whom data from financial accounts can be fruitfully combined with information on the international investment position to study connections within the financial system. Based on annual data for the Netherlands for 2016, we provide first examples of how this approach might yield useful insights by depicting the structural differences in the networks of the Dutch financial sectors.

Our analysis suggests two points. First, the nature of intra-country exposures can vary considerably depending on the financial sectors involved. An exposure originating from SPEs, for instance, will likely have little or no connection to the immediate counterpart country. For exposures originating from banks or pension funds, this is likely to be very different. The reaction of exposure holders in times of stress –in the receiving country, originating country, or both – can as a result be potentially different. This finding would be something for policymakers to take into account, while also underlining why analyses using sectoral breakdowns are important. Second, our paper shows the added value of looking at intermediation chains rather than stand-alone sectors. Based on the analysis of a single sector, one might think that its exposures are largely domestic even though the direct recipient of its funds in fact channels it abroad. In the process, we also show that longer intermediation chains tend to inflate financial sectors' balance sheets. This may decrease the value of balance sheet figures as an accurate measure of risk in the financial sector.

The analysis in this paper is not without limitations. Most importantly, our measurement of interlinkages is limited to exposures involving the Dutch economy. A more complete analysis of interlinkages would require similar data from multiple countries to be combined, thus creating a (near) global network. Performing such an analysis does seem to be an advanced ambition at this stage, however. Even insofar as similar data for this analysis exists in other countries, data sources such as the IMF Coordinated Portfolio Investment Survey show that there are numerous bilateral discrepancies between countries' mirror data. It will likely require time and effort to create more consistent and complete global network data in the future.

Building on the dataset and analyses presented in this paper, several potential avenues for further research suggest themselves. First, the properties of the constructed network could be examined and serve as an important complement to the growing body of literature studying the interactions between financial institutions (e.g. Billio et al., 2012, Demirer et al., 2018, or Geraci and Gnabo, 2018). In this regard, more formal methods could also be used to assess the extent to which sectoral, interconnected clusters exist as observed in the data. Second, the available time dimension, i.e. annual data from 2010 to 2015, can be used to assess the response of different exposures during periods of financial stress – e.g. during the European sovereign debt crisis or the US taper tantrum. Third, a more long-term research agenda would be to consider how these macro networks could be integrated in stress-test analyses, for instance in the context of examining second-round effects via contagion channels.

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BANK FOR INTERNATIONAL SETTLEMENTS

Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

Building a multilayer macro-network for the Netherlands: A new way of looking at financial accounts and international investment position data[1]

Melle Bijlsma, Malka de Castro Campos, Raymond Chaudron and David-Jan Jansen,

Netherlands Bank

[1] This presentation was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

Building a Multilayer Macro-Network for the Netherlands: A New Way of Looking at Financial Accounts and International Investment Position Data

M. Bijlsma, M. Castro Campos, R. Chaudron, D. Jansen

DeNederlandscheBank

EUROSYSTEEM

Literature and paper’s contribution

- Great Financial Crisis highlights the importance of mapping interconnectedness and contagion channels; network analysis has become an increasingly popular tool.
- Chinazzi et al. (2013) and Castrèn and Rancan (2014) are examples of papers using network analysis.

Our contribution is twofold:

1. Provide a look on how financial network analysis can be further explored by extending the level of detail from the rest of the world sector (S.2).
2. Show that different economic sectors have different properties that lead to possible contagion paths across multiple economic instruments and countries.

Data

- Data from national accounts (from-whom-to-whom matrix) combined with data from the international investment position (IIP)
- IIP data is made consistent (scaled) with national accounts ‘rest of the world’ account positions
- Time series 2010-2016, exposures between sectors at instrument level (e.g. bonds, equity, loans)
- Data regarding counterpart rest of the world (in billion of euros):

Variable	Obs	Mean	Std. Dev.	Min	Max
Original	9	1043.4	1079.1	21.4	3156.4
Augmented data	3,242	2.8	13.6	0.0	280.9

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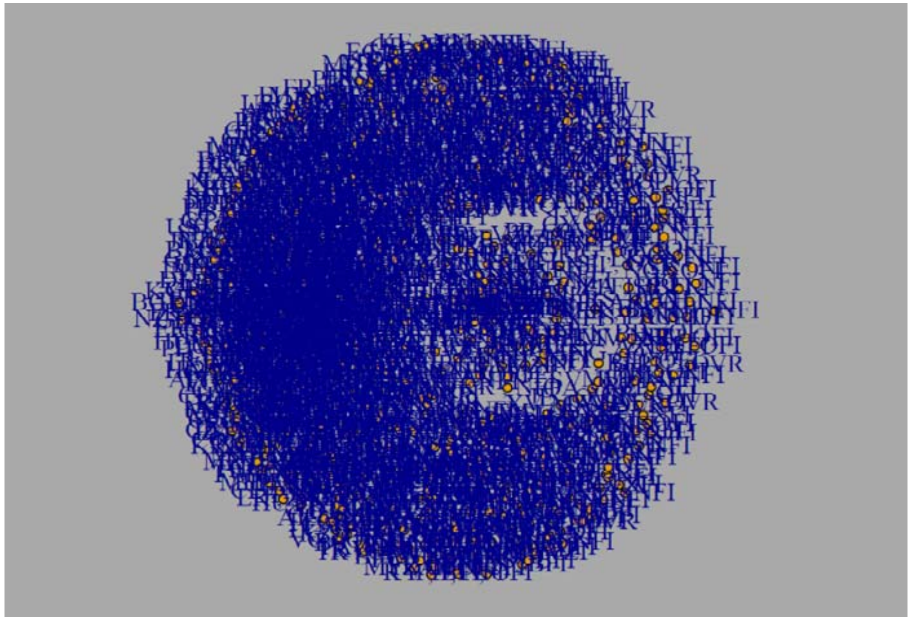
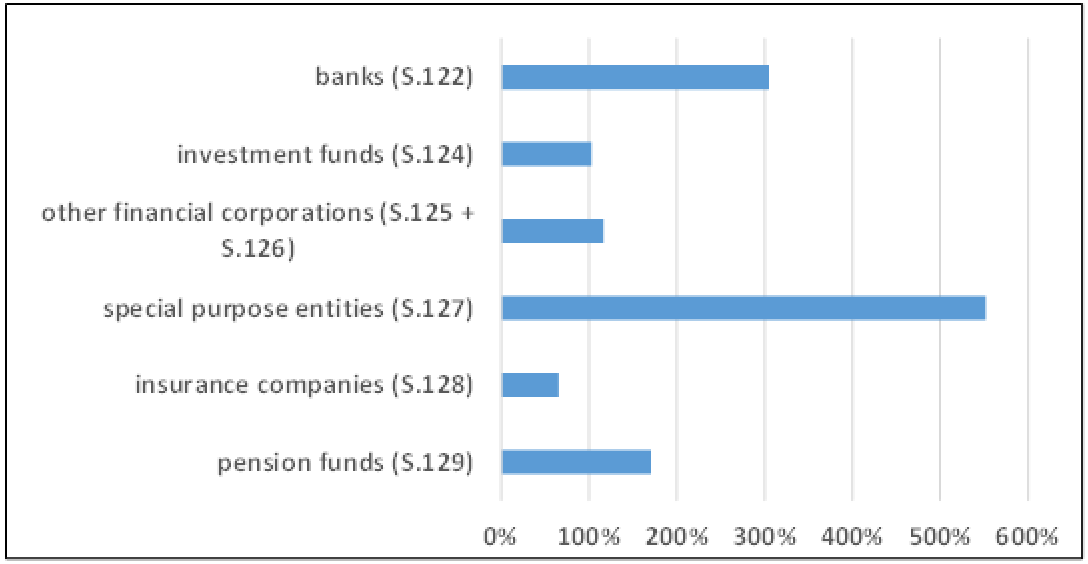
Data

- When visualizing, we take away some levels of granularity

- Country groups (Europe, United States, Asia, Other countries)
- Combine all instruments
- Use data for 2016



Size Dutch financial sectors (2016, % gdp)



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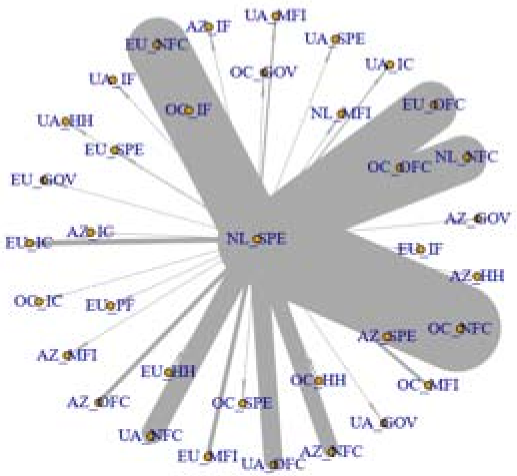
SPE (S.127)

Assets



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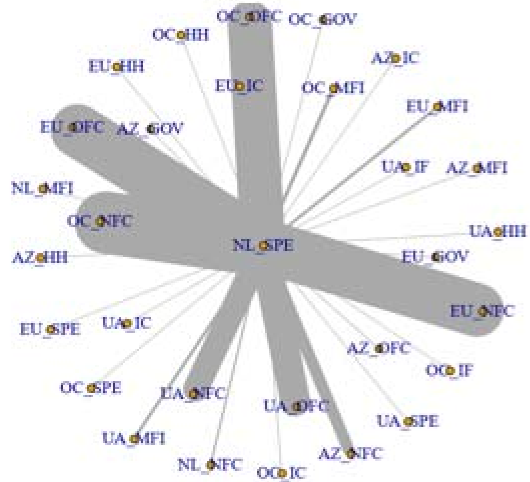
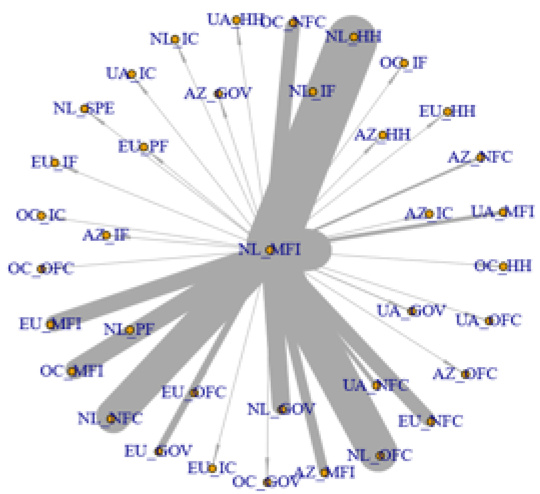


MFI (S.122)

Assets



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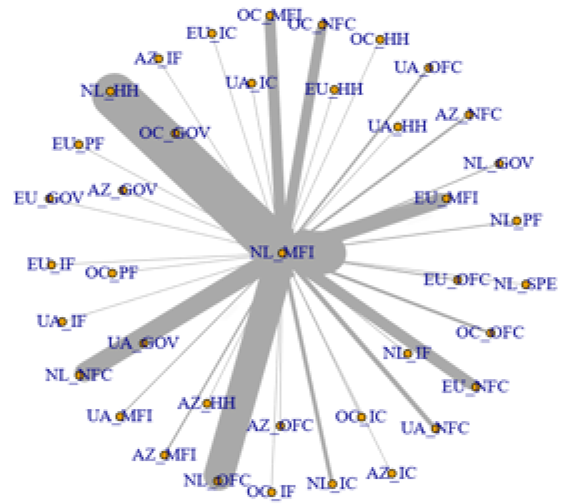
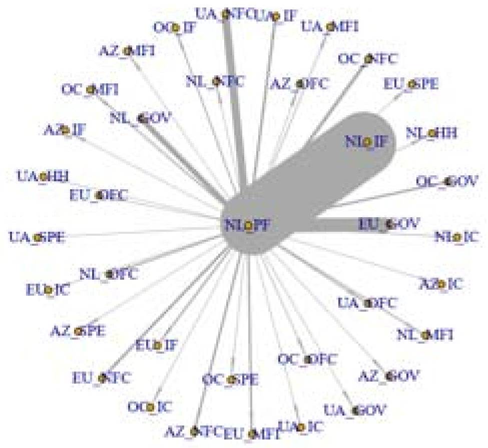


PF (S.129)

Assets



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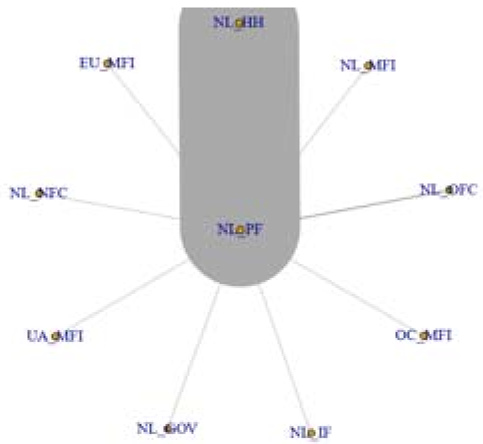

IF (S.124)

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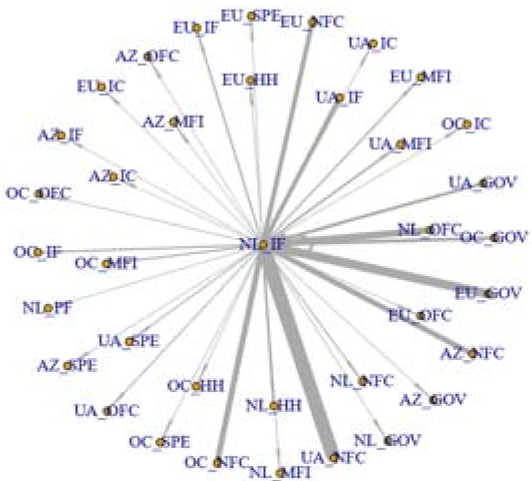

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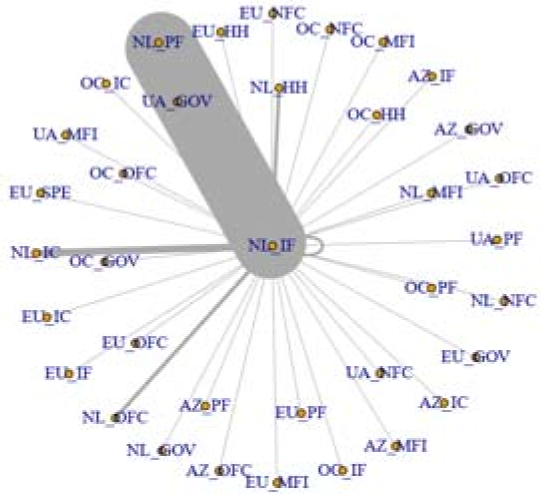

Conclusion

- Network data analysis is a powerful tool to depict structural differences between economic sectors across the world.
- It shows that the nature of intra-country exposures can vary by financial sector.
- It also improves the analysis of intermediation chains and helps identify different contagion layers.
- Data are limited to Dutch exposures.
- Many paths for future research: evaluate de properties of the network, evaluate time series effect, include stress-test analyses.

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Basel, 30-31 August 2018

Who holds banks' debt securities? Statistical methods for allocation by holders[1]

Meng He, China State Administration of Foreign Exchange,
and Zuzana Filkova, Bank for International Settlements

[1] This paper was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

Who holds banks' debt securities? Statistical methods for allocation by holders[1]

Meng He,[2] Zuzana Filková[3]

It is difficult for issuers to precisely identify the holders of their securities, especially if the securities are held via custodians and are actively transacted in financial markets. In our case study of the BIS locational banking statistics (LBS), holders are currently unallocated by residence for almost 40% of banks' debt securities liabilities, as opposed to practically zero for their deposit liabilities. At the same time, banks in some countries allocate holders fully, but not necessarily accurately. To improve the data quality, we review practices in the LBS-reporting countries and propose conceptual options for improving counterparty allocation of liabilities.

Keywords: debt securities, banking statistics, compilation practices.

JEL classification: C8, C82, G15.

1 The views expressed in this paper are those of the authors and do not necessarily reflect those of the Bank for International Settlements or the State Administration of Foreign Exchange of China. We thank Stefan Avdjiev, Guodong Chang, Hong Hu, Pablo García Luna, Siew Koon Goh, Sebastian Goerlich, Swapan-Kumar Pradhan, Svitlana Tyahlo, Phillip Wooldridge, Can Yang and participants in a seminar at the BIS for their input. We are also grateful to statisticians at the central banks and agencies surveyed in the project for helpful comments and discussions.

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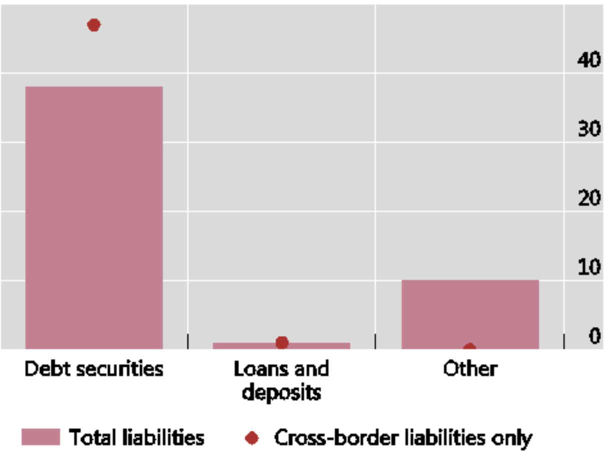
Contents

1. Introduction

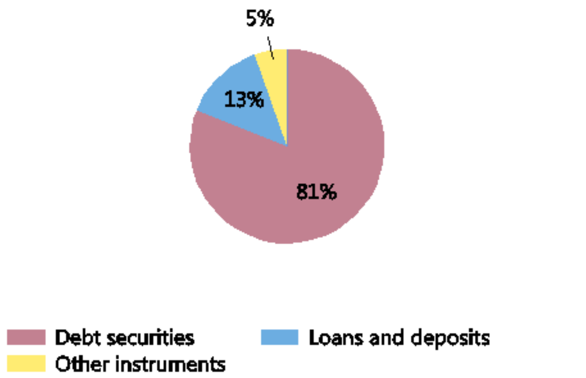
It is more difficult for issuers to identify the holders of their securities than to identify the counterparties of other types of liabilities. For example, in the locational banking statistics (LBS) of the Bank for International Settlements (BIS), around 38% of all reported debt securities liabilities are unallocated by residence of holders, as opposed to practically zero for deposit liabilities (Graph 1). To improve data quality, we review practices in the LBS-reporting countries and propose conceptual options for improving counterparty allocation of liabilities. To collect the most accurate data on the market size of debt securities issues and their holders, we recommend the combined approach of a custodian and an issuer survey complemented with estimation and cross-checking using mirror data.

Unallocated liabilities across instruments, end-2017 Graph 1

Unallocated residence in total per instrument[1]



Distribution of unallocated residence across instruments



[1] The measure using total liabilities is more reliable in estimating the unallocated proportion, despite the amount being underreported due to missing local or cross-border liabilities for some countries. See full list of proportions of local and cross-border liabilities within total liabilities in Appendix Table A1.

Source: BIS LBS by residence

The identification challenge comes from two features of debt securities: negotiability and participation of intermediaries. Because of their negotiability, debt securities can easily change hands in secondary markets without issuers being notified. It is common to hire custodians to safeguard and administer the holdings of debt securities on behalf of investors, and banks as issuers rarely have direct contact with investors. The non-resident participation increases the difficulty of collecting data on counterparties, especially when the debt securities are issued in foreign markets and foreign investors and custodians are beyond the legal scope of domestic compilers. Moreover, in the LBS, outstanding positions rather than transactions are reported, making the exact identification of individual counterparties more difficult.

Interest in data on holders is increasing among policymakers, analysts and researchers alike. First, debt securities account for a growing proportion of corporate liabilities. For example, in the LBS, the share of debt securities in cross-border liabilities increased from 19% at end-2000 to 35% at end-2017. Second, the Great Financial Crisis of 2007–09 revealed the inadequacy of information on securities holdings, in particular its lack of granularity and imprecision. For example, when Lehman Brothers collapsed, supervisors and policymakers had very limited information on holders' exposure to securities and most of the then available official statistics were just aggregate information (ECB (2015)) with no residence or sectoral split. In 2009, the G20 initiated the Data Gaps Initiative[4] to address these data gaps with a view to supporting enhanced policy analysis. In its second phase, "from-whom-to-whom" matrices[5] of the System of National Accounts are recommended to allow for analysis of sectoral and locational financial interconnectedness (IMF (2016)). The new data provide answers to innovative types of questions, eg development of new indicators of financial integration (Fache Rousová and Rodríguez Caloca (2014)) or system-wide funding risk (Fender and McGuire (2010), Cerutti et al (2012)).

In this paper, we use the BIS LBS data by residence as a case study of how holders can be identified for statistical purposes. The LBS are designed to capture outstanding assets and liabilities of internationally active banks, split by instrument and sector and across more than 200 counterparty countries. They capture around 95% of all cross-border banking activities The same problem exists in the BIS consolidated banking statistics,[6] where banks report their local liabilities (vis-à-vis the residents of the country in which they are located) denominated in the "local" currency of the respective country. For that, banks need to know who the holders of their liabilities are (BIS (2017)). Yet the issue of identifying debt securities holders is also essential for Balance of Payments, International Investment Position and other statistics.

2. Conceptual options

There are at least four different options available to statisticians to collect information on securities holders: (i) survey the issuers of the securities; (ii) survey the custodians; (iii) survey other data owners; and (iv) use mirror data. We explain the advantages and disadvantages of each of these options below.

Data collection methods can differ depending on where debt securities are issued. Before choosing the right method, it is essential to understand the mechanics of debt securities holdings in different markets.

When banks issue debt securities in the domestic market, resident and non-resident investors can either buy and hold the debt securities directly there or, more commonly, hire a domestic custodian to administer the investment. In addition,

[4] Moreover, recommendation II.12 of the Coordinated Portfolio Investment Survey in this initiative targets an improved reporting of securities, especially the sectoral and counterparty split which is related to our work.

[5] Introduced as long ago as 1993 (Table 13.3a, SNA 1993). The integrated framework on a from-whom-to-whom basis makes it possible to determine who is financing whom, in what amounts and with what type of financial instrument (Shrestha et al (2012)).

[6] Measures international banking activity from a nationality perspective, focusing on the country where the banking group's parent is headquartered.

non-resident investors can hire a foreign custodian who in turn can hire a domestic custodian to safeguard their securities.

When banks issue debt securities in a foreign market, foreign custodians are more involved than domestic custodians. Foreign and domestic investors can either hold directly from the foreign market, or hire a foreign custodian. Alternatively, resident investors can first hire a domestic custodian who then hires a foreign custodian.

a. Issuer survey

If compilers would like to collect information on debt securities, the most straightforward option would be to survey their issuers (also advocated by TFFS (2013)). Such a survey requests the issuing banks, or their underwriters, in the compilers' jurisdiction to report all debt securities issued, including total amount issued, positions, residence and sectoral information on holders.

The issuer survey has several advantages. As most LBS compilers are central banks, they should have the authority to collect data directly from domestic banks. Where the debt security is issued in a direct investment relationship and is held to maturity, the issuer is supposed to have all the relevant information. Moreover, when debt securities are issued in a foreign market, foreign custodians cannot be required to report and domestic custodians are less involved in the transactions, issuers become the preferred data source. Finally, issuers have a natural edge in reporting the whole size of debt securities they issued, so that underreporting of the total amount is less likely to occur.

The main shortcoming of the issuer survey is that banks may keep only information on the primary purchasers when the securities were issued. The counterparty country and sectoral breakdown might consequently be outdated. In summary, the data collected from the issuers can be a very precise estimate of the size of debt securities issues, but contain inherently less accurate counterparty information if the debt securities have changed hands.

b. Custodian survey

If debt securities are issued in the domestic market and domestic custodians are commonly hired to safeguard the holdings, it is more appropriate to approach domestic custodians to obtain more precise counterparty data. This approach is neatly described in the Handbook on Securities Statistics (BIS-ECB-IMF (2016)).

A custodian survey requires domestic custodians to report on their customers when they are hired to safeguard the debt security investment. Based on "know your customer" legislative requirements in most economies (IMF (2014)), custodians are supposed to record information on whom they are acting for. Therefore, by surveying domestic custodians, the residence and sectoral information of holders can be captured without approaching the holders directly.

The main advantage of the custodian survey is that the information on holders is more precise, reliable and up-to-date. Another is its cost-effectiveness. By surveying the largest custodians, most holders' information can be captured since there are fewer custodians than investors.

The main shortcoming is that the central banks may have no power to collect information from non-bank entities like non-bank custodians. In addition, a domestic custodian can be hired by a foreign custodian and is therefore less capable of identifying the end-beneficiary. This could introduce a bias considering that the beneficiary is not necessarily a resident of the same country as the foreign custodian (TFFS (2013)), and highly likely belongs to another sector.

Additionally, solely surveying custodians may result in both *underreporting* and *overreporting*. The result can be *underreported* because custodians do not necessarily know the whole amount of the debt securities issued. Since custodians can report only the amount of the debt securities that they are entrusted with administering, they omit other parts invested directly by investors or entrusted to foreign custodians. The result can also be *overreporting* of resident positions if more than one domestic custodian is involved in the investment chain. If an investor hires a domestic custodian to administer the account, and this custodian then hires another domestic custodian, these two custodians would report the same investment amount twice. The latter custodian would always report a local position, being unable to distinguish whether it is administering the former custodian's own account, or the account of the former custodian's customer.

In the compilation guides of *Balance of Payments and International Investment Positions Manual sixth edition (BPM6,* IMF (2014)), *Handbook on Securities Statistics* (BIS-ECB-IMF (2016)) and *Coordinated Portfolio Investment Survey (CPIS,* IMF (2018), similar surveys of custodians and end-investors are introduced. They focus more on the asset side, but the logic of the data collection is similar on the liability side.

To conclude: while custodians collect precise data in an efficient manner, surveying solely custodians can introduce a bias to the data.

c. Combined approach

Combining an issuer survey with a custodian survey can ensure that all debt securities are reported and improve the accuracy of data at the same time. When the debt securities are issued in domestic markets and domestic custodians are commonly hired, information on most holders can be collected using the custodian survey. When the debt securities are issued in foreign markets and domestic custodians are less involved, issuers become the main data source. This survey method should produce the most precise data on the size of debt securities liabilities from the issuer part of the survey and their exact residence and sector allocation from the custodian part (summarised in Table 1).

The pros and cons of different surveys

Table 1

	Pros	Cons
Issuer survey	• Precise amount of total debt securities issued • Precise information in case of direct investment • Already covered in central banks' jurisdiction • If no domestic custodian hired, issuer may have superior information	• Information potentially outdated
Custodian survey	• Precise and up-to-date information • Cost-effectiveness	• Non-bank custodians potentially not covered in central banks' jurisdiction • If hired by another custodian, may still not identify the end-beneficiary • Risk of over- and underreporting
Combined approach	• Precise amount of total debt securities issued • Precise and up-to-date information from custodians • Precise information from issuers in case of direct investment • Issuers already covered in central banks' jurisdiction • If no domestic custodian hired, issuer may have superior information • Cost-effectiveness in covering custodians	• Non-bank custodians potentially not covered in central banks' jurisdiction • If hired by another custodian, may still not identify the end-beneficiary • Risk of over-reporting

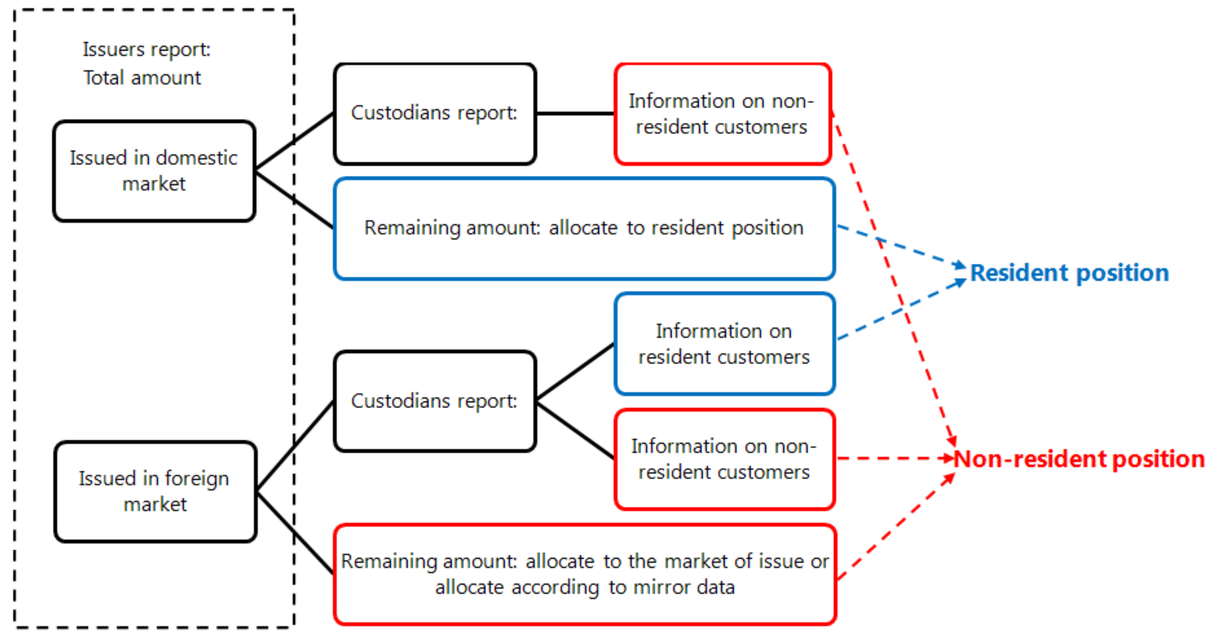
However, despite the considerable advantages of the combined approach, it also inherits the shortcomings of the custodian survey (Table 1): the lack of legal authority to cover non-bank custodians, and double-counting. The double-counting may occur not only between domestic custodians, as discussed in the custodian survey, but also between custodians and issuers. To avoid it, we suggest instructing issuers to report the amount of debt securities issued and the market of issue for each security. Custodians should report information on non-resident customers for debt securities issued in the domestic market, and on all customers for debt securities issued in foreign markets (for a full list of information to be reported by each party, see Appendix Table B1).

Resident positions can be then calculated as the difference between the total size of the domestic issue from the issuers minus domestic positions held by non-residents from the custodians.[7] The remaining amount in the foreign market not allocated by custodians is then attributed to the market of issue, or attributed according to mirror data (Graph 2).

7 This potentially understates the domestic positions, as nothing prevents domestic investors from holding securities administered by a foreign custodian hiring the domestic custodian.

Combined-approach solution to double-counting

Graph 2



To conclude: the combined approach maximises the advantages of both issuer survey and custodian survey, although particular care should be taken to avoid double-counting and estimation of the unallocated part.

d. Other surveys

There is no one-size-fits-all solution. The best methodologies for countries with different market situations, compilers' jurisdiction and data availability may be quite different, and basic surveys could be complemented with data from other institutions.

For countries with a central securities depository (CSD), the CSD becomes a preferred source of the requested data. Securities issued locally are usually required to be registered with the CSD in countries where one exists. All transactions in the domestic securities market must be communicated to or settled with it, including private sales transacted outside the market. A CSD enables values registered under custodian accounts, and thereby the ownership of debt securities, to be recognised. It thus serves as a high-quality data source in the domestic market, with the added advantage of cost reduction through the possibility of dealing with a single entity.

Countries with capital controls usually have institutions to monitor capital fund flows to and from the country, and have approved agencies to invest in domestic or foreign markets on behalf of resident and non-resident customers. Such institutions have reliable data on debt securities counterparties.

CSDs and monitoring organisations are good sources for data collection and cross-checking. Often they already collect data for regulatory and supervisory purposes, and compilers need only legal clearance to be able to access such data.

A complementary survey of stock exchanges and dealers (TFFS (2013)) could be another useful source of information. This approach is particularly useful in countries with smaller markets, where domestic banks tend to issue debt securities in foreign markets and domestic custodians may not provide sufficient information.

e. Estimation methods

As discussed above, surveying issuers and custodians, or even including other institutions that hold the relevant information, may not fully and precisely capture the description of holders. The question is how to fill in the remaining gap between the size of debt securities issued and what has been identified. As shown in Graph 2, besides allocating the remaining part to the market of issue, compilers can also split the unallocated remainder according to the distribution of the known part or using a distribution based on other reliable data sources.

The most prominent sources for this kind of mirror data are the Eurosystem's Securities Holding Statistics (SHS) and the IMF's Coordinated Portfolio Investment Survey (CPIS).

The SHS mainly focus on holdings of securities by euro area investors. The data are split by instrument type, issuer country and sector, maturity and other classifications. There are currently 26 euro area and non-euro area countries reporting to the SHS security by security by investor and custodian, and the data are released quarterly. By selecting debt securities issued by bank sector, the amounts of debt securities held by different euro-area countries can be determined. A big advantage is the availability of granular information ISIN by ISIN, which enables a higher degree of data accuracy and helps avoid double-counting.

What the SHS are for the euro area, the CPIS is for the world. This database collects information on a semiannual basis on the stock of cross-border holdings of securities, split by instrument (equity and debt securities), maturity, and counterparty country and sector. The data reported in the CPIS mainly focus on the asset side. In March 2018, data for 74 economies were available, but there are fewer series when filtering for debt securities issued by banks.

However, since different databases focus on different dimensions, they cannot match each other perfectly, so that caution should be exercised. Consider an example of the use of CPIS mirror data. First, the data reported in the CPIS comprise only positions of portfolio investments, while the data reported to the LBS also include direct investment. Therefore the quantities reported in the CPIS should in principle be smaller than those in the LBS. Second, the debt securities liabilities in the LBS are (by definition) issued by the bank sector, so that the "counterparty sector" in the CPIS should be narrowed down to banks excluding central banks. Third, instruments in the CPIS contain both equity and debt securities, so only debt securities assets should be selected. Fourth, the CPIS has a lower frequency and a longer lag than the LBS. Finally, although conceptually the LBS and the CPIS are both aligned with BPM6 and follow a uniform market valuation principle, in practice the valuation standards may vary across countries. For example, if the market price for a liability is not available, the nominal or contractual value can be used instead within the LBS (BIS (2013)).

There are three less prominent uses of the mirror data. First, and most importantly, for countries collecting full information from domestic institutions, these external databases can be used to check the quality of the collected data.

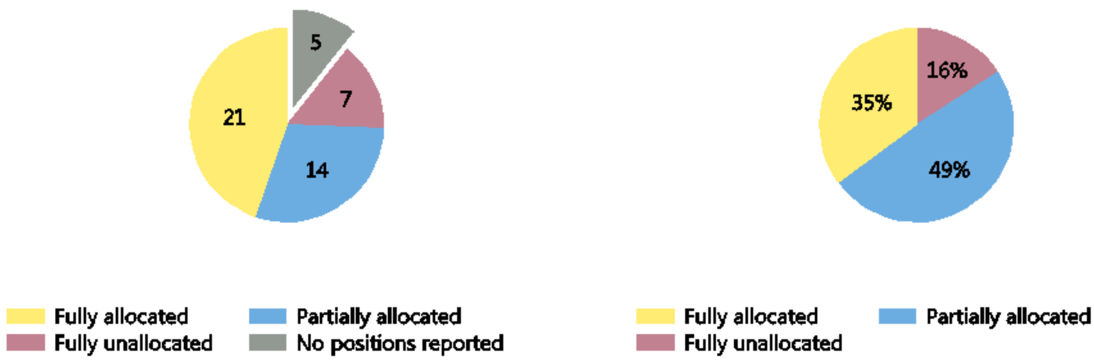
Falcão-Silva and Pradhan (2018) describe extensive methods for the cross-checking of reported data. Second, for countries that do not require any information on holders from their reporters, compilers can use mirror data to allocate the entire bulk of reported debt securities (BIS (2017)). Third, reported data may not be complete. At end-2017, the debt securities liabilities reported in the LBS add up to only a fourth of interbank claims (USD 413 billion vs USD 1,615 billion). This is a reiteration of the same problem: if banks do not know who holds their securities, they cannot identify them as banks. However, looking at the claims, we know the total size of the market and the identity of the holders. Mirror data could therefore help allocate the missing three quarters of liabilities. As a complement to that, ISIN-by-ISIN mirror data can be used to enrich the reported data with additional dimensions by matching those data to other reference databases (for example, missing currency or maturity information from the ECB's Central Securities Database matched to the SHS).

3. Country practices

Out of 47 countries reporting the LBS data by residence, 11% do not report any debt securities liabilities positions. This means that the total amount of debt securities of these countries is certainly underestimated. Among the rest, 15% report all the positions unallocated, or classify all positions as cross-border but with no counterparty country being identified; one third report positions that are at least partially allocated; and the remaining portion of countries report a detailed counterparty country and sector breakdown (Graph 3, left-hand panel). The securities with detailed breakdowns account for only one third of total debt securities reported, and the securities allocated partially have a much bigger share (right-hand panel).

Reporting of debt securities liabilities in the LBS — Graph 3

Number of countries reporting different data granularity — Proportion of debt securities liabilities reported using different data granularity



Source: BIS LBS by residence.

Country practices as gleaned from our survey[8] are summarised in Table 2 (details of the methods used are discussed in the following subsections). Interestingly, the countries reporting no unallocated debt securities are not necessarily those that are following the most sophisticated data collection methods, as most of these countries allocate counterparties according to market of issue or residence of primary purchaser. In parallel, we do observe a positive relationship between use of the combined survey and the proportion of debt securities allocated by country and sector. Where only the issuer survey is used, the results are "noisier" and can be less reliable, though maybe granular.

Which methods do the central banks choose for the LBS?

Based on the survey of 18 LBS-reporting countries

Table 2

Issuer survey	Market of issue	1	*6%*
	Primary purchaser	4	*22%*
	Mix	5	*28%*
Combined survey	Method 1	2	*11%*
	Method 2*	1	*6%*
Estimation	External or internal sources	3	*17%*
Not replied or no allocation		2	*11%*
Total		18	*100%*

*Method 1 and 2 are discussed in detail in section b below.

Moreover, we hypothesised that countries with capital controls or a CSD could have better data sources supporting more precise information. Our survey shows that countries do not always take advantage of such sources. Whether they do or not depends on the legal authority to cover such institutions and on the data-sharing arrangements between government institutions.

a. Countries surveying only issuers

Countries that decide to survey only issuers do so due to three main constraints. The most binding constraint is the lack of legal authority over non-bank custodians or CSDs, so that compilers settle for less precise data and avoid the major underreporting problem. Several surveyed countries are facing this constraint. Second, in small open economies, domestic banks often issue debt securities in overseas market, in which case domestic intermediaries may not be a better information source than issuers. This is the case with three fourths of the countries in our sample surveying only issuers, where a significant proportion of bank debts are held by offshore investors who may be served by foreign custodians. Finally, a less prominent issue is the concern that the burden of covering financial

[8] To learn about the experience of countries that fully allocate debt securities to different counterparty countries and the rationale for their data collection design as well as to understand the main constraints on improving data quality, we surveyed groups of countries reporting debt securities fully, partially and unallocated. In total, we contacted 18 countries in the period May–June 2018. For survey questions, see Appendix C.

intermediaries in reporting could outweigh the benefits of more granular data (only one country in our sample cited this issue).

Reporting banks can have outdated data, and may therefore need to estimate data themselves. There are several ways to do that, often explicitly encouraged by the compiling central bank (first block of Table 2). For example, issuers could report the positions and residence of the primary purchasers when the debt security is issued and report them until maturity. Alternatively, banks in some other economies are required to report markets of issue as the counterparty countries. The third option would be to assign all foreign securities as unallocated and all domestic as local. Finally, a quarter of compilers in our sample require issuers to report using a mix of methods, sometimes called the "best efforts" basis: if banks can identify the current holders, they report the information accordingly; if banks cannot identify them, they report either primary purchasers or the market of issue.

These assumptions used to hold as far as the securities were held by resident investors in the market of issue, or were not traded across borders. However, financial markets have become considerably more sophisticated. Debt securities are often issued internationally and actively traded across countries. As a result, this assumption could lead to sizeable discrepancies (Gruić and Wooldridge (2012)).

Our survey results show that no country requires exclusively custodians to report. This is reasonable because, first, most LBS compilers are central banks and have direct legal authority to collect information from banks, whereas comparable legal authority over custodians may be absent. Second, banks have more comprehensive information on the debt securities they issued, and by surveying them, compilers can at least obtain the correct total volume of debt securities. Finally, it is difficult to cover the whole domestic market using only the custodian data without the risk of double-counting.

However, what is even more surprising is that, in some countries, very detailed data from custodians are collected but not shared across government institutions or even within the same institution.

b. Countries surveying both issuers and custodians

Two different surveying methods are provided by countries surveying both custodians and issuers.

In Method 1 (Table 3), compilers require both banks having liabilities and custodians holding positions for customers over a certain set of thresholds[9] to report. Issuers are required to report all debt securities issued by them in foreign markets, and attribute the market of issue to the counterparty country. Resident custodians are required to report the debt securities issued by resident banks they hold for non-resident customers, security by security. Double-counting could occur when custodians report that they are administering the debt securities issued abroad, which are also reported by issuers. Since both parties report security by

[9] Threshold 1: a certain level of total debt securities issued (for issuers) or total debt securities holdings (for custodians). Threshold 2: a certain level of amount of debt securities issued in a single country (for issuers) or amount of debt securities held by investors from a single country (for custodians). Institutions are required to report if at least one of these thresholds is exceeded.

security, the overlapping part can be easily tracked by matching the ISIN codes and dropped, and the extent of double-reporting would be equal to the part reported by custodians (Bertaut and Judson (2014)). Beyond that, a good deal of additional attention is paid to double-counting of repos and short sales (FRBNY (2016)).

Method 1

Reporting practices depending on where a domestic bank issues — Table 3

Market	Respondent	Information
All markets	Resident custodian	Security by security
Foreign markets	Issuing bank	Market of issue as counterparty country with no resident custodians involved, security by security

In Method 2 (Table 4), issuers, custodians or the CSD are required to report depending on the circumstances. If the debt securities are issued in a foreign market, issuers report positions and counterparties on a best efforts basis, ie they report the current holder's residence if they know it and the market of issue if they do not. If the debt securities are issued in the domestic market and resident custodians are employed to administer the account, resident custodians are required to report the positions, residence and sector information of their non-resident customers; if no resident custodians are involved, the CSD reports the information on non-resident holders based on trading records in its system. Moreover, when domestic banks issue credit-linked notes to foreign customers, they can identify their residence and report accordingly. With this method, all debt issued by banks is covered and no overreporting can occur. The CSD is not used as a unique data source as discussed in the Chapter 2 but as a complementary source.

Method 2

Reporting practices depending on where and how a domestic bank issues — Table 4

<table>
<tr><th>Market</th><th>Situation</th><th>Respondent</th><th>Information</th></tr>
<tr><td rowspan="2">Domestic</td><td>Non-resident investors invest directly</td><td>Central security depository</td><td>Residence and sector of non-resident investors, positions</td></tr>
<tr><td>Non-resident investors entrust domestic custodians with administering transactions</td><td>Domestic custodian (bank and non-bank)</td><td>Residence and sector of non-resident trustee, positions</td></tr>
<tr><td rowspan="2">Foreign</td><td>Bank issues debt security directly</td><td>Issuing bank</td><td>Residence and sector of non-resident trustee, positions
Holders' residence: if holders can be identified, they are allocated accordingly; if holders cannot be identified, the market of issue is reported as the counterparty country</td></tr>
<tr><td>Bank issues credit-linked notes to specific countries</td><td>Issuing bank</td><td>Residence of holders, positions</td></tr>
</table>

c. Countries using mirror data

Other countries avail themselves of other reliable data sources to estimate the bank-issued debt securities liabilities held in other countries (third block of Table 1).

As discussed in Section 3, one of the available data sources in the euro area is the ECB's SHS database used by some of the euro area countries. To use this database to determine counterparty allocation, compilers first require issuing domestic banks to report the ISIN codes of their debt securities. With the ISIN codes, compilers search for information on holders within the SHS database. If full information on holders is available in the database, then it is straightforward to allocate the counterparty countries accordingly. If no information on holders is available, the debt security is assigned as unallocated. If only partial information can be found, then the remaining unknown amount is allocated according to the proportions of known amounts. Using the SHS can be viewed as an attractive alternative to a custodian survey – it is possible to cover some non-resident custodians and investors and the costs of the survey are pooled among all participating countries.

4. Conclusion

Our paper makes two main contributions. First, we conduct a unique survey of current practices among countries reporting the BIS LBS to understand the best practices in and the main obstacles to reporting good-quality data. Second, as the best feasible conceptual solution, we recommend a combined approach of surveying issuers and custodians (Appendix Table B1), complemented by an estimation and a quality check using mirror data. Alternatively, we suggest using CSD data as the main source for the domestic market.

However, detailed information may not be fully captured even with the most sophisticated method. The debt securities left unallocated after the surveys have been completed can be filed using estimation. Compilers could avail themselves of mirror data to allocate the debt securities in this overhang, or to cross-check the quality of the data reported. In addition, if countries opt not to collect data from domestic institutions, they could apply the known mirror data distribution of counterparties to their estimated size of the market of issue.

Again, there is no one-size-fits-all solution for all countries. In practice, there are various challenges that countries with different jurisdictions and market circumstances may face, and therefore they may not be able to adopt the best survey we recommend. Compilers are strongly encouraged to thoroughly research their market and related institutions and to adjust their collecting framework with reference to the methods discussed in this paper.

Last but not least, the proportion of unallocated positions in debt securities liabilities is by no means a good indicator of data quality. In our survey sample, we find evidence of countries perfectly allocating their positions, only to discover that they are reporting exclusively those positions which they can attribute easily, or attributing the counterparty country using overly simplistic estimation methods. While it is recommended that compilers look for ways to determine a breakdown of debt securities counterparties by residence and sector, misallocating the positions to wrong counterparties could worsen the quality of the data and thereby undermine the data comparability for research and policy analysis.

It may be useful for researchers employing the LBS debt securities liabilities data to be aware of reporting practices. To that end, our recommended list of questions for collecting information on such practices is provided in Appendix D.

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Appendix A

Reported debt securities liabilities, end-2017					Table A1
Reporting country	Total liabilities	Cross-border	*Of which: unallocated by country*	Local	Unallocated
Australia	648,160	37%	*0%*	53%	10%
Austria	154,827	39%	*0%*	41%	19%
Bahamas	26,595	94%	*0%*	6%	
Bahrain					
Belgium	115,752	40%	*0%*	60%	
Bermuda	117	100%	*0%*		
Brazil	437,108	3%	*0%*	97%	0%
Canada	26,834	/	*/*	/	72%
Cayman Islands	34,487	100%	*100%*		
Chile	66,547	14%	*0%*	86%	
China	183,919	100%	*9%*		
Chinese Taipei	53,208	3%	*0%*	97%	
Curaçao					
Cyprus	755	34%	*0%*	27%	39%
Denmark	550,519				100%
Finland	102,719	93%	*0%*	7%	
France	1,372,027	53%	*0%*	47%	
Germany	1,371,754	50%	*100%*	50%	
Greece					
Guernsey	31,766	29%	*0%*	40%	31%
Hong Kong SAR	194,072	17%	*0%*	83%	0%
India	84,654	0%	*0%*	100%	
Indonesia	14,354	27%	*0%*	73%	
Ireland	70,121	74%	*0%*	26%	
Italy	455,158	1%	*0%*	79%	20%
Isle of Man					
Japan	/				/
Jersey	14,093	11%	*0%*	0%	89%
Korea	393,624	20%	*0%*	80%	
Luxembourg	76,540				100%
Macao SAR	9,286	52%	*0%*	48%	
Malaysia	/	/	*/*	/	
Mexico	38,130	39%	*0%*	61%	
Netherlands	564,779				100%
Norway	/	/	*/*	/	
Panama	15,832	99%	*0%*	1%	0%
Philippines	3,853	57%	*0%*	43%	
Portugal	47,316	1%	*0%*	99%	
Russia	50,481	11%	*48%*	89%	
Singapore					
South Africa	70,623	3%	*100%*	97%	
Spain	272,630	/	*/*	/	
Sweden	536,430			40%	60%
Switzerland	94,132				100%
Turkey	36,942				100%
United Kingdom	1,209,324	75%	*98%*	25%	
United States	130,376	100%	*0%*		

As some countries do not report local or cross-border liabilities, the total number is underestimated. This simple distinction between local and cross-border potentially harbours the same problem as identifying debt security holders by issuing bank.

"/" means the data are classified as confidential or restricted by reporting countries; a blank space means no position is reported; "0%" means a position is reported but is practically zero as a fraction of the total liabilities.

Source: BIS LBS by residence.

Appendix B

Information to be reported by issuers and custodians Table B1

Items to be reported	Issuer	Custodian
ISIN codes	√	√
Amounts outstanding	√	√
Counterparty country	√	√
Counterparty sector	√	√
Currency denomination	√	
Maturity	√	
Primary purchaser	√	
Market of issue	√	

Data collection on a quarterly or monthly basis is recommended, to comply with the quarterly schedule of the LBS data.

Appendix C

Survey questions

1. *What kind of institutions are required to report to you data on holders of debt securities liabilities? (Select as many as are applicable):*

    a. *Banks.*

    b. *Bank custodians.*

    c. *Non-bank custodians.*

    d. *Central securities depository.*

    e. *End-investor.*

    f. *Other data source. Please specify: ____________.*

2. *If only banks are required to report, what are the constraints from surveying other institutions? (Select as many as are applicable):*

    a. *Legal authority to cover non-bank custodians.*

    b. *Most custodians are foreign.*

    c. *Consideration of reporting benefit and burden.*

    d. *Other reason. Please specify: ______________.*

3. *Do you use external databases to allocate reported debt securities by holder (eg CPIS, SHS)?*

4. *How do you allocate counterparties of debt securities liabilities?*

    a. *Market of issue.*

    b. *Primary purchaser.*

    c. *Mix (current holder complemented with primary purchasers or market of issue).*

5. *Do you take measures to avoid double-counting of securities covered in different surveys?*

6. *Do you use mirror data to cross-check the quality of the reports?*

Appendix D

Reporting practices for debt securities liabilities

1. *What concept do you use to define the issuers and holders of debt securities?*

    a. *Nationality.*

    b. *Residence (consistent with BPM6).*

    c. *Other. Please specify: _____________.*

2. *What valuation principle do you employ in reporting debt securities liabilities?*

    a. *Market value or market equivalent value.*

    b. *Nominal value.*

    c. *Face value.*

    d. *Other. Please specify: ______________.*

3. *How do you allocate counterparties of debt securities liabilities?*

    a. *Market of issue.*

    b. *Primary purchaser.*

    c. *Mix (current holder complemented with primary purchasers or market of issue).*

4. *How do you require institutions to report data?*

    a. *On a security-by-security basis.*

    b. *On an aggregate basis.*

    c. *Left to the discretion of reporters, provided the information required is appropriately reported.*

Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

Who holds banks' debt securities? Statistical methods for allocation by holders[1]

Meng He, China State Administration of Foreign Exchange,
and Zuzana Filkova, Bank for International Settlements

[1] This presentation was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

Who holds banks' debt securities?
Statistical methods for allocation by holders

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IFC Conference, *Are post-crisis statistical initiatives completed?*

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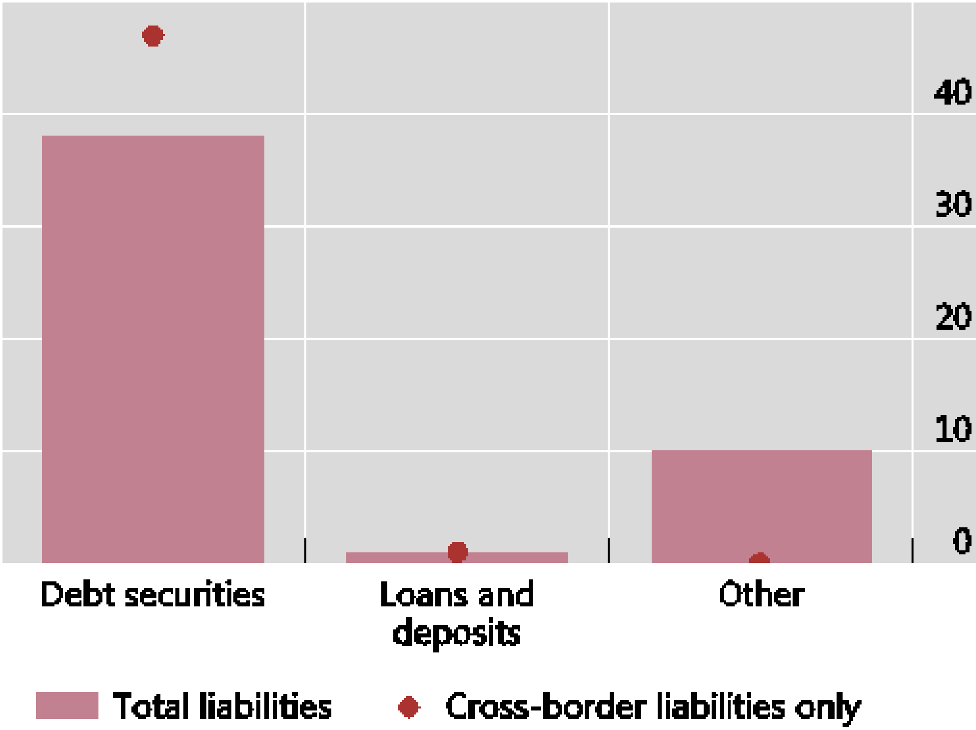
40% of total debt securities liabilities is unallocated

Unallocated residence in total per instruments



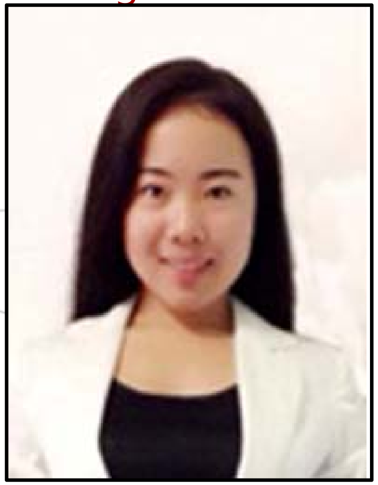
For issuers it is more difficult to identify the holders of their debt securities than other instruments

→ And that's why they report them as unallocated

Data source: BIS locational banking statistics (LBS) by residence

Zuzana's bank

Meng's bank



Issuer survey

Custodian survey

cross-border

local

Amounts issued

Holders allocation

Two main challenges:

A. Negotiability

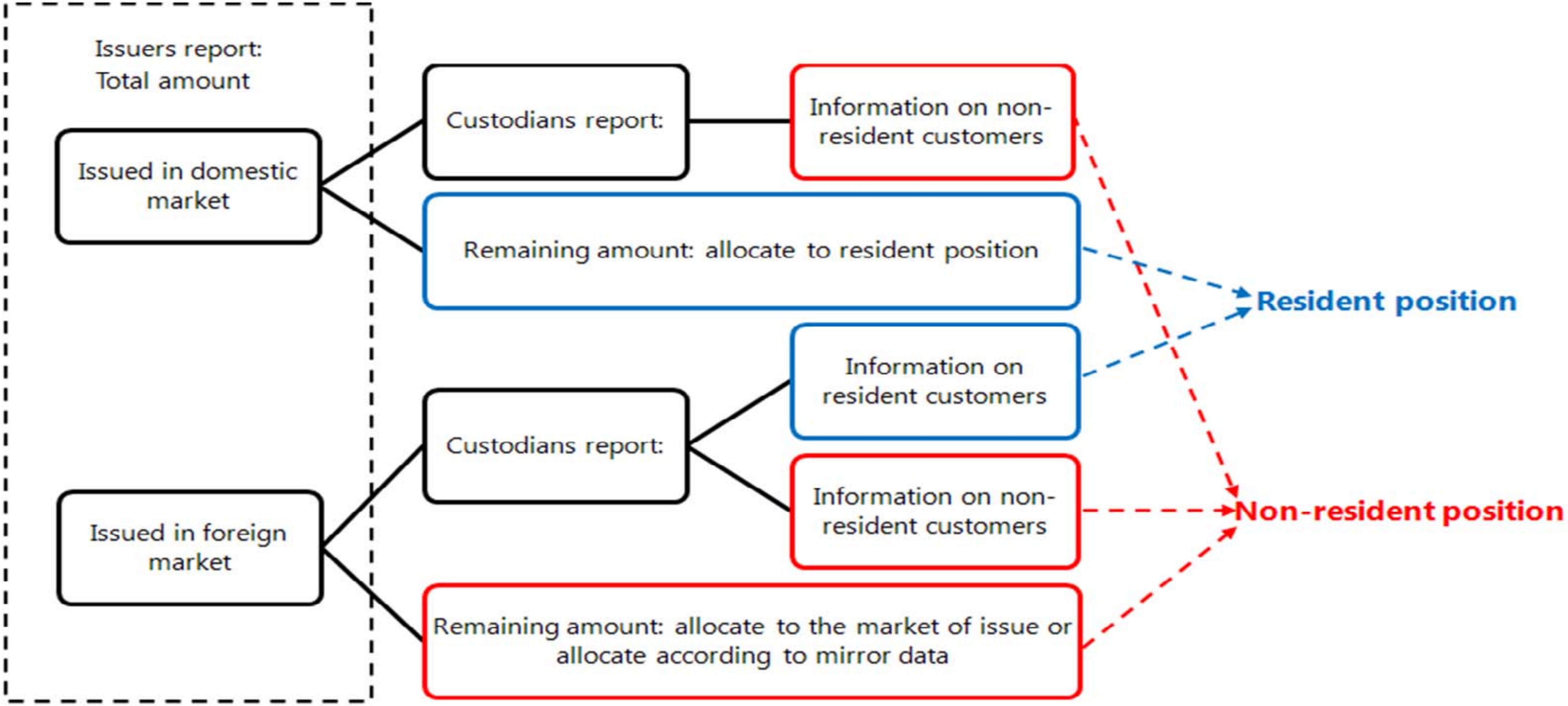
B. Intermediation

Conceptual Options

Pros and cons of different surveys

	Pros	Cons
Issuers survey	• Precise amount of total debt securities issued • Precise information in case of direct investment • Already covered in central banks' jurisdiction • If no domestic custodian hired, issuer may have superior information	• Information potentially outdated
Custodian survey	• Precise and up-to-date information • Cost-effectiveness	• Non-bank custodians potentially not covered in central banks' jurisdiction • If hired by another custodian, may still not identify the end-beneficiary • Risk of over- and under-reporting
Combined approach	• Precise amount of total debt securities issued • Precise and up-to-date information from custodians • Precise information from issuers in case of direct investment • Issuers already covered in central banks' jurisdiction • If no domestic custodian hired, issuer may have superior information • Cost-effectiveness in covering custodians	• Non-bank custodians potentially not covered in central banks' jurisdiction • If hired by another custodian, may still not identify the end-beneficiary • Risk of over-reporting

Combined approach - solution to double counting



Survey results

Results		Number	Percentage
Combined survey	Method 1	2	*11%*
	Method 2	1	*6%*
Issuer survey	Market of issue	1	*6%*
	Primary purchaser	4	*22%*
	Mix	5	*28%*
Estimation	External or internal sources	3	*17%*
Not replied or no allocation		2	*11%*
Total		18	*100%*

Country practices: Combined survey

Method 1 **Reporting practices depending on where a domestic bank issues**

Market	Respondent	Information
All markets	Resident custodian	Security-by-security
Foreign markets	Issuing bank	Market of issue as counterparty country with no resident custodians involved, security-by-security

Method 2 **Reporting practices depending on where and how a domestic bank issues**

Market	Situation	Respondent	Information
Domestic	Non-resident investors invest directly	Central security depository	Residence and sector of non-resident investors, positions
	Non-resident investors entrust domestic custodians to administer transactions	Domestic custodian (bank & non-bank)	Residence and sector of non-resident trustee, positions
Foreign	Bank issues debt security directly	Issuing bank	Residence and sector of non-resident trustee, positions Holders' residence: if holders can be identified, they are allocated accordingly; if holders cannot be identified, the market of issue is reported as counterparty country
	Bank issues credit linked notes to specific countries	Issuing bank	Residence of holders, positions

Country practices: Issuer survey and mirror data

Countries surveying issuers

Main Constraints

- Lack of legal authority
- Domestic banks often issue debt securities in overseas market
- Costs

Main practices

- Report primary purchasers
- Report market of issue as counterparty country
- Mix

Countries using mirror data (ECB's SHS)

1. Require issuing domestic banks to report the ISIN codes of their debt securities.
2. With the ISIN codes, compilers search for information on holders within the SHS database.

2.1 If in the database full information on holders is available, then it is straightforward to allocate the counterparty countries accordingly.

2.2 If no information on holders is available, the debt security is assigned as unallocated.

2.3 If only partial information can be found, then the remaining unknown amount is allocated according to the proportions of known amounts.

How we contribute to the post-crisis statistical initiatives

① Unique survey of current practices of identifying debt securities counterparty countries;

② Combined approach using mirror data for cross-checking, possibly with a centralized security depository as the main data resource for domestic market

Suggestions for compilers:

① To thoroughly research their market and related institutions and to adjust their collecting framework with reference to the methods discussed in here.

② To use estimation and cross-checking by taking advantage of established databases.

Unallocated position is not necessarily a good indicator of data quality: It is indeed recommended that compilers search for ways to break down residence and sector of debt securities counterparties, but allocating the positions to wrong counterparties could worsen the data quality and thereby undermine the comparability of data for research and policy analysis.

Thank you!

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Challenges for macro data on non-bank financial intermediaries[1]

Anna Maria Agresti and Celestino Giron,
European Central Bank

[1] This paper was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

9th IFC Conference "***Are post-crisis statistical initiatives completed".***

Challenges for macro data on non-bank financial intermediaries.

Agresti Anna Maria, Giron Celestino

Abstract

There is an increasing user demand for macro data on non-bank financial intermediation, coming both from a monetary policy angle – for instance to understand its potential impact on the transmission mechanism - and from macroprudential requirements to monitor its financial stability implications, including those stemming from "shadow banking" trends. However, data gaps still exist that might prevent an adequate assessment of all related developments. Thus, part of the euro area financial sector currently remains to be covered by harmonised, complete and high-frequency balance sheet data.

This paper presents the ECB initiatives to address these data gaps. It focuses on the efforts to cover the "OFI residual" which includes institutions such as securities dealers, financial auxiliaries or captive financial institutions. In addition, the paper discusses on the usage of regulatory information newly available at euro area level that might be key to reducing the existing macro data gaps.

Section 1: Introduction.

Since the start of the financial crisis there has been an interest in analysing the differences in financial intermediation patterns across the various classes of intermediaries and in assessing how these differences affect the formation of leverage, the building-up and transfer of risks or the impact on the monetary policy transmission mechanism. In particular, there is an increasing interest in entities that share certain features with traditional banking - like the presence of high leverage and maturity and liquidity transformation - but which do not operate under the regulatory and supervisory framework, nor have access to the backstop mechanisms that banks do. These entities have been denominated "shadow banks" and have been identified as major sources of systemic risk, as main contributors to the latest financial crisis and as key to better understanding the overall dynamics of agent balance-sheets.

In the second section of this paper we summarise the various recent initiatives in the European Union aimed at improving the availability of data on the financial sector. It focuses on the so-called "OFI residual", a set of financial institutions currently not covered by reporting schemes designed for statistical purposes. We examine initiatives to enhance primary statistics in a harmonised, methodologically-compliant manner, including micro databases, but also the efforts undertaken in the context of integrated sector accounts or others to cover the financial sector by making use as well of counterpart statistical information and/or data available from non-statistical sources, notably from regulatory sources. The second section in this paper describes the data gaps, in particular focusing on the FSB and ESRB requirements regarding shadow banks, and presents initiatives taken to address those gaps. The third section examines the impact of the regulatory requirements on data needs and availability, and explores the possible usage of regulatory data, to narrow informational gaps. Section four presents the initiatives taken to enhance financial accounts, worldwide and also in the European Union in developing a ESCB STC medium-term strategy for financial accounts. The fifth section summarises other initiatives to reduce the OFI residuals, and the sixth sections concludes.

Section 2: Data availability for non-bank credit intermediaries (shadow banks) and their gaps[1].

A first challenge to provide with analytical tools for understanding credit intermediation outside the traditional baking channels is establishing a perimeter for the phenomenon and appropriate measures of it. The FSB defines a broad measure of shadow banking as a grouping of institutional sectors within the framework of the national accounts, i.e. .the ESA sectors[2] S.123 "Money Market Funds (MMFs)", S.124 "Non-MMFS investment funds", S.125 "Non-monetary financial intermediaries other than insurance corporations and pension funds(OFIs)" and S.127 "Captive financial institutions and money lenders", excluding public units in S125 and S.127.

Beside this first metric that provides an assessment at a broad scale, work has been undertaken to narrow down the definition of shadow banking focusing more on activities and risks than on institutional groupings. Thus, equity investment funds are excluded from the definition of shadow banking as they do not primarily engage in credit intermediation, although some of their activities (e.g. the use of securities lending or derivatives) may imply systemic risk of the kind of some shadow banks. Second, retained securitisation – i.e. where the asset-backed securities are held by the bank(s) originating the assets, generally for use as collateral in central bank refinancing operations – is excluded on the basis that there is no transfer of credit risk out of the banking system. Moreover, entities consolidated within banking groups are to be excluded as they enjoy indirectly through their mother banks of a similar regulatory, supervisory regime and of adequate stress backstops[3][4].

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[1] This section presents the Euro area data availability for non-bank financial intermediaries from monetary and financial account prospective.

[2] FSB uses SNA sectors. In the EU framework we refer to the ESA classification.

[3] However, this criterion is still difficult to implement due to the lack of the total list of entities not consolidated (as it will become clear later), the data gaps, and different regulatory frameworks

[4] See "Data needs and Statistics compilation for macroprudential analysis" Statistical work on shadow banking: development of new datasets and indicators for shadow banking December 2017
Anna Maria Agresti. Rok Brence European Central Bank https://www.bis.org/ifc/publ/ifcb46p.pdf

In addition, the ESRB joint ATC-ASC Expert Group on Shadow Banking (JEGS) has also taken a dual approach to the measurement of shadow banking and has further added to the FSB framework risk indicators constructed for the subsector of OFIs On the one hand, an entity-based approach draws on aggregated balance sheet data of financial institutions taken from financial accounts and monetary statistics, based on the ESA 2010 framework. However, this entity-based approach is recognised as incomplete due to the limitations of the available balance sheet data for risk analysis. For example, off-balance sheet exposures and use of financial derivatives, which constitute additional sources of risks or, if used prudently, may provide a valuable tool for risk mitigation, are not well covered by the available data. On the other hand, an activity-based approach aims at complementing the entities-based approach to have all the segments of the shadow banking system monitored: “An entity based mapping approach cannot fully capture shadow banking risks arising from specific markets that cut across entities”. While the entity-based approach uses aggregate balance sheet data, the activity-based monitoring approach employs higher frequency transaction-based information to capture risks that cut across different types of entities in financial markets.[5]

”Constituents of non-bank financial intermediaries and used for the ESRB entities approach are summarised in Table 1.

Table 1: Overview of investment funds and OFIs (based on ESA 2010 classification)

[5] Also leveraging on new EU-wide datasets that will provide relevant information, like data on derivatives and SFT markets, both from a micro and macro perspective.
https://www.esrb.europa.eu/pub/pdf/reports/20170529_shadow_banking_report.en.pdf

Entities: sectors and subsectors			Description
Investment funds	Money Market Funds (S.123)		*Part of the monetary financial institutions (MFI) sector*
	Non-MMF investment funds (S.124)	Bond funds	*Allocated to investment policy according to assets in which they primarily invest*
		Equity funds	
		Mixed funds	
		Real estate funds	
		Hedge funds	
		Other funds	
		Exchange-Traded Funds (ETFs)	*ETFs and private equity funds included within above types depending on the strategy of the fund*
		Private equity funds	
Other Financial Institutions (OFIs)	Other Financial Intermediaries (S.125)	Financial Vehicle Corporations engaged in securitisations (FVCs)	*i.e. securitisation special purpose vehicles*
		Financial Corporations engaged in Lending (FCLs)	*e.g. financial leasing, factoring, hire purchase*
		Securities and Derivatives Dealers (SDDs)	*i.e. dealers on own account*
		Specialised financial corporations (SFCs)	*e.g. venture capital, export/import financing, central clearing counterparties (CCPs)*
		OFI residual	*Calculated as the difference between total OFIs sector and the assets held by all known subsectors and subgroupings; in most cases only entities under S.125 are included in this residual*
	Financial auxiliaries (S.126)		*e.g. insurance or loan brokers, fund managers, head offices of financial groups, financial guarantors*
	Captive financial institutions and money lenders (S.127)		*e.g. SPVs not engaged in securitisation, 'brass plate' companies, holding companies*

The table above shows the entities considered in the JEGS and the related ESRB "EU Shadow Banking Monitor" which presents recent developments and financial stability risks in the EU shadow banking system applying both an "entity based" and an "activity-based" mapping approach.[6]. The ESRB shadow banking monitor contains also a good overview of the various subsectors´ risks and data availability.

As indicated, the data used for the JEGS report for the assessment of shadow banking mostly come from macro sources within the national accounts framework, namely monetary statistics and financial accounts. For MMFs (sector S.123 in ESA), data reported by these institutions, defined as collective investment undertakings of which the units are close substitutes for bank deposits in terms of liquidity[7],to the national central banks (NCBs) in accordance with Regulation ECB/2001/13 concerning the consolidated balance sheet of the monetary financial institutions sector (as amended). MMFs are. For Investment funds (other than MMFs, sector S.124), data have been collected from the ECB (and are published) from end-2008 in accordance with Regulation ECB/2007/8 concerning statistics on assets and liabilities of investment funds[8] . Most of the activities that could be labelled as shadow banking are undertaken by institutions covered by the ESA 2010 sector "Other financial intermediaries other than insurance corporations and pension funds (S.125)". However, only selected subgroupings within the sector are available, often covering a limited set of information.

Reporting of financial vehicle corporations (FVC) statistics began in the first quarter of 2010 for the reference period end-December 2009 under the umbrella of Regulation ECB/2013/40. These statistics, complemented by an enhanced reporting by monetary financial institutions (MFIs) involved in securitisation transactions, as laid down in Regulation ECB/2013/33, provide harmonised information on the securitisation market and risk transfer. Annual Balance sheet data for the euro area aggregated of Euro area financial corporations engaged in lending (FCLs)[9] has recently published by ECB. However, the national breakdowns will not be available since in some jurisdictions the phenomena does not exists, or the data are not collected, or are of insufficient quality. As regard data on securities and derivatives dealers (SDDs), ECB is also working on constructing the euro area aggregate. For these entities data are not available for all countries and might have to be derived from supervisory sources which raise issues with confidentiality of the national data[10]. Proposed changes in the EU legislation might affect the classification of these entities and their risk assessment for shadow banking purpose (see next section).

[6] http://www.esrb.europa.eu/pub/pdf/reports/20170529_shadow_banking_report.en.pdf

[7] Furthermore, these funds primarily invest in money market instruments with a residual maturity up to one year, and/or in bank deposits. The reporting population comprises MMFs resident in the euro area, including the MMFs managed from outside the euro area. Conversely, the statistics do not cover MMFs established in offshore locations outside the euro area, even if the management companies of these MMFs are resident in the euro area. The list of individual MMFs forming the reporting population is available on the ECB website, together with the other institutions which are part of the MFI sector.

[8] Data on investment funds shares/units issued are collected monthly, by investment policy of the fund, with a full balance sheet collected quarterly.. Along with investment funds, MMFs may be regarded as an alternative to bank deposits and some have been a funding source for lending – i.e. credit intermediation – outside the banking sector. However, in the current low interest rate environment there have been contractions in MMF shares/units issued
See https://www.ecb.europa.eu/stats/pdf/money/aggregates/if_explanatorynotes.pdf?a2dd9ca9e2a22c9a156cc8ad689a0bf5

9 Financial corporations engaged in lending to households and non-financial corporations (FCLs) resident in the euro area, which is a sub-sector of "Other financial intermediaries, except insurance corporations and pension funds" (OFIs), S.125, in the European System of Accounts 2010 (ESA 2010). The statistics are reported by the national central banks (NCBs) to the ECB in accordance with Part 11 of Annex II of Guideline ECB/2014/15 on monetary, financial institutions and market statistics (recast).

[10] In other cases data quality is insufficient for these data to be reported to the ECB

Moving beyond these identified financial sectors, the larger part of shadow banking assets is still concentrated in the so called OFI residual[11], which is around 50% of the broad non-bank financial sector measure that still could not be classified according to the type of entity. The residual is defined as the difference between the total OFIs aggregate (see table 1) as compiled in the financial accounts context (see section 4) and the part known from the various source statistics. In most cases the OFI residual includes entities that belong in the sector "Other financial intermediaries other than insurance corporations and pension funds (S.125)", and as the availability of data on non-bank financial intermediaries varies a lot across country the precise perimeter of the OFI residual also changes from country to country.

A number of initiatives have been undertaken by the Eurosystem and at a national level in recent years to better identify types of entities within the non-bank financial sector that could help to reduce the OFI residual and hence improve the monitoring of shadow banking entities (see ERSB Shadow banking Monitor 2017) [12]. To mention the most recent euro-wide development, after the ECB publication of the euro area aggregate for FCLs the OFI residual diminished by around 2% points, due to the relative small size of this subsector in the total OFI assets.

Section 3: Data and regulatory perimeter. Two interrelated issues

As mentioned in the previous section some work still needs to be done on the data side for the so called OFI residuals. At the same time, this additional data work also needs to be undertaken with a better understanding of the regulatory requirements in order to assess the data gaps and the risks of the entities in the OFI residuals. This section focuses on the analysis of the each of the OFI subsectors and how changes in the regulatory framework for the financial sector might affect the measure of shadow banking and also the related risk assessment. In order to better understand the treatment of the OFIs entities (S.125, S126 and S127)[13] and their data gaps, this section presents the regulatory framework of the OFIs based on the EBA assessment[14] and match them with the data availability at the ECB.

We start our analysis with the on-going work on the SDDs (securities and derivatives dealers), where the proposed new EU regulatory requirements for the SDDs might change the statistical classification of many of these entities as well as the risk of these entities for shadow banking. Here below the new regulatory proposal and the potential statistical reclassifications of these entities.

Investment firms play an important role in facilitating savings and investment flows across the EU. They provide a range of services which give investors access to securities and derivatives markets. Their services concern financial instruments, which unlike deposits are not payable but fluctuate according to market movements. According to the Markets in Financial Instruments Directive (MIFIDII)[15] Article 4 Definitions. 'investment firm' means any

[11] https://www.esrb.europa.eu/pub/pdf/reports/20170529_shadow_banking_report.en.pdf

[12] https://www.esrb.europa.eu/news/pr/date/2017/html/esrb.pr170529.en.html

[13] For entities included in each sub-sectors see table 1
[14] https://www.eba.europa.eu/documents/10180/1720738/Report+on+OFIs.pdf
[15] Markets in Financial Instruments (MiFID II) - Directive 2014/65/EU https://ec.europa.eu/info/law/markets-financial-instruments-mifid-ii-directive-2014-65-eu_en

legal person whose regular occupation or business is the provision of one or more investment services to third parties and/or the performance of one or more investment activities on a professional basis[16]. Up to now, all investment firms have been subject to the same EU prudential rules as credit institutions[17]: The Capital Requirements Regulation and Directive (CRR/CRDIV) lays down the amount of capital, liquidity and other risk management requirements which credit institutions and investment firms have to comply with. The prudential framework for investment firms in the CRR/CRD IV works in conjunction with MiFID. The Markets in Financial Instruments Directive (MiFID) (MiFID II/MiFIR as of January 2018) sets out the conditions for the authorisation of investment firms. It also determines how they should behave on financial markets when providing their services (e.g. in terms of conduct of business). Credit institutions are also subject to some MiFID provisions when providing investment services. Unlike credit institutions, investment firms do not accept deposits, nor do they provide loans on a significant scale. Investment firms are less exposed to credit risk and the liquidity risk of depositors withdrawing their money at short notice, rather the risks they pose are more specifically related to potential undue and unexpected harm for their clients and the markets they operate in.

The proposal for the regulation of the prudential requirements of investment firms in the EU will distinguish three main Categories of investment firms. Class 1: investment firms, with total assets above €30bn and which provide underwriting services and dealing on own account. Systemic investment firms constitute and would remain under the CRR/CRDIV. Class 2 firms are (ART 12 of proposal) assets under management higher than €1.2billion bn; Class 3 firms are those which don't conduct the above activities and which are below all the above thresholds. Class 3 firms are not required to meet a capital requirement. With the EU Commission proposal[18] , the definition of "credit institution" in the CRR/CRDIV could be amended to cover also systemic investment firms based on the nature and size of investment services. Specifically, the proposal amends the definition of a credit institution in the CRR by including firms: whose business includes dealing on own account in financial instruments, or underwriting or placing financial instruments on a firm commitment basis; where the total value of the assets of the undertaking exceeds €30 billion[19] . The reasoning behind reclassifying systemic investment firms as credit institutions, is because their activities expose them to credit risk, mainly in the form of counterparty credit risk, as well as market risk for positions they take on own account, client related or not. They accordingly

[16] Based on the Annex I of MIFIDII 'investment services undertake the following activities(1) Reception and transmission of orders in relation to one or more financial instruments; (2) Execution of orders on behalf of clients; (3) Dealing on own account; (4) Portfolio management; (5) Investment advice; (6) Underwriting of financial instruments and/or placing of financial instruments on a firm commitment basis; (7) Placing of financial instruments without a firm commitment basis. In analysing the investment firms different types of issues need to be addressed : 1) there are different types of investment firms|: largest and most interconnected investment firms which have business models and risk profiles that are similar to those of significant credit institutions and small and non-interconnected investment firms with limited risks and 2) risks are different from banks

[17] Past prudential framework for investment firms is thus largely based on the risks faced and posed credit institutions. The requirements are largely calibrated to secure the lending and deposit-taking functions. CRR/CRDIV buffers of capital and liquidity for most of low systemic relevance investment firms may be misplaced and represent disproportionate costs for them. compliance and implementation costs are likely to exceed their prudential benefits, given their low risk to financial stability. Existing rules, only partially achieve their aims in terms of (i) ensuring sufficient capital for the risks of most investment firms; securing a level playing field across the EU. Brexit: large systemic firms may decide to relocate part of their activities to the EU. These firms should remain subject to CRR/CRDIV.

[18] http://europa.eu/rapid/press-release_IP-17-5304_en.htm

[19] Other changes to other pieces of EU legislation which refer to the CRR/CRDIV-definition of 'credit institution', Directive on Deposit Guarantee Schemes and the Bank Recovery and Resolution Directive. Also there will be implications for the SSM Regulation and thereby imply not only that systemic investment firms would remain subject to the CRR/CRDIV, but also that their prudential supervision is ensured by the SSM to the extent that they are established in Member States participating in the Banking Union. Their authorisation and prudential supervision would be carried out by European Central Bank as would be the case for significant credit institutions in the Banking Union

present a higher risk to financial stability, given their size and interconnectedness. The proposals aim to prevent regulatory and supervisory arbitrage.

Based on this proposal of the EU commission, it will imply inconsistency in the Union legislation between the CRR and the definition in the Regulation in the European system of national and regional accounts Regulation (EU) No 549/2013.[20] From a statistical point of view, the definition of 'credit institution' in CRR will be replaced[21] with the inclusion of the systemic investment firms captured by this definition[22.] The effect will be to reduce the entities in the SDDs subsector of OFI, the residuals will also be reduced and the risk of the SDDs will diminish due to the new regulatory regime

A similar analysis can be done for the other entities contained in the OFI residuals. In undertaking the analysis of the residuals, we will try to map the recent EBA survey on OFIs[23] with the data available at the ECB in order to better assess data gap for the monitoring of risks associated with these entities. This is a very preliminary work and it might require further analysis in order to map data gaps and regulatory regime.

BOX: EBA survey on OFI

OFI survey recently undertaken by the European Banking Authority (EBA) [24].. EBA published an opinion and a report on matters related to the other financial intermediaries (OFIs) and the regulatory perimeter issues under the Capital Requirements Directive/Regulation (CRD IV/CRR). These matters include the use of Articles 2(5) and 9(2) CRD IV (Directive 2013/36/EU) and the interpretation of the terms "financial institution" and "ancillary services undertaking," as defined in the CRR (Regulation (EU) No 575/2013).

The results of this assessment are included in a Report also published the same day. The EBA's findings are relevant to the consideration of the legislative proposals to amend the CRDIV/CRR. This Report aims to present a comprehensive analysis of the prudential treatment of OFIs carrying out credit intermediation activities beyond the perimeter of prudential regulation established by specific EU sectoral legislation[25]. Based on the

20 Regulation (EU) No 549/2013 of the European Parliament and of the Council of 21 May 2013 on the European system of national and regional accounts in the European Union

[21] by the following definition (see Art. 60 of the proposed regulation): 'credit institution' means an undertaking the business of which consists of any of the following: (a) to take deposits or other repayable funds from the public and to grant credits for its own account; and also

[22] b) to carry out any of the activities referred to in points (3) and (6) of Section A of Annex I of Directive 2014/65/EU, where one of the following applies, but the undertaking is not a commodity and emission allowance dealer, a collective investment undertaking or an insurance undertaking:
i) the total value of the assets of the undertaking exceeds EUR 30 billion, or ii) the total value of the assets of the undertaking is below EUR 30 billion, and the undertaking is part of a group in which the combined total value of the assets of all undertakings in the group that carry out any of the activities referred to in points (3) and (6) of Section A of Annex I of Directive 2014/65/EU and have total assets below EUR 30 billion exceeds EUR 30 billion, or iii) the total value of the assets of the undertaking is below EUR 30 billion, and the undertaking is part of a group in which the combined total value of the assets of all undertakings in the group that carry out any of the activities referred to in points (3) and (6) of Section A of Annex I of Directive 2014/65/EU exceed EUR 30 billion, where the consolidating supervisor in consultation with the supervisory college so decides in order to address potential risks of circumvention and potential risks for the financial stability of the Union.

[23] https://www.eba.europa.eu/documents/10180/1720738/Report+on+OFIs.pdf
EBA Survey: Entities carrying out credit intermediation activities and not subject, on an individual basis, to a prudential framework under EU law

[24] https://www.eba.europa.eu/documents/10180/1720738/Report+on+OFIs.pdf

[25] It is important to observe that outside the EBA analysis and scope are several entities, which subject to other regulatory treatment. According to the EBA, competent authorities were requested to describe the prudential regime applicable to the reported entities pursuant to national law, choosing between the following: (i) subject to a CRDIV/CRR-like regime (with or without modifications) under national law; (ii) subject to a bespoke prudential regime under national law; (iii) subject to no prudential regime. Competent authorities were further required to detail the prudential requirements, if any, in place under national law.

information on the OFIs provided by the competent authorities the EBA observes that the prudential treatment varies significantly between the Member States. The EBA concludes that at this stage no regulatory intervention is required at the EU level. However, should credit intermediation activity by OFIs continue to grow, the state of regulation of these risks will require further monitoring and analysis. There is a wide range of OFIs in the Member States carrying out credit intermediation activities which are not subject, on an individual basis, to a prudential framework under EU law. National prudential regimes differ substantially (both within and across the clusters identified).

It is important to observe that the scope of EBA action is only related with the credit intermediation activities[26]. As matter of fact, this survey only covers part of the OFIs activities and entities, consequently, in order to have a complete coverage of the prudential treatment the OFI entities according to statistical classification, this might require additional investigation.

In order to run its assessment, EBA grouped the entities into the following clusters based on the activities undertaken (following, wherever possible, the activities classifications listed in Annex I to the CRDIV): ***Cluster 1***: consumer and corporate lenders, including factoring, leasing, consumer credit/retail credit/microcredit, guarantee providers, mortgage lenders, saving institutions and other types of lenders; this forms the largest cluster in terms of the frequency of reporting of entities by the competent authorities; ***Cluster 2:*** securitisation vehicles; ***Cluster 3***: crowdfunding; ***Cluster 4***: credit unions. While details of the survey can be found in EBA survey[27], the main result of the survey is that not all the OFIs entities are regulated. Furthermore, the analysis does not cover other OFIs which might undertake other shadow banking activities and risks beside the credit intermediation. These entities might be part of the remaining S.125, S.126 and S.127 for which the EBA survey does not collect information on the regulatory regime: this might require additional investigation.

EBA results can be mapped with the availability of the statistical data at the ECB. Linking the supervisory provisions with statistical data availability at the ECB, will make clear if additional data and regulatory information are needed to be collected in order to assess the OFI sector risks. Starting with Cluster 1, which includes consumer and corporate lenders, including factoring, leasing, consumer credit/retail credit/microcredit, guarantee providers, mortgage lenders, saving institutions and other types of lenders; this forms the largest cluster in terms of the frequency of reporting of entities by the competent authorities. In this cluster entities are not regulated/not subject to individual prudential requirements[28]. Cluster 1 may be mapped with the entities grouped in the SNA FCLs financial corporations engaged in lending to households and non-financial corporations (FCLs) resident in the euro area, which is a sub-sector of "Other financial intermediaries, except insurance corporations and pension funds" (OFIs), S.125[29], newly published by the ECB.

[26] Competent authorities were asked to identify entities carrying out credit intermediation activities, including unregulated entities (which were asked to be reported by the authorities on a best efforts basis), in their jurisdictions that are not subject, on an individual basis, to a prudential framework under EU law

[27] https://www.eba.europa.eu/documents/10180/1720738/Report+on+OFIs.pdf

[28] EBA ….

[29] Annual data are now available at the ECB as data on FCLs have been recently published by the ECB. However, no complete breakdown by entities is available.(i.e factoring, leasing, consumer credit). The statistics are reported by the national central banks (NCBs) to the ECB in accordance with Part 11 of Annex II of Guideline ECB/2014/15 on monetary, financial institutions and market statistics (recast).The statistics on FCLs are at annual frequency and are available dating back to the end of 2010. The asset side typically represents the loan portfolio of FCLs and other assets

The second EBA cluster 2, includes the following entities: securitisation vehicles. As for the 2014 EBA Report[30], some Member States have referred to special purpose vehicles (SPVs) used to set up securitisations (SPVs-Sec) as possibly carrying credit intermediation activities. This can be mapped with the securitisation vehicles otherwise known as Financial Vehicle Corporations (FVCs). According to the ECB Regulation [31], this requires the collection of data on securitisation vehicles otherwise known as Financial Vehicle Corporations (FVCs)[32].). According to EBA, special purpose vehicles (SPVs) used to set up securitisations (SPVs-Sec) as possibly carrying credit intermediation activities and in some jurisdictions were specified as unregulated on an individual basis

The third cluster considered by EBA is crowdfunding, an activity that is not in the scope of the ECB data collection framework (and not mentioned as such in ESA 2010).

As regard the cluster 4 (credit unions), have a simplified prudential regime for credit unions given their limited scale and size compared with credit institutions generally. While according to the ECB these entities Credit unions are credit institutions subject to Eurosystem minimum reserves, even if exempted under Article 2 CRD. These entities are covered within the balance sheets of monetary financial institutions (MFIs) Data are covered under the legal basis for collecting harmonised balance sheet statistics is laid down in Regulation ECB/2013/33[33].

In conclusion, as the EBA analysis is focused to identify entities carrying out credit intermediation activities, this analysis leaves out those OFIs entities which might engage in shadow banking risks other than those emerging directly from credit intermediation. These entities not covered might be part of the remaining S.125 (as Venture and development capital companies, Financial intermediaries which acquire deposits and/or close substitutes for deposits, or incur loans vis-à-vis monetary financial institutions only; these financial intermediaries cover also central counterparty clearing houses (CCPs) carrying out inter-MFI repurchase agreement transactions)[34] and S.126 (financial auxiliaries i.e corporations which arrange derivative and hedging instruments, such as swaps, options and futures), for which data are anyway not available from harmonised and regulated European collection frameworks. Finally also entities in S.127(captive institutions) , are out of the scope of the EBA analysis; data are not available at euro area level and an effort to close this gap would be desirable. Additional analysis is then required on the consolidation, regulatory treatment and data of these entities that might be part of the remaining S.125 S.126 and S.127 and this will be analysed section 4.

[30] EBA publishes an Opinion on the perimeter of credit institutions
https://www.eba.europa.eu/-/eba-publishes-an-opinion-on-the-perimeter-of-credit-institutions

31These statistics, as laid down in Regulation ECB/2013/33, provide harmonised information on the securitisation market and risk transfer

[32] The FVC data refer to assets and liabilities, covering end-of-quarter outstanding amounts and financial transactions provided on a quarterly basis. Outstanding amounts, or stock data, refer to the value of the assets and liabilities at the end of the reference period. Transactions, or flows data, refer to the net acquisition of a given type of asset during the period, or the net incurrence of a given type of liability. The MFI data also include relevant information on securitisation activities. Firstly, this includes data on the net transfers of securitised loans to FVCs (with or without derecognition from the MFI balance sheet). Data on these loan transfers are used for example in adjusting loans to euro area residents for loan sales and securitisations. Data are also available on MFIs' holdings of debt securities issued by euro area FVCs, and MFI loans to and deposits from euro area FVCs. See table 1 at the end.

[33] This Regulation is complemented by Guideline ECB/2014/15, which sets out the procedures to be followed by NCBs when reporting money and banking statistics information to the ECB.

34 MFIs may act as CCPs. If a CCP is not a credit institution it is in S.125 (which is most on the ESMA list of authorised institutions).

Section 4: Financial account initiatives in the area of non-bank financial intermediation.

Financial accounts provide an integrated framework for the analysis of financial balance-sheets, their changes, their interlinkages across the economy and their relation with developments in income and expenditure. Users of financial accounts, as of the other macro statistics, have been demanding a richer detail on financial institutions within the framework, in particular as regards non-bank credit intermediation, or shadow banking.

As mentioned above, shadow banking activities are mainly undertaken by entities in the sector "Other financial intermediaries other than insurance corporations and pension funds (S.125)" (see table 1). However, that sector is not identified separately in the so-called MUFA Guideline[35], the ECB's legal instrument for the compilation and exchange of quarterly financial accounts data within the Eurosystem (data for all non-euro area EU countries are exchanged on a voluntary basis). This was due to the lack of developed, complete primary sources for this and other financial subsectors at the time of the preparation of the last version of the Guideline in 2013. Thus sector S.125 is included within the largely residually-defined grouping "other financial institution (OFI)" grouping that covers miscellaneous financial institutions of very different nature. OFI comprises three ESA subsectors (S.125, S.126 and S.127) and includes as diverse units as factoring corporations, holding companies or securities brokers and dealers (table 1). From a compilation point of view, OFI are often estimated from secondary statistical and non-statistical sources – such as business registries and other administrative sources- ad-hoc surveys, and/or counterpart sector data. However, these sources might not allow for complete adherence to the applicable statistical standards or may lack adequate frequency and/or timeliness, and do not generally permit a sufficient subsector granularity.

To address this drawback and others, the European financial accountant community has embarked in 2018, within the framework of the ESCB Statistics Committee (STC), on a medium-term strategy for quarterly financial accounts. The general intention of the endeavour is to address the increasing demand for richer information and to take advantage of the availability of new data sources, institutional frameworks and technologies for the compilation of financial accounts. The strategy is being designed consistently and in cooperation with the developments in primary statistics and covers areas like the integration of sector accounts and balance of payments, the use of micro data or the development of compilation schemes on a who-to-whom basis, but also the extension of the detail provided to better serve analysis in the areas of globalisation, interconnectedness or the households sector.

Enhancing the detail of the financial sector is one of the areas considered for the medium-term strategy. In particular, it is recognised that the use of financial accounts for shadow banking analysis requires at least the separate identification of sector S.125. Preliminary investigations carried out by the Working Group Financial accounts (WG FA, reporting to the STC) since 2016 reveals that has been more than 90% of the OFI sectors' assets in the EU are available with a subsector breakdown, and that in particular a sector split following the ESA classification (S.125, S.126 and S.127) might be feasible in 23 member states, albeit with problems for estimating backdata and requiring further clarification for the delineation of

[35] ECB/2013/24

sectors S126, S127. This breakdown, in principle feasible, would allow narrowing down the monitoring of shadow banking to S.125, and exclude from the target universe institutions like holding companies and financing conduits (covered by S.127 and not engaging in bank-like kind of intermediation).

At the same time, a proper monitoring of shadow banking probably requires an even more granular sector split as some of the institutions in S.125 might be argued not to really engage in bank-like activities, or to pose financial risks that are very different in nature from each other. Similarly, institutions not included in S.125, like certain investment funds, might be seen as to be included within the shadow banking perimeter.

This need for subsector splits that goes beyond the ESA standard sector detail is not only circumscribed to shadow banking related issues. For instance, as mentioned above, holding companies and other special purpose entities (SPEs) included within the subsector S.127 might need to be separated from other institutions in that sector given the specific characteristics of their activities that hardly qualify as financial intermediation, while they can be of high interest in the context of globalisation. Similarly, the transfer of risks associated to defined contribution pension funds is very different to that of defined benefit pension funds, while both are included within the same ESA subsector “Pension funds (S.129)”. The preliminary investigations by the WG FA on such additional sector breakdowns indicate that data availability for the compilation of financial accounts would be very different from country to country, but at the same time that such availability would be highly correlated with the importance of the various groupings in the corresponding economies (e.g. information on SPEs being available in countries where this industry is relevant). That would suggest the possibility of establishing differentiated commitments in terms of publication and dissemination across European Union countries in this respect.

To enhance the financial accounts ability to capture the subtleness of the various financial activities and associated risks, a greater sector detail has to be complemented by additional financial instrument breakdowns designed to capture specific risks. An obvious candidate is the introduction of remaining maturity splits, as opposed to the standard original maturity splits, to cover maturity mismatches and associated liquidity risks. Similarly, breakdowns by currency of denomination would help monitor the corresponding risks. Moreover, very specific markets and asset classes might have to be targeted, like repurchase agreements - currently indistinguishable from loans and deposits in financial accounts- which have been involved in much of the liquidity and maturity transformation undertaken by shadow banks, in particular when the institutions depend on wholesale financing. At the same time, many of these additional details are of more relevance for the euro area than for the individual countries, in particular those more related to monetary policy analysis, and also entail a high development cost if implemented at country level. A possible outcome of the strategy might be that such enhancements are only implemented at euro area level levering on the new euro area wide micro-level data sources: CSDB, SHS, AnaCredit, EMIR data…

Before the work on the medium-term strategy for financial accounts in the EU started, a number of initiatives worldwide had already promoted the use of financial account data to understand shadow banking. Since 2013 a regular FSB annual monitoring exercise has included a specific template for macro-mapping to be filled in with financial accounts data (complemented by monetary statistics data). Financial accounts data can also serve to fill in some of the other templates for the monitoring exercise (notably the specific one on interconnectedness). Moreover, since 2015 a specific recommendation under the G-20 Data Gap Initiative II (DGI-2), Recommendation #5, calls *"the G-20 economies to enhance data collection on the shadow banking system by contributing to the FSB monitoring process, including through the provision of sectoral accounts data. (…)"*.. This makes the development of "shadow-banking-enhanced" financial accounts, as envisaged by the ongoing ESCB medium-term strategy for financial accounts, a prominent need.

Furthermore, the ongoing work in the framework of yet another of the DGI-2 recommendations, Recommendation #8 on sector accounts led by the OECD, is contemplating the inclusion of additional sector and instrument detail to pinpoint shadow banking activities. A specific "more advanced ambition" template will cover stock data for sub groupings of S125 and S127 in line with the discussion above, together with splits of investment funds by investment policy and/or share liquidity and of insurance corporations and pension funds by kind of insurance and risk pass-through profile respectively. Similarly, a template on financial instruments includes detail on remaining maturity, non-performing loans, nominal value for debt securities liabilities, currency denomination and exposures on derivatives and contingent liabilities.

Even though these shadow banking requirements are labelled as "more advanced ambitions" and are not part of the target requirements for 2021, their inclusion within the set of templates indicates the relevance that is given to shadow banking within the financial accounts framework and encourages advanced countries to work on them. The templates were approved by the DGI-2 Global Conference in June 2018. Final discussion on a final template is in progress on the thematic Workshop on Institutional Sector Accounts.

Section 5: Other initiatives to reduce the OFI residual.

In section 3 we saw that, from the regulatory point of view, the EBA focuses only on those entities carrying out credit intermediation activities that are not subject, on an individual basis, to a prudential framework under EU law, while other entities in S.215, such as venture and development capital companies, and entities in S.126 and S.217 are not considered at all. However, these entities might not be engaging in credit intermediation, but still knowing more about them is useful for monetary and financial analysis and macroprudential monitoring, all the more when they might undertake certain shadow banking related activities, even if not as their main activity.

More specifically, for the entities in S.125, S.126 and S.127 that are not part of banking groups there is an absence of data and knowledge of their regulatory requirements[36]. In order to address these issues, the ECB is currently undertaking a survey questionnaire on these OFIs groupings to investigate the regulatory requirements, the prudential consolidation within banking groups and the data availability. The current work is taking a broader approach combining supervisory and statistical sources, including financial accounts[37].

[36] However, there might be activities included in part of Annex 1 of CRDIV.
[37] It takes into consideration 1) the list of activities and entities of the ANNEX I of the CRD IV (Directive 2013/36/EU of the European Parliament (see also the appendix); and 2) the list of the entities/activities according to the new breakdown of the

Also at national level there are initiatives being taken by EU NCBs to analyse and reduce the OFI residual, which also contribute to enhancing financial accounts data availability (see section 4). For example, Luxembourg in a recent work concluded that its OFI residuals are concentrated in captive financial companies within S.127 as institutions in S.126 and S.125 are not so relevant in that particular case[38].

Similarly, De Nederlandsche Bank collects data on special purpose entities (SPEs) involved in financial activities other than securitisation, called "Special Financial Institutions" (SFIs)[39]. Data on resident SFIs imply that assets of these institutions by an amount of approximately €300 billion would have a relevant bearing from a shadow banking perspective.

Moreover, the Central Bank of Ireland collects data on "non-securitisation SPVs" which cover entities undertaking a wide range of activities, often related to intra-group financing; around €280 billion would correspond to credit instruments. In general most of these country initiatives refer to SPEs that are "*Vehicles linked to banks or engaging in loan origination [which] appear as the main areas of focus from a shadow banking perspective, due to the interconnectedness to the banking sector and their involvement in credit intermediation, respectively"*[40].

Section 6: Summary and conclusions

With the recent financial crisis, there has been an increasing demand for macro data on non-bank financial intermediation for economic, financial and monetary policy analysis and for macroprudential and financial stability monitoring, including that of "shadow banking" trends. However, and in spite of the efforts made recently to reduce the so-called OFI residual, data gaps still exist and a significant part of the euro area financial sector remains yet to be covered by harmonised, complete and high-frequency balance sheet data.

Further work needs to be done to combine the statistical data available for non- bank financial intermediaries with data stemming from the corresponding regulatory regimes, which in many cases needs to be better understood by statisticians.

Work in this direction has been recently undertaken by the ESCB with a questionnaire addressing data availability and regulatory aspects. The questionnaire was also aimed at facilitating the development of further sector and instrument detail within financial accounts, and in the framework of a medium-term strategy for those statistics in the European Union. Following this example, combined, coordinated efforts from all these angles - primary statistics, regulatory data and integrated sector accounts - would need to be pursued in order to improve our understanding of non-bank intermediation in the future.

ESA 2010 which can capture by the entities breakdown of shadow banking. The proposed analysis consists in combining data availability, the scope of consolidation and the involvement in activities within the shadow banking perimeter.

[38] Based on FSB recommendations and methodology, a step-wise approach is adopted to exclude non-relevant entities from the shadow banking perimeter, which reduces by 50% the residual for the year 2014. See Duclos, C. and Mohrs, R., "Analysis of the shadow banking content of captive financial companies in Luxembourg", working document.

[39] These entities often engage in transactions on behalf of their parent companies, or are set up as part of multinational groups with the purpose of facilitating intra-group financing. For some SPEs, the business model is similar to FVCs in terms of transforming illiquid assets into more liquid debt securities.

[40] EU Shadow Banking Monitor No 2 / May 2017 https://www.esrb.europa.eu/news/pr/date/2017/html/esrb.pr170529.en.html

Ninth IFC Conference on “Are post-crisis statistical initiatives completed?”

Basel, 30-31 August 2018

Challenges for macro data on non-bank financial intermediaries[1]

Anna Maria Agresti and Celestino Giron,
European Central Bank

[1] This presentation was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

“Challenges for macro data on non-bank financial intermediaries”

Anna Maria Agresti
Celestino Giron
DG-Statistics/MFS

Irving Fisher Committee
9th biennial IFC Conference on "Are post-crisis statistical initiatives completed?" at the BIS 30-31 August 2018

The views expressed in this presentation are those of the authors and do not necessarily reflect those of the European Central Bank

Overview of presentation

Introduction

- European Systemic Risk Board (ESRB) **broadly** endorsed the **Macro-mapping"** exercise recommended by the Financial Stability Board as *methodological framework and* use of aggregated data

- **Dual approach: activity and entities approach to overcome data gaps**

- New data and on-going initiatives by ECB:
  - e.g. new statistics published on *financial corporations involved in lending* (FCLs) and in the future, on *Securities and derivatives dealers* (SDDs)

- Still data gaps in so called **OFI residuals**.

- **New survey to collect information on the data sets** and regulatory frameworks in different jurisdiction for the **OFI residuals**

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2 Shadow banking: ESRB and FSB approaches

3 Data availability: data used

4 Data availability and EU regulatory framework

5 Use of Macro data and current work

6 Conclusions

Macro measurement: FSB and ESRB approach

Practical two-step approach by FSB for **monitoring Shadow Banking System (SBS) -** implementation (so far) mainly entities-based:

1. **Broad measure:**
   - *"System of credit intermediation that involves entities and activities outside the regular banking system"*
   - Approximated by financial assets of *Other Financial Intermediaries* (OFIs, S.125) sector *plus Money Market Funds* (MMFs, S.123)
2. **Narrowing down** the broad measure in the *Global Shadow Banking Monitoring Report 2015*:

Two-Step approach of ESRB

- ESRB framework distinguishes between *risks stemming from financial institutions* or *"**entity-based approach**"* or *their activities* or *"**activity-based approach**"*

FSB and ESRB approach: narrowing down

- FSB **narrowing down approach** excludes *equity investment funds* from the broad definition as they do not primarily engaged in credit intermediation

- **Retained securitisations** – i.e. securitisations where the asset-backed securities are held by the originating banks
  - are excluded as no transfer of credit risk from the banking system.
  - *Non-securitisation special purpose entities* might be excluded if they are not part of a credit intermediation chain

- The **FSB** excludes *entities prudentially-consolidated* within banking groups from the narrow perimeter of the shadow banking

- The main reason why **ESRB** measures do not exclude consolidated entities is the *lack of reliable data identifying consolidated entities at euro area and EU level*

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Data availability : Data used (1/2)

✓ **Monetary statistics**:

- collected under **ECB Regulations**:
  - *MMFs (S123)* (from BSI data)
  - *Non-MMF investment funds (S124)*
  - *Financial vehicle corporations –FVCs (part of S125)*
- collected under **ECB Guideline** (*incomplete coverage*)
  - *Securities and derivatives dealers -SDDs (part of S125)*
  - *Financial corporations engaged in lending- FCLs (part of S125)*

✓ **Financial accounts:** S124, S125+S126+S127 (**OFIs**) (**see Annex**)

➢ **Sizeable *“OFI residual”:*** difference between the financial accounts aggregate OFIs and the parts covered by monetary statistics

Data availability : Data used (2/2)

- **OFI residual is large**, includes sub-sectors not included within the Other Financial Intermediaries **(S.125)** Sector, e.g. Special Purpose Vehicles **(SPVs),** as part of Captive financial Institutions and money lenders **(S.127)**
  - Despite some advances, **over 50%** of the broad non-bank financial sector measure still cannot be classified according to the type of entity,

- Risk assessment of financial intermediation (in particular of shadow banking) would also benefit from the availability of data on both a **consolidated and non-consolidated basis.**
  - For some types of entities, statistical and supervisory information on the level of consolidation are not readily available, and for others it is not systematically collected

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Data availability and regulatory framework (1/ 3)

- **Changes in the regulatory framework** might affect the measure of shadow banking and also the related risk assessment.
- **SSDs** (securities dealers) , proposed new EU regulatory requirements SDDs might change the statistical classification and risks
- With the EU Commission proposal , the definition of "credit institution" for capital requirements **(CRR/CRDIV) could be amended to cover also systemic investment firms** based on nature/size of investment services.
- From statistical point of view, the definition of ‘credit institution’ in CRR might be extended with the inclusion of the systemic investment firms captured by this definition.
  - The effect **will be to reduce the number of entities in SDDs subsector of OFI, the residuals will also be reduced** and the risk of the SDDs will diminish due to the new regulatory regime

Data availability and regulatory framework (2/3)

- **European Banking Authority (EBA) Opinion on prudential treatment of OFIs** carrying out credit intermediation beyond perimeter of prudential regulation

- **EBA results can be mapped with the availability** of data at ECB.
  - Additional data and regulatory information are needed to be collected in order to assess the OFI sector.

- **Cluster 1** includes consumer and corporate lenders, **Mapped FCLs (FCLs)** resident in the euro area,

- **EBA cluster 2**, securitisation vehicles: mapped to Financial Vehicle Corporations (FVCs) ECB Regulation data .

- **Cluster 3 considered by EBA is crowdfunding**, no data.

- **Cluster 4 (credit unions),** according to the ECB these entities are covered within monetary data of the ECB.

Data availability and regulatory framework (3/3)

Some other OFIs entities are not covered by the EBA survey.

These entities might **be part of the remaining S.125** (as i.e. Venture and development capital companies)

S.126 financial auxiliaries (i.e corporations which arrange derivative and hedging instruments) for which data are anyway not available from harmonised and regulated European collection frameworks.

S.127 Captive financial institutions, are out of the scope of the EBA analysis; data are not available at euro area level and an effort to bridge this gap would be desirable.

Additional analysis is then required on the consolidation, regulatory treatment and perimeter and data availability of these

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G 20 Data Gap Initiatives- DGI-2 and the financial sector

✓ **Recommendation # 8 includes specific templates for shadow banking and beyond … but not as part of core templates required by 2021**

✓ **Additional detail on instruments (compared with core templates) in the specific templates for shadow banking:**

- Remaining maturity split for debt securities and loans
- Non-performing loans
- Nominal value for debt securities, liabilities
- Domestic-currency denominated instruments, first-digit sector level
- Exposures for:
  - ➢ Derivatives, with split by options, forwards
  - ➢ Contingent liabilities: guarantees, credit insurance

G 20 Data Gap Initiatives- DGI-2 and the financial sector

Additional detail for sectors in the specific shadow banking templates (in blue, yellow cells) compared with core templates(grey)

S12 - Financial corporations
S121+S122+S123 - Monetary financial institutions
S121 - Central bank
S122 - Other deposit-taking corporations
S123 - Money-market funds
S123A - Stable NAV MMFs
S123B - Floating NAV MMFs
S124+S125+S126+S127 - Other financial corporations
S124 - Non-MMF investment funds
S124A - Open end funds
S124A1 - Bond funds
S124A2 - Equity funds
S124A3 - Mixed or balanced funds
S124A4 - Real estate funds
S124A5 - Hedge funds
S124A6 - Other funds
S124B - Closed end funds
S124B1 - Bond funds
S124B2 - Equity funds
S124B3 - Mixed or balanced funds
S124B4 - Real estate funds
S124B5 - Hedge funds
S124B6 - Other funds

S125 - Other financial Intermediaries, except Ins.corp. and pen. funds
S125A - Financial vehicle corporations engaged in securitisation
S125B - Financial corporations engaged in lending
S125C - Security and derivative dealers
S125D - Specialised financial corporations
S125D1 - Of which: Clearing houses
S125E - Other OFIs
S126 - Financial Auxiliaries
S127 - Captive financial institutions and money lenders
S127A - Trusts, estate and agency accounts
S127B - Brass place companies
S127C - Special Purpose Entities or conduits
S127D - Other captive finance companies and money lenders
S128+S129 - Insurance corp. and pension funds
S128 - Insurance corporations
S1281 - Non-life insurance corporations
S1282 - Life insurance corporations
S129 - Pension funds
S129A - Defined benefit funds
S129B - Defined contribution funds

= Tier 1

= Tier 2

Already part of current data collection (Tier 1)

The financial sector in the financial accounts medium-term strategy

- ✓ **Medium-term strategy for financial accounts to address compilation challenges and new user demands**
- ✓ **Mainly leveraging on development of new primary statistical sources**
- ✓ **Plan to be presented at the STC in March 2019**

➢ ***Main areas of work identified for theme 3 (financial sector):***

Split of OFIs into ESA sectors (S125, S126, S127): methodological guidance and practical implementation

Further subsector split: exploring differentiated reporting obligations

Subsector and instrument detail in EAA: national approach versus euro area (building block) approach

Current initiatives: Follow up of Previous work

- In 2015 , the ECB WGMFS and ESRB JEGS undertook a questionnaire on entities consolidated in the banking sector, focusing on the on sectors **S.123, S.124 and part of S.215**.

- In 2016, the **WG FA** ran a **questionnaire** on availability of subsector data for the **OFIs** aggregate:

  - ✓ outcome suggested that at least a three sector split into S125, S126 and S127 might be feasible in the medium term (corroborated by the joint ECB/ EUROSTAT questionnaire on voluntary data transmissions in 2017)

*To complete this assessment **ECB is currently undertaking a survey** with objective to clarify which entities and activities are classifed to new breakdowns of the financial sector introduced with ESA 2010. In particular a new sub-sector is created for Captive Financial Institutions (S.127).*

The main focus of survey questionnaire:

- **Make a more comprehensive assessment of the data availability** and quality (for potential development and future dissemination/ publication, at least in the form of experimental statistics).
- It is targeted subdivisions of **S.125** not covered by 2014 WG MFS/ JEGS survey, and the other subsectors **financial auxiliaries (S.126) and captive financial institutions and money lenders (S.127).**
- Supplementary information requested on the definitions and consolidation of the different entities
- Try to determine **how the prudential consolidation of non-bank financial entities** within regulatory banks' balance sheets should be handled so as to better define and measure shadow banking

Conclusions and way forward

- To better follow developments in EU shadow banking sector it is recognized the increasing need for more statistical data: **OFI residuals**.
- New initiatives at Eurosystem are ongoing with aim to close existing **data gaps in primary statistics and better understand the regulatory framework: new WG MFS/ WG FA questionnaire**
- **Entities consolidated in the banking groups** is also addressed by the new survey
- **Financial accounts** to be enhanced and better serve analysis of shadow banking and other financial sector phenomena in an integrated framework: STC medium term-strategy, also designed taking into account DGI-2 requirements

ANNEX: Subcategories of non-bank financial corporations

Category	Scope (entities)	
MM Funds (S.123)	**Money market funds**	
Funds (S.124)	**Funds total**	
	of which	**Open-ended bond funds**
		Open-ended real estate funds
		Private Equity Funds
		Hedge funds
		Synthetic ETFs
OFIs (other than IFs) S.125	**Financial Vehicle Corporations**	
	Securities and Derivatives Dealers	
	Financial Corporations involved in Lending Total	**Financial Corporations involved in Lending Total**
		(of which) financial companies
		(Of which) leasing and factoring
Other OFIs *(Specialised financial corporations are financial intermediaries, (remaining S125)*	**Other OFIs (Specialised financial corporations are financial intermediaries Total**	**Other OFIs (Specialised financial corporations are financial intermediaries Total**
		Of which a) Venture and development capital companies
		Of which b) Export/import financing companies
		Of which c) Financial intermediaries which acquire deposits and/or close substitutes for deposits, or incur loans vis-à-vis monetary financial institutions only; these financial intermediaries cover also central counterparty clearing houses (CCPs) carrying out inter-MFI repurchase agreement transactions.

ANNEX: Subcategories of non-bank financial corporations

Category	Scope (entities)	
Financial auxiliaries (S.126)	Financial auxiliaries (S.126) Total	Financial auxiliaries (S.126) Total
		(a) insurance brokers, salvage and average administrators, insurance and pension consultants, etc.;
		(b) loan brokers, securities brokers, investment advisers, etc.;
		(c) flotation corporations that manage the issue of securities;
		(d) corporations whose principal function is to guarantee, by endorsement, bills and similar instruments;
		(e) corporations which arrange derivative and hedging instruments, such as swaps, options and futures (without issuing them);
		(f) corporations providing infrastructure for financial markets; (g) central supervisory authorities of financial intermediaries and financial markets when they are separate institutional units; (h) managers of pension funds, mutual funds, etc.; (i) corporations providing stock exchange and insurance exchange; (j) non-profit institutions recognised as independent legal entities serving financial corporations, but not engaged in financial intermediation (see point (d) of paragraph 2.46); (k) payment institutions (facilitating payments between buyer and seller). Subsector S.126 also includes head offices whose subsidiaries are all or mostly financial corporations.
Captive financial institutions and money lenders (S.127)	Captive financial institutions and money lenders (S.127) Total	Captive financial institutions and money lenders (S.127) total
		(a) units as legal entities such as trusts, estates, agencies accounts or 'brass plate' companies;
		(b) holding companies that hold controlling-levels of equity of a group of subsidiary corporations and whose principal activity is owning the group without providing any other service to the businesses in which the equity is held, that is, they do not administer or manage other units;
		(c) SPEs that qualify as institutional units and raise funds in open markets to be used by their parent corporation;
		(d) units which provide financial services exclusively with own funds, or funds provided by a sponsor, to a range of clients and incur the financial risk of the debtor defaulting. Examples are money lenders, corporations engaged in lending to students or for foreign trade from funds received from a sponsor such as a government unit or a non-profit institution, and pawnshops that predominantly engage in lending;
		(e) special purpose government funds, usually called sovereign wealth funds, if classified as financial corporations.

AppendiX; Proposal : Investment groups classification

- Summary of Proposal for EU regulation on the prudential requirements of investment firms

WHAT WILL CHANGE IN THE FUTURE?

		REGULATION	SUPERVISION
Class 1	TODAY	CRR/CRD	National arrangements
	NEW REGIME	CRR/CRD	Banking supervisor (SSM for Banking Union)
Class 2&3	TODAY	CRR/CRD	National arrangements
	NEW REGIME	New prudential regime for investment firms	National arrangements

ESRB approach: Macro measurement

- "**Broad measure**" includes **all entities in the financial sector** except *banks*, *insurance corporations* and *pension funds*

- The **entity-based approach** focuses on aggregated balance sheet data of financial institutions *based on ESA 2010 framework*
  - Limitations of ESA-based balance sheet statistics *for risk analysis*
  - Off-balance sheet exposures and data on trade in financial derivatives provide *additional information on sources of risks*
  - ***Data used and available for this*** *approach come from SNA framework: Monetary and financial accounts data*

- The **activity-based approach** aims to capture activities contributing to *interconnectedness* between shadow and regular banking system
  - e.g. through secured financing transactions (SFTs), derivatives and credit hedging or enhancements
  - Initial use of microdata

Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

Other financial corporations survey in Japan –-compilation measures and recent features[1]

Daiki Date, Keita Takemura and Haruko Kato,
Bank of Japan

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[1] This paper was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

Other Financial Corporations Survey in Japan

- Compilation measures and recent features -

Daiki Date Keita Takemura Haruko Kato[1]

Abstract

As a part of post-crisis international statistical initiatives, the Bank of Japan worked on the Other Financial Corporations Survey (OFCS) and started releasing the data in January 2018. The OFCS classifies assets and liabilities of other financial corporations (OFCs) -- financial corporations other than the central bank and depository corporations -- broken down by counterparty sector. The OFCS is an important step forward to understanding the trends of OFCs. In compilation, we used various measures for example by utilizing other statistics including the breakdown data of the Flow of Funds Accounts (J-FFA).

In this paper, we first provide an overview of the compilation measures including new estimation methods, and evaluate the accuracy of the estimates for each item by sector. We then examine the OFCS data that shows a growing trend in the outstanding amounts of assets and liabilities of OFCs. We focus on several breakdowns of the data of the OFCS and confirm that OFCs play a significant role while depository corporations extend their business overseas.

Keywords: other financial corporations, financial assets and liabilities, Flow of Funds Accounts

JEL classification: C13, E59, G11, G20, G22, G23

Contents

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Introduction

In response to the global financial crisis and the resulting perception that there is room for improvement to understand the risks inherent in financial activities, there is a growing movement to enhance statistics. In particular, a series of initiatives referred to as the G-20 Data Gaps Initiative (DGI) followed by the Second Phase of the G-20 Data Gaps Initiative (DGI-2) were carried out in response to the report "The Financial Crisis and Information Gaps." This report included a set of recommendations adopted at the meeting of the G-20 Finance Ministers and Central Bank Governors in November 2009. IMF's Special Data Dissemination Standard Plus (SDDS Plus) was established in concert with the DGI to reinforce and supplement the existing data standards initiatives[2].

As one of those statistical initiatives, the Bank of Japan worked on the Other Financial Corporations Survey (OFCS) and started releasing the data in January 2018[3]. Other financial corporations (OFCs) cover financial corporations other than the central bank and depository corporations[4]. OFCs include various financial entities such as insurance and pension funds, broker dealers, securities investment trusts, government financial institutions, and finance companies. The asset size of OFCs as a whole is nearly three quarters of that of depository corporations as of FY2017 (Chart 1). In the Japanese financial system, financial corporations other than depository corporations also play a significant role and it is important to understand their financial activities. OFCs cover a considerably broad range of entities compared to other financial intermediaries (OFIs) that are often regarded as shadow banking entities. The OFCS provides a framework that seeks to capture the wide range of financial activities of financial entities other than depository corporations.

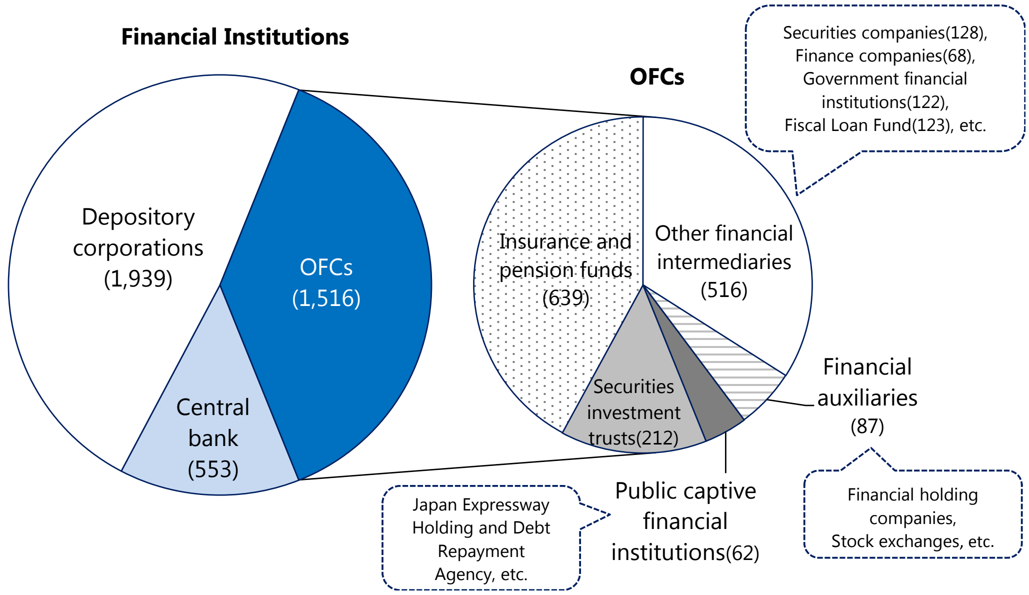
[2] The IMF's Special Data Dissemination Standard (SDDS) was established in 1996 to guide countries that have access to international capital markets in the dissemination of economic and financial data to the public. The SDDS applies to 18 categories of economic and financial statistics and covers four sectors of the economy. Although subscription to the SDDS is free to each country, once a country has decided to subscribe, it commits to providing data according to specified standards. The SDDS Plus was established in 2012 as the highest tier of data standards Initiatives and applies to 9 additional categories. A transition period is available for the SDDS Plus. The transition period allows countries to be considered adherents to the SDDS Plus when 1) they meet the requirements for five of the nine additional categories and 2) have plans in place to meet all of the requirements within five years of the date of adherence.

[3] The release of OFCS is one of the SDDS Plus requirements (see note 2).

[4] Throughout this paper, we include the central bank in "other sectors" and distinguish it from depository corporations, whereas in the released OFCS data the central bank is included in "depository corporations."

Asset Size of OFCs (tril. yen)

Chart 1



Note: The data are as of March 2018.

The Bank of Japan compiles and releases the Flow of Funds Accounts (J-FFA), which shows an overview of financial transactions in Japan. The J-FFA records both financial transactions and the corresponding outstanding balances of financial assets and liabilities of each financial instrument (transaction item) by economic entity (sector) (Chart 2). In response to the global financial crisis, the Bank of Japan worked to enhance and expand the J-FFA as the importance of enhancing statistics has been discussed globally. The Bank of Japan started to release the new data series; from-whom-to-whom data of debt securities and loans in September 2011 and in December 2013, respectively[5]. Those data clarify from whom funds move to whom and how potential vulnerabilities are transferred through financial transactions (Chart 3). Yet, those data do not reveal the creditor-debtor relationships between depository corporations and OFCs as there is no sector breakdown of financial institutions on the debtor side.

Financial Assets and Liabilities Table, Flow of Funds

Chart 2

	Financial institutions							
			Central bank		Depository corporations		OFCs	
	Asset	Liability	Asset	Liability	Asset	Liability	Asset	Liability
Currency and deposits Loans Debt securities … …		Counterparties are not specified.						
Total								

[5] For details, see Konno (2015).

From-Whom-to-Whom of Loans, Flow of Funds

Chart 3

Lender sector \ Borrower sector	to Financial institutions	to Nonfinancial corporations	to General government	...	Total
Financial institutions					
Central bank					
Depository corporations					
Insurance and pension funds					
Other financial intermediaries					
Financial auxiliaries					
Nonfinancial sector					
Nonfinancial corporations					
General government					
Overseas					
...					
Total					

Transactions within Financial institutions are not specified.

The OFCS records the outstanding balances of OFCs' financial assets and liabilities by counterparty sector, shedding light on financial entities other than depository corporations (Chart 4). The creditor-debtor relationship in the from-whom-to-whom format captures the credit accommodation and works as an early indicator of the build-up of risk via transactions through OFCs. The OFCS is based on the ongoing J-FFA (2008SNA basis). The data period is from March 2005 onward; the data frequency is quarterly, and the timeliness of the release is 4 months.

Items Recorded in OFCS

Chart 4

Asset of OFCs (Credit to ～)
Overseas
Central government
Depository corporations
Other sectors
Liability of OFCs (Credit from ～)
Overseas
Central government
Depository corporations
Other sectors
Capital (Shares and other equity)[1]
Other items (net)[2]

Notes: 1. Shares issued by OFCs are not included in Liability, but in Capital.

2. "Other items" records not only shares issued by OFCs that OFCs hold, but also items not included in any other categories.

In this paper, we first introduce the compilation measures including new estimation methods. Then, we evaluate accuracy of the estimates for each item based on those estimation methods. In compilation, we used various measures by utilizing other statistics. We also used some micro data such as the breakdown data of the J-FFA, if necessary. In the latter part of the paper, we examine the recent features of the financial system and financial intermediation activities in Japan by examining estimates and breakdown data of the OFCS.

Compilation methods

In the OFCS compilation, the J-FFA is mainly used as source data. When the counterparty sector is obvious for a certain transaction item, the J-FFA figures are then reconfigured for the OFCS. However, while the J-FFA records the assets and liabilities balance of each sector by detailed transaction items, it is hard to identify the counterparty sector for the majority of the items. Therefore, in the OFCS compilation, we make estimations in order to identify the counterparty sector based on certain assumptions while utilizing the source data of the J-FFA or other statistics.

For example, for transaction items such as "treasury discount bills" and "outward investment in securities" held by the OFCs, it is obvious that the counterparty sector is the "central government" and "overseas," respectively. In those cases, we allocate the amount outstanding of each transaction item as credit to the corresponding sector.

On the other hand, for transaction items such as "repurchase agreements and securities lending transactions," "industrial securities," "commercial paper," "listed shares," and "deposits money," it is hard to identify the counterparty sector for both OFCs' assets and liabilities. In the case of "loans by private financial institutions," although the from-whom-to-whom data are recorded in the J-FFA framework, the transaction between OFCs and depository corporations are not specified. With respect to such transaction items, depending on the nature of the transaction items or the availability of relevant statistics, we make estimates by utilizing other existing statistics or their source data based on certain assumptions. We show some examples of the estimation methods in the following sections.

(1) Lending between OFCs and depository corporations

Although the Bank of Japan releases the from-whom-to-whom data of loans as a part of the J-FFA, those data do not reveal creditor-debtor relationship between depository corporations and OFCs since there is no breakdown of financial institutions for debtor sector. In the OFCS compilation, we use the source data of the J-FFA and first estimate the lending from OFCs to depository corporations, whose components seem relatively easy to be identified. In concrete terms, we estimate the lending from OFCs to depository corporations as an aggregation of the following three items: 1) lending from bank holding companies (classified as "financial auxiliaries") to their subsidiary banks, 2) borrowing from trust accounts in pension trusts, and 3) lending from Fiscal Loan Funds to the Japan Post Bank. Other creditor-debtor relationships between OFCs and depository corporations are calculated by filling out the matrix below (Chart 5).

Matrix of Loans between OFCs and Depository Corporations

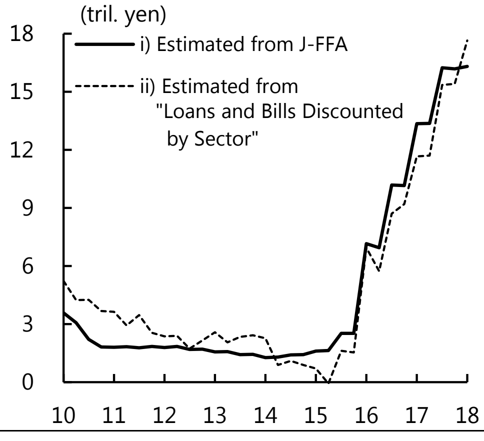
Chart 5

Borrower sector / Lender sector	Depository corporations	OFCs	Financial institutions (Depository corporations + OFCs)
Depository corporations	Obtained by subtraction	Obtained by subtraction	Specified in J-FFA
OFCs	Estimated by adding up the breakdown items.	Obtained by subtraction	Specified in J-FFA
Financial institutions (Depository corporations + OFCs)	Specified in J-FFA	Specified in J-FFA	Specified in J-FFA

As a cross check of the results obtained here, we use the data of loans to "Finance and Insurance" and "Banking, and Financial Institutions for Cooperative Organizations" in the "Loans and Bills Discounted by Sector" statistics released by the Bank of Japan. In particular, loans to "Banking, and Financial Institutions for Cooperative Organizations" is regarded as lending to depository corporations and then the ratio to the loans to "Finance and Insurance" is calculated[6]. Using this ratio, we decompose "loans from depository corporations to financial institutions" in the J-FFA into "loans from depository corporations to depository corporations" and "loans from depository corporations to OFCs." Comparing the figures with those obtained by the aggregation of the three items in the J-FFA source data, the two move in almost the same way suggesting that the estimation accuracy is considerably high (Chart 6).

Loans from OFCs to Depository Corporations (cross check)

Chart 6



Note: The latest data are as of March 2018.

In this estimation method, however, if the items that are included in aggregation of the lending from OFCs to depository corporations are not appropriate, it can lead to a larger estimation error. In order to avoid this estimation error, it is necessary to check from time to time if the items included are adequate.

[6] In the actual calculation, we use the ratio for each business category (banks, credit unions, and other financial institutions) in the decomposition. Also, we use additional data of borrowed money from trust accounts in collectively managed trusts, which are not covered in "Loans and Bills Discounted by Sector."

(2) Repurchase agreements and securities lending transactions

While the J-FFA records the amount of outstanding repurchase agreements and securities lending transactions by each sector, it does not identify the counterparty. Here again, we use a matrix by sector and specify the balance outstanding of the creditor-debtor relationships between OFCs and each sector by filling in the matrix (Chart 7). Specifically, the creditor-debtor relationship between each sector and overseas is identified by using the Balance of Payment Statistics. Then, given that repurchase agreements and securities lending transactions by depository corporations are basically through broker dealers, it is assumed that there is no transaction between depository corporations. Regarding the transactions between depository corporations and other sectors, only those between depository corporations and the central bank are included. Regarding the transactions between other sectors, only transactions between the central government and the central bank (sales under repurchase agreements by the Bank of Japan) are included. With these transactions, the remaining cells of the matrix can be filled in and the creditor-debtor relationship between OFCs and each sector can be calculated.

Matrix of Repurchase Agreements and Securities Lending Transactions Chart 7

Liability / Asset	Depository corporations	OFCs	Overseas	Other sectors	Total
Depository corporations	Assumed to be zero	(2)	Balance of Payments	Depository corp. ⇔Central Bank	Specified in J-FFA
OFCs	(2)	(4)	(1)	(3)	
Overseas	Balance of Payments	(1)		Balance of Payments	
Other sectors	Depository corp. ⇔Central Bank	(3)	Balance of Payments	Central Government ⇔Central Bank	
Total	Specified in J-FFA				

<Estimation steps>

- Use Balance of Payments for transactions with Overseas
- Calculate (1)
- Assumption of [ ] and [ ]
- Calculate (2) and (3)
- Calculate (4) as a residual

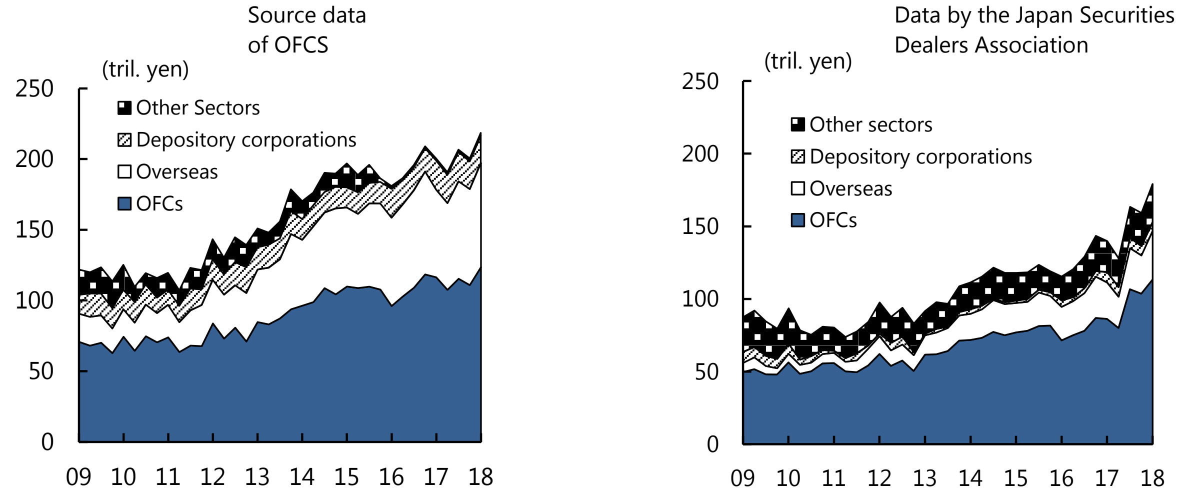
In order to maintain the accuracy of this estimation, it is necessary to keep eyes on if the assumptions of the zero or limited transactions between certain sectors are plausible.

For the results obtained here, it is difficult to cross check the from-whom-to-whom data with other statistics due to data constraints. However, the amount of outstanding assets or liabilities by sector can be compared with the data released by the Japan Securities Dealers Association. When the amount of outstanding repurchase agreements and securities lending transactions used in the OFCS compilation is compared to the sum of "Balance of Bond Transactions with Repurchase Agreements (by investor type)" and "Bond Margin Loans" released by the Japan Securities Dealers Association[7], there is a significant difference for the overseas sector and OFCs on the asset side, and for depository corporations and OFCs on the liability side (Chart 8). This is mainly because of the difference in coverage. While the data used in the OFCS compilation include repurchase agreements in foreign securities, the data released by the Japan Securities Dealers Association do not.

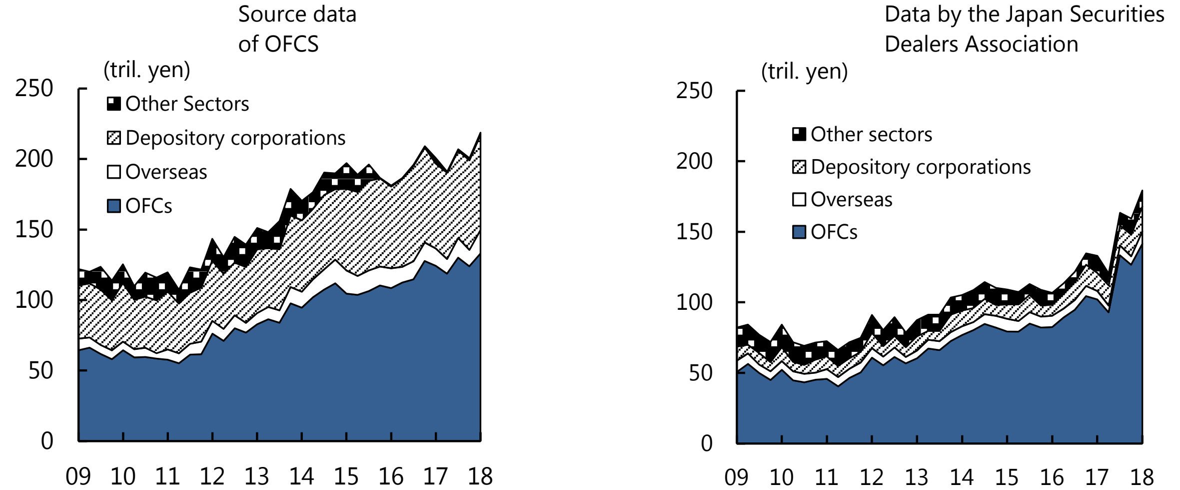
Repurchase Agreements and Securities Lending Transactions (comparison with other statistics)

Chart 8

Investment side



Funding side



Notes: 1. The latest data are as of March 2018.

2. "Data by the Japan Securities Dealers Association" are the sum of "Bond Margin Loans" and "Balance of Bond Transactions with Repurchase Agreements."

3. "Data by the Japan Securities Dealers Association" include the Japan Post Bank and Japan Post Insurance in "Other sectors", while data in the J-FFA include those in "depository corporations" and "OFCs," respectively.

[7] The trust account that is not counted in the J-FFA is excluded from the data.

(3) Deposits money (margin and collateral for financial transactions, and deposits from customers)

Deposits money on the asset side of OFCs in the J-FFA is mainly composed of margin and collateral for financial transactions. In addition to these, deposits from customers are the main components on the liability side of OFCs.

With regard to deposits money, although the balance outstanding of assets and liabilities of each sector is reported in the J-FFA, the counterparty is not identified. Again, we use a matrix by sector and fill in the cells in order to calculate the creditor-debtor relationship between OFCs and each sector (Chart 9). We used the Balance of Payments Statistics to obtain the data on margin and collateral for financial transactions for the overseas sector[8].

Matrix of Deposits Money

Chart 9

Liability / Asset	Depository corporations	OFCs	Overseas	Other sectors	Total
Depository corporations	Assumed to be zero	Assumed to be zero	(1)	Assumed to be zero	Specified in J-FFA
OFCs	Assumed to be zero	(3)	(2)	Assumed to be zero	
Overseas	(1)	(2)		Assumed to be zero	
Other sectors	Assumed to be zero	(4)	Assumed to be zero		
Total	Specified in J-FFA				

<Estimation steps>

- Assumption of , and
- Calculate (1)
- Calculate (2)
- Calculate (3) and (4)

In the J-FFA, when comparing the margin and collateral for financial transactions of the depository corporations and overseas sector, the assets of depository corporations and the liabilities of the overseas have similar trends. In the same way, the liabilities of depository corporations and the assets of overseas move similarly to each other[9] (Chart 10).

Based on these figures, we assume here that the counterparty sector for depository corporations in deposits money transactions is overseas only. Furthermore, given that most part of the deposits money of overseas is collateral for derivatives, we assume that the counterparty sector is financial institutions only.

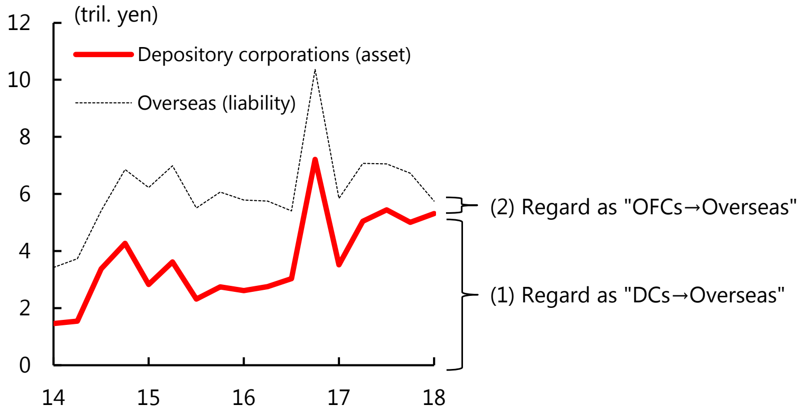
8 The data became available from 2014 onwards due to the revision of the balance of payments with the aim of achieving conformity with the sixth edition of the Balance of Payments and International Investment Position Manual (BPM6) published by the IMF. Before 2014, the transactions between OFCs and overseas were not recorded due to data constraints.

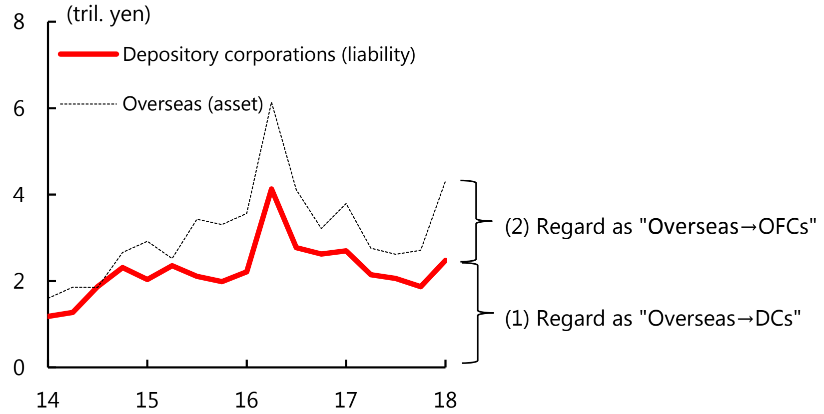
9 The transaction would basically be the exchange of margin for currency or foreign exchange swap. From the time series data, it is inferred that when the yen depreciated in the first half of 2016, additional margin was paid from the overseas sector to depository corporations. Similarly, when the yen appreciated in the latter half of 2016, additional margin was paid from depository corporations to the overseas sector.

With this, the creditor-debtor relationships between overseas and OFCs can be calculated. Regarding the counterparty sector of OFCs other than overseas, given that the asset side of OFCs is mostly margin and collateral for financial transactions, we assume that the balance from OFCs to other sectors is zero, and calculate the balance from OFCs to OFCs as a residual. Finally, we calculate the balance from other sectors to OFCs as a residual to complete the matrix.

Margin and Collateral for Financial Transactions of Depository Corporations and Overseas

Chart 10





Notes: 1. The latest data are as of March 2018.

2. The number (1) and (2) correspond to those of Chart 9.

In this section, we presented three examples of the estimation methods applied in the OFCS compilation. Other than those discussed above, the creditor-debtor relationships regarding listed shares are estimated by "Shareholding at Market Value by Sector by Investor Category" released by the Tokyo Stock Exchange to calculate the ratio of each invested sector by holding sector[10]. Regarding industrial securities, commercial paper, and public corporation securities, it is difficult to

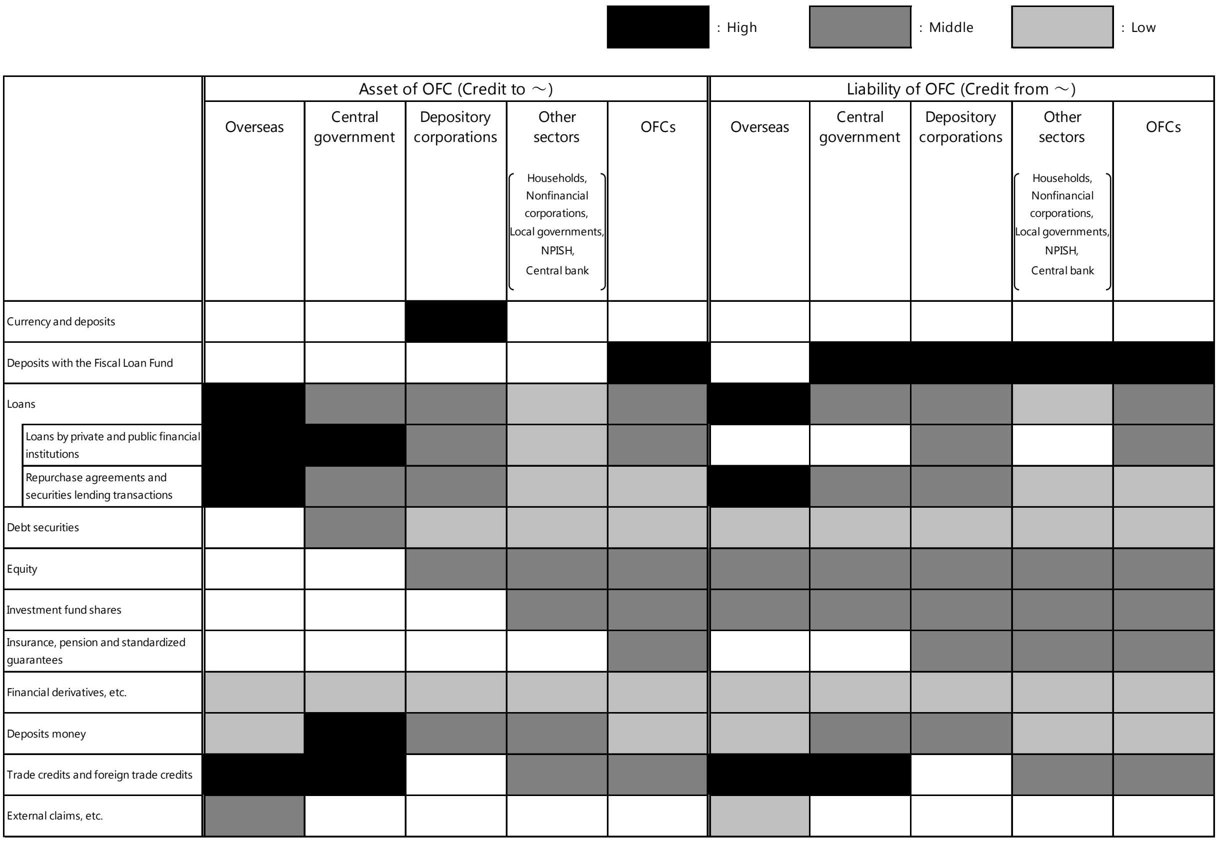
10 Since issuance by "banks" includes that by "bank holding companies" in "Shareholding at Market Value by Sector by Investor Category," we adjust the data using the liability side data (share issuance) of the J-FFA.

identify the holding sector due to data constraints. For those securities, estimates are made assuming that each sector holds each type of securities according to the ratio of each issuance sector's issuance amount to the total issued amount.

Accuracy of the estimates of the OFCS

As explained in the earlier section, the estimation methods vary among transaction items depending on the nature of transaction or on the availability of related statistics. Therefore, we need to keep in mind that the accuracies of estimates differ from item to item. For reference, a rough sketch of the accuracies for transaction items is illustrated in the following chart (Chart 11).

Estimation Accuracy of the Estimates that comprise OFCS (rough sketch) Chart 11



Notes: 1. "High" indicates that the figures are compiled directly by using the original source data. "Middle" indicates that the figures are estimated by using original source data where the information on estimations is generally available. "Low" indicates that the figures are estimated where the information on estimations is not available, or where the figures are estimated as residuals. Empty cells indicate that there is no figure compiled.

2. "Financial derivatives, etc." indicates "Financial derivatives and employee stock options." "External claims, etc." indicates the total of "Outward direct investment," "Outward investment in securities," and "Other external claims and debts."

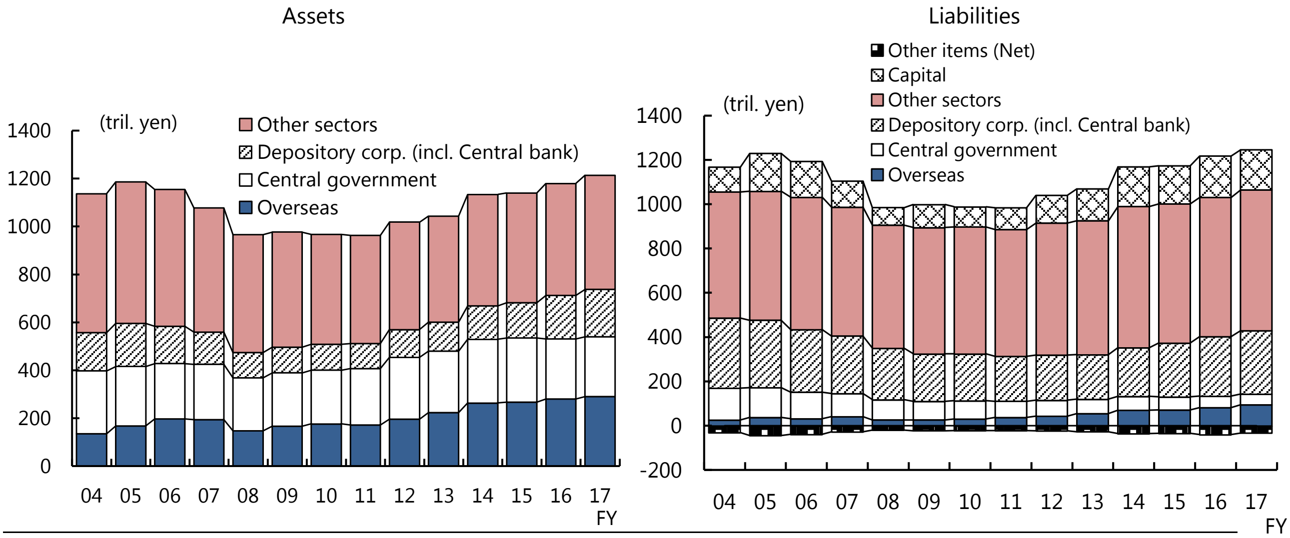
Looking by sector, in the overseas sector in which the Balance of Payments Statistics are directly used, or in the government sector for which a transaction item basis data are available as source data of the J-FFA, the estimation accuracy is relatively high. According to the estimation methods presented earlier, the items are with reasonable accuracy in depository corporations. On the other hand, the accuracy is relatively low for other sectors as many of the items are calculated as residuals.

Recent development in the OFCS

With the above mentioned from-whom-to-whom data regarding OFCs, a more complete picture of the creditor-debtor relationship between different sectors is available, especially of the relationship between OFCs and depository corporations.

In the time series data, from around 2010, both the asset and the liability side of the OFCs are on increasing trends especially vis-à-vis overseas and depository corporations (Chart 12). In the following part, we present some distinctive features of the trend.

Assets and Liabilities of OFCs by Counterparty — Chart 12

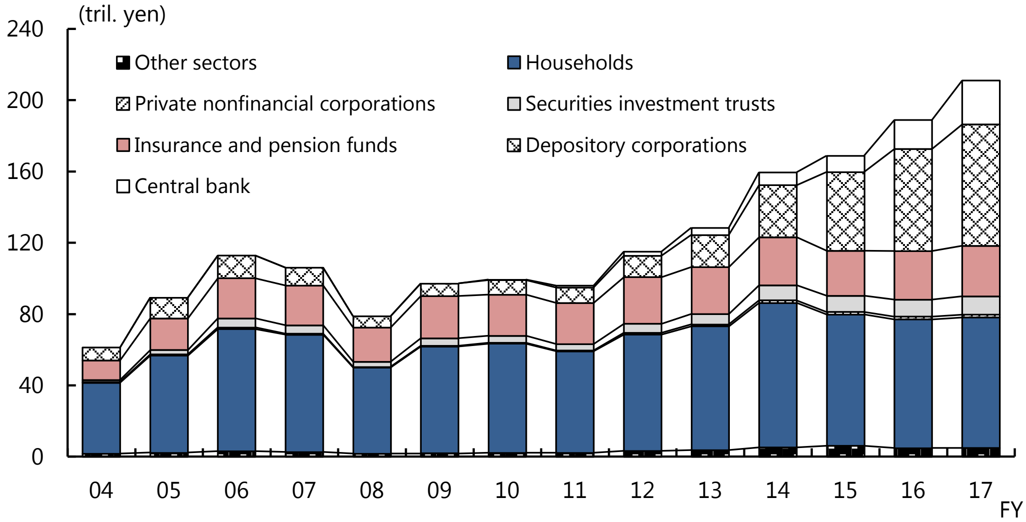


(1) Increase in investment trusts

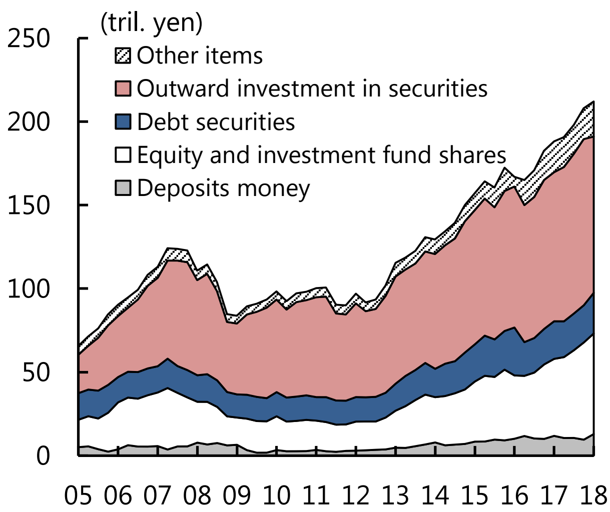
Securities investment trusts are classified as OFCs. The amount of outstanding investment trusts is expanding rapidly in recent years and is mainly attributable to the increase in holdings by depository corporations (Chart 13). As has often been pointed out, lending margins, which constitute the core profits of Japanese depository corporations, have been on a declining trend[11]. In such circumstances, depository corporations are taking a more proactive stance toward investing in investment trusts and foreign bonds as part of their portfolio allocation strategy. The breakdown data by investment assets show that foreign securities investment accounts for a significant portion and is on an increasing trend. Equities are also increasing (Chart 14).

[11] For details, refer to Financial System Report (http://www.boj.or.jp/en/research/brp/fsr/index.htm/) by the Bank of Japan, for example.

Amount Outstanding of Investment Trust by Holders Chart 13



Amount Outstanding of Investment Trust (excl. REIT) by Item Chart 14



Note: The latest data are as of March 2018.

(2) Increase in repurchase agreements and securities lending transactions

The amount of outstanding repurchase agreements and securities lending transactions are calculated using the method described earlier. The time series data show that the OFCs' funding through the overseas sector as well as OFCs' investment to depository corporations is increasing (Chart 15).

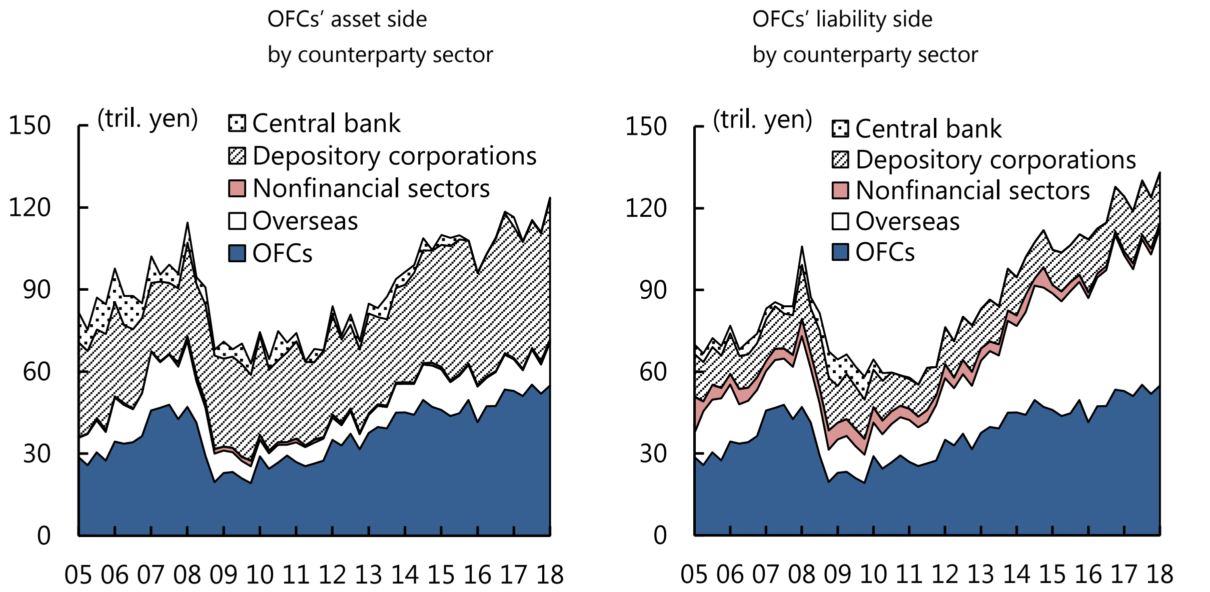
This presumably reflects the trend of the expanding needs of foreign currency funding by depository corporations and insurance companies due to the increase in their foreign credit exposure including overseas loans and foreign bond holdings. OFCs, typically broker dealers, are working as intermediaries and overseas are responding to these demands.

Foreign financial institutions that have ample funds in dollars convert their money into yen and invest in safe assets such as Japanese government bond through repurchase agreements. In the background of the increase in repurchase agreements were these sorts of transactions, which expanded as the dollar funding premium widened in the FX swap and cross-currency basis swap market from around 2014.

These figures confirm that OFCs in particular broker dealers play a significant role in repurchase agreements between depository corporations and the overseas sector.

Repurchase Agreements and Securities Lending Transactions of OFCs by Counterparty

Chart 15



Note: The latest data are as of March 2018.

(3) Debt securities issues and intra-group lending by bank holding companies

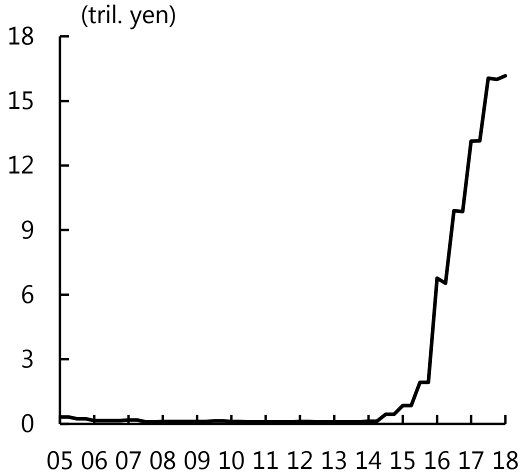
Lending between OFCs and depository corporations is calculated using the method described earlier. In the time series data of OFCs' lending to depository corporations, the amount outstanding has been on a declining trend due to the contraction of Fiscal Loan Funds. However, in recent years, the outstanding amount is picking up mainly because of the internal TLAC[12] from bank holding companies to their subsidiary banks (Chart 16, 17).

[12] The Internal Total Loss-Absorbing Capacity of G-SIBs (Internal TLAC) is designed to shore up the host authorities of cross-border subsidiary banks without harming the host country's financial system, by transferring losses from the subsidiary banks to the holding companies.

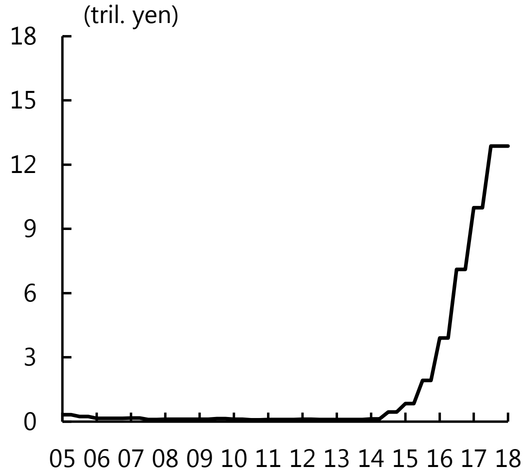
Loans from OFCs to Depository Corporations, Loans from Financial Holding Companies to Subsidiaries

Chart 16, 17

Loans from OFCs to Depository Corporations



Loans from Financial Holding Companies to Subsidiaries



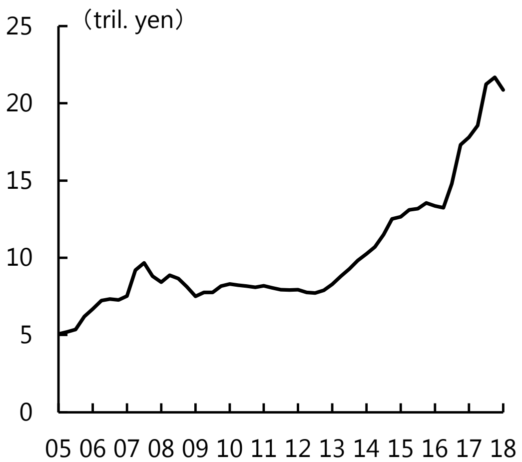
Note: The latest data are as of March 2018.

At the same time, although the estimation accuracy is relatively low, the holder breakdown of the bond issued by OFCs indicates that holding in the overseas sector is on an increasing trend in recent years (Chart 18). One of the main related factors is the bond issuance by bank holding companies. Global systemically important banks (G-SIBs) have been working to come into line with TLAC regulations by issuing debt securities from holding companies in foreign currency (Chart 19). The capital raised in that manner is used as aforementioned loans from the holding companies to their subsidiary banks, which is one of foreign currency funding measures of depository corporations.

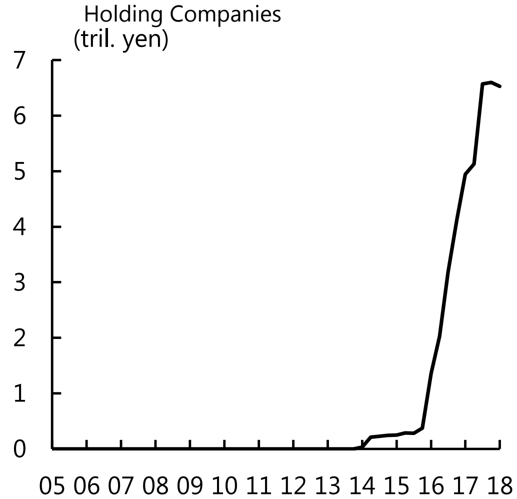
Securities Issued by OFCs Held by Overseas, External Securities Issued by Financial Holding Companies

Chart 18, 19

Securities Issued by OFCs Held by Overseas



External Securities Issued by Financial Holding Companies



Note: The latest data are as of March 2018.

The features raised in this section came about by focusing on certain OFCS breakdown data. These figures confirm that OFCs, typically broker dealers and investment trusts, play a significant role in terms of intermediation while both funding and investing transactions grow between financial institutions and overseas.

Conclusions

In this paper, we introduced some of the estimation methods that were applied in the OFCS compilation. We considered some measures to maintain the estimation accuracy even though there are difficulties in obtaining granular data. In efforts to enhance statistics, how to compile and verify data especially in areas with data constraints is a common problem globally. We hope that the measures described in this paper are of some help in compiling other statistics.

In the latter part of the paper, we examined the breakdown data of the OFCS and confirmed that OFCs play a significant role especially when depository corporations extend their business overseas. Transactions by financial institutions through OFCs are important means of obtaining funding from and investing in overseas. They also contribute to the promotion of financial intermediation activities.

At the same time, given that international financial transactions are becoming more complex, it is increasingly important to understand capital flows through the financial system including institutions other than depository corporations in order to understand the risks inherent in financial transactions. The G20 and the FSB have pursued discussions with the aim of addressing the risks as part of an initiative to mitigate financial stability risks caused by non-bank financial intermediation. The Bank of Japan participates in FSB's global non-bank financial intermediation monitoring exercise. In addition, the Bank of Japan and the Financial Service Agency are taking part in the FSB Data Experts Group (DEG) and are working on the details of the data collection framework of repurchase agreements and securities lending transactions[13].

The OFCS classifies the balance of OFCs' assets and liabilities by counterparty sector. As shown in this paper, it is important to grasp the trends in the OFCs' assets and liabilities with the OFCS data, and then to seek more detailed data together with other statistics in order to understand OFCs' role in the financial system or in financial intermediary activities. The OFCS is an important step forward for the development of the data regarding OFCs to understand capital flows and potential vulnerabilities involved in financial transactions. Since the global financial crisis, the Bank of Japan has been working to enhance statistics in line with international initiatives and intends to continue to make further efforts in order to narrow the data gaps thereby helping to understand the risks inherent in financial activities.

[13] See Ono et al. (2015).

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Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

Other financial corporations survey in Japan –- compilation measures and recent features[1]

Daiki Date, Keita Takemura and Haruko Kato,
Bank of Japan

[1] This presentation was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

Other Financial Corporations Survey in Japan
- Compilation measures and recent features -

9th IFC Biennial Conference
"Are post-crisis statistical initiatives completed?"

Haruko Kato
Bank of Japan

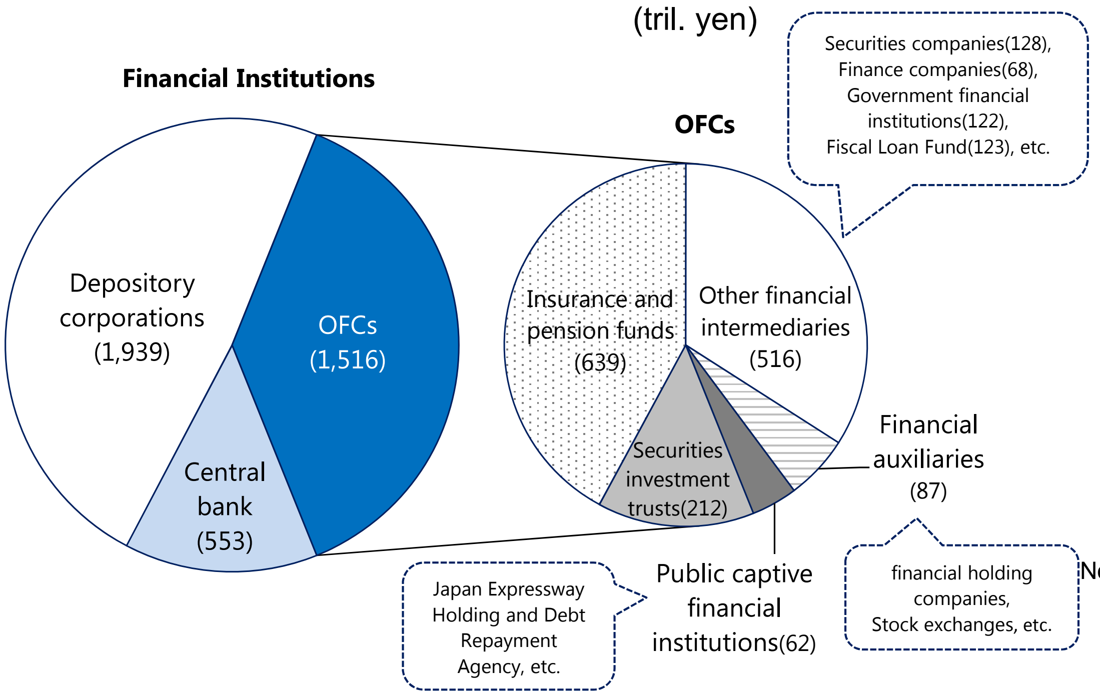
30-31 August 2018
BIS, Basel

• Other Financial Corporations Survey (OFCS)

A framework that seeks to capture a wide range of financial activities and risks inherent in these activities of Other Financial Corporations (OFCs) - financial entities other than the central bank and depository corporations -.

✓ **One of the nine data categories of the SDDS Plus**

Asset size of OFCs



Note: The data are as of March 2018.

Items recorded in OFCS

Asset of OFCs (Credit to ～)	
	Overseas
	Central government
	Depository corporations
	Other sectors
Liability of OFCs (Credit from ～)	
	Overseas
	Central government
	Depository corporations
	Other sectors
Capital (Shares and other equity)[1]	
Other items (net)[2]	

Notes: 1. Shares issued by OFCs are not included in Liability, but in Capital.
2. "Other items" records not only shares issued by OFCs that OFCs hold, but also items not included in any other categories.

• OFCS Compilation

Basic policy in compilation:

✓ **Make full use of existing statistics**

- The Flow of Funds Accounts (J-FFA)
- The Balance of Payment statistics
- External statistics

✓ **Use micro data depending on the needs**

- Source data of J-FFA

◆ Example 1 (treasury discount bills)

➢ Reconfiguration of J-FFA figures

J-FFA data

	Financial institutions							
			Central bank		Depository corporations		OFCs	
	Asset	Liability	Asset	Liability	Asset	Liability	Asset	Liability
…								
T-bills								
…								
Total								

reconfiguration

OFCS data

Asset of OFCs (Credit to ～)		
	…	
	Central government	
	…	
Liability of OFCs (Credit from ～)		
	…	
Capital (Shares and other equity)[1]		
Other items (net)[2]		

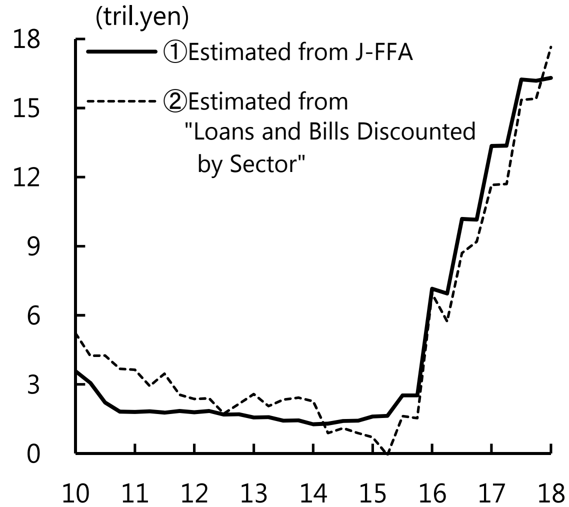
• OFCS Compilation

◆ Example 2 (lending between OFCs and depository corp.)

➢ Use J-FFA + its source data

Borrower sector / Lender sector	Depository corporations	OFCs	Financial institutions (Depository corporations + OFCs)
Depository corporations	Obtained by subtraction	Obtained by subtraction	Specified in J-FFA
OFCs	Estimated by adding up the breakdown items.	Obtained by subtraction	
Financial institutions (Depository corporations + OFCs)	Specified in J-FFA		

Lending from OFCs to Depository Corp.
(Consistency check)



◆ Example 3 (repurchase agreements & securities lending transactions)

➢ Use J-FFA + Balance of Payments + certain assumptions

Liability / Asset	Depository corporations	OFCs	Overseas	Other sectors	Total
Depository corporations	Assumed to be zero	②	Balance of Payments	Depository corp. ⇔Central Bank	Specified in J-FFA
OFCs	②	④	①	③	
Overseas	Balance of Payments	①		Balance of Payments	
Other sectors	Depository corp. ⇔Central Bank	③	Balance of Payments	Central Gov. ⇔Central Bank	
Total	Specified in J-FFA				

- Use BoP for transactions with Overseas
- Calculate ①
- Assumption of [pink] and [green]
- Calculate ③
- Calculate ④ as a residual

• Estimation accuracy

✓ The estimation accuracy is relatively high in the overseas sector (direct use of Balance of Payment statistics) and government sector (transaction item basis data are available as source data of the J-FFA).

✓ According to the estimation methods presented earlier, the items are with reasonable accuracy in depository corporations.

	Asset of OFC (Credit to ～)					Liability of OFC (Credit from ～)				
	Overseas	Central government	Depository corporations	Other sectors (Households, Nonfinancial corporations, Local governments, NPISH, Central bank)	OFCs	Overseas	Central government	Depository corporations	Other sectors (Households, Nonfinancial corporations, Local governments, NPISH, Central bank)	OFCs
Currency and deposits			High							
Deposits with the Fiscal Loan Fund					High		High	High	High	High
Loans	High	Middle	Middle	Low	Middle	High	Middle	Middle	Low	Middle
Loans by private and public financial	High	High	Middle	Low	Middle			Middle		Middle
Repurchase agreements and securities lending	High	Middle	Middle	Low	Low	High	Middle	Middle	Low	Low
Debt securities		Middle	Low	Low	Low	Low	Low	Low	Low	Low
Equity			Middle	Middle	Middle	Middle	Middle	Middle	Middle	Middle
Investment fund shares				Middle	Middle	Middle	Middle	Middle	Middle	Middle
Insurance, pension and standardized guarantees					Middle			Middle	Middle	Middle
Financial derivatives, etc.	Low	Low	Low	Low	Low	Low	Low	Low	Low	Low
Deposits money	Low	High	Middle	Middle	Low	Low	Middle	Middle	Low	Low
Trade credits and foreign trade credits	High	High		Middle	Middle	High	High		Middle	Middle
External claims, etc.	Middle					Low				

：High

：Middle

：Low

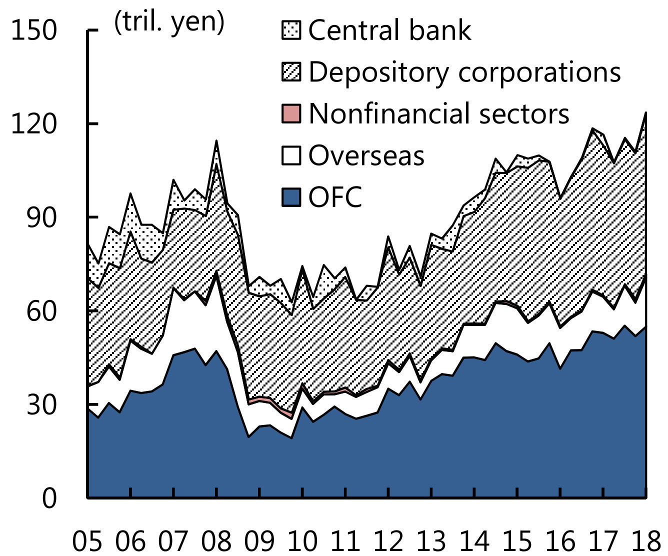
Note: Empty cells indicate that there is no figure compiled.

• Recent features in the OFCS

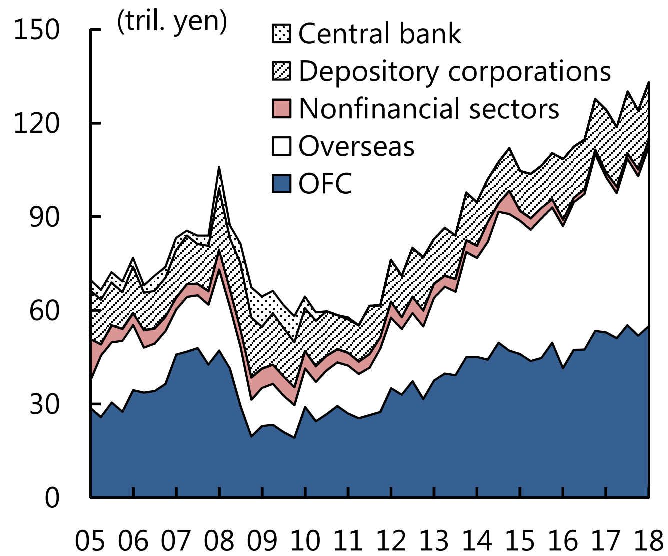
◆ Repurchase agreements & securities lending transactions

- ✓ Expanding needs of foreign currency funding by depository corporations and insurance companies due to the increase in their foreign bond holdings as part of their portfolio allocation strategy.
- ✓ OFCs, in particular broker dealers, are working as intermediaries and overseas are responding to these demands.

OFCs' asset side by counterparty sector



OFCs' liability side by counterparty sector



Note: The latest data are as of March 2018.

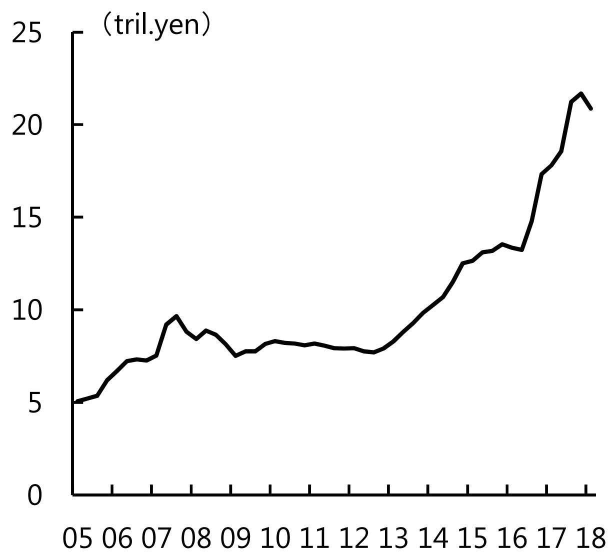
• Recent features in the OFCS

◆ Debt securities issues and intra-group lending by bank holding companies

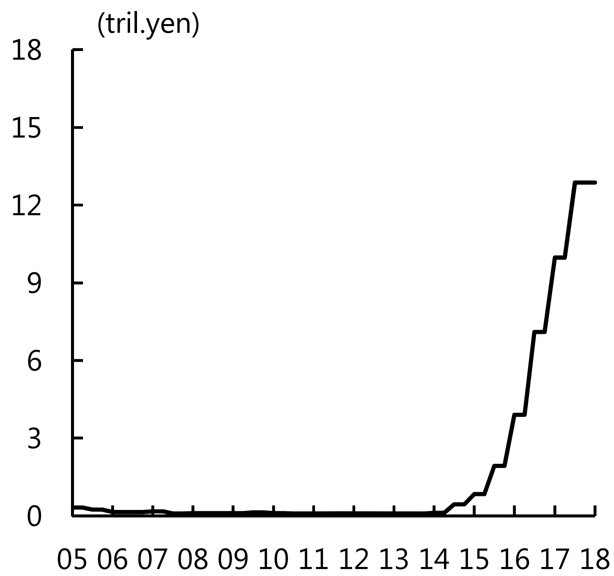
✓ G-SIBs have been working to come into line with TLAC regulations by issuing debt securities from holding companies (OFCs) in foreign currency.

✓ The capital raised in that manner is used as holding companies' lending to their subsidiary depository corporations (internal TLAC)

Securities Issued by OFCs
Held by Overseas



Loans from Holding Companies
to Subsidiaries



Note: The latest data are as of March 2018.

• Summary

- ➢ The OFCS is an important step forward to understanding the trend of OFCs.
- ➢ In the OFCS compilation, we use various measures by utilizing other statistics and some micro data depending on the needs.
- ➢ The breakdowns of the OFCS data confirm that OFCs play a significant role while Japanese depository corporations extend their business overseas.

Thank you!

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Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

Real estate fund investment in post-crisis Ireland[1]

Barra McCarthy,

Central Bank of Ireland

[1] This paper was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

Real Estate Fund Investment in Post-Crisis Ireland

Barra McCarthy

Abstract

In the wake of the financial crisis and set against a recovering but fragile banking system, Ireland's economy has seen new players enter many different markets. In few areas has this been more evident than in the expanding role of Irish resident real estate funds (IREFs) in the Irish property market. Their rapid growth has led to IREFs property holding increase from €1bn in 2012 to €14.5bn at end-2016. Despite this, the role of IREFs in Ireland's post-crisis economic story is still largely unexplored. This paper aims to shine some light on the sector in two ways. Firstly, it uses a novel dataset to determine where and what type of property IREFs have invested. Secondly, using granular investor level data it asks what are the key policy and economic variables driving investment into Irish real estate funds over 2014-2017. The paper has three key findings: 1). IREF property holdings are overwhelmingly concentrated commercial real estate located in Dublin. 2). Variables measuring the return on IREF equity are predictive of investor net inflows, while alternative investment opportunities for investors are not. 3). Tax changes for foreign IREF investors over 2014-2017 have no significant impact on investment.

Keywords: Real Estate Funds, International Investment, Investor Taxation

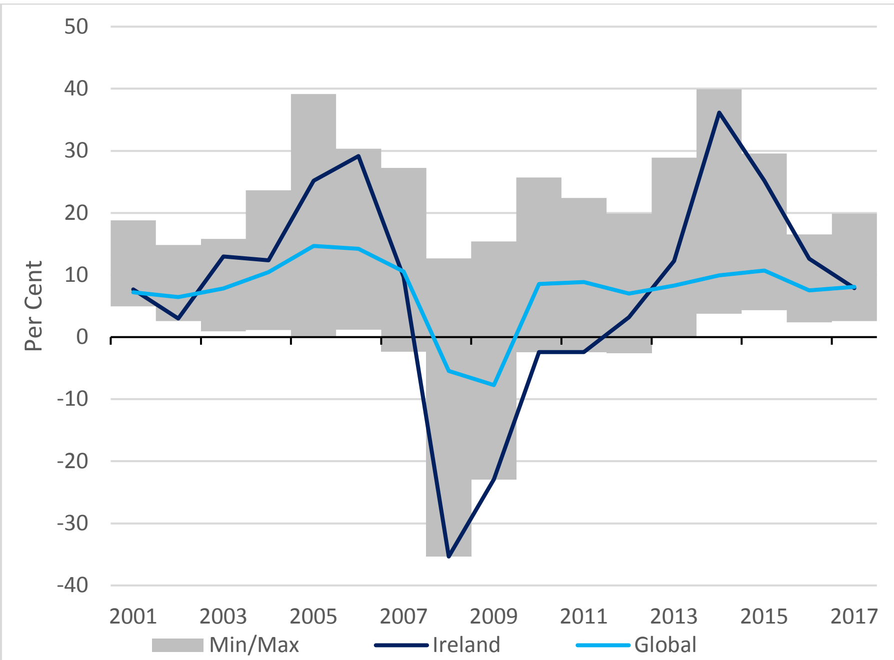
Contents

Introduction

One of the most striking changes to Ireland's property market following the financial crisis has been the growing importance of Irish real estate funds (IREFs). IREFs' total Irish property assets under management have grown from €1bn in 2012 to €14.5bn at end-2016.

This has been driven by two factors: valuation gains on Irish property and a large supply of property assets for sale. As can be seen in Chart 1, returns on Irish property have been high following the crisis, with total returns in the range of 30-40 per cent over 2014. This follows a period where property prices fell substantially with annual declines well in excess of 20 per cent in 2008 and 2009. Therefore, this growth has in part reflected the appreciation in the value of property already held by IREFs. However, IREFs have also been prolific purchasers of Irish property over the past 6 years. In some cases, existing IREFs expanded their property holdings, but most growth came from new investors entering the market using fund structures as their investment vehicle of choice.

Chart 1: Total Returns on Commercial Real Estate Across International Property Markets



Source: MSCI Real Estate/IPD.
Note: Grey bars signify the relevant maximum and minimum annual total returns observation excluding Ireland (in local currency) across 32 international markets. For more details on country coverage see: https://www.msci.com/real-estate.

In addition, large portfolios of property were being sold throughout the period. The Irish government set up the National Asset Management Agency to purchase non-performing property loans from the Irish banks. In 2010 NAMA purchased loans with a book value of €71.2bn for €30.2bn in 2010 (NAMA, 2010), and proceeded to sell the loans or the collateral (property) on which those loans were secured over the following years. In addition, debtors who did not see their loans taken by NAMA but still defaulted commonly had the collateral on which their loans was secured sold ((RTE, 2012; Hancock, 2015). Recently, some IREFs have begun purchasing residential and commercial new builds (Fagan, 2016a; Fagan, 2016b), which has further contributed to the growth of their holdings of Irish property assets.

Despite their popularity, and maybe in part because of the pace of change, the role of IREFs in Ireland's post-crisis economic story is still largely unknown. Previous discussion of them has been limited to McCarthy (2017) and market commentary by real estate agents. This paper aims to shed light on IREFs by answering two questions. Firstly, how is IREF investment distributed geographically and across market segments? Secondly, what are the key policy, financial and economic variables that drive investment into IREFs?

To answer the first question the paper uses a novel property-by-property dataset created from regulatory data to understand how IREF investment is distributed across Ireland and in what sectors it is concentrated. To answer the second question, the paper uses a granular investor level dataset and tries to determine which economic, financial and policy variables drove investment into Irish real estate funds over the period 2014-2017.

This paper is not focusing on all funds that are classified as real estate funds in the Central Bank of Ireland (CBI) Investment Funds dataset, but rather the subset that have invested in Irish property directly or indirectly through partnerships and limited companies.[1] Thus, this paper does not include funds that only hold property located outside of Ireland, and funds that invest only in the debt or equity of real estate companies or funds. Real estate investment trusts are also not included.

Literature

Descriptive analysis on the activities of real estate funds in the Irish market has been limited. One source of information has been the market commentary produced by real estate agents, which reports on 'private equity investors', 'property companies' and 'institutional investors', who would commonly invest through an IREF. This commentary provides estimates of how active such investors are in the Irish property market, as well as providing some information on where such investors are focusing their investment and what types of property they are investing in (Savills World Research, 2018; Colliers International, 2016; DTZ Sherry FitzGerald, 2016).

Descriptive work using the CBI's Investment Fund return data is undertaken in McCarthy (2017). It provides a high-level overview of the sector, and shows that IREFs only invest in property in the UK and Ireland, and that on a first counterparty basis Irish investors held around 35 per cent of total IREF equity at Q1 2017. The current

[1] Real Estate Funds in the Investment Fund data include funds that primarily invest in the equity or debt of real estate companies.

paper will build on that work and market commentary, by providing a detailed geographic and property type breakdown of IREF investment over 2012-2016.

The literature on factors affecting investment into real estate funds, and other fund types, is more extensive. Research on investment flows into real estate funds and REITs tend to focus on establishing the relationship between returns and net subscriptions. Downs et al. (2016) examine German open real estate funds using a VAR and find that returns predict investor flows, but that investor flows do not predict returns. Ling and Naranjo (2006) and Lin and Yung (2006) perform similar analyses with data for US REITs, and come to a similar conclusion. This paper will differ to these two examples in its use of individual investor level data, rather than data aggregated at the fund level.

Other studies focus on returns to alternative investments and how they impact fund flows. Grose (2011) analyses the determinants of inflows and outflows into mutual bond funds in Greece, and finds that returns on the Athens Stock Exchange share a negative relationship with investment into bond funds.

The period is also characterised by a change in the withholding tax levied on foreign investors in IREFs, and thus the paper ties in with literature on investment taxation. The most salient example is Desai and Dharmapala (2011), which looks at the impact of the impact of the US 2003 Jobs and Growth Tax Relief Reconciliation Act on the country composition of portfolio equity investment. The Act provided favourable tax treatment of dividends for a subset of foreign countries. Using a difference-in-difference design the authors show that holdings of equity from affected countries increased following the tax reform.

Finally, this paper broadly relates to the literature studying the determinants of direct cross border real estate investment. Baum et al. (2013) attempt to estimate institutional and regulatory cross border determinants of cross border real estate investment, but find that regulatory and institutional variables have no impact on cross border flows. Muack and McKay Price (2017) attempt to determine the economic and property specific characteristics that make publicly traded retail investment firms to invest abroad. Both of these studies focus on features of the investment location that attract investment, whereas this paper will focus on determining how domestic factors influence investors decisions to invest abroad.

Data

Property-by-Property Dataset

IREFs supply data on aggregate property holdings broken down by country in the quarterly Investment Fund return collected by the Central Bank of Ireland. To understand how this investment was distributed across Ireland additional sources of data collected by the CBI were utilised. Location information for the properties held by IREFs is available in their annual audited financial statements. In the small number of cases where this information was unavailable in a funds audited financial statement, the author request this data from fund administrators, ensuring that the dataset would be complete. The data was subsequently cross-checked with industry publications and the commercial property section of Irish newspapers. A quarterly dataset on purchases and holdings of Irish real estate between 2012-2016 was created.

There are a minimum of 2,400 unique properties in the dataset. The exact figure is higher due to properties in the same multifamily development being aggregated into one item in audited financial statements.

Investor Level Dataset

Similarly, the data the Investment Fund return provides is insufficient for rigorously analysing the determinants of investment into IREFs. This is due to the aggregation of fund equity holder positions by country and sector. If investors are investing across multiple funds, the observations will not be independent. Failure to take this account would undermine the validity of any hypothesis test conducted.

Shareholder registers were requested and received for all but a handful of IREFs in operation over the period 2014-2017. These registers provide individual level data for the subscriptions, redemptions, opening and closing position of each investor in each quarter, as well as the country in which each investor resides.

The dataset that has been constructed is a multidimensional panel dataset, with 128 funds and 1,895 unique investors. Multiple relationships exist between funds and investors in the data, with funds having multiple investors and investors investing across multiple funds.

One potential issue exists with the investor dataset. The investor country data is reported on a first counterparty basis, rather than an ultimate counterparty basis. This can be problematic, as the analysis aims to understand how domestic investment opportunities affect investors' decisions to invest in IREFs. To give an example, economic and financial variables for the British Virgin Islands are unlikely to explain the investment behaviour of investments that are held there. Unless the ultimate counterparty location can be determined, investors located in offshore financial locations are dropped from the analysis.[2]

However, this issue may also affect investors located in non-offshore financial centre locations if their investment is held on their behalf by a third party, for example in a nominee account with a broker. The robustness checks will attempt to determine whether this is an issue.

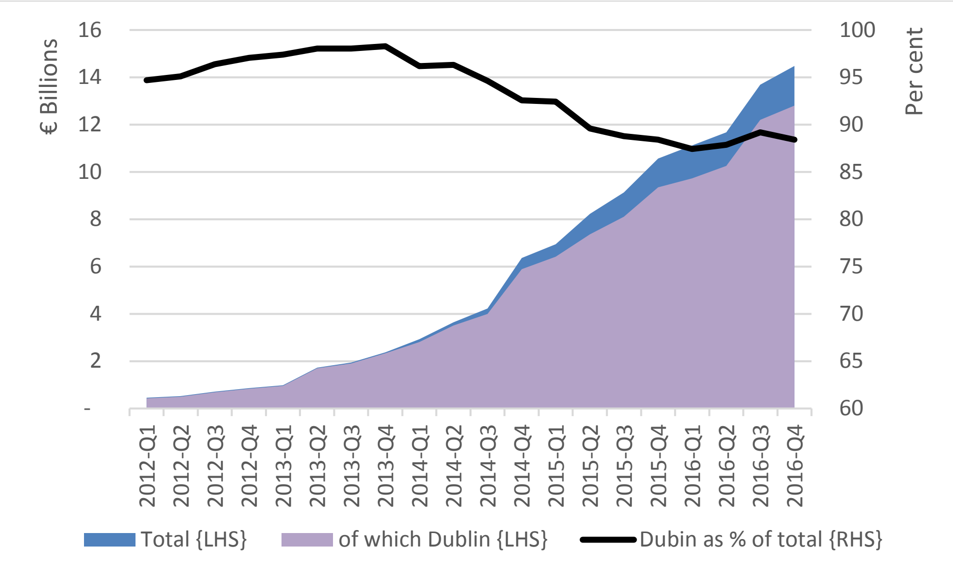
[2] Countries excluded include the Bahamas, the West Indies, Guernsey, Jersey, the British Virgin Islands, Panama, the Isle of Man and Malta.

Distribution of IREF Investment

Considering the geographical spread of investment across Ireland, the first thing that becomes obvious is that it is highly concentrated in Dublin, Ireland's capital, and is weakly dispersed throughout the rest of Ireland. As of 2016 Q4, some 88 per cent (€12.8bn) of investment property by value held was located in Dublin. By comparison, Ireland's second largest county by population, Cork, only accounts for 3 per cent of the total.[3]

The concentration of investment in Dublin is a consistent feature of the data, although there does seem to be a trend of decreasing concentration since 2014 (see Chart 2). Dublin's share of total assets was highest in 2013 Q4, when it accounted for approximately 98 per cent of total property assets by value before declining to a low of 87 per cent in 2016 Q1.

Chart 2: Total Property holdings of IREFs – Dublin and the Rest of Ireland



Source: Central Bank of Ireland

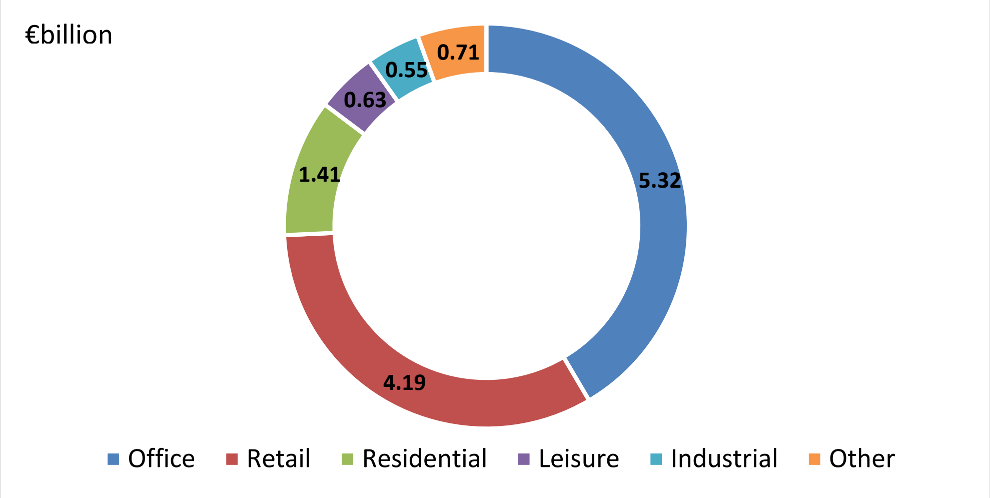
Given the clear split in investment between Dublin and the rest of Ireland, it seems apt to consider how investment varies across property categories within each region. Considering stocks of property at end 2016, the majority of Dublin located property held by IREFs is commercial. Using a generous definition of residential accommodation[4], IREFs hold €1.4bn of residential property out of the total Dublin located stock of €12.8bn. Retail and Office property make up the largest

3 As of 2016, Dublin county had a population of approximately 1.3 million while Cork county had a population of roughly 0.5 million.

4 Student accommodation, mixed use residential-commercial accommodation and pure residential accommodation.

components of this stock, accounting for €4.2bn and €5.3bn respectively (see Chart 3). Leisure and industrial property make up the largest remaining components.

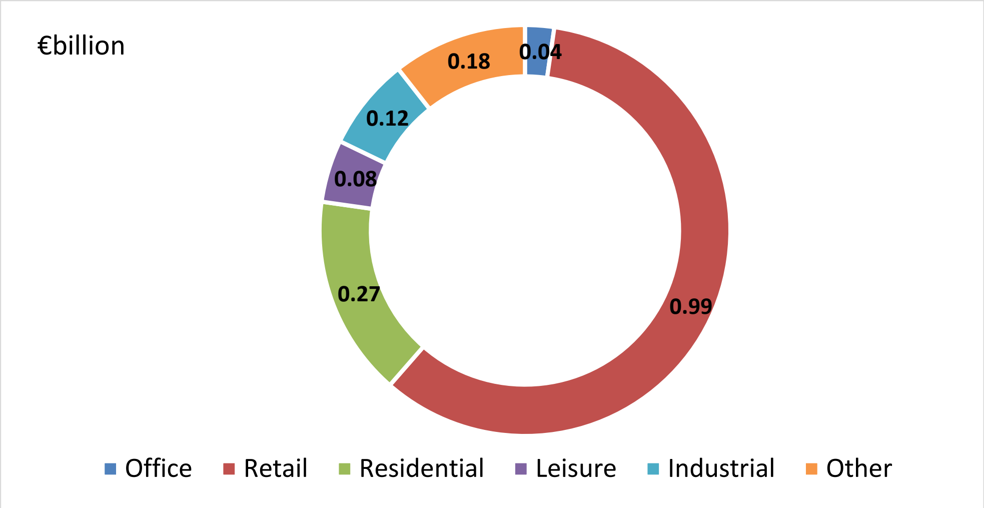
Chart 3: Holdings of Dublin property by category in €bn – Q4 2016



Source: Central Bank of Ireland

The composition of property holdings differs significantly in the rest of Ireland. Firstly, there is a sharp decrease in the amount of office property held - only around €38mn worth of office property is held by IREFs outside of Dublin (see Chart 4). Secondly, retail property accounts for a much greater share of the total. The stock of retail property is worth about €1bn relative to a total stock of €1.7bn in property held outside Dublin, whereas in Dublin it accounts for about €4.2bn of a total of €12.5bn. This is mainly explained by retail focused funds buying many shopping centres and retail outlets outside of Dublin. Finally, residential property makes up a somewhat larger proportion of the total stock outside of Dublin. It comes in at 17 per cent outside of Dublin, relative to 11 per cent in Dublin.

Chart 4: Holdings of non-Dublin property by category in €bn – Q4 2016



Source: Central Bank of Ireland

The property-by-property dataset provides two policy relevant insights. Firstly, to whatever extent IREF investment is a policy issue, it is a regional one – investment is highly concentrated in Dublin. Secondly, the vast majority of these funds are focused on commercial real estate. Therefore, they should be viewed as marginal players in the residential real estate market for the time being.

Modelling Framework

Modelling Investment into IREFs

To answer the second question set out in the introduction, we need a framework in which to analyse investors' demand for IREF shares. Ultimately, what is being analysed is investment choice. Therefore, the analysis is set within a portfolio choice framework such as Desai and Dharmapala (2011). Demand, as measured by net subscriptions, for IREF shares is determined by the return on fund equity, the returns of alternative investments and changes in each investor's wealth constraint (i.e. income, as proxied by real GDP growth).

A number of factors determine the return on IREF equity. At the fund level, it is determined by the capital appreciation and dividend yield of the shares held and changes in the FX rate.

What remains is to model alternative investment opportunities for investors. Let us state that the set of all countries in which an investor can invest is W, and that there are n countries in the sample where n is a subset of W (i.e. $n \subset W$), with W=[1,..,k]. Simplifying by assuming there is only one investor from each country and that income does not influence their decision, for a set of investors from countries $1,2,3,4 \in n$ investing in the equity of fund j, their investment decisions can be modelled as follows:

$$\begin{aligned}
Y_{1jt} &= \beta_{11}X_{11t} + \beta_{W1}(X_{21t} + X_{31t} + X_{41t} + .. + X_{n1t} + X_{(n+1)1t} + .. + X_{k1t}) + u_{1jt} \\
Y_{2jt} &= \beta_{22}X_{22t} + \beta_{W2}(X_{12t} + X_{32t} + X_{42t} + .. + X_{n2t} + X_{(n+1)2t} + .. + X_{k2t}) + u_{2jt} \\
Y_{3jt} &= \beta_{33}X_{33t} + \beta_{W3}(X_{13t} + X_{23t} + X_{43t} + .. + X_{n3t} + X_{(n+1)3t} + .. + X_{k3t}) + u_{3jt} \\
Y_{4jt} &= \beta_{44}X_{44t} + \beta_{W4}(X_{14t} + X_{24t} + X_{34t} + .. + X_{n4t} + X_{(n+1)4t} + .. + X_{k4t}) + u_{4jt}
\end{aligned}$$

Where Y_{1jt} is an investor from country *1*'s net subscriptions in fund j for period t, X_{21} represent the returns of investor from country *1* investing in country *2* and $\beta_{W1,2,3,4}$ are k by 1 vectors of parameter estimates for the impact of alternative investment opportunities in foreign countries.

To start, let us consider that each investor faces a choice to invest domestically or internationally. This distinction is important because It is generally acknowledged that a 'home bias' exists which leads to investors having a greater preference for investing domestically. Whether its cause is informational (Suh, 2005), due to excessive optimism about domestic markets (Strong & Xu, 2003) or due to cultural factors (Anderson, Fedenia, Hirschey, & Skiba, 2011) it is well established, and should be taken into account when analysing investment choice.

To do so it is assumed that the relationship between returns and investment faced by an investor investing in their own country, country *1*, is different to that of an investor from a different country, country *2*, investing in country *1*. Letting β be the relationship between investment in IREF shares and returns on alternative investment opportunities, formally this can shown with:

$$\beta_{11} \neq \beta_{12} \qquad 1, 2 \in W$$

Due to this feature of investor behaviour, it makes sense to isolate domestic investment from international investment for each investor, as has been done in the previous set of four equations.

What remains is to model international investment for each investor. Let us assume that two investors investing in the same foreign country should find the return on fx adjusted foreign investment equally attractive. For example, Spanish and UK investors should find the return on German equities equally attractive, after adjusting for FX rates. The author acknowledges that factors such as trust, language and proximity all play important roles in determining foreign investment. However, these factors are generally stable or fixed over the medium term, and thus should be captured by investor fixed effects. Formally, this can be stated as:

$$\beta_{12} = \beta_{13} \qquad 1,2,3 \in W$$

The set of all countries outside the n in the sample, those between n+1 and k in the equations, are common and equally attractive (given previous assumptions) investment opportunities to all investors. Thus, they can be picked up using a period fixed effect for each quarter.

What remains is investment between the set of countries present in the sample, the 1 to n countries. For each investor, this represents cross sample investment. To capture the impact of alternative cross sample investment opportunities a weighted average return for each investor country for bond, equity and real estate returns is constructed. Weights for each country are calculated as the market size for a given company as a percentage of the total market size of the countries in the sample.

To minimise the risk of dynamic misspecification quarter-on-quarter percentage returns are used for all alternative investment opportunities, real GDP growth, and growth in the value of a fund’s equity.

One further factor that needs to be taken into account is the changing policy environment for investors over this period. The 2016 Finance Act levied a new withholding tax on foreign investors in IREFs. From 1st January 2017, investors not resident in Ireland and not part of an exempted group[5] were subject to a 20 per cent withholding tax on capital gains and dividend income. As this tax change affected investors differentially, it needs to be controlled for.

Empirical Model

Formally, our model can be expressed by the following equation:

$$Y_{ijt} = X_{it} + Z_{jt} + T_{it} + F_{it} + u_{ijt}$$

Where Y_{ijt} is net subscriptions of investor i in fund j at time t, as percentage of the opening position of that investor's equity holding.

X_{it} covers investor covariates, including alternative investment opportunities and the proxy for income growth, quarter-on-quarter (QoQ) real GDP growth (*gdp*). For, Ireland real GDP growth has been replaced with growth in real modified domestic demand due to distortions in Irish GDP due to multinational corporations.

It would be expected that all alternative investment opportunities share a negative relationship with net subscriptions for an investor. The only exception is the return on Irish property for Irish investors, which should share a positive relationship with net subscriptions. To account for this an interaction term between a dummy for Irish nationality of investors and the return on property is included.

QoQ total returns for domestic and cross sample equity (*eqi, eqw*) are calculated using the total return index for each investor nationality's benchmark stock exchange. Coverage for these indices is extensive, and easy to source for all non-offshore financial centre locations.

QoQ total returns for domestic and cross sample bonds (*bnd, bdw*) are calculated using the total return index for each investor nationality's sovereign bonds. Sovereign bonds indices were chosen as they had the best country coverage relative to aggregate bond indices or corporate bond indices. Total return indices were not available in all cases, so on occasion price indices had to be used.

QoQ returns for domestic and cross sample property (*rre, rrw*) are calculated using indices of residential retail prices for each country. Unfortunately, quarterly commercial real estate indices do not have the same coverage. Interaction terms with a dummy for whether an investor is Irish are also recorded (*rre_ie*).

Z_{jt} symbolises fund covariates, namely dividend yield (*div*) and QoQ growth in the value of the fund's equity (*cap*). The dividend yield measures the value of dividends distributed in a quarter as a percentage of the total NAV.

[5] Investors who were pension funds, investment funds and life assurance companies located in the EEA were exempt from the tax change. UK charities were also deemed to be exempt from the tax change. This exemption was only valid if the investor was not using the fund as a personal investment vehicle.

The impact of the 2016 Finance Act is captured in the T_{it} variable (*tax*), which is structured as a difference-in-difference estimator.

F_{it} captures varieties of fixed effects and interaction fixed effects. The fixed effects used in various models include quarter fixed effects, investor-fund fixed effects, investor class-quarter interaction fixed effects and sole investor-quarter interaction fixed effects.

For the investor class-quarter fixed effects investor are divided into two groups to try and distinguish between retail investors and institutional investors. This is done by choosing a cut off point for the maximum shareholding an investor has over the period, and is tested at the €1mn, €2.5mn, €5mn and €10mn level. For parsimony, only results of the €1mn threshold are shown, but they do not differ from that of the others.

The data are characterised by many funds with only one investor. These investors may have different investment opportunities to other investors, and thus an interaction between being the sole investor in a fund and quarter fixed effects (i.e. sole investor – quarter fixed effects) are also included.

Finally, care needs to be taken with the error term u_{ijt}. Investors in the same fund will be subject to the same shocks, but investors also invest across multiple funds and their observations will not be independent either. Picking only one type of cluster would misspecify the data generating process for the error term, so two-way clustered standard errors are used, with errors clustered on investor and fund.

Data for fund covariates comes from the Investment Fund return and data for investor covariates comes from Bloomberg, Eurostat, IMF and BIS.

Empirical Analysis

The results of 5 models are detailed below (Table 1). Model 1 only includes fund covariates and quarter and investor-fund fixed effects. Model 2 adds investor covariates. Model 3 includes the tax variable; as it is structured as a difference-in-difference variable, all investors who were not present in the quarter preceding its announcement are dropped. Models 4 and 5 include different types of investor characteristic-quarter interaction fixed effects, to capture the possibility that types of investors may have different investment opportunities unique to them that vary over time. Model 4 includes investor size-quarter interaction fixed effects and model 5 includes sole investor-quarter interaction fixed effects.

The modelling framework considers investment in IREFs to be a function of their return, the return of alternative investment opportunities and income of investors. The results provide limited support for this view.

Table 1: Main Regression Specifications

Dependent Variable: Net subscriptions as percentage of opening position

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
Fund Covariates					
Div	0.13 (0.04)***	0.13 (0.04)***	0.14 (0.03)***	0.15 (0.03)***	0.15 (0.03)***
Cap	0.00 (0.01)	0.00 (0.01)	0.01 (0.01)	0.01 (0.01)	0.00 (0.01)
Investor Covariates					
gdp		0.28 (0.3)	0.27 (0.33)	0.21 (0.32)	0.22 (0.31)
eqi		-0.26 (0.19)	-0.26 (0.19)	-0.28 (0.18)	-0.21 (0.2)
bnd		0.34 (0.53)	0.36 (0.54)	0.35 (0.55)	0.35 (0.54)
rre		0.82 (0.65)	0.87 (0.67)	1.21 (0.64)*	0.67 (0.68)
rre_ie		0.15 (0.5)	0.14 (0.52)	0.03 (0.51)	0.35 (0.39)
rrw		-1.84 (1.95)	-2.01 (2.04)	-1.42 (2.1)	-2.24 (2.14)
bdw		0.55 (1.34)	0.63 (1.42)	0.44 (1.46)	0.51 (1.4)
eqw		0.5 (0.42)	0.54 (0.43)	0.37 (0.45)	0.45 (0.37)
fx		1.43 (0.82)*	1.48 (0.83)*	1.21 (0.84)	1.75 (0.81)**
Policy Covariates					
tax			-0.2 (1.69)	2.03 (2.71)	-1.57 (1.99)
Fixed Effects					
Sole Investor-Quarter Interaction	No	No	No	No	Yes
Investor Class-Quarter Interaction	No	No	No	No	Yes
Quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes
Investor-Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes
N	16,479	16,083	15,211	15,211	15,211

Notes: Standard errors are in parentheses and significance level displayed as * p<0.1; **p<0.05; ***p<0.01

Variables affecting the return of the fund show expected and mostly significant relationships with the investment. The dividend yield (*div*) on IREF shares is consistently significant at the 1 per cent level. A 1 per cent increase in the dividend yield is associated with a 0.13-0.15 percentage point increase in net subscriptions. This can be interpreted in two ways: funds that pay dividends see more investment, and that investors have a moderate propensity to reinvest dividends into the fund they receive them from.

The return on a fund's equity is also determined by the value of its equity, which depends on the fx rate (*fx)* and the price growth of the equity (*cap*). Both variables share an expected positive relationship with investment, such that growth in the value of a fund's equity is associated with increased investment. However, neither variable attains the same level of significance as the dividend yield variable. The fx rate variable achieves significance in 4 of 5 models, but only once at the 5 per cent level. While the growth in the value of a fund's equity has the expected sign, it does not attain statistical significance in any model.

The variables capturing alternative investment opportunities are statistically indistinguishable from zero in all but one case, and frequently have the wrong sign. Of the 7 variables measuring alternative investment opportunities, only 3 show the expected sign; the interaction term for property prices and an investor being Irish (*rre_ie*), the domestic equity return variable (*eqi*) and the weighted cross sample real estate return variable (*rrw*).

The other 4 variables are all unexpectedly positive, but are nearly all statistically significant. The exception is the domestic residential real estate variable (*rre*) in model 4, which attains statistical significance at the 10 per cent level.

Investor income growth (*gdp*) shares a positive relationship with investment across all models, but never attains statistical significance.

Looking across the three specifications including tax (*tax*), there seems to be no clear evidence that the 2016 Finance Act had an impact on net subscriptions of affected investors. While the tax change has the expected sign in two of three cases, it never approaches statistical significance in any model. However, the increase in the estimate from model 3 to 4 suggests that larger investors are driving the negative estimate observed in model 3. In future work, the author will explore potential heterogeneity of the taxes impact amongst different categories of investors.

Robustness Test

The counterintuitive signs and general lack of significance for our alternative investment covariates may lead us to be concerned that some form of endogeneity is biasing the estimates. One possibility is measurement error arising from the country of the first counterparty and the ultimate counterparty of investors being different[6]. Such measurement error could explain the results for alternative investment opportunities and it is quite possible that some measurement error of this variety is present in the dataset - 1324 of the 1895 unique investors are recorded as nominee accounts.

To determine whether this is affecting the estimates investors who have invested through nominee accounts are dropped and the five models are estimated with a reduced sample. Other investor types do not suffer from this problem, so if the same relationships exist within this smaller sample then it can be concluded that measurement error arising from first counterparty reporting is not a significant concern.

[6] For example if a shareholding held in a nominee account with an Irish broker belongs to a US investor, then regressing alternative Irish investment opportunities for this investor will introduce measurement error into the model.

Dropping approximately 2/3rds of the units in the sample does not have a considerable effect on the results (Table 2). While point estimates change, the signs of most estimates do not. Only the tax variable (*tax*) and the interaction term between domestic real estate QoQ returns and whether an investor is Irish see sign changes. Both variables remain insignificant, but now also have signs contradictory to what would be expected.

Table 2: Robustness Test

Dependent Variable: Net subscriptions as percentage of opening position

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
Fund Covariates					
div	0.13 (0.04)***	0.13 (0.04)***	0.14 (0.03)***	0.15 (0.03)***	0.15 (0.03)***
cap	0.00 (0.01)	0.00 (0.01)	0.01 (0.00)	0.01 (1033.31)	0.01 (1033.31)
Investor Covariates					
gdp		0.13 (0.36)	0.07 (0.38)	0.09 (0.37)	0.04 (0.36)
eqi		-0.18 (0.23)	-0.2 (0.24)	-0.2 (0.23)	-0.16 (0.26)
bnd		0.46 (0.7)	0.5 (0.71)	0.58 (0.74)	0.43 (0.71)
rre		0.84 (0.73)	0.94 (0.75)	1.05 (0.79)	0.79 (0.75)
rre_ie		-0.08 (0.58)	-0.08 (0.58)	-0.13 (0.63)	0.13 (0.46)
rrw		-1.22 (2.42)	-1.81 (2.38)	-1.63 (2.62)	-2.08 (2.65)
bdw		0.44 (1.52)	0.9 (1.55)	0.88 (1.65)	0.75 (1.64)
eqw		0.35 (0.5)	0.42 (0.5)	0.35 (0.53)	0.42 (0.46)
fx		0.9 (1.07)	0.97 (1.07)	0.9 (1.12)	1.28 (1.05)
Policy Covariates					
tax			2.89 (3.46)	3.5 (3.83)	1.13 (3.72)
Sole investor-quarter fixed effects	No	No	No	No	Yes
Investor class-quarter interaction effects	No	No	No	Yes	No
Quarter fixed effects	Yes	Yes	Yes	Yes	Yes
Investor-fund fixed effects	Yes	Yes	Yes	Yes	Yes
N	5,921	5,639	5,338	5,338	5,338

Given the change in the estimates, it must be asked whether this is evidence of measurement error being removed from the sample. Thankfully, clear predictions can be made for the effect that removing this bias would have on the tax variable. Dropping nominee accounts should remove an upwards bias in the parameter estimates. Affected investors should reduce investment relative to unaffected investors, so misclassifying them as unaffected should reduce the expected negative difference between the two groups. Likewise, it would be expected that unaffected investors would not change their behaviour, ceteris paribus, following the tax change. By including them in the group of affected investors, the mean impact of the tax change is diluted and the difference between the two groups becomes less negative.

Dropping nominee accounts leads parameter estimates for the tax variable across all models to increase. This is contrary to what should happen if an upward bias is removed. Given this, and the fact that the signs of most variables remain unchanged, it can be concluded that measurement error due to differences in first and ultimate counterparty is not a significant issue.

Conclusion

This paper has sought to provide a better understanding of the investment activity of Irish real estate funds and the factors that have driven investor inflows. Using a new property-by-property dataset the paper has found that investment by these funds is overwhelmingly focused in commercial real estate located in Dublin. The geographic and sectoral concentration of these funds investment is a consideration for future policy discussions

The paper then analysed what factors drove investment by domestic and foreign investors into IREFs. The regressions results suggest that factors affecting a funds return are relevant for determining investment are relevant (i.e. dividend yield, foreign exchange rate), but that alternative investment opportunities perform poorly in predicting investment. In addition, it appears that a 20 per cent tax on foreign investors levied at the beginning of 2017 seems to have had no influence on their investment behaviour on average, relative to those investors who were not taxed. However, the results do suggest that the tax may have had a heterogeneous effect on investors according to their size, and the author intends to explore this in future work.

Robustness checks assessing whether the limited explanatory power of alternative investment opportunities arose from measurement error in investor location were run. The results suggest that such measurement error this is not the case.

It is possible that the absence of statistically significant relationships between the dependent variable and the alternative investment opportunity variables is due to the panel data structure used. Firstly, most investors will neither purchase nor sell/redeem shares during a given quarter. This means that the dependent variables is characterised by a lack of variation, while the dependent variables show much greater variance. In addition, it's possible that investment opportunities at a global level, or Irish economic conditions may be the main factors driving investors decisions. It is not possible to analyse the impact of either set of factors with the current Investment Fund series as to do so would require a time series approach, and the series is too short. Thus, analysis on understanding what other factors might drive investment into IREFs is left to future work.

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Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

Real estate fund investment in post-crisis Ireland[1]

Barra McCarthy,

Central Bank of Ireland

[1] This presentation was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

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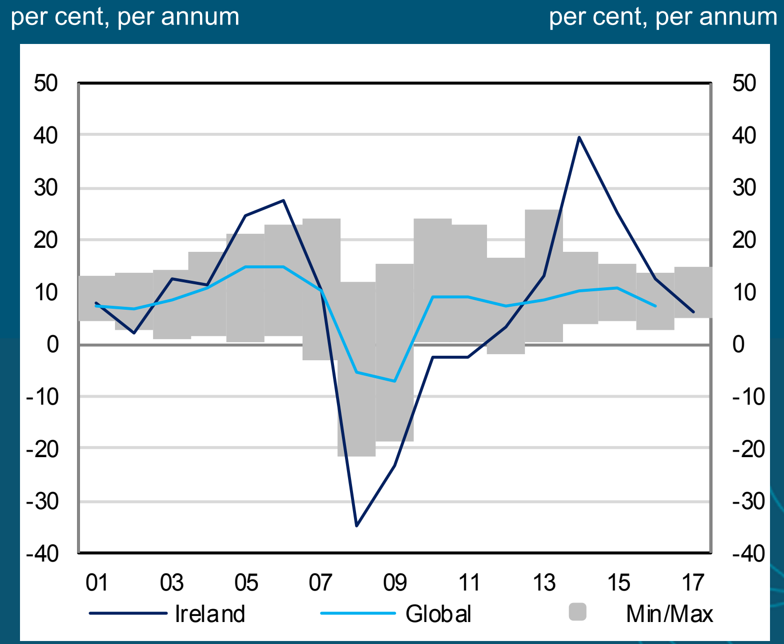
Real Estate Fund Investment in Post-Crisis Ireland

Barra McCarthy, Central Bank of Ireland

Introduction

- Ireland's property market has had an exceptional experience over the past 17 years.
- Irish domiciled real estate funds (IREFs) have seen their Irish property assets increase from €1bn to €14.5bn between end-2012 and end-2016.
- Now own 53% of total CRE stock as of end-2016.
- Despite this, little is known about them. This paper seeks to answer two questions on them:
  - Where and in what are they investing?
  - What drives investment into them?

Total returns across international markets



Source: Source: MSCI/IPD.
Note: Grey bars signify the relevant maximum and minimum annual total returns observation (in local currency) across a number of international markets,

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Eurosystem

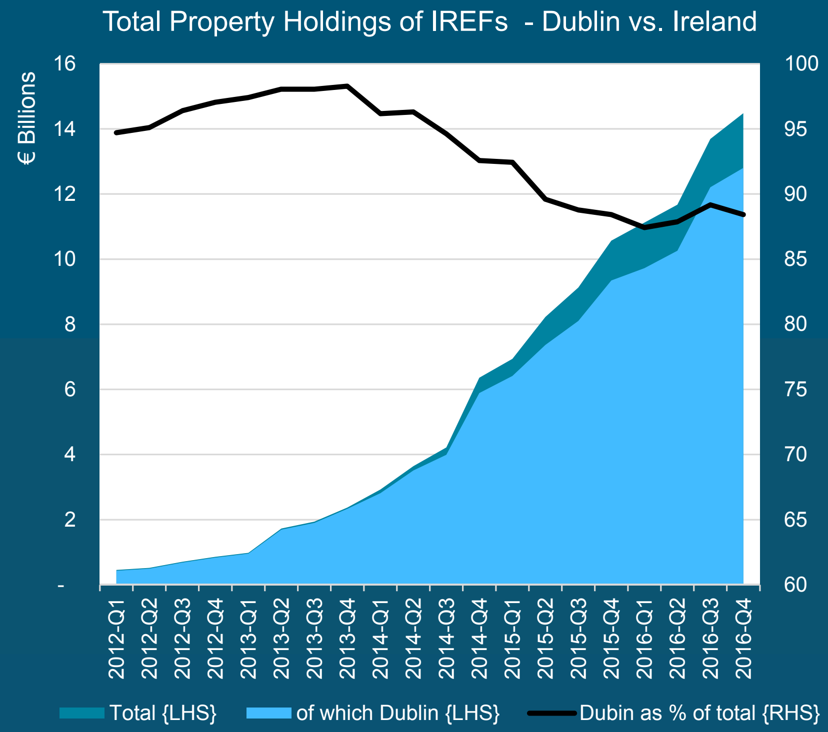
Literature and Data

- Previous literature includes:
  - Descriptive work: McCarthy (2017) and real estate agent market commentary.
  - Real estate fund investment flows and Fund Return: Ling and Naranjo (2004), Yung (2006) and Downs et al. (2016).
  - Mutual fund investment flows and alternative investment opportunities: Grose (2011) and Sebastien and Weistroffer (2007).
  - Cross border real estate investment: Baum et al. (2013).

Data

- Questions being asked require data beyond standard statistical return. To answer them, I construct:
  - A property-by-property dataset from audited financial statements.
  - An individual shareholder dataset from each fund's shareholder register.

The where of IREF Investment

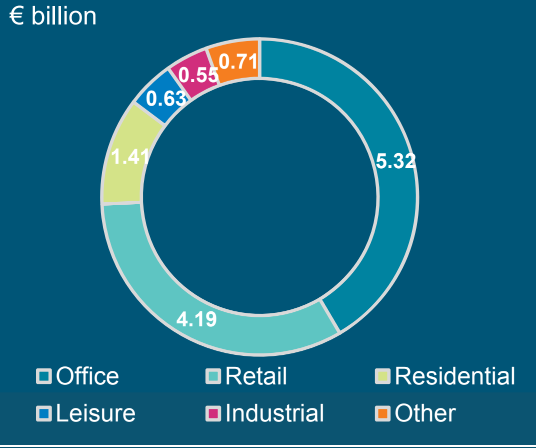


Source: Audited financial statements, author's calculations

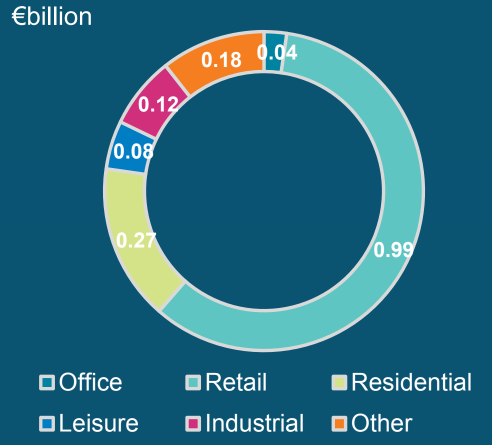
- Investment is overwhelmingly focused in Ireland's capital, Dublin.
- This is a consistent feature of the data.
- Decreasing concentration since 2014.

The what of IREF Investment

Dublin property holdings by property type- at Q4 2016



Ireland ex-Dublin property holdings by property type – at Q4 2016



- Looking at Dublin vs. Rest of Ireland:
- Both consist of mostly commercial property…
- …but the composition of commercial property holdings differs.
- Residential property makes up small amount of total for each area.

Modelling Investment into IREFs

- In essence the analysis is one of portfolio choice.
- Therefore, changes in an investors wealth constraint, the expected return on IREF equity and the expected return on alternative investment opportunities are the relevant explanatory variables.
- Alternative investment opportunities can be modelled as domestic, cross-sample and out of sample.
- Larger investors may have different investment opportunities available to them.
- Taxes change for foreign investors at beginning 2017.

Model

- Analysis is conducted with a panel fixed effects model.

$$Y_{ijt} = B_0 + B_1 Z_{jt} + B_2 X_{it} + B_3 T_{it} + B_4 F_{it} + u_{ijt}$$

Where:

- Z_{jt} is a matrix of fund covariates
- X_{it} is a matrix of investor covariates
- T_{it} is a difference in difference estimator
- F_{ijt} is a matrix of fixed effects.
- u_{ijt} is the error term, two way clustered ony fund and investor.

Results

Variable	Model (1)	Model (2)	Model (3)	Model (4)
Investor Covariates				
GDP	0.3 (0.31)	0.18 (0.29)	0.27 (0.33)	0.16 (0.31)
Equity - Domestic	-0.24 (0.21)	-0.25 (0.18)	-0.22 (0.23)	-0.25 (0.21)
Bond - Domestic	0.14 (0.67)	0.2 (0.65)	0.11 (0.7)	0.21 (0.67)
Real Estate - Domestic	0.94 (1.06)	0.84 (0.96)	1.02 (1.13)	0.96 (1.07)
Real Estate (Ireland)– Domestic	0 .00 (0.96)	0.18 (0.82)	-0.08 (1)	0.09 (0.88)
FX	0.49 (0.4)	0.34 (0.36)	0.45 (0.42)	0.36 (0.4)
Equity – Cross Sample	0.15 (0.37)	0.13 (0.37)	0.2 (0.43)	0.15 (0.42)
Bond – Cross Sample	-0.24 (0.57)	-0.79 (0.72)	-0.29 (0.59)	-0.62 (0.63)
Real Estate – Cross Sample	-3.87 (5.34)	-5.28 (5.5)	-3.89 (5.67)	-6.27 (5.94)
Fund Covariates				
Dividend Yield	0.13 (0.04)***	0.13 (0.04)***	0.14 (0.03)***	0.15 (0.03)***
Capital Appreciation	0.00 (0.01)	0.00 (0.01)	0.01 (0.01)	0.01 (0.01)
Policy Covariate				
Tax			-1.23 (2.58)	1.14 (3.31)
Investor-Fund Fixed Effects	Yes	Yes	Yes	Yes
Quarter Fixed Effects	Yes	Yes	Yes	Yes
Investor Size-Quarter Interaction Fixed Effects	No	Yes	No	Yes
N	16,108	16,108	15,230	15,230

Key Results:

- Investor covariates show no statistically significant relationships.
- Fund covariates have expected relationship, but only dividend yield attains statistical significance.
- Tax change appears to have had an impact indistinguishable from zero.

Conclusion

- To conclude, I'll give an answer to the two questions raised at the start:

Where and what are IREFs investing in?

- IREFs are predominately invested in commercial real estate located in Dublin.

What drives investment into IREFs?

- Fund dividends the only variable to share a statistically significant relationship with investment.
- Tax change in 2016 Finance Act seems to have had no impact on affected investors.
- Domestic and cross-sample alternative investment opportunities do not appear relevant for investors.

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Looking through cross-border positions in investment funds: evidence from Italy[1]

Valerio Della Corte, Stefano Federico and Alberto Felettigh,
Bank of Italy

1 This paper was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

Looking through cross-border positions in investment funds: evidence from Italy

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Abstract

Motivated by the increasingly large weight of foreign investment funds on the portfolio of Italian residents, this paper provides an estimate of the composition, by instrument and by issuer country, of Italy's portfolio assets after "looking through" cross-border positions in investment funds. Our main findings suggest that removing the statistical opacity arising from cross-border positions in investment funds has a significant impact on the composition of Italy's portfolio investments. After "looking through" foreign funds' holdings, the share of debt securities on portfolio assets, which is equal to 40 per cent in the unadjusted data, rises to 75 per cent. The country composition of external portfolio assets also fundamentally changes in the direction of increasing its geographical diversification. The United States becomes Italy's main destination country; the shares of France, Germany, the United Kingdom and Spain also increase, while that of Luxembourg, where most of the foreign investment funds are domiciled, drastically falls.

Keywords: external statistics, mutual funds, portfolio investment.

JEL classification: F36, F65, G11.

Contents

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1. Introduction and main findings[2]

In the wake of large purchases over the last five years, the stock of foreign investment fund shares held by Italian investors has more than doubled since the end of 2012, reaching the value of €754 billion at the end of September 2017. Almost 30 per cent of Italy's overall external assets are now held in the form of investment fund shares; in almost all of the other European Union countries, investment funds account for no more than 5-10 per cent of foreign assets. Cross-border positions in investment funds add two layers of opacity to the composition of a country's external assets, as highlighted in Felettigh and Monti (2008). The first regards the geographical diversification of risk: as investment fund issuers tend to be concentrated in a small number of countries, selected financial centres disproportionately appear as the main destination of a given country's portfolio investments. The second layer of opacity is related to the "ultimate" composition of foreign assets by instrument (equity versus debt instruments), which depends on the individual funds' allocation strategies.

Motivated by the increasingly large weight of foreign investment funds on the portfolio of Italian investors, this paper makes two contributions. First, it summarizes the recent trends in Italian investments in foreign mutual fund shares. Second, it provides an assessment of the composition, by instrument and by issuer country, of Italy's portfolio assets after "looking through" cross-border positions in investment funds, thus updating the estimates originally published in Felettigh and Monti (2008).

The "look through" method is based on two main approaches. The "ultimate" composition by instrument is approximated using Assogestioni's detailed classification of foreign funds according to their investment policy. [3] Each category of funds (like money market, balanced bonds, balanced equity funds, etc.) is defined with reference to specific regulatory restrictions on the fund's allocation strategy: this allows us to estimate the foreign funds' portfolio allocation between equity and debt securities. The geographical allocation of foreign funds held by Italian investors is instead estimated by assuming that it resembles that of the entire investment fund industry in Luxembourg, Ireland and France, which are the countries where the large majority of Italian investments in foreign mutual funds is concentrated.

Our work focuses on the cross-border portfolio holdings of the total economy and does not therefore provide a "look through" analysis for specific institutional

2 We would like to thank Assogestioni for the detailed database on asset management products ("Mappa del risparmio gestito") which is publicly available on their website, Fabiana Gallo and Giuseppina Marocchi for assistance with additional Bank of Italy data on portfolio investment, Silvia Fabiani, Luigi Federico Signorini and Roberto Tedeschi for useful comments and suggestions. The views expressed herein are solely ours; in particular, they do not necessarily reflect those of the Bank of Italy or the Eurosystem.

3 Assogestioni is an association that represents most of the Italian and foreign investment management companies operating in Italy, as well as banks and insurance companies involved in investment management.

resident sectors (e.g. households). Such an analysis would be much more complex: on the one hand, it would require detailed information on the portfolio allocation of the foreign funds held by a specific institutional sector; on the other hand, it would also require estimating the foreign exposure to which the specific institutional sector is subject via the financial instruments issued in Italy (i.e. domestic mutual investment funds, pension funds, insurance products, etc.).[4] Ideally, one would also like to take into account the actual distribution of risks between issuers and holders; for instance, risks are not entirely borne by the holder in the case of financial products that guarantee a minimum return.

Our main findings suggest that removing the statistical distortions arising from cross-border positions in investment funds has a significant impact on the composition of Italy's portfolio investments, both by instrument and by destination country.

The share of debt securities on portfolio assets, which is equal to 40 per cent in the unadjusted data, rises to 75 per cent after "looking through" foreign funds' holdings. This correction stems from the relatively large weight of debt securities on the allocation strategy of foreign funds held by Italian investors (around two thirds of the funds' investments). The share of equities correspondingly rises from 7 to 25 per cent after the adjustment.

The "look through" adjustment also fundamentally changes the geographical composition of Italian investors' external portfolio assets, in the direction of increasing their geographical diversification. Luxembourg's share falls from above 40 per cent to less than 4 per cent, while the United States becomes Italy's main destination country; the shares of France, Germany, the United Kingdom and Spain also increase.

The structure of the work is as follows. Section 2 provides a summary of the main trends in Italian investments in foreign funds. Section 3 explains the methodology behind the adjustment for cross-border positions in investment funds and presents the main findings. Section 4 concludes.

2. Italian investments in foreign funds

Balance of payments data on portfolio investment can be broken down into three types of financial instruments: debt securities, equities and investment fund shares. Net purchases by Italian residents of investment fund shares, typically issued in financial centres such as Luxembourg and Ireland, have been particularly high since 2013 (€351 billion between the beginning of that year and the end of 2017).[5]

[4] The work of Cardillo and Coletta (2017) estimates the final destination of Italian asset management products held by households and manages to fill the second gap, but not the first one, due to the lack of information on the final destination of investments in foreign funds held directly or indirectly by the household sector.

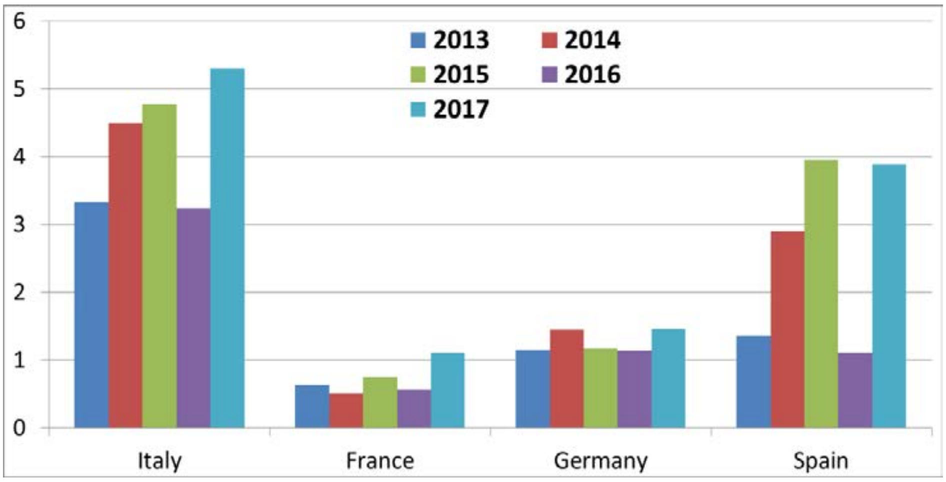
[5] Here we do not address the determinants of these outflows. For a descriptive analysis of the overall portfolio rebalancing in Italy, see Banca d'Italia (2017). For an empirical examination of the drivers of cross-border flows in investment fund shares in Luxembourg, see Di Filippo (2017).

Relative to GDP, these outflows were much higher than those observed in the other main euro-area countries over the same period (Figure 1).

At the end of 2017, the stock of foreign funds held by Italian investors amounted to €776 billion, the highest value among all European Union countries both as a percentage of portfolio assets (54 per cent) and as a percentage of external assets (29 per cent; Figure 2). This stylised fact reflects, among other factors, the much higher penetration of foreign intermediaries in Italy's asset management sector. Indeed, according to the stock data available in the financial accounts, at the end of December 2017 the weight of foreign funds on overall funds held by residents stood at 70 per cent in Italy, against 17 per cent in France, 24 in Germany and 42 in Spain. In Italy, the institutional sectors with the largest holdings of foreign funds were households (36 per cent of the total), insurance and pension funds (31 per cent) and "other financial intermediaries" (31 per cent), which include resident non money-market investment funds (8 per cent). [6]

Figure 1 – Net purchases of foreign investment fund shares in the main euro-area countries

(flows during the period as a percentage of GDP)

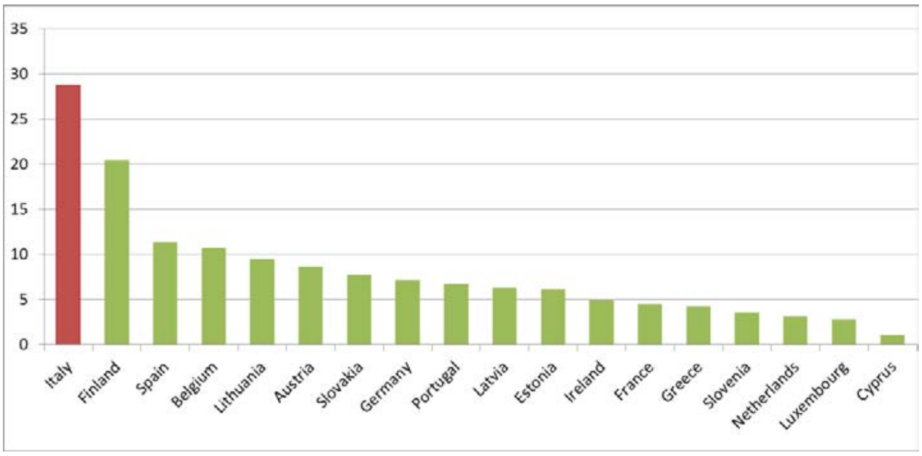


Sources: ECB for balance of payments data and Eurostat for GDP data.

Figure 2 – Share of foreign investment fund units on total foreign financial assets in EA countries

(percentage points; stocks at the end of 2017)

[6] Italian investment funds often reinvest part of their assets in foreign fund shares. With reference to the portfolio of Italian mutual funds held by Italian households, Cardillo and Coletta (2017) report that 22 per cent of their value was invested in shares of foreign mutual funds at the end of 2016.



Sources: ECB for balance of payments data and Eurostat for GDP data. Data not available for Malta.

In order to better understand the characteristics of foreign funds purchased by Italian residents we draw on information gathered by Assogestioni from the subjects authorized to undertake asset management activity (i.e. asset management companies, banks, etc.) and published in the document "Mappa del risparmio gestito". It is relatively easy to map the breakdowns available in Assogestioni data into aggregates which are consistent with the criteria implemented by balance of payments statistics. Investment funds are indeed separately reported by Assogestioni in terms of the applicable legislation (Italian versus foreign law), which is related to the issuer's residence. Furthermore, the corresponding holdings usually refer to the share that pertains to Italian customers (except in cases where they own a "prevalent share" of a given fund).[7] Given the high representativeness of the sample, Assogestioni data are quite consistent with the corresponding positions and flows recorded in Italy's official external statistics.[8]

According to Assogestioni data, net purchases of foreign funds by Italian investors in the 2013-2016 period were concentrated in flexible funds (37 per cent) and bond funds (30 per cent); the shares referring to balanced, equity and money market funds were significantly lower (15, 13 and 4 per cent, respectively; Table 1). This composition was substantially stable during the period under review, with the exception of 2016 when demand for bond funds increased, mainly to the detriment of equity funds.

7 In this circumstance, which only materializes in the case of foreign funds managed by Italian groups, data published by Assogestioni refer to the fund's entire portfolio and not to the component owned by Italian customers only. This entails an overestimation of Italian holdings of foreign funds managed by Italian groups by about 15 per cent. The results presented in this study have been corrected for this overestimation and therefore do not coincide with the data published by Assogestioni.

8 Although very high, Assogestioni's data coverage in terms of the number of reporting agents is not complete (around 90 per cent); it follows that mutual fund assets are underestimated relative to external statistics.

Composition of foreign funds held by Italian investors: flows

(Flows in EUR billions unless otherwise stated

Table 1

	2013	2014	2015	2016	2013-2016 cumulated inflows	2013-2016 composition (%)
Balanced	6.7	7.1	8.0	3.0	24.8	15.1
Bond	6.7	18.9	10.4	13.3	49.3	30.1
Equity	7.3	6.4	8.9	-1.2	21.4	13.1
Flexible	14.1	15.6	23.6	8.0	61.4	37.5
Money-market	-0.2	-0.2	6.7	0.6	7.0	4.3
Total (1)	34.7	47.8	57.6	23.8	163.9	100.0

Source: calculations based on data from Assogestioni (adjusted as explained in footnote 7). Notes: (1) Including hedge funds (not shown herein), which are negligible in value terms.

Assogestioni data also provide information on whether foreign funds are managed by Italian or foreign intermediaries; the share managed by Italian groups has progressively decreased over time while the share managed by foreign intermediaries rose from around 40 per cent at the end of 2012 to 50 per cent four years later (it was only about 30 at the end of 2008; Figure 3).

Composition of foreign funds held by Italian investors: stocks

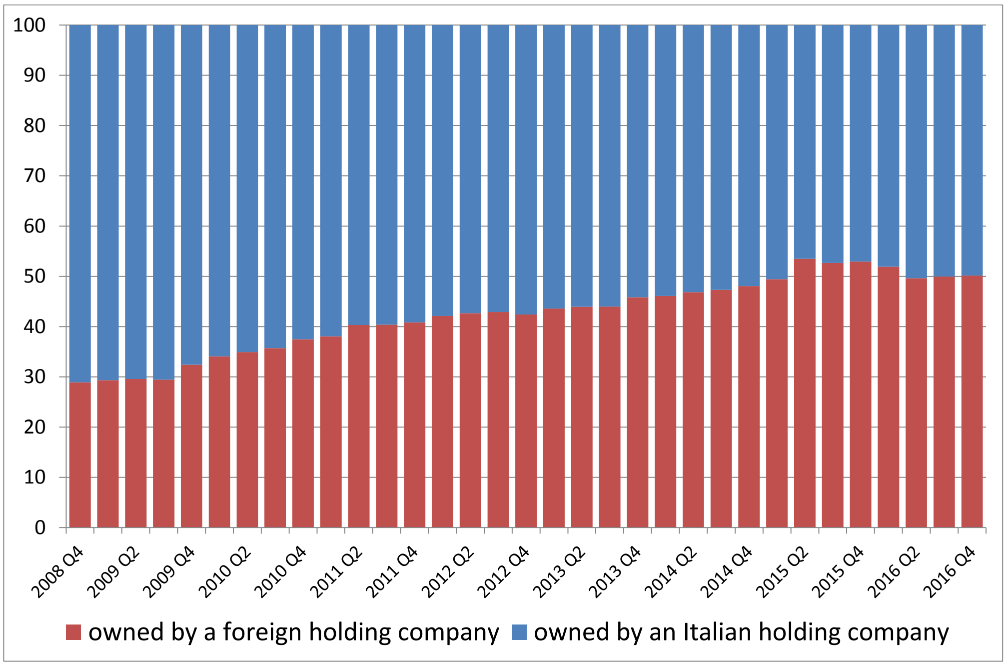
(percentage points unless otherwise stated)

Table 2

	2012	2013	2014	2015	2016
Balanced	3.9	5.5	6.8	8.6	8.8
Bond	50.6	46.2	44.7	40.1	43.7
Equity	25.9	27.5	26.9	28.2	25.7
Flexible	12.6	15.3	17.1	17.9	17.2
Money-market	6.6	5.2	4.3	5.0	4.4
Total (1) (EUR billions)	279.1	335.7	408.8	527.0	592.3

Source: calculations based on data from Assogestioni (adjusted as explained in footnote 7). Notes: (1) Including hedge funds (not shown herein), which are negligible in value terms.

Figure 3 – Breakdown of foreign funds owned by Italian investors by residency of their financial group



Source: calculations based on data by Assogestioni (adjusted as explained in footnote 7).

3. An estimate of the composition of Italy's foreign portfolio holdings adjusted for the intermediation of foreign funds

3.1. The distortion induced by foreign funds

According to external statistics, the geographical diversification of Italy's portfolio investment abroad appears rather limited: at the end of 2016 the first five destination countries represented almost three quarters of the total (Table 3, last column). Just under half of the portfolio assets were issued by Luxembourg and Ireland, which accounted for almost 90 per cent of foreign investment funds held by Italian residents.

This is due to the large weight of foreign investment funds in Italian residents' portfolio holding which, together with their concentration in Luxembourg and Ireland, causes a significant bias in the composition by instrument and by issuer country of the overall foreign portfolio. As highlighted in Felettigh and Monti (2008), balance of payments statistics are based on the legal residence of the investment fund and do not provide information on either the type of securities (e.g. equities or debt securities) in which the investment fund's assets are actually invested ("intermediation veil"), or on their "location" (that is, where the issuer of the securities held in the fund's portfolio resides; "geographical veil").

A more accurate picture of the actual exposure implicit in Italian residents' foreign portfolio holdings therefore requires adjustments which remove the statistical distortions arising from the intermediation of foreign funds. Ideally one would do that looking at the portfolio of each and every foreign fund held by Italian residents, but granular data as such are typically not available. We therefore develop a method to remove these distortions combining publicly available sources.

First ten destination countries of Italian portfolio investment abroad at the end of 2016

(stocks; percentage points)

Table 3

ranking	Equity		Investment fund units		Debt Securities		Total portfolio	
	country	%	country	%	country	%	country	%
1	United States	25.9	Luxembourg	73.7	France	15.3	Luxembourg	40.5
2	France	14.5	Ireland	13.4	Spain	14.0	France	11.6
3	Germany	13.3	France	8.3	United States	13.8	Ireland	8.2
4	United Kingdom	10.8	United Kingdom	2.4	Germany	11.3	United States	7.8
5	Netherlands	8.5	Germany	0.8	Netherlands	8.4	Germany	5.9
6	Switzerland	6.2	United States	0.6	United Kingdom	7.2	Spain	5.9
7	Spain	3.4	Austria	0.4	International org. (1)	6.2	United Kingdom	5.0
8	Japan	3.1	Switzerland	0.2	Luxembourg	4.4	Netherlands	4.0
9	Luxembourg	1.4	Cayman Islands	0.1	Ireland	2.7	International org. (1)	2.6
10	Belgium	1.2	Curaçao	0.0	Belgium	1.8	Belgium	0.8
others	-	11.8	-	0.2	-	14.9	-	7.8
memorandum item: share on total portfolio investment (%)		*7.3*		*52.4*		*40.3*		*100.0*

Source: Calculations based on IIP data from Banca d'Italia. Notes: (1) Includes investments in securities issued by EU institutions and intergovernmental organizations (e.g. European Investment Bank, Bank of International Settlements, European Bank for Reconstruction and Development).

3.2. The adjustment by instrument

Assogestioni's classification of funds into about 40 categories, based on the underlying investment policy, is sufficiently detailed to allow for a correction by instrument (thus removing the "intermediation veil") if we limit ourselves to the distinction between equity and debt instruments. Each category of funds, with the exception of flexible funds, is defined on the basis of specific regulatory restrictions on the composition of the portfolio, assessed according to the "look-through" principle, namely, taking into account indirect exposure through investments in other funds or in financial derivatives. To give an example, the share of equities in a fund's portfolio is zero for money market funds and bond funds (excluding mixed bond funds, in which it cannot exceed 20 per cent); it can instead vary between 10 and 50 per cent for "balanced bond" funds and between 70 and 100 per cent for equity funds (see Table 4). We identify a fund's investment policy by the quota of equities in its allocation strategy and assume that the residual part of the fund's assets are invested in debt securities; the impact of this simplification, which mainly ignores assets held as bank deposits, should indeed be rather limited, also considering that the share of equities is determined according to the "look-through" principle.[9]

9 According to ECB data, at the end of 2016 the weight of debt securities, equities and investment fund shares on a fund's overall portfolio was 99 per cent for funds in Ireland, 94 per cent for those in Luxembourg and 93 per cent for those in France.

By using these quotas or, in the case of intervals, their midpoint value, it is possible to estimate the asset allocation of each category of funds. The only exception arises in the case of flexible funds, for which, as already mentioned, there is no formal restriction on investment policies; in this case, we use the weighted average of the share of equities in the portfolio of "mixed" funds from Luxembourg, Ireland and France.[10]

At the end of 2016 equities intermediated by foreign funds were estimated to be about one third of their total assets and within a range of between 25 and 40 per cent. The average share invested in equities remained fairly stable between 2009 and 2016, although it temporarily decreased between the second half of 2011 and the second half of 2013.

Without adjusting for the positions intermediated by foreign funds, the share of foreign portfolio assets invested in debt securities stood at 40 per cent at the end of 2016, compared with a 7 per cent quota for equities (with the remaining 53 per cent associated with positions in foreign funds; Figure 4a).

The results of the adjustment are reported in Figure 4b, where the dashed bars indicate the debt and equity assets indirectly held by Italian investors through the intermediation of foreign funds. The overall incidence of debt securities rises to 75 per cent, while that of equity securities to 25 per cent. Around these average values we have defined two estimation intervals, depending on the range of assumptions concerning foreign funds' portfolio allocation.

[10] We were constrained to using data on "mixed funds", which groups together flexible and balanced funds, since flexible funds are not separately identified in official statistics.

Assogestioni's taxonomy and equity allocation

(Percentage points) Table 4

Macro-category/category	restrictions on the equity allocation (Assogestioni)		equity allocation assumed in the adjustment by instrument of the positions in mutual funds		
	min	max	**baseline**	min	max
Money-market/liquidity *(all categories)*	0	0	0	0	0
Bond					
- mixed	0	20	10	0	20
- all others	0	0	0	0	0
Balanced					
- bond	10	50	30	10	50
- no indication	30	70	50	30	70
- equity	50	90	70	50	90
Flexible	0	100	40 (*)	20 (*)	46 (*)
Equity *(all categories)*	70	100	85	70	100
All funds as a whole					
2009 Q4 - 2016 Q4 (average)	21	47	32	25	38
At the end of 2016	20	50	33	25	40

Sources: Assogestioni (2003) and, for flexible allocation funds, calculations based on ECB data (Investment Funds statistics). Notes: (*) The values are purely indicative. The baseline is calculated using the average value, and the lower and upper limits by using the minimum and maximum values in the reference period. The values actually used for the correction exercise are time-varying.

The first and widest range (grey area in Figure 5) is obtained by considering the "regulatory" limits (minimum and maximum value) to the share of equities in the portfolio of each fund category. For flexible funds, this approach therefore takes into account the very unlikely cases in which the share of equity investments is either zero (minimum limit) or 100 per cent (maximum limit). Such "extreme events" result in an upper and lower bound of 82 per cent and 67 per cent respectively for the portion invested in debt securities at the end of 2016.

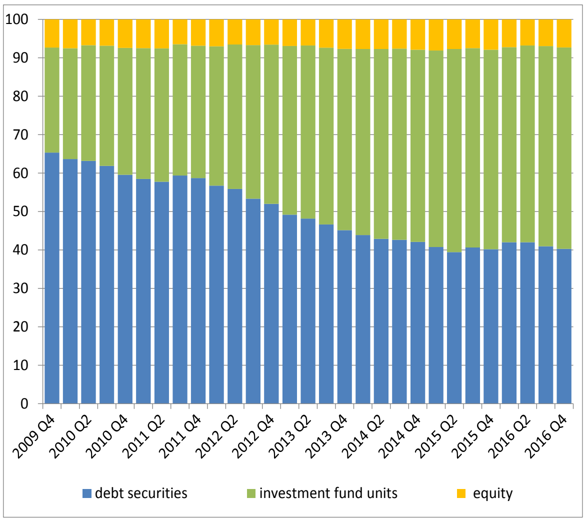
The second estimation interval is narrower: for foreign flexible funds purchased by Italian residents, the minimum and maximum equity share observed in the mixed funds of Luxembourg, Ireland and France are now used in place of their regulatory limits. This estimation interval is almost symmetrical and equal to about 4 percentage points above or below the central estimate; in the "adjusted" figures, the share invested in debt securities at the end of 2016 therefore varies between 72 and 79 per cent (red lines in Figure 5).

As already mentioned, the portfolio allocation between equity and debt securities by foreign funds is fairly stable over time, with the weight of debt securities standing at around two thirds. The directly held portfolio is even more biased towards debt securities, although their percentage declined slightly over time (from around 90 per cent at the beginning of the period to around 85 at the end of 2016). However, these differences between the two portfolio allocations constitute only a second-order effect relative to the weight of foreign funds in foreign portfolio investment. The "adjusted" share (dotted blue line in Figure 5) indeed tends to broadly follow the trend in the share of debt securities in the directly held portfolio (black line in Figure 5).

Figure 4 –Foreign portfolio assets: breakdown by instrument

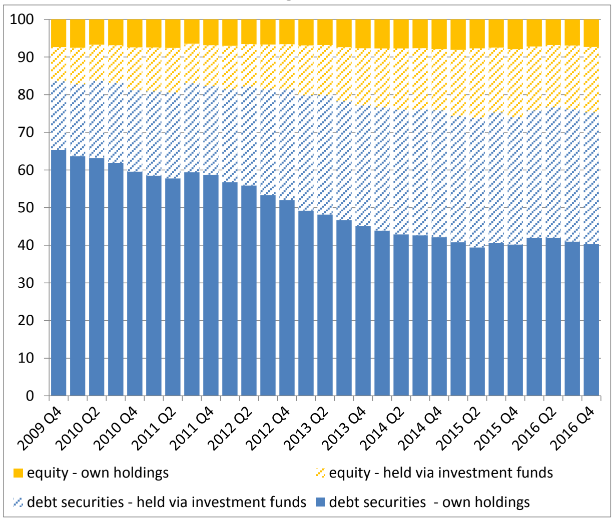
(stocks; percentage points)

(a) According to IIP data



Source: calculations based on Banca d'Italia IIP data.

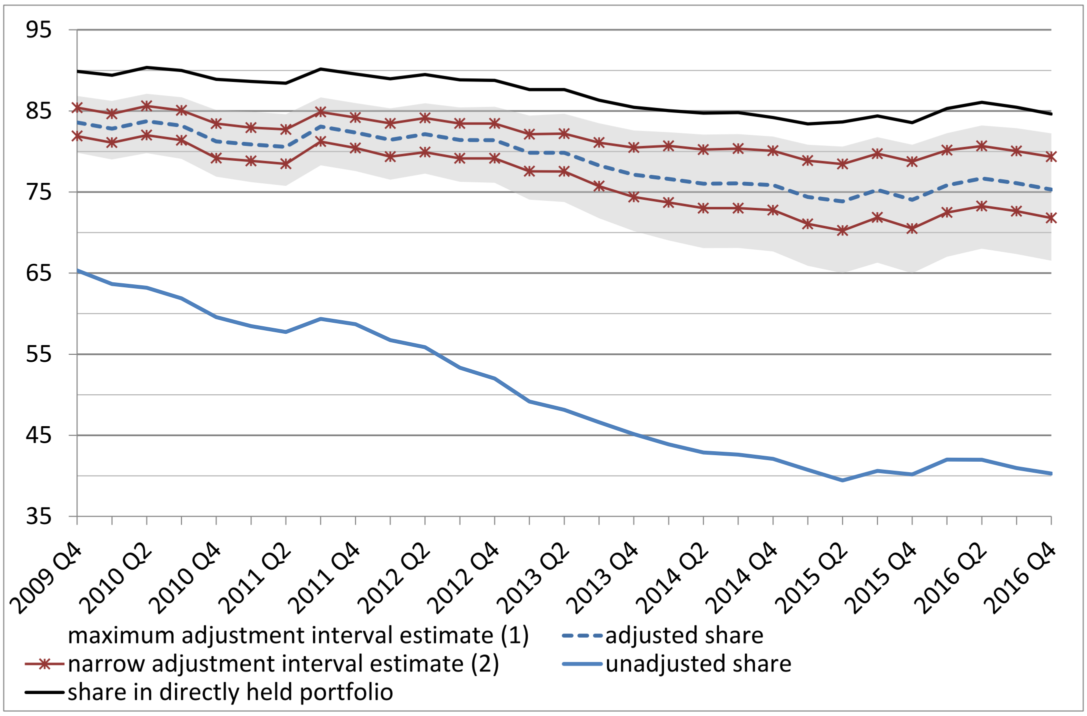
(b) Adjusted for the positions intermediated by foreign funds



Sources: calculations based on Banca d'Italia, Assogestioni and ECB data.

Figure 5 – Share of debt securities on foreign portfolio assets holdings

(percentage points)



Sources: calculations based on Banca d'Italia IIP data and Assogestioni and ECB data. Notes: (1) The range is constructed on the basis of the minimum and maximum equity composition limits of the various fund types according to the Assogestioni classification. (2) The range assumes that the equity quotas of the flexible funds portfolio mirror those of "mixed" funds domiciled in Luxembourg, France and Ireland in each period.

3.3. The geographical adjustment

The information provided by Assogestioni is not sufficiently complete as regards the adjustment for geographical exposure ("geographical veil"). The taxonomy does not provide information on the issuer country of the assets held by flexible funds, balanced funds and funds specialized in certain industrial sectors. There are "geographical" categories within some specific types of funds (for example, funds specialized in euro-area equities), which are typically based on different levels of aggregation: by continent or geographical area in the case of equity funds and usually by currency in the case of bond funds and money market funds. For the geographical adjustment we have therefore opted for a methodology that, while necessarily based on more restrictive assumptions, combines the estimate on the breakdown by instrument obtained from Assogestioni data with information on the geographical allocation of Luxembourgian, Irish and French mutual funds (which, as mentioned above, represent almost the entirety of the holdings of foreign funds by Italian investors).

The methodology for the geographical adjustment is based on the following hypotheses:

1) the composition by instrument of the assets intermediated by foreign funds held by Italian residents is estimated on the basis of Assogestioni data, regardless of the fund's country of residence;

2) the geographical diversification of Luxembourgian funds held by Italian residents is assumed to coincide with that of the overall Luxembourgian fund industry, separately considering investments in debt securities and equities, and a similar assumption holds for Irish and French funds;

3) the geographical diversification attained by funds resident in the remaining foreign countries (whose total weight is less than 5 per cent) is assumed to equal that averaged by the funds resident in Luxembourg, Ireland and France;

4) any investment undertaken by foreign funds in other funds (either foreign or domestic) are assumed to have no impact on the geographical diversification of intermediated equities and debt securities (non-distortionary second-round effects).

Based on these assumptions, the value $Y\_via\_IF_{i,k}^{IT}$ of Italian portfolio investments indirectly made in each destination country i and instrument k (equity or debt securities) through foreign mutual funds can be estimated using the following formula:

$$Y\_via\_IF_{i,k}^{IT} = \left[\sum_{j \in \{LU,IE,FR\}} Y_{j,IF}^{IT} * IF\_share_k * geo\_allocation\_IF_{i,k}^{j} \right] * \frac{Y_{world,IF}^{IT}}{\sum_{j \in \{LU,IE,FR\}} Y_{j,IF}^{IT}} \qquad [1]$$

Where:

$Y_{j,IF}^{IT}$ is the amount of Italian portfolio investment in mutual funds that reside in country *j*, with *j* being one of the following: Luxembourg, Ireland, France or all other countries (except Italy) as a whole (*world*);

IF_share_k is the share allocated to the instrument k by the foreign mutual funds in the hands of Italian investors according to our estimates based on data from Assogestioni hypothesis 1);

$geo\_allocation\_IF^{j}_{i,k}$ is the geographical composition of the portfolio of the mutual funds resident in country *j* by instrument (hypothesis 2).

Finally, the term on the right-hand side of the square brackets is needed to scale up the investment made by Luxembourgian, Irish and French mutual funds to take into account the investment made by Italian investors in mutual funds resident in other countries (assuming, for simplicity, that these are allocated as those in Luxembourg, Ireland and France; hypothesis 3).

It is then possible to estimate the "adjusted" share of portfolio investment abroad made by Italian residents in the financial instrument *k* issued in country *i* as the ratio between these investments and the whole portfolio investment abroad in the instrument *k* (including investments indirectly made through foreign investment funds):

$$adjusted\_share^{IT}_{i,k} = \frac{Y^{IT}_{i,k} + Y\_via\_IF^{IT}_{i,k}}{Y^{IT}_{world,k} + Y^{IT}_{world,IF}} \qquad [2]$$

where $Y^{IT}_{i,k}$ is the value of Italian portfolio investment abroad in the financial instrument *k* issued in country *i* (direct holdings).

As an alternative to the second of the previous four hypotheses, one could assume that there are no significant differences between investment strategies of foreign funds and those of Italian funds; the adjustment could then be estimated by using the geographical allocation of the portfolio held by Italian funds. However, foreign funds are typically aimed at a different set of customers (typically international customers) than of resident funds, whose customer base is almost entirely domestic and might therefore have a very different investment strategy. In partial support of this argument, Assogestioni data provide evidence suggesting that foreign funds held by Italian residents differ appreciably from the corresponding Italian funds in terms of category and, therefore, composition by instrument.

It should also be noted that, on the one hand, Figure 3 shows that foreign funds held by Italian residents are no longer predominantly round-trip funds,[11] on the other hand empirical literature reports that the portfolio choices of mutual funds, as well as other categories of investors, differ significantly between countries, both in terms of home bias and geographical diversification.[12]

Going back to the implementation details of our geographical adjustment, the country allocation of Luxembourgian, Irish and French funds have been derived, separately for each instrument, from the following sources: data from the Banque Central du Luxembourg for funds based in this country; data from the IMF (Coordinated Portfolio Investment Survey, CPIS) for funds based in Ireland and

11 The term "round-trip" can take on different nuances. Assogestioni (2006) uses the term to denote mutual funds domiciled abroad but "purchased mainly by Italian investors", while the official definition is currently that of "foreign funds promoted by Italian intermediaries"; similarly, Mediobanca (2017) uses the expression to denote funds promoted by Italian managers but domiciled abroad. In practice, the definitions coincide substantially with foreign funds belonging to groups governed by Italian law.

12 See, for example, Hau and Rey (2008) and Anderson et al. (2011).

France, supplemented with data on the funds' domestic assets from the Central Bank of Ireland and from the ECB (Investment Funds Statistics).

The adjustment makes it possible to more accurately evaluate the actual exposure of Italian residents' portfolio holdings to the various countries' financial markets and to fluctuations in the euro's bilateral exchange rates. In particular, the adjusted data show that the exposure of Italian investors to US portfolio assets (about a fifth of the total; Table 5) is more than double compared with the unadjusted data; the United States remains the first destination of Italian investments in equities and becomes the first destination for investments in debt securities. The results confirm that France is the second country of destination, with a weight of 12 per cent on the total foreign portfolio of residents. The third country is Germany, with a share of 9 per cent, followed by the United Kingdom (8 per cent) and Spain (7 per cent). Taking into account the geographical adjustment, investments in these five countries account for slightly less than 60 per cent of Italy's foreign portfolio, against 37 per cent without the adjustment.

First ten destination countries of Italy's portfolio investment abroad at the end of 2016, adjusted for the positions intermediated by mutual funds

(stocks; percentage points) Table 5

ranking	Equity		Debt Securities		Total portfolio		*memorandum item:* Total portfolio unadjusted	
	country	%	country	%	country	%	country	%
1	United States	25.9	United States	19.0	United States	20.7	Luxembourg	40.5
2	France	10.8	France	12.7	France	12.2	France	11.6
3	Germany	9.3	Germany	9.1	Germany	9.2	Ireland	8.2
4	United Kingdom	8.5	Spain	8.9	United Kingdom	8.3	United States	7.8
5	Japan	5.2	United Kingdom	8.2	Spain	7.3	Germany	5.9
6	Netherlands	5.1	Netherlands	7.3	Netherlands	6.7	Spain	5.9
7	Switzerland	4.4	Luxembourg	4.1	Luxembourg	3.8	United Kingdom	5.0
8	Luxembourg	2.9	International org. (1)	3.7	Italy *(round trip)* (2)	2.9	Netherlands	4.0
9	Spain	2.3	Italy *(round trip)* (2)	3.4	International org. (1)	2.8	International org. (1)	2.6
10	Cayman Islands	2.1	Ireland	2.2	Ireland	2.0	Belgium	0.8
others	-	23.5	-	21.4	-	24.0	-	7.8
memorandum item: share on total portfolio investment (%)		*24.6*		*75.4*		*100.0*		*100.0*

Sources: calculations based on Banca d'Italia IIP data and ECB, IMF, Banque Centrale du Luxembourg and Central Bank of Ireland data using equation [2]. Notes: due to rounding, numbers may not sum to 100; (1) Includes investments in securities issued by EU institutions and intergovernmental organizations (e.g. European Investment Bank, Bank of International Settlements, European Bank for Reconstruction and Development); (2) Investment in Italian portfolio assets through the intermediation of foreign mutual funds.

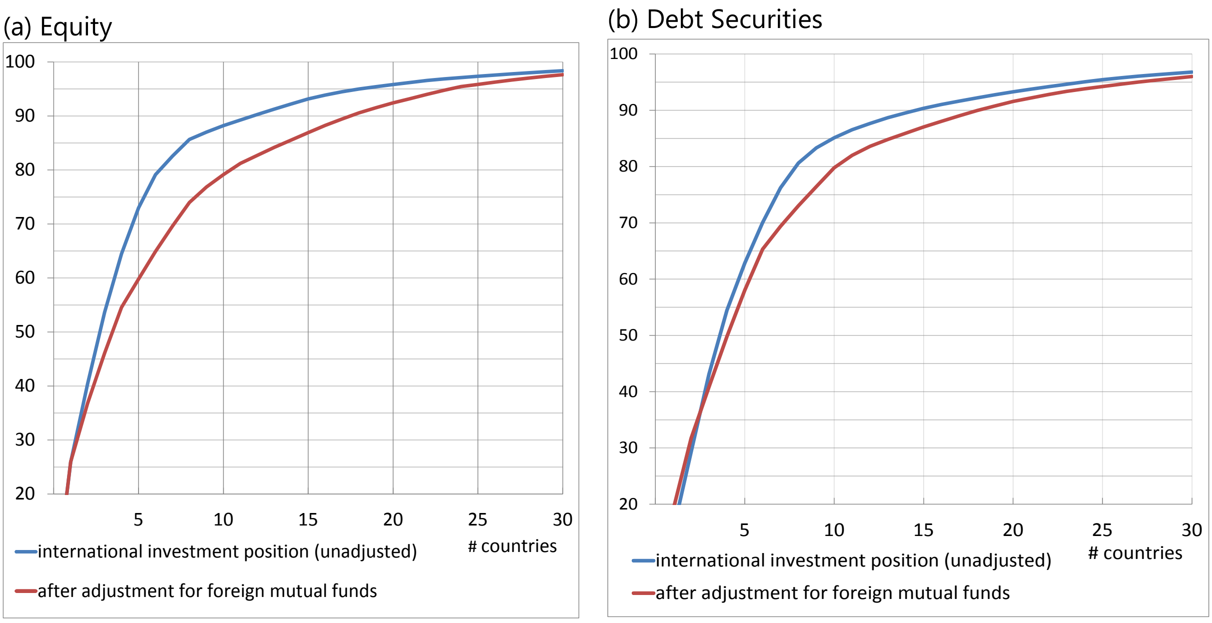
The reclassification exercise also estimates that the share of "round-trip" portfolio investments (namely, purchases of foreign funds which reinvest in Italy, so these assets are better described as domestic rather than foreign) stood at 2.9 per cent at the end of 2016 (€37 billion).[13]

[13] This share, indicated in Table 4 as "Italy (round-trip)", is mainly the result of investments by foreign funds in Italian debt securities. The value is close to that estimated in Felettigh and Monti (2008) for the average of the period 2002-2005 (about two per cent).

Investments in foreign funds increase the geographical diversification of the foreign portfolio of Italian residents in two ways. The first is a mechanical effect, related to the redistribution of positions in funds that predominantly reside in a few countries to a much larger number of destination countries. The second effect arises from the wider international diversification of foreign funds compared with that of residents' direct portfolio investments, especially in the case of equity instruments (Figure 6). Instead, round-trip investments go in the opposite direction: they increase, albeit slightly, the home bias that characterizes the geographical allocation of the *overall* portfolio of Italian investors.

Figure 6 – Cumulated share of the first 30 destination countries on Italy's portfolio investment abroad at the end of 2016

(stocks; percentage points)



Sources: Calculations based on Banca d'Italia IIP data and ECB, IMF, Banque Centrale du Luxembourg and Central Bank of Ireland data.

4. Concluding remarks

Cross-border positions in investment funds account for a significant share of Italy's external assets, also in comparison with the other EU countries. As already highlighted in Felettigh and Monti (2008), the domicile of investment fund vehicles leads to a disproportionate weight of financial centres among Italy's main portfolio investment destinations. More generally, this phenomenon is an example of how the growing intermediation of mutual funds located in financial centres makes it more difficult to properly assess the extent of "genuine" cross-border portfolio diversification (Lane and Milesi-Ferretti, 2017).

In order to remove the statistical distortions arising from such positions, in this paper we provide estimates of the composition of Italy's portfolio assets, by instrument and by issuer country, after "looking through" the intermediation of foreign funds.. The share of debt securities on Italy's external portfolio significantly rises as a consequence of our "look-through" exercise; its declining trend in the last decade is also less pronounced than that observed in the unadjusted data. Moreover, the adjustment has a large impact on the geographical composition of Italian investors' external portfolio assets: the shares of Luxembourg and other financial centres fall dramatically, while those of the United States and other main advanced economies rise. In general, the geographical diversification of the portfolio tends to increase and the home bias for equities and debt securities is significantly smaller.

Our estimates should, however, be taken with caution, as they rely on several assumptions and on fairly aggregated data. Given the large weight of foreign investment funds in the country's portfolio and, more generally, the strong growth of mutual funds worldwide, further work should be undertaken in this area. To this end, collecting data at a more micro level (i.e. on the portfolio allocation of individual funds) would definitely yield richer insights for a more complete "look-through" perspective.

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BANK FOR INTERNATIONAL SETTLEMENTS

Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

Looking through cross-border positions in investment funds: evidence from Italy[1]

Valerio Della Corte, Stefano Federico and Alberto Felettigh,
Bank of Italy

[1] This presentation was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

Looking through cross-border positions in investment funds: evidence from Italy

Valerio Della Corte, Stefano Federico and Alberto Felettigh
(Banca d'Italia)

9th biennial IFC Conference
"Are post-crisis statistical initiatives completed?"
BIS, Basel, 30-31 August 2018

Introduction

- Total net assets of worldwide regulated funds have more than doubled in the past 10 years (to $49 trillion at year-end 2017 according to the *IIFA*)

- Growth of foreign investment funds might affect external statistics (Felettigh and Monti, 2008)

- Italy as an extreme case: foreign investment fund shares (almost 800 EUR billion at end-2017) account for almost 30 % of the country's IIP assets (in most EU countries between 5-10%)

- Issues
  - What is the actual asset class exposure (bond vs equity) of the country's portfolio investment abroad?
  - What is its geographical exposure? Investment fund domicile ≠ ultimate destination

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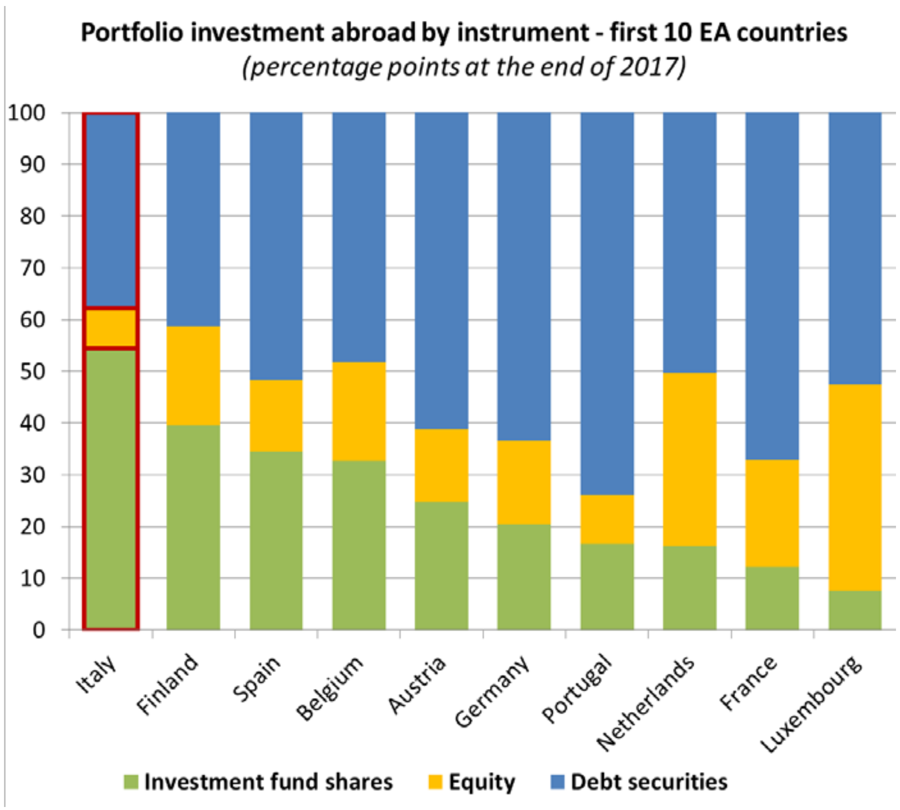
The veil of foreign investment funds

1) What is the actual asset class exposure (bond vs equity) in portfolio investment abroad?



Source: ECB

2) What is the geographical exposure? investment fund domicile ≠ ultimate destination

Italian portfolio investment abroad - country composition at end of 2016

country	%
Luxembourg	40.5
France	11.6
Ireland	8.2
United States	7.8
Germany	5.9
Spain	5.9
United Kingdom	5.0
Netherlands	4.0
International org.	2.6
Belgium	0.8
Others	7.8
	100.0

Source: Banca d'Italia

“Looking through” foreign investment funds

- For economic analysis purposes, need to correct the distortions arising from these positions

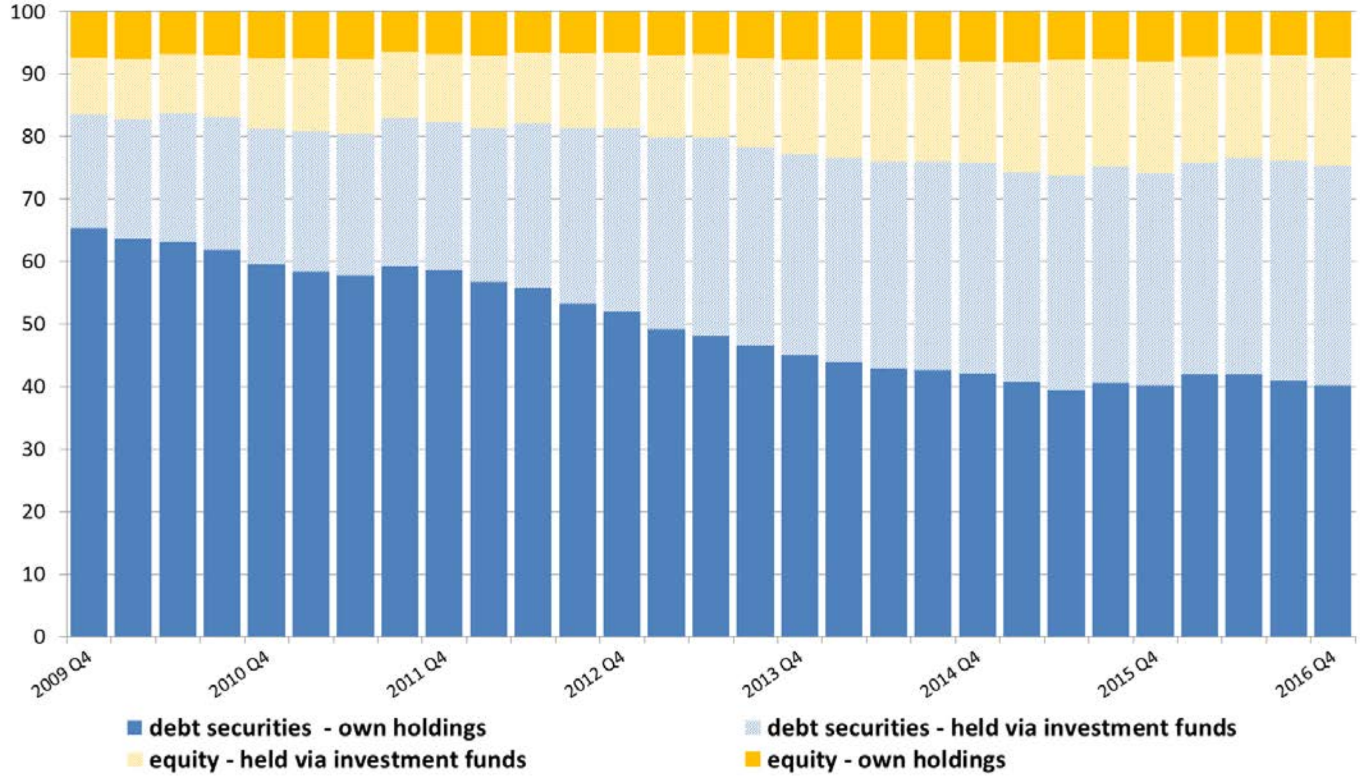
- Data availability is an issue: compilers typically do not know foreign funds portfolios

- Our approach (Della Corte, Federico and Felettigh, 2018) relies on a combination of sources to derive an approximation of foreign investment funds allocation:
  1. as for the composition <u>by financial instrument</u>: data from the Italian Association of investment management companies
  2. as for the <u>geographical diversification</u>: data from partner countries and CPIS (IMF)

- *Macro* approach: based on publicly available <u>aggregate</u> data, so we are making some stringent assumptions

Asset class exposure

- Without adjustments, the debt (equity) share in foreign portfolio assets stood at **40%** (7%) at the end of 2016; the overall share rises to **75%** (25%) after the adjustment
- The debt share remains in a maximum interval of +/-7 points around this value as we relax our assumptions



Sources: calculations based on Banca d'Italia IIP data and Assogestioni and ECB data.

The "ultimate" geographical exposure

- Main (strong) assumption: geographical allocation of Italian-owned foreign funds equal to that of the entire fund industries in Luxembourg, Ireland and France (over 95% of these funds are domiciled in these three countries)
- USA becomes the first destination of Italian portfolio investment
- Shares of the other main EU partners also increase
- Overall, geographical diversification rises

ranking	Total portfolio unadjusted		Total portfolio (adjusted)	
	country	%	country	%
1	Luxembourg	40.5	United States	20.7
2	France	11.6	France	12.2
3	Ireland	8.2	Germany	9.2
4	United States	7.8	United Kingdom	8.3
5	Germany	5.9	Spain	7.3
6	Spain	5.9	Netherlands	6.7
7	United Kingdom	5.0	Luxembourg	3.8
8	Netherlands	4.0	Italy *(round trip)*	2.9
9	International org.	2.6	International org.	2.8
10	Belgium	0.8	Ireland	2.0
others	-	7.8	-	24.0
		100.0		*100.0*

Sources: calculations based on Banca d'Italia IIP data and ECB, IMF, Banque Centrale du Luxembourg and Central Bank of Ireland data.

Conclusions

- Growing importance of foreign investment funds might affect external statistics

- Italy as an example
  - Foreign investment fund shares account for almost 30 per cent of the country's IIP assets
  - Disproportionate weight of financial centres among the country's portfolio investment destinations

- After the "looking through" exercise:
  - the share of debt securities in the country's external portfolio significantly rises
  - the shares of the United States and our main euro-area partners as destination countries increase too

- *Caveat*: our approach relies on strong assumptions and "macro" data

→ **Data needs**: micro data (i.e. fund-level data on portfolio allocation)

Data needs: advantages to collect fund level data

Accuracy:

- Large heterogeneity among investment funds (Hau and Rey, 2008)
- Different funds reach different clienteles (Anderson *et al.*, 2011)

→ assumption of investing in the average fund likely violated

Much richer insights for economic analysis:

- e.g. what is the risk profile of funds held by the household sector ?
- what the implied vulnerabilities to specific market scenarios (e.g. rise in yields)?

Micro-approach adopted by new research in progress at Banca d'Italia:

- Coletta M. and Santioni R. (2018) rely on fund-level data to assess the exposure and returns of Italian households via foreign funds
- Della Corte and Santioni are working on extensions to other euro-area countries

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Back-ground slides

Financial instrument composition of foreign investment funds

Assogestioni's classification of foreign funds into about 40 categories according to their investment policy enables us to estimate a range for the composition by financial instrument (equity vs debt securities)

Macro-category/category	restrictions on the equity allocation (Assogestioni)		equity allocation assumed in the adjustment by instrument of the positions in mutual funds		
	min	max	baseline	min	max
Money-market/liquidity *(all categories)*	0	0	0	0	0
Bond					
- *mixed*	0	20	10	0	20
- *all others*	0	0	0	0	0
Balanced					
- *bond*	10	50	30	10	50
- *no indication*	30	70	50	30	70
- *equity*	50	90	70	50	90
Flexible	0	100	40 (*)	20 (*)	46 (*)
Equity *(all categories)*	70	100	85	70	100
All funds as a whole					
2009 Q4 - 2016 Q4 (average)	21	47	32	25	38
At the end of 2016	20	50	33	25	40

Sources: Assogestioni and, for flexible allocation funds, calculations based on ECB data (Investment Funds statistics).

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The "ultimate" geographical exposure (by instrument)

Equity				
ranking	country (unadjusted)	%	country (adjusted)	%
1	United States	25.9	United States	25.9
2	France	14.5	France	10.8
3	Germany	13.3	Germany	9.3
4	United Kingdom	10.8	United Kingdom	8.5
5	Netherlands	8.5	Japan	5.2
6	Switzerland	6.2	Netherlands	5.1
7	Spain	3.4	Switzerland	4.4
8	Japan	3.1	Luxembourg	2.9
9	Luxembourg	1.4	Spain	2.3
10	Belgium	1.2	Cayman Islands	2.1
others	-	11.8	-	23.5
memorandum item: share on total portfolio investment		*7.3*		*24.6*
Debt Securities				
	country (unadjusted)	%	country (adjusted)	%
1	France	15.3	United States	19.0
2	Spain	14.0	France	12.7
3	United States	13.8	Germany	9.1
4	Germany	11.3	Spain	8.9
5	Netherlands	8.4	United Kingdom	8.2
6	United Kingdom	7.2	Netherlands	7.3
7	International org. (1)	6.2	Luxembourg	4.1
8	Luxembourg	4.4	International org.	3.7
9	Ireland	2.7	Italy *(round-trip)*	3.4
10	Belgium	1.8	Ireland	2.2
others	-	14.9	-	21.4
memorandum item: share on total portfolio investment		*40.3*		*75.4*

Sources: calculations based on Banca d'Italia IIP data and ECB, IMF, Banque Centrale du Luxembourg and Central Bank of Ireland data.

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An insight into the derivatives trading of firms in the euro area[1]

Nicola Benatti and Francesco Napolitano,
European Central Bank

[1] This paper was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

An insight into the derivatives trading of firms in the euro area

Nicola Benatti, European Central Bank

Francesco Napolitano, European Central Bank

Abstract

Financial institutions are not the only traders of derivative contracts. Non-financial corporations (NFCs) also use derivatives to mitigate their risks. But which are the characteristics of these firms and what are the implicit entry barriers to derivatives trading for non-financial corporations? In this paper we first analyse how demographic and financial characteristics of firms determine their recourse to derivative markets in Europe. Subsequently we use a multinomial logit model to identify patterns in the trading preferences, using transaction-level data on derivatives contracts collected under the European Market Infrastructure Regulation (EMIR).

Keywords: OTC derivatives, firm data, risk mitigation

JEL classification: D22, D25, D53, G32

Table of contents

1. Introduction: the usage of financial derivatives by NFCs

The immediate impact of the 2007–2008 crisis on the non-financial sector has been relatively limited. According to Bartram et al. (2015), the main reason for this is that firms' stock volatility is mostly influenced by economic factors, such as competition and price fluctuations, and less so by market-based financial risks which are often accounted for in the firm's risk management policies which may include, among others, mitigating external risks using financial derivatives.

The use of financial derivatives by non-financial firms has increased notably in the last 3 decades (Nguyen 2011). As a result, we notice the substantial development of a specific empirical literature which studies the nature of this phenomenon and investigates the main reasons driving a firm's decision to invest in this type of financial instruments.

Typically, the firm's decision to use financial derivatives is related to the need of hedging against a specific risk. The established financial risk management literature identifies the most common determinants of the use of financial derivatives by firms around the need to mitigate cash flow volatility. In particular, the main case studies can be summarised as follows:

- Costs of financial distress:
  Cash flow volatility can have a negative impact on the firm's available liquidity and limit its capacity to meet regular payment obligations on time, such as salaries and interest payments. Financial risk management can reduce the likelihood of incurring such liquidity constraints and thus lower the expected costs associated with periods of financial distress (Mayers and Smith, 1982; Myers, 1984; Stulz, 1984; Smith and Stulz, 1985; Shapiro and Titman, 1998, among others).

- Taxes:
  When firms are subject to progressive taxation on income, then financial derivatives can be used to reduce the volatility of taxable income and thus the expected value of tax liabilities (Smith and Stulz, 1985; Nance et al., 1993; Graham and Smith, 1999; Graham and Rogers, 2002).

- Underinvestment:
  Cash flow volatility increases the likelihood that the firm may be faced with costly external financing for planned investment projects due to cash shortages. Empirical evidence based on this rationale shows that firms with substantial investment plans that are facing high costs of access to financing are more willing to hedge against liquidity risks that would hamper their investment capacity (Bessembinder, 1991, Froot et al., 1993).

The theories of hedging mentioned above show how firms can increase their "debt capacity" in a context of imperfect capital markets. However, the empirical literature shows only mixed evidence about the positive relation between hedging with financial derivatives and increasing firm value.

Further streams of the literature indicate that hedging strategies are used by managers to reap the benefits of informational asymmetries which exist between themselves and the shareholders of the company, since managers typically have better information about the risks of the firm (Smith and Stulz, 1985; Duffie and DeMarzo, 1991). Similarly, some narratives on financial risk management focus on the risk aversion of managers and the nature of their compensation contracts (Smith and Stulz, 1985; Tufano, 1996; Berkman and Bradbury, 1996).

Industry and size effects are broadly consistent across different studies which find positive correlation between firm scale and financial derivative usage. Indeed, due to the high set-up and implementation costs related to corporate risk-management policies, it is often the case that for smaller firms these costs may exceed the benefits of a hedging program. There are, however, some valid arguments pointing to the existence of a negative relation between firm size and hedging activity: for example, some studies suggest that small firms may have a greater incentive to hedge as they face higher bankruptcy costs (i.e. the increased costs of financing with debt that result from higher probability of bankruptcy) compared to larger firms (Smith and Stulz, 1985). Small firms are also faced with greater information asymmetries and costs of external financing and thus they are more likely to incur financial distress and, as a result, they might be more inclined to hedging activities.

Due to the limited coverage of available data, many studies limit the scope of the analysis to specific categories of derivatives, or to selected industries and geographic areas, while the sample of the analysis is often limited to publicly listed firms. The vast majority is focused on the US market while very few empirical studies have examined the determinants of derivatives usage in a European context, using mainly survey data (e.g. Bodnar and Gebhardt, 1999; De Ceuster et al, 2000; Bodnar et al, 2013 and Jankensgård, 2015).

With respect to the empirical models employed, most of the studies can be split into two main groups: those that focus on firms' usage of derivatives as qualitative information (mostly based on probability models) and those that aim at capturing the extent of firms' derivatives usage through measures of notional amounts (mostly using truncated probability models or two-part models where the decision to use derivatives is analysed separately from the decision on the extent of usage).

Due to the considerations that will follow in the next section, in this study we use multivariate logit to draw some insights into the financial profile of firms using financial derivatives.

The main distinctive feature of this study is the exploratory analysis of transaction-level data on derivative contracts collected under the European Market Infrastructure Regulation (EMIR) as well as the investigation of the analytical potential of this dataset with reference to the non-financial sector. The EMIR dataset covers all counterparties established in the euro-area and all contracts where one of the two counterparties is located in the euro area or where the reference obligation is sovereign debt of a euro area member. As a result, the analysis benefits from the following distinctive characteristics:

- All NFCs in the euro area which make use of derivatives in the period of analysis are included in the sample (i.e. not only larger and/or listed firms).
- All types of derivatives and asset classes are included in the sample, regardless of whether they are traded over the counter (OTC derivatives) or on a regulated exchange (ETD derivatives).

- We identify the characteristics of firms trading on derivative markets compared to those non-trading when controlling for size, sector, and country they belong to.
- We identify which types of firms are more likely to trade a specific type of contract based on the underlying asset class.

2. The EMIR dataset: a brief overview

2.1. The EMIR reporting framework

In the aftermath of the financial crisis in 2008, new regulatory initiatives have been developing worldwide, following the decisions taken by G20 leaders in the Pittsburgh Summit of 2009, to start a process of reforms aiming at improving functioning and transparency within the OTC derivatives markets.

In the EU, the European Market Infrastructure Regulation (EMIR)[1] established the obligation to report, since February 2014, data on all OTC and exchange-traded derivatives transactions conducted by counterparties resident in the EU. Information is currently collected by six authorised trade repositories (TRs) that validate and store the data received by the reporting agents and share them with more than 60 competent authorities in the EU.

The EMIR legal framework was developed by the European Securities and Market Authority (ESMA), which received the mandate to define the reporting requirements as well as to authorise and supervise TRs.

2.2. Dataset structure

Through EMIR, the European Central Bank (ECB) has access to transaction-level derivatives data for all counterparties established in the euro-area and all contracts where the reference entity is located within the euro area or where the reference obligation is sovereign debt of a euro area member.

The data cover five instrument classes (equity derivatives, credit derivatives, interest rate derivatives, commodity derivatives, foreign exchange derivatives), both exchange-traded (ETD) and over-the-counter (OTC) contracts, including trades cleared via Central Clearing Counterparties (CCPs). The data are collected transaction-by-transaction and include more than 120 reported fields[2].

The information to be reported in compliance with EMIR is comprehensive and includes so-called "counterparty data", pertaining to each counterparty individually considered, and "common data", i.e. information about the contract that are expected to be the same for both counterparties. When both counterparties are subject to the reporting obligation, EMIR establishes a "double-reporting" regime,

[1] Regulation (EU) 648/2012 of the European Parliament and of the Council of 4 July 2012 on OTC derivatives, central counterparties and trade repositories.

[2] As of November 2017.

by which both of them are bound to individually report the same transaction after agreeing on the content of common fields (Ascolese et al. 2017).

The high volume and granularity of the EMIR data provides an unprecedented analytical perspective on the European derivatives markets which is particularly valuable for macro-prudential policy and financial stability purposes. In fact, the wide data coverage would allow for the calculation of aggregate level data, however several caveats must be considered due to important data quality limitations in particular with reference to the level of standardisation in the main data fields (i.e. counterparty and product ID, trade ID and valuation information).

In this respect, several EU-level initiatives have been taken to reduce these data quality issues by amending EU regulations and guidelines and by supporting international efforts on the standardisation of OTC derivatives data. The recent adoption of the amended regulations[3] paved the way to significant data quality improvements as of 1 November 2017, in particular with reference to a more widespread adoption of global identification standards (such as LEI or ISIN codes[4])[5].

The current paper makes use of the EMIR granular data as collected from TRs as of November 2017 (i.e. in compliance with the latest regulatory standards).

3. Matching EMIR and balance sheet data of NFCs

3.1. EMIR and Orbis: the scope of the analysis

In this study we aim at the identification of patterns and correlations within euro area NFCs which participate in the derivatives market as opposed to those which do not make use of these financial instruments. In particular, we focus on demographic characteristics such as the size, age and sector of the firm as well as financial information coming from the firms' balance sheet and profit and loss accounts.

3.1.1. The Orbis database

Demographic and financial firm-level information comes from Orbis Europe, a cross-country database on NFCs financials provided by Bureau van Dijk (BvD). Orbis Europe is a commercial database, containing firm-level balance sheet and other company information (e.g., among others, various identification codes, ownership data and directors) for around 86 million European firms. The data is collected by BvD's information providers at each national official body in charge of collecting annual accounts in the respective country. The coverage of the database by legal form varies across countries.

3.1.2. Timing considerations

Orbis data come at an annual frequency (following the disclosure of the annual financial reports) and as of today the latest available information is dated end-

[3] Regulation (EU) 104/2017 and Regulation (EU) 105/2017.

[4] Legal entity identifier (LEI), International Securities Identification Number (ISIN).

[5] See Ascolese et al. (2017) for more details on EMIR reporting standards and data quality considerations.

2016[6]. On the other hand, EMIR daily data on derivatives transactions covers the period between November 2017 and May 2018. Therefore, we face a mismatch between the timeliness of the two datasets.

In order to circumnavigate this issue and obtain a useful preliminary analysis of the behaviour of non-financial corporations on the derivative markets, we opted for averaging the balance-sheet information utilised over the period 2014-2016.

Using this approximation, although the Orbis data for 2017-2018 is not available yet (as annual financial data for these reference periods has not been compiled entirely by the reporting entities), we expect to be able to obtain the most significant set of parameters available to conduct our analysis.

3.2. The matching process

The data matching process follows the steps listed below:

1. On the EMIR side, we identify those entities which have entered a new derivative transaction of any kind during the available time period (Nov17-May18).
2. On the Orbis side, we aggregate (by averaging values through the considered period) all firms with the following characteristics:
    a. They have an LEI code.
    b. They belong to the non-financial sector[7].
    c. They report unconsolidated financial statements in 2014, 2015 or 2016.
    d. They are resident in the euro area at the time of reference.
3. We match the two datasets coming from 1. and 2. through the LEI code. Due to the structure of the EMIR tables, the matching is done in two steps:
    a. The EMIR "reporting counterparty IDs" are matched with the Orbis LEI codes to enrich the dataset with information from EMIR (e.g. contract type, asset type, etc.)
    b. The EMIR "other counterparty IDs" are matched with the Orbis LEI codes to enrich the dataset with information from EMIR (e.g. contract type, asset type, etc.)
4. As the same entities can appear as reporting counterparties and other counterparties, and given that in our analysis we do not look at amounts traded, we keep every unique transaction by LEI code and contract characteristics (type of contract and asset class).
5. A dummy variable is finally created in the dataset to indicate whether a firm is involved in a derivative transaction or not (i.e. whether it appears both in the EMIR and in the ORBIS datasets or only in the ORBIS dataset).

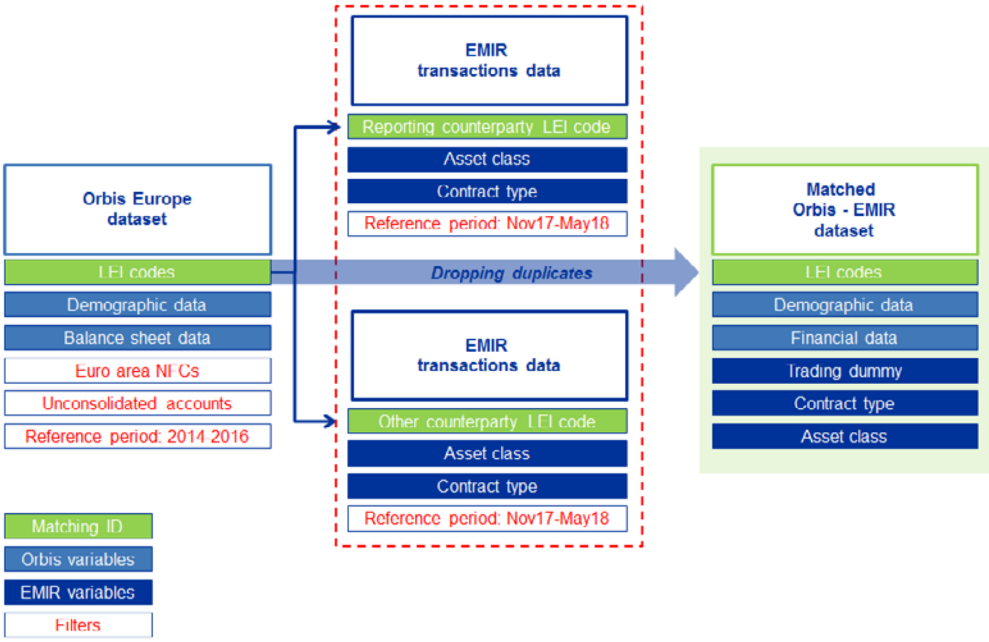
[6] Data for 2017 are still provisional and have much lower coverage.

[7] See Section 4 for the list of NACE rev2 1-digit sectors included in the dataset.

Therefore, the final matched dataset includes:

a. financial information for all firms with a LEI code (as available in Orbis).
b. a dummy variable indicating whether a firm traded derivatives in the period of analysis.
c. for those firms which traded derivatives, information on the type of contract and underlying asset class.

Figure 1. Orbis-EMIR matching process



Sources: EMIR and Orbis Europe.

As anticipated, due to the structure of the EMIR dataset which currently does not allow a fully unique trade and product identification, we simplify the data extraction by focusing on the identification of the entities and the related categorical information (e.g. contract types, asset classes, ETD vs OTC, etc.) while quantitative information on trading volumes or notional amounts as well as on the number of contracts signed by each entity are excluded from the analysis.

3.3. Main matching results

Given the very high availability of LEI codes throughout the NFCs population in EMIR, the results of the matching procedure with the Orbis data are quite satisfactory. Overall, 56% of euro area entities reported in EMIR as NFCs can be matched with Orbis through the LEI code. Table 1 summarizes these results by country.

Table 1. Matched firms / total firms in EMIR[8]

Country	Orbis coverage of NFCs trading in EMIR
AT	60%
BE	75%
CY	4%
DE	72%
EE	17%
ES	54%
FI	61%
FR	57%
GR	62%
IE	18%
IT	50%
LT	35%
LU	7%
LV	31%
MT	14%
NL	59%
PT	73%
SI	72%
SK	66%

Sources: calculations based on EMIR and Orbis Europe data.

Therefore, considering the comprehensive coverage of the EMIR reporting scheme, we can assume that the matched dataset we have obtained can offer (in particular for bigger countries) a representative picture of the euro area NFCs population participating in the derivatives market during the period of analysis.

However, due to the very limited time coverage of the EMIR transaction data in the database we use, the analysis is not looking at this small group of firms in comparison with the overall NFCs population reported in Orbis. Instead, as described above, we compare the group of firms identified in EMIR with all the firms which are reported in Orbis with an LEI code. This choice will bias our sample towards larger firms but if functions as a good proxy for firms in the Orbis dataset with similar quality of reported information, fundamental for the comparison we carry on in the next steps. Table 2 summarizes the total number of firms included in the two clusters of the dataset.

8 The matching results by countries refer only to the "reporting counterparties" (thus exclude the "other counterparties") in EMIR.

Table 2. The structure of the matched dataset – distribution across countries[9]

Country	NFCs non-trading derivatives (Orbis Europe)		NFCs trading derivatives (EMIR)		NFCs with LEI (Orbis Europe)
	n	%	*n*	%	*n*
AT	2,953	81%	685	19%	3,638
BE	4,085	72%	1,614	28%	5,699
CY	45	65%	24	35%	69
DE	21,983	75%	7,278	25%	29,261
EE	141	77%	43	23%	184
ES	4,983	65%	2,705	35%	7,688
FI	1,133	71%	458	29%	1,591
FR	7,763	69%	3,527	31%	11,290
GR	301	76%	97	24%	398
IE	1,153	78%	331	22%	1,484
IT	27,805	86%	4,391	14%	32,196
LT	156	73%	59	27%	215
LU	622	77%	182	23%	804
LV	99	77%	30	23%	129
MT	61	78%	17	22%	78
NL	7,371	78%	2,109	22%	9,480
PT	806	68%	379	32%	1,185
SI	297	76%	93	24%	390
SK	964	85%	175	15%	1,139
euro area	82,721	77%	24,197	23%	106,918

Sources: calculations based on EMIR and Orbis Europe data.

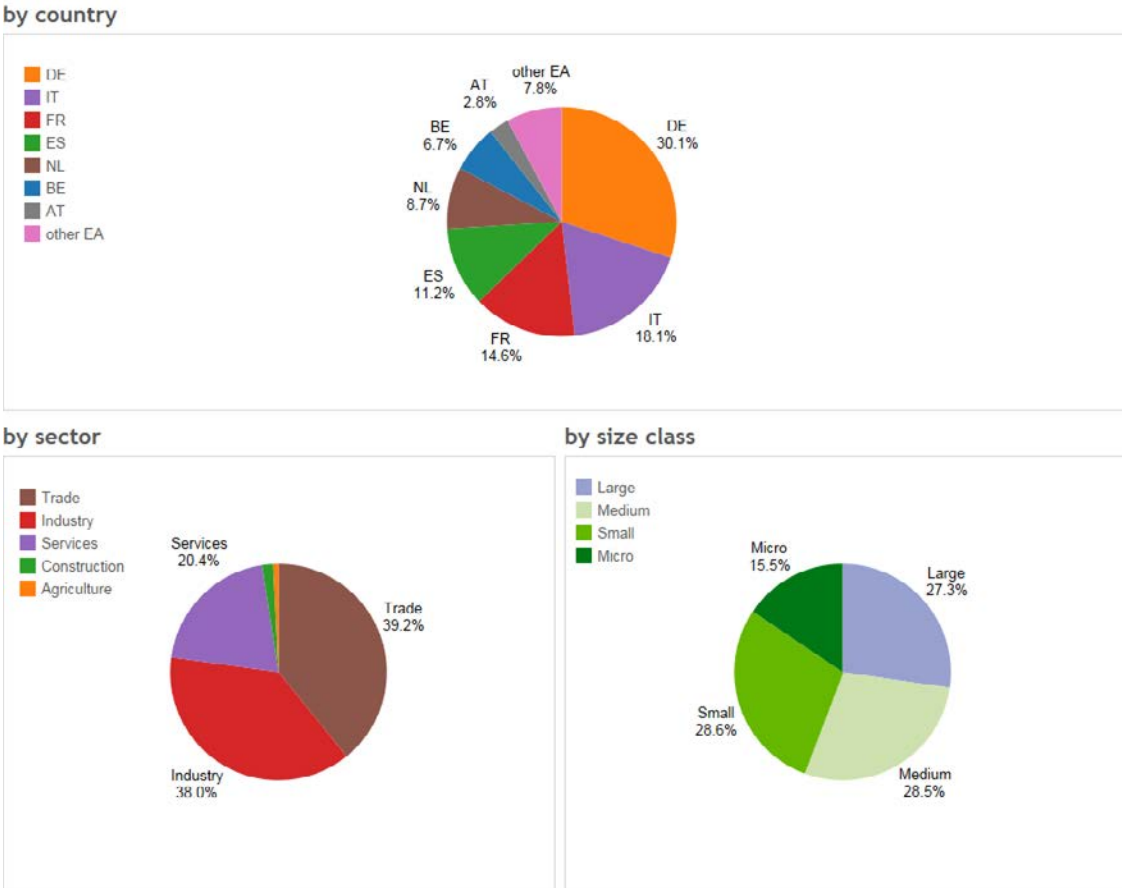
4. An insight into euro area NFCs trading derivatives

4.1. Demographic characteristics

In this section the analysis will focus on the group of firms using derivatives, namely those NFCs which have registered at least one derivative transaction during the period of analysis (from November 2017 to May 2018). Using information from Orbis we can break down this group of firms to identify relevant demographic characteristics. Figure 2 provides the composition by country, size class and sector of activity.

[9] Orbis data refer to annual reports from 2014 to 2016. EMIR data refer to the number of NFCs involved at least in one derivative transaction between November 2017 and May 2018.

Figure 2. Firms using derivatives, breakdown by country, size and sector



Sources: calculations based on EMIR and Orbis Europe data.

The country composition is broadly in line with the overall NFC population composition within the euro area. About 80% of the firms trading derivatives in the euro area are resident in Germany, Italy, France, Spain and the Netherlands. However, German firms constitute 30% of the overall sample which is notably a high proportion with respect to official business population statistics[10] and means that there is a higher heterogeneity in the composition of derivatives trading firms in Germany compared to other countries (i.e. when looking at which firms are trading which type of contract with which underlying asset).

The sectors of activity have been clustered into five main groups, namely agriculture, construction, industry, services and trade[11]. Most of the firms trading

10 According to Eurostat's Structural Business Statistics, German NFCs population is about 15% of the overall NFCs population in the euro area.

11 The split by sector is based on economic activities at the one-digit level of the European NACE classification (Rev. 2):

- "Agriculture" includes only agriculture, forestry and fishing (A),
- "Industry" includes mining and quarrying (B), manufacturing (C), and electricity, gas, steam and air conditioning supply (D), and water supply, sewerage, waste management and remediation activities (E).
- "Construction" is simply construction (F).
- "Trade" includes wholesale and retail trade; repair of motor vehicles, motorcycles and personal and household goods (G).

derivatives operate in either industry or trade (about 77%, split almost equally between the two sectors) while 20% are active in services. Very few firms belong to the agriculture and construction sectors however the proportions compared to the total are in line with those in the Orbis dataset.

Regarding the size of firms, the definition applied throughout this paper follows the EU recommendation 2003/361. The two criteria used to determine the size of the firm are (i) the number of employees and (ii) either turnover (operating revenues) or total assets. They are applied as follows:

- Small and Medium-sized enterprises (SMEs):
    - Micro firms: < 10 *employees* and (*turnover* <= EUR 2 mln or *total assets* <= EUR 2 mln)
    - Small firms: < 50 *employees* and (*turnover* <= EUR 10 mln or *total assets* <= EUR 10 mln)
    - Medium firms: < 250 *employees* and (*turnover* <= EUR 50 mln or *total assets* <= EUR 43 mln)
- Large firms:

    > 250 *employees* or (*turnover* > EUR 50 mln and *total assets* > EUR 43 mln)

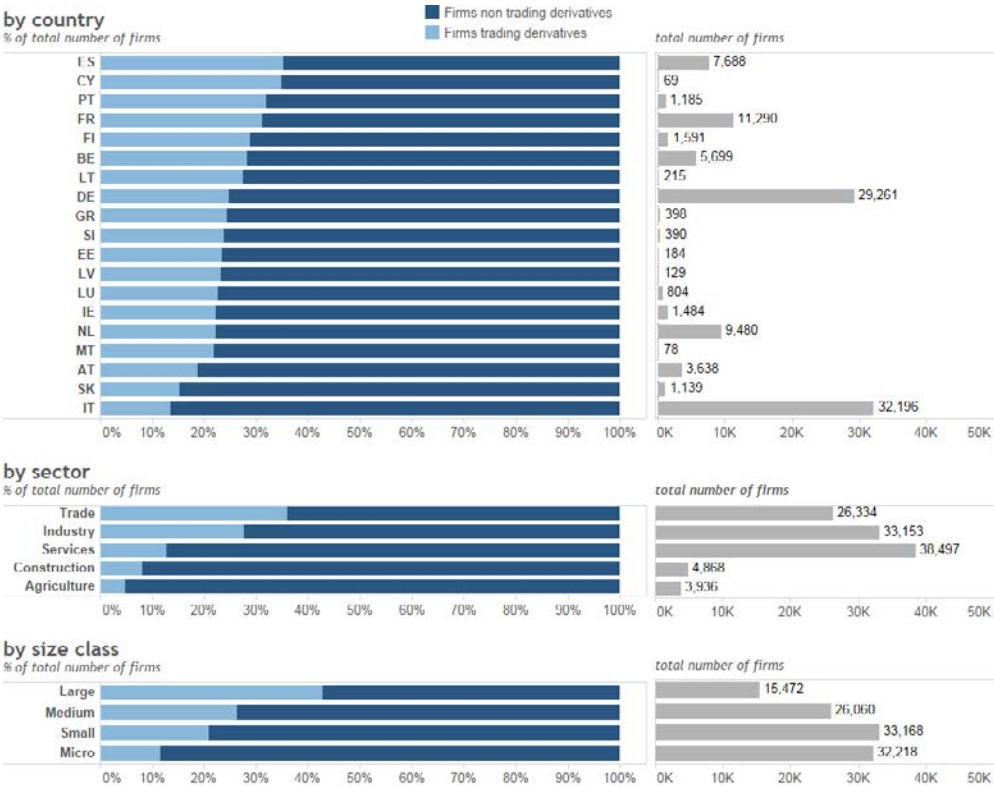
Using the above definitions, large firms constitute 27% of the sample while the rest of the firms using derivatives are SMEs. Considering that in terms of number of firms SMEs constitute about 99% of the European business economy we can already see a bias toward larger firms within the sample of firms using derivatives.

Figure 3 reports, for all countries, sectors and size classes, the percentage of firms using derivatives in the dataset. Across the entire sample of 106,918 firms, 23% used some type of derivatives during the period of analysis. Usage ratios do not vary substantially across countries while they are higher for the trade sector and increase significantly with firm size.

- "Services" includes enterprises in transport and storage (H), accommodation and food service activities (I), information and communication (J), real estate activities (L), professional, scientific and technical activities (M), administrative and support service activities (N), education (P), human health and social work activities (Q) arts, entertainment and recreation (R) and other service activities (S).

The following activities were excluded from the sample: financial and insurance activities (K), public administration and defence, compulsory social security (O), activities of households as employers; undifferentiated goods- and services-producing activities of households for own use (T), activities of extraterritorial organisations and bodies (U).

Figure 3. Percentage of firms using derivatives, breakdown by country, size and sector



Sources: calculations based on EMIR and Orbis Europe data.

4.2. Types of derivatives

From the EMIR side of the matched dataset we retrieve information about the type of derivative contract and the underlying asset class for every firm. In particular, we know whether a firm is investing in one or more types of derivatives.

In general, 98% of the firms are using OTC derivatives and thus only 2% of the reporting entities uses exclusively exchange traded derivatives (ETD). Thus the data confirms the common view that most of the trading activity on derivatives in the euro area occurs "over the counter".

As shown in Figure 4, 60% of the firms trade currency derivatives, 13% interest rates derivatives and almost 6% commodity derivatives. This finding is broadly in line with the literature on derivatives usage by NFCs (e.g. Bartram et al, 2009). Unfortunately, for 40% of the records in the sample we do not have information about the asset class in EMIR.

In terms of contract type, 70% of the identified cases firms use forwards, 29% swaps and 20% options.

Figure 4. Firms trading derivatives, breakdown by contract type and asset class[12]

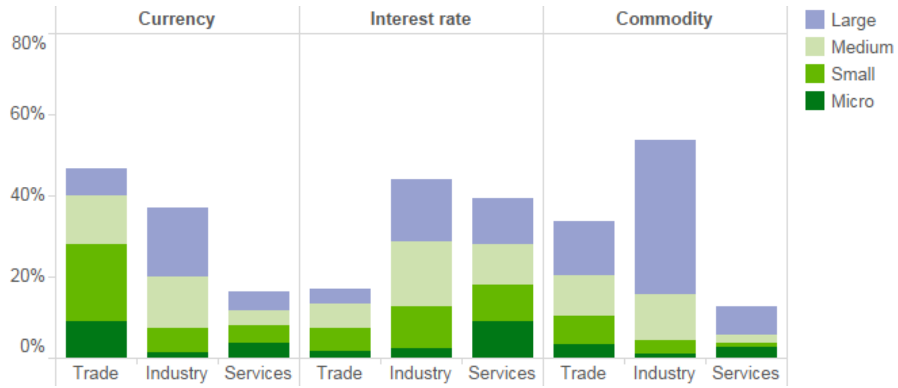
Asset Class	Forwards	Swap	Option	Other	Futures	Financial contracts for difference	Swaption	Forward rate agreements	Unspecified	Grand Total
	Contract Type									
Currency	52.77%	9.11%	0.04%	9.03%	0.08%	0.25%		0.02%	0.05%	60.05%
Unspecified	28.56%	14.45%	9.72%	2.36%	0.41%	0.46%	0.02%	0.02%		42.27%
Interest rate	0.05%	8.11%	3.19%	3.63%	0.10%	0.01%	0.12%	0.02%	0.00%	13.17%
Commodity	1.54%	2.57%	0.93%	0.31%	1.87%	0.12%	0.01%	0.01%	0.02%	5.75%
Equity	0.11%	0.11%	1.01%	0.41%	0.29%	0.19%			0.01%	1.81%
Credit		0.08%		0.01%			0.01%			0.09%
Grand Total	70.49%	29.23%	20.18%	14.63%	2.45%	0.84%	0.14%	0.08%	0.07%	100.00%

Sources: calculations based on EMIR and Orbis Europe data.

The high frequency in the use of forwards is a reasonable finding as these types of derivatives are very specific for the OTC market. In particular, currency forwards are used by the highest proportion of firms inside the sample (53%).

Figure 5 shows that most of the firms using currency derivatives belong to trade and industry. However, in the case of industry most of these firms are medium and large in size while they are mostly micro and small in the trade sector. Commodity-based derivatives are also mostly used in industry and trade although in this case medium and large firms are the most common investors. Interest rate derivatives are more popular in both industry and services.

Figure 5. Firms using derivatives, breakdown by sector and size class (% by asset class)



Sources: calculations based on EMIR and Orbis Europe data.

[12] All percentages (including totals) refer to the number of firms and thus they do not sum up to row and column totals as one firm can fall into more than one category (i.e. use more than one contract type or asset class).

4.3. Firm size and derivatives usage

Most of the current literature on NFCs and derivatives usage[13] shares the idea that larger firms are more likely to use derivatives as they can rely on more sophisticated financial management practices and the economies of scale provide a competitive advantage on information and transaction costs in the derivatives market. On the other hand, other empirical findings[14] suggest that, since smaller firms can be more vulnerable during periods of financial distress and face higher bankruptcy costs, they are more likely to use derivatives to hedge against financial risks.

We can test these hypotheses on our matched dataset using different measures of firm size coming from the balance sheet data and comparing the results across country and sector in order to identify possible patterns in the sample.

We measure firm size using (i) total assets, (ii) turnover (operating revenues) and (iii) number of employees. All measures are expressed as natural logarithm transformations.

In order to highlight patterns in the dataset, we plot the distributions of the two clusters of the sample (i.e. firms using derivatives / firms not using derivatives) along the above mentioned measures of firm size and we compare the results across sectors and country.

Figure 6 compares the distributions of the two clusters of firms on total assets. For all the three main sectors, the distribution of the group of firms using derivatives (light blue shaded area in the chart) is shifted to the right with respect to the one of the firms not using derivatives (dark blue bars), with industry showing the highest difference. Also, the level of dispersion does not vary significantly across the two clusters especially in the case of trade where the difference in variance is minimal.

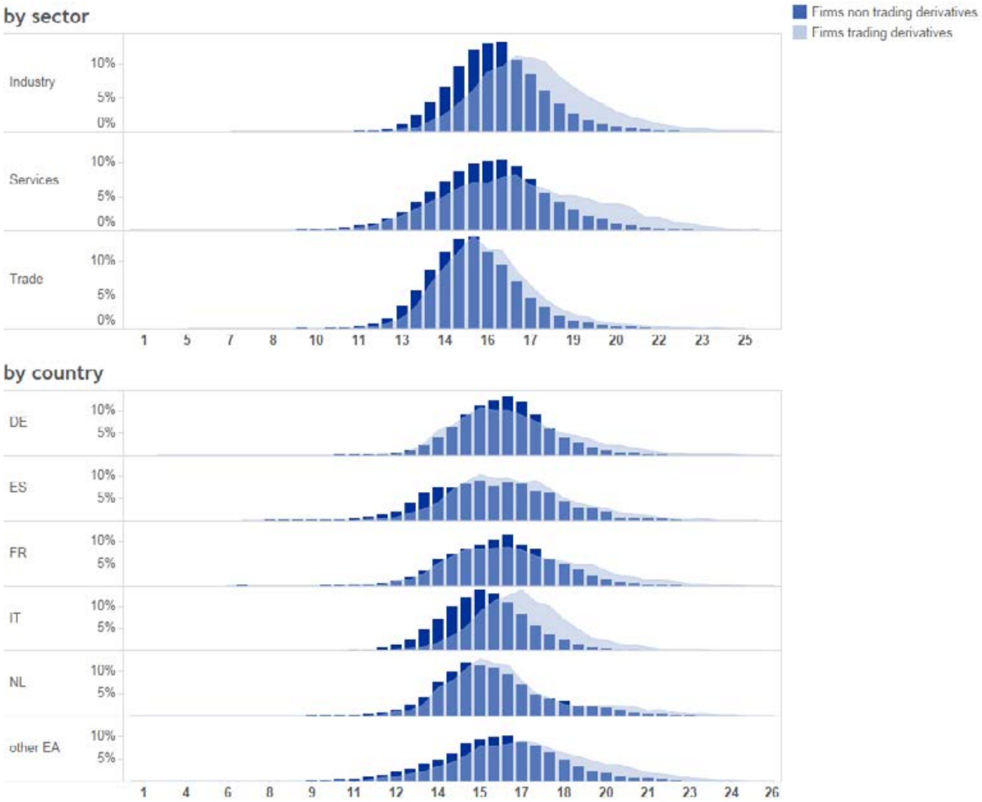
The difference in firm size between the two distributions (firms trading and firms not trading) is statistically significant (according to the kolmogorov-smirnov test[15]) both across sectors and across countries. We reach very similar conclusions when using turnover and number of employees as proxies for the firm size (see Figure 7 and 8). Particularly in the case of turnover, the positive relation between size and derivatives is more pronounced across all sectors and countries.

13 Among others, Berkman and Bradbury (1996), Borokhovich et al. (2004), Carroll et el (2017), Fok et al. (1997), Geczy et al. (1997), Graham and Rogers (2002), Guay (1999), Judge (2006) Lel (2012), Lin and Smith (2007), Mian (1996), Nance et al. (1993), Rogers, (2002).

14 Among others, Ang et al. (1982), Nance et al. (1993), Smith and Stulz (1985), Warner (1977).

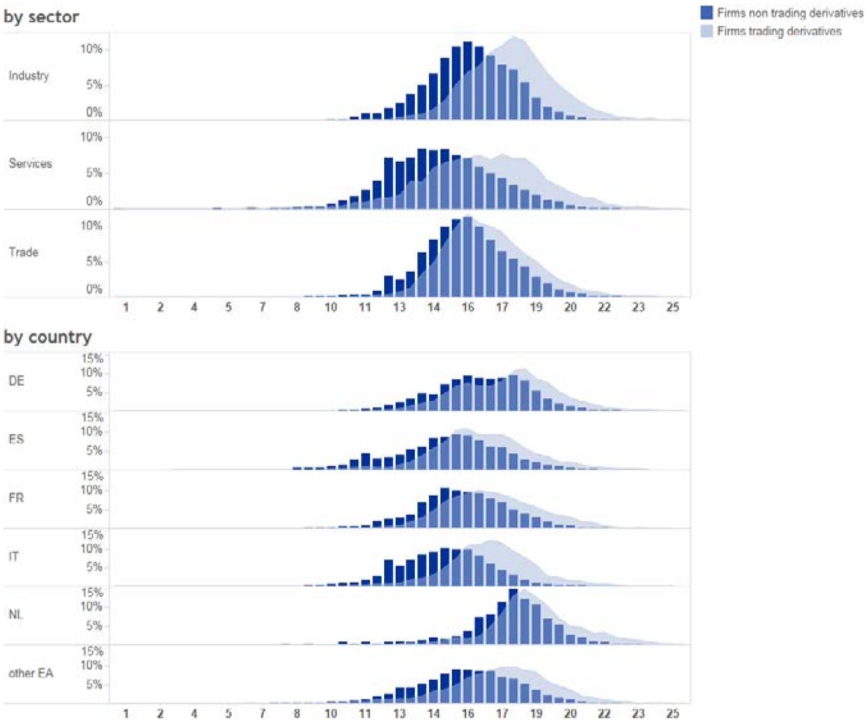
15 The two-sample Kolmogorov–Smirnov test is a common statistical test to determine whether the underlying probability distributions of two functions are statistically different (Massey, Frank J. 1951).

Figure 6. Distribution of firms by total assets (natural log), breakdown by sector and country



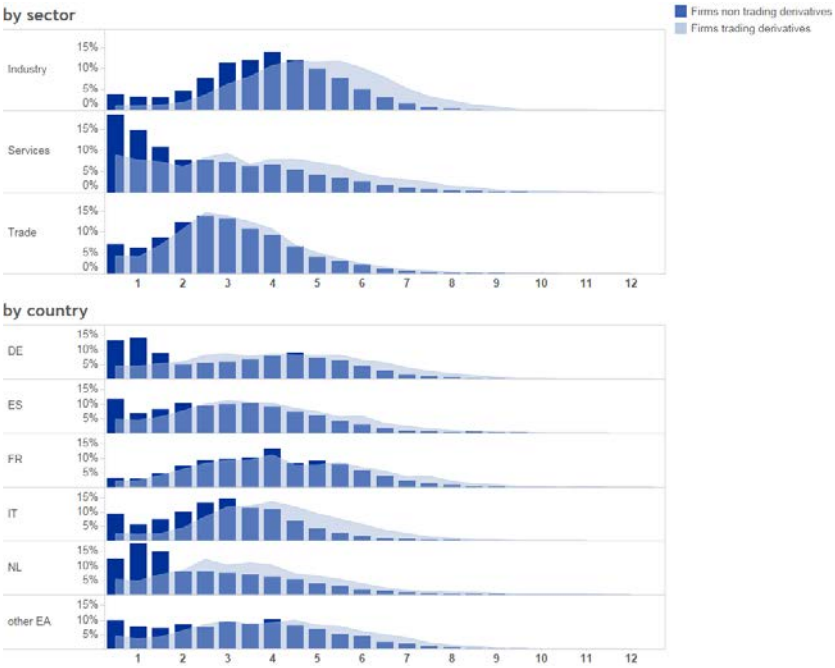
Sources: calculations based on EMIR and Orbis Europe data.

Figure 7. Distribution of firms by turnover (natural log), breakdown by sector and country



Sources: calculations based on EMIR and Orbis Europe data.

Figure 8. Distribution of firms by number of employees (natural log), breakdown by sector and country



Sources: calculations based on EMIR and Orbis Europe data.

Therefore, descriptive statistics suggest that in general the scale of the firm is a relevant factor among those determining the euro area NFCs usage of the derivatives market.

In the following section we will thus clean the analysis from the firm size effect on derivative usage and study the impact of other financial characteristics using a probability regression models. We first use a logit regression (i.e on a dichotomous dependent variable which identifies firms trading derivatives versus non-trading firms) to determine the financial characteristics of NFCs trading derivatives against those not participating in this market. We later use a multinomial logit regression (i.e. a probability model on a categorical variable which identifies the 5 types of assets underlying the reported transactions) to determine the financial characteristics influencing preferences of firms for different types of underlying asset classes.

4.4. One step further in the analysis of the characteristics of firms trading derivatives

As the demographic analysis above demonstrates and as suggested by large part of the literature on this topic, the larger the firm, the more likely it is to trade derivative contracts. To prove this concept further we analyse which is the probability of trading derivatives for firms belonging to each of the size classes described above when compared to micro firms, controlling for the country and the sector they belong to. The estimation in Table 3 proves indeed the size[16] to be significantly important and positively correlated with the probability of a firm trading derivatives contracts.

Table 3. Logit regression results – country, sector and size class

Variables	Trading odds ratio
Small	1.604***
	(0.0372)
Medium	2.256***
	(0.0539)
Large	4.831***
	(0.124)
Country dummies	***
Sector dummy	***
Constant	0.0284***
	(0.00254)
Observations	106,908
Pseudo R-squared	0.123

SEs in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Sources: calculations based on EMIR and Orbis Europe data.

The estimated model, however, also highlights how country and sector dummies are still strongly significant and suggests us to further investigate whether the model can be improved by adding other variables in our logit regression.

Based on data availability, we look then at a set of financial indicators suggested by the literature analysed above which could provide us with further explanations. In particular, we focus on leverage and debt maturity, liquidity, solvency, profitability, capital/R&D investments and exports.

16 The probabilistic models reported below report contributions from variables in the format of odds ratios. An odds ratio higher than 1 determines the positive contribution of an independent variable on the outcome variable. An odds ratio lower than 1 determines the negative contribution of an independent variable on the outcome variable

Table 4. Logit regression results – financial indicators

Variables	Trading odds ratio
Small	1.568***
Medium	2.058***
Large	4.205***
Country dummies	2.083***
Sector dummies	7.987***
Leverage and debt maturity	
debtequityratio	1.000
liabilitiesassetratio	1.000
ltdebteqratio	1.000
ltdebttotalassetsratio	0.439***
Liquidity	
currentratio	1.000
liquidityratio	0.996***
Solvency	
solvencyratio	1.003***
Profitability	
ebitdamargin	0.990***
ebitmargin	1.003***
profitmargin	1.008***
Capital/R&D investments	
capexpendituresturnoverratio	1.000
randdexpensesturnoverratio	0.534
capexpendituressalesratio	1.000
randdexpensessalesratio	1.105
marketbookratio	0.992
ntangbookratio	1.000
Exports	
exportrevenueratio	1.929***
Constant	0.0289***
Observations	106,908
Pseudo R-squared	0.135

*** p<0.01, ** p<0.05, * p<0.1

Sources: calculations based on EMIR and Orbis Europe data.

As shown in Table 4, the probability of trading derivatives is now strongly related not only to the size of the company, its sector or where it is located but also by its main financial indicators. In particular, the solvency ratio, the long-term-debt-to-asset ratio, the export-revenue ratio and the profitability ratios seem to be the most significant drivers.

The results seem to suggest that high-exporting firms and those with shorter debt maturity are the more likely to trade derivatives in the sample analysed. This finding is in line with our demographic analysis which highlighted how firms in this sample are using for a vast majority currency forwards which are common in the trading sectors. Moreover, even though less significant, the impact of the solvency ratio and liquidity ratio is in line with the literature suggesting that firms which are financially stable firms[17] but at the same time also less-liquid firms[18] are the main actors on the derivative markets. With respect to profitability instead, we find significant but diverging results depending on the ratios used: if we consider profits including those coming from financial activities (i.e. profit margin) these show a positive sign as such activities are typically more relevant for larger firms. On the other hand, if we focus solely on operating profits (i.e. the ebitda margin) then we find that less profitable firms are more likely to use derivatives as suggested by the literature on financial distress.

Once defined the characteristics of firms trading derivatives against those non-trading, we decided to investigate whether there are differences among trading firms in the choice of the asset class of the financial contract.

From our demographic analysis in the paragraphs above we could already identify an intense concentration of firms on the trading of forward contracts with currency as the underlying asset. Therefore, in order to obtain results easy to interpret we use currency contracts as benchmark to run a multinomial logistic regression (Table 5).

17 Among others, Berkman and Bradbury (1996), Borokhovich et al. (2004), Carroll et el (2017), Fok et al. (1997), Geczy et al. (1997), Graham and Rogers (2002), Guay (1999), Judge (2006) Lel (2012), Lin and Smith (2007), Mian (1996), Nance et al. (1993), Rogers, (2002).

18 Among others, Ang et al. (1982), Nance et al. (1993), Smith and Stulz (1985), Warner (1977).

Table 5. Multinomial logit regression results – asset classes

Variables	COMM odds ratio	CRD odds ratio	CURR odds ratio	EQUI odds ratio	INTR odds ratio
Small	0.805*	1.375		0.243***	0.925
Medium	1.590***	14.35**		0.180***	1.044
Large	3.865***	17.31**		0.433***	0.883
Country dummies	*	*		*	*
Sector dummies	*	*		*	*
solvencyratio	1.000	0.999		0.995***	1.000
ltdebttotalassetsratio	1.615***	0.518		1.628**	7.049***
exportrevenueratio	0.294***	0.359		0.320**	0.237***
ebitdamargin	0.996	0.997		1.002	1.027***
ebitmargin	0.996	1.032**		0.997	0.996
profitmargin	0.994**	0.968**		1.004	0.995**
liquidityratio	1.001	0.991		1.030***	0.988**
Constant	0.203***	0		0.0720**	0.391***
Observations	19,562	19,562	19,562	19,562	19,562
Pseudo R-squared	0.205	0.205	0.205	0.205	0.205

*** p<0.01, ** <0.05, * p<0.1

Sources: calculations based on EMIR and Orbis Europe data.

The results allow us to draw the following "identikit":

- Currency derivatives are strongly exchanged by the most exporting firms, with a lower long term debt and with higher profit margins.
- Commodity derivatives are more likely to be traded by large, relatively less exporting and less profitable firms.
- Credit derivatives are generally traded by the same type of firms trading currency derivatives, with the difference that credit derivative trading firms are generally much bigger.
- Equity derivatives are generally traded by firms which are less solvent but more liquid and significantly smaller than those trading currency derivatives.
- Interest rate derivatives are generally traded by more indebted and less liquid firms.

The effects of country and sector dummies are often significant and further analysis should be done on the differences arising across these categories but in this paper we want to keep them as control variables and focus our analysis on financial ratios.

These results, although statistically significant, might be driven by the limited temporal window of available data we are looking at and might therefore not take into account the seasonality of derivative markets. Moreover, the high percentage of missing values among the reported asset classes and the bias towards currency derivatives in the sample might also hide different data dynamics. However, such first identification of predominant characteristics of trading firms and how these vary by type of traded product can add value to the existing literature which so far did not have such a wide database available.

5. Conclusions

The study we carried on is a first analysis of a novel dataset obtained by merging the EMIR data with Orbis Europe. After analysing the literature on the use of derivatives by non-financial corporations, we describe the first findings obtained by looking at the descriptive statistics on demographic variables such as country, sector and size of the entity. These suggest, in line with the research already carried out in this field, that size matters when trading derivatives. We then take a look more in depth into which are the financial ratios described by the literature as having higher impact on the probability of trading derivatives and we discover that the high export ratios and low long-term-debt ratios strongly characterise firms trading derivatives, in line with the fact that the most traded derivatives in our sample are currency forwards.

Last but not least, we go further trying to identify differences in the characteristics of the firms trading derivatives across different types of asset classes and we introduce a novel identikit of financial ratios which makes more likely for a non-financial corporation to be trading a specific type of derivative contract.

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Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

An insight into the derivatives trading of firms in the euro area[1]

Nicola Benatti and Francesco Napolitano,
European Central Bank

[1] This presentation was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

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An insight into the derivatives trading of firms in the euro area

9th IFC Conference on

Are post-crisis statistical initiatives completed?

30-31 August 2018, BIS, Basel

Overview

Why do firms decide to use financial derivatives?

Hedging against cash flow volatility by increasing "debt capacity" in a context of imperfect capital markets

Common cases in the literature:

- Reducing risk of financial distress[1]
- Reducing expected value of tax liabilities[2]
- Financing investment plans[3]

Our contribution:

- Exploratory analysis of EMIR transaction-level data on derivatives traded by NFCs focusing on euro area countries
- Research questions: *Does firm size matter? Which types of firms use derivatives? Which firms prefer which types of derivatives?*

[1] Mayers and Smith, 1982; Myers, 1984; Stulz, 1984; Smith and Stulz, 1985; Shapiro and Titman, 1998
[2] Smith and Stulz, 1985; Nance et al., 1993; Graham and Smith, 1999; Graham and Rogers, 2002
[3] Bessembinder, 1991, Froot et al., 1993

Data sources

Orbis Europe balance sheet data

- Firm-level data on annual balance sheets and other financial information
- Commercial data provider (Bureau van Dijk) collecting data from national offices in charge of collecting annual accounts in the respective country.
- About 86 million European firms. Data coverage varies across countries.

EMIR data

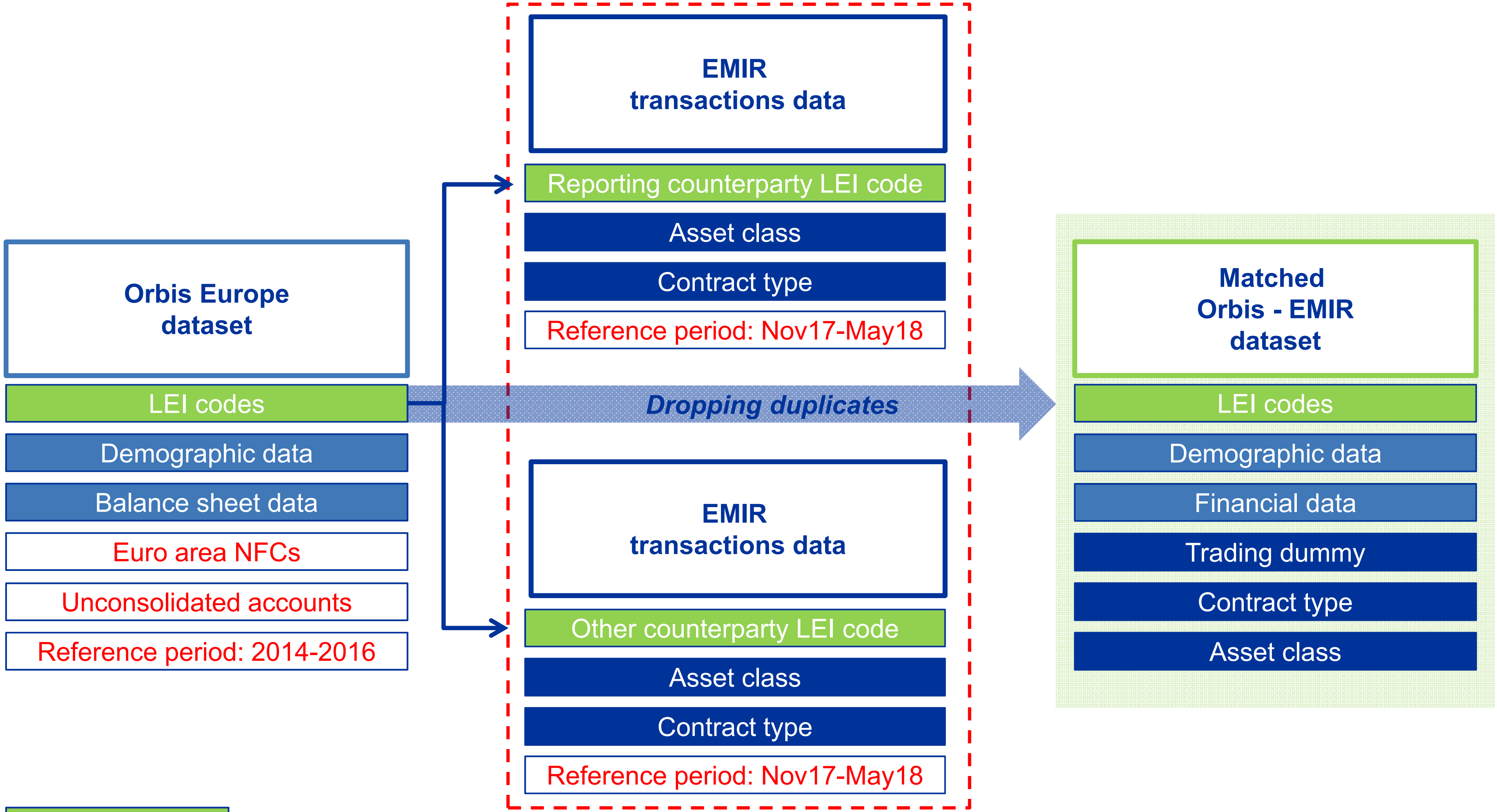
- Transaction-level derivatives data for all counterparties established in the euro area and all contracts where the reference entity is located within the euro area or where the reference obligation is sovereign debt of a euro area member.
- Collected by six Trade Repositories (TRs) under the European Market Infrastructure Regulation (EMIR) since February 2014 and shared with 60 competent authorities (including the ECB).
- All contract types (OTC and ETD) and instrument classes (equity, credit, interest rates, commodities, foreign exchanges).
- More than 120 reporting fields.
- “Double reporting regime” ensuring validation and consistency controls but standardisation problems (i.e. the lack of a global trade ID) generate data reconciliation issues.

Focus of the analysis

- ➢ EMIR data collected as of November 2017 (in compliance with the latest regulatory standards).
- ➢ Orbis data for firms identifiable with an LEI
- ➢ Qualitative information on derivatives usage by NFCs (use/no use, contract type, asset class).
- ➢ Timing considerations: Orbis (2014-2016 reports) – EMIR (Nov17-May18 new transactions)

Matching EMIR and Orbis

ECB-UNRESTRICTED



Matching ID

Orbis variables

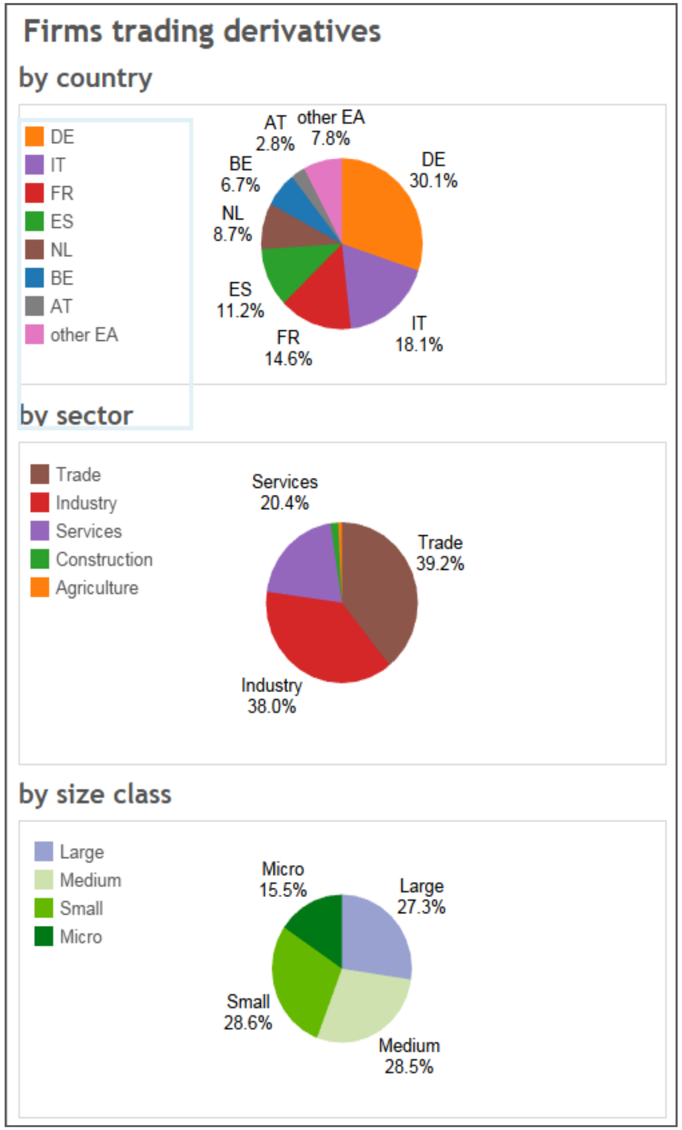
EMIR variables

Filters

__56%__ of euro area NFCs reported in EMIR can be matched with Orbis through the LEI code!

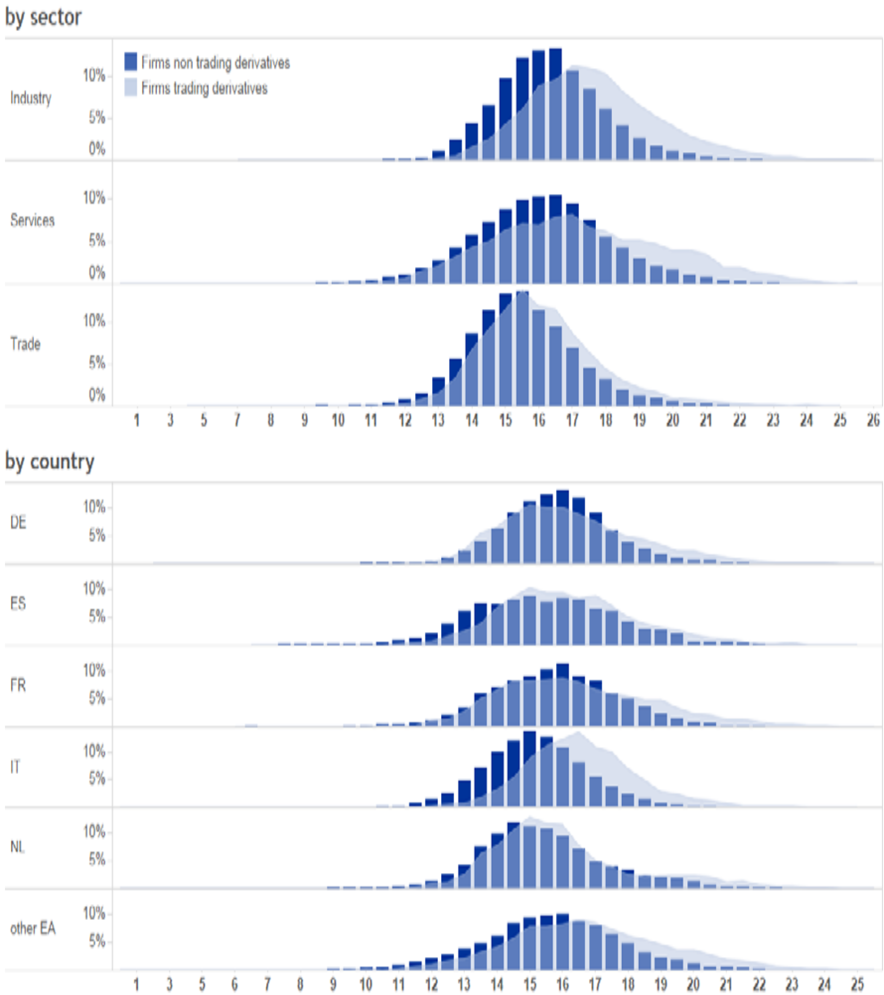
An insight into euro area NFCs trading derivatives

ECB-UNRESTRICTED

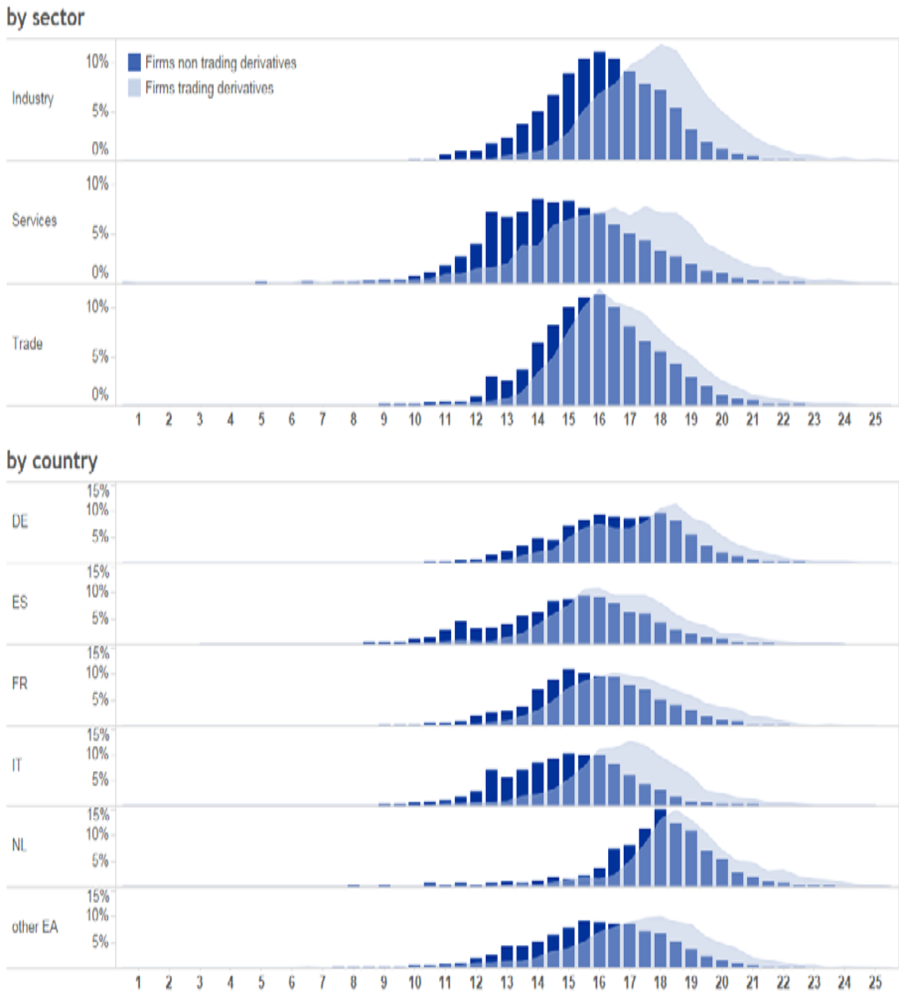


Firm size matters but the impact is different across countries and sectors

Total assets (natural log)



Turnover (natural log)



Variables	Trading odds ratio
Small	1.568***
Medium	2.058***
Large	4.205***
Country dummies	2.083***
Sector dummies	7.987***
Leverage and debt maturity	
debtequityratio	1.000
liabilitiesassetratio	1.000
ltdebteqratio	1.000
ltdebttotalassetsratio	0.439***
Liquidity	
currentratio	1.000
liquidityratio	0.996***
Solvency	
solvencyratio	1.003***
Profitability	
ebitdamargin	0.990***
ebitmargin	1.003***
profitmargin	1.008***
Capital/R&D investments	
capexpendituresturnoverratio	1.000
randdexpensesturnoverratio	0.534
capexpendituressalesratio	1.000
randdexpensessalesratio	1.105
marketbookratio	0.992
Exports	
exportrevenueratio	1.929***
intangbookratio	1.000
Constant	0.0289***
Observations	106,908
Pseudo R-squared	0.135

*** p<0.01, ** p<0.05, * p<0.1

Moving beyond firm size…

- Export-oriented (majority of firms in the sample use currency forwards)
- Short-term debt maturity
- Financially stable but also less liquid firms
- Mixed results on profitability
- Country and sector characteristics play a significant role

Variables	COMM odds ratio	CRD odds ratio	CURR odds ratio	EQUI odds ratio	INTR odds ratio
Small	0.805*	1.375		0.243***	0.925
Medium	1.590***	14.35**		0.180***	1.044
Large	3.865***	17.31**		0.433***	0.883
Country dummies	*	*		*	*
Sector dummies	*	*		*	*
solvencyratio	1.000	0.999		0.995***	1.000
ltdebttotalassetsratio	1.615***	0.518		1.628**	7.049***
exportrevenueratio	0.294***	0.359		0.320**	0.237***
ebitdamargin	0.996	0.997		1.002	1.027***
ebitmargin	0.996	1.032**		0.997	0.996
profitmargin	0.994**	0.968**		1.004	0.995**
liquidityratio	1.001	0.991		1.030***	0.988**
Constant	0.203***	0		0.0720**	0.391***
Observations	19,562	19,562	19,562	19,562	19,562
Pseudo R-squared	0.205	0.205	0.205	0.205	0.205

*** p<0.01, ** p<0.05, * p<0.1

…and looking at asset classes, we get the following profiles:

- Currency derivatives are strongly exchanged by the most exporting firms, with a lower long term debt and with higher profit margins.
- Commodity derivatives are more likely to be traded by large, relatively less exporting and less profitable firms.
- Credit derivatives are generally traded by the same type of firms trading currency derivatives, with the difference that credit derivative trading firms are generally much bigger.
- Equity derivatives are generally traded by firms which are less solvent but more liquid and significantly smaller than those trading currency derivatives.
- Interest rate derivatives are generally traded by more indebted and less liquid firms.

Conclusions

- First exploratory analysis of EMIR transaction-level data on derivatives traded by NFCs
- Demographic analysis suggests that firm size matters but differences exist across countries and sectors.
- Logit regression results confirm the role of firms size and suggest that high exports and lower long-term debt ratios are common characteristics of firms trading derivatives in our sample. Financially stable but less liquid firms also decide to use derivatives.
- We go further in trying to identify specific profiles of firms in relation to different types of derivatives.

Challenges and way forward:

- Enlarge the time coverage of the dataset.
- Go deeper in the analysis of NFCs' derivatives trading using quantitative information on number of contracts and notional amounts.
- Country and sector analysis.

Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

The risk-taking channel of monetary policy in Macedonia: evidence from credit registry data[1]

Mite Miteski, Ana Mitreska and Mihajlo Vaskov,

National Bank of the Republic of Macedonia

[1] This paper was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

The Risk-Taking Channel of Monetary Policy in Macedonia: Evidence from Credit Registry Data

Mite Miteski[1], Ana Mitreska[1] and Mihajlo Vaskov[2]

Abstract

This paper is the first effort to empirically investigate the potential existence of the monetary policy risk-taking channel in Macedonia. For this purpose we use a rather unique and confidential database of corporate loans, taken from the Credit Registry of the National bank, which is complemented with data from banks' balance sheets. By using pooled OLS on semi-annual data for the 2010-2017 period, our study points to an inverse relationship between the policy rate and the ex-ante risk rating assigned by the banks, a finding that is supportive to the existence of the risk-taking channel. The results prove to be robust after controlling for several bank, loan and time specific variables. We also test for possible difference in the risk-taking by banks conditioned on the leverage level, but the results do not point to a significant difference in the reaction.

Keywords: Monetary policy, risk-taking, ex-ante credit risk, leverage, POLS

JEL classification: E43, E44, E52, G21

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The opinions and views expressed in this paper are only those of the authors and do not necessarily reflect the position and views of the National Bank of the Republic of Macedonia. The authors are grateful to Marko Josimovski for his assistance in the design of the database. Any errors or omissions are the responsibility of the authors.

Contents

1. Introduction

The latest global crisis revisited many of the previously conventional economic paradigms, including those related to monetary policy transmission. The main "novelty" in this area was the increasing focus on the link between policy rates and the quality of the credits extended by banks, and hence the risk undertaken. In a low interest rate environment, the incentive of banks to assume more risk in their balance sheets rises. They lax their lending standards or start a yield searching path, thus shifting from safe to riskier assets.

Borio and Zhu (2008) noted that prior to the crisis not sufficient emphasize was put on understanding the link "between monetary policy and perceptions and pricing of risk by economic agents", what they mark as monetary policy "risk-taking channel". They argue that the central bank through the changes in its policy reaction can affect risk-taking, by imposing changes on risk perceptions and tolerance to risk.

In this paper, we attempt to explore the risk-taking channel of monetary policy in Macedonia. For this purpose, we employ micro data on individual corporate loans, utilizing the confidential database from the Credit Registry of the Central bank. We study the linkage between the effective interest rate of the central bank and the so-called ex-ante risk-taking by the banks, while controlling for several loan, bank and time specific variables. To our best knowledge, this is a first attempt to estimate the risk-taking monetary police channel for Macedonia, and a first attempt to use the rich data set from the Credit Registry for a more comprehensive empirical investigation. Hence the paper has two important contributions, the first one related to the specifics of the topic, which has not been explored before, and the second related to the first-time utilisation of a unique database.

The paper is organised as follows. Section 2 briefly discusses the literature on risk-taking monetary policy channel, with focus on the empirical literature on the issue, only. Section 3 reflects on the model specification, while Section 4 explains the data used. Section 5 refers to the chosen empirical methodology and discusses the main findings. Section 6 presents the results of several robustness checks, and finally, Section 7 concludes.

2. Related literature

Despite the rising policy interest on the risk-taking channel, the empirical literature on the issue is rather new and scant. It does not come as surprise, given the fact that the discussion on the monetary policy risk-taking channel, particularly came to the fore after the outburst of the global crisis. In addition, the estimate of this channel often requires granular micro, or survey data, which has not been easily and readily available across countries.

Gaggl et al. (2010) explored the risk-taking channel in Austria, using a unique dataset that matches lenders and borrowers, accounting for a major part of Austrian business lending. Data is taken from the annual balance sheets and income statements of companies, as well as from the Credit Registry in the Austrian central bank. The research does support the risk-taking channel for the Austrian case.

López et al. (2010) estimate the monetary policy risk-taking channel on the case of Columbia, using database with a quarterly frequency for more than two million loans for the period 2000-2008. By using a duration model they find a significant link between low interest rates and banks' risk-taking based on evidence from Colombia. Lower interest rates raise the probability of default on new loans, but reduce that on outstanding loans.

Dell'Ariccia et al. (2013), which our paper is closely related to, study the link between the short term interest rate and risk-taking, using confidential data on individual U.S. banks' loan rating from the Federal Reserve's Survey of Terms of Business lending. In the paper, the authors explore the link between the ex-ante risk rating of the banks and the short-term policy rate. They employ panel estimate on a loan level data, on a stratified sample of about 400 banks, over the 1997-2011 period, with a quarterly frequency. They reveal a negative relation between risk rating and the interest rate, providing strong evidence that low short-term interest rate environment increases bank risk-taking. They also provide evidence that this effect is strongly dependant on the level of bank's capitalization, with the effect of risk-taking being more pronounced for well capitalized banks.

Bonfim and Soares (2013) use the data on loans to non-financial corporations from the Portuguese Credit Register for the 1999-2007 period. Credit registry data is used, and firm-bank relationship in a given quarter is the main unit of observation. The authors use discrete choice models to assess the probability of borrowers with bad credit history or no credit history being granted loans. The approach also allows to test whether banks grant more loans to risky borrowers, when interest rates are lower. The results from the discrete choice models show that lower interest rates increase the probability of bank granting a loan to a borrower with recent bad credit history, and the risk-taking is more evident in smaller banks. While ex-ante risk is higher, the survival analysis does not confirm the increase in risk-taking ex-post, i.e. over the life of the loan.

Jiménez et al. (2014) explore the existence of the monetary policy risk-taking in Spain by using a comprehensive database from the credit registry of Spain. The authors assess the monthly information on loan application, from 2002 until 2009, matched with the resulting granting loans and the main bank and firm-level information. They use a two-stage model, in which they explain the monthly granting in the first stage and the actual outcome in the second stage, while controlling for both observed and unobserved, time varying, firm and bank heterogeneity. They infer that a lower overnight interest rate induces banks that are less capitalized to grant more loans to ex-ante risky firms and to extend larger loan volumes with less of collateral, but with a higher ex-post probability of default.

Karapetyan A. (2016) explores the risk-taking channel in Norway, by using a unique dataset of corporate borrowers. Within the model, data on newly extended loans or the change in the total credit exposure between the bank and the firm is used as dependant variable, while the risk rating of the firm, policy rate and several bank specific and macro variables are employed as control variables. The paper finds that a lower benchmark interest rate induces the bank to grant more loans to risky firms.

3. Model specification

In the paper, we follow the model of Dell'Ariccia et al., where authors argue that the policy rate affects banks' deposit rates and bank motivation for risk-taking through two different channels. First, the so-called pass-through effect exists, when the increase of the policy rate affects deposit rates, and then lending rates. Hence, if the bank is successful in managing the credit portfolio, the reward for the success is higher. Therefore, it is highly motivated to monitor the quality of the credit portfolio closely and to maximize the return on it. The second channel is the classical risk-shifting, when due to the increase of the policy rate, costs of funding increase as well, reducing banks' profit margins (other things equal) in case of success and hence reduces its incentive to monitor its portfolio. They also emphasize that the relative size of the two channels is conditioned on the bank leverage, or in other words on bank's capitalization. The risk-shifting effect is high for fully leveraged banks, and it descends to zero for a bank fully funded with capital. In the model that they use, the first effect prevails, and the main expected outcome of the model is to find a negative relationship between banks' risk-taking and the policy rate of the central bank. When the policy rate is low or declining, banks assume more ex-ante credit risk, and vice versa. Another important, but a very strong assumption in the model is that monetary policy changes, i.e. changes in the policy rate, are fully exogenous to the banks' risk-taking.

Following Dell'Ariccia et al., our main empirical model specification takes the following form:

$$LRR_{kit}=\lambda_i+ \beta r_t+ \eta K_{it}+\mu L_{kit}+\Omega B_{it}+\varepsilon_{kit}$$

where, LRR_{kit} is the loan risk rating of loan k, extended by bank i during the semester t, and this is the measure used in the model specification to gauge the ex-ante risk rating that the bank assigns to the specific loan party. λ_i are bank-specific effects, r_t is the Central bank's effective interest rate, K_{it} refers to a measure of bank's capitalisation at the end of time t, L_{kit} embeds a set of loan specific variables (size, maturity, indicator of collateral backing), and B_{it} refers to a set of bank specific variables at the end of time, other than capitalisation (in essence it includes total assets, as a measure of bank's size). The main coefficient of interest, which is the essence of our research question, is the β coefficient, which is expected to be negative and hence, indicative for a presence of risk-taking channel in Macedonia.

Furthermore, we proceed with the second block of estimation, where an interaction term between policy rate and the capitalisation measure is employed. The inclusion of the interaction term aims to test the hypothesis that low interest rates do increase banks' risk-taking, especially for banks with relatively high capital, i.e. low leverage. To support this notion the expected sign of the coefficient ν in front of the interaction terms is expected to be negative.

$$LRR_{kit}=\lambda_i+ \beta r_t+ \eta K_{it}+\nu K_{it}r_t+\mu L_{kit}+\Omega B_{it}+\varepsilon_{kit}$$

4. Data

4.1. Credit Registry of the National Bank of the Republic of Macedonia

Given that the Credit Registry of the National bank is the main data source, in the paper we provide a separate section on its main features. The National Bank of the Republic of Macedonia is legally obliged to establish and maintain a Credit Registry of domestically founded banks' and saving houses' credit exposures to legal entities and individuals. This Credit Registry constitutes an electronic base of data and information on the credit exposures of deposit-taking financial institutions to their clients[3], the main purpose of which is to contribute to improvement in the loan quality and the maintenance of the stability of the banking system.

The Credit Registry of the National Bank was established in 1998. Ever since its establishment, the Credit Registry has undergone several changes, with some more substantial improvements taking place in 2008/2009. Hence, when performing any data series analysis, 2009/2010 is usually taken as a starting point, as for consistency of data employed to be ensured. Since 2009, deposit-taking financial institutions are obliged to submit data to Credit Registry for any individual contract made with clients (legal entities and individuals), that is (even potentially[4]) generating exposure to credit risk, with a monthly frequency. Some minimum thresholds in the amount of individual credit contracts are imposed when submitting data to Credit Registry.

4.2. Dataset and definition of variables

The dataset used in our empirical model covers the seven largest banks in the country (out of 15[5]), with a market share on the corporate credit segment, varying between 87-89%. We use data with a semi-annual frequency over the period 2010H1-2017H1.

Loan specific variables

We use data on individual new loans[6] extended to non-financial companies during each half-year of the time period covered. New loans extended in a process of restructuring of previously approved loans (when replacing old loan with a new one) are also included in the study. Due to the huge number of loans extended in relatively small amounts, we have reduced our sample, focusing only on loans with individual amounts exceeding the mean value calculated for each analysed period.

3 Banks and saving houses are the only functional (and allowed by Law) deposit-taking financial institutions in the Republic of Macedonia.

4 Off-balance sheet activities, e.g. irrevocable credit commitments and overdrafts, uncovered guarantees and letters of credit, etc.

5 There were 18 banks in 2010.

6 For the sake of simplicity, we will be using the term "loan" throughout the remaining of the paper. However, besides classical agreements for loans, data on newly concluded leasing contracts and factoring and forfaiting agreements made with banks' clients are covered as well (although having negligibly small amounts), as such data is also reported by our banks. Additionally, off-balance sheet activities with non-financial companies, which could potentially generate credit risk to the bank, are also taken into account.

Risk rating is the risk category assigned[7] by the bank to a given loan, as reported in the Credit Registry of the National Bank of the Republic of Macedonia. According to regulation, when classifying any credit exposure to a certain risk category, the bank should take into account the creditworthiness of the client, its regularity in debts repayment and the collateral provided for the particular credit exposure. Thus, the loan is classified in one of the five risk categories, as prescribed in the regulation, from A (having the lowest level of riskiness) up to E (having the highest level of riskiness). For the purpose of our study, the risk categories are translated into corresponding numerical values, thus obtaining a discrete index that increases with higher perceived risk (A=1, B=2, C=3, D=4 and E=5)[8]. The risk categories assigned to loans extended in each half-year period covered in the analysis refer to loans classification made as of the end of the respective half-year period. As such, these risk categories might be considered as proper ex-ante risk ratings assigned by the bank to a given new loan.

We also consider several control variables, pertaining to some of the basic loan characteristics: the size of the loan (measured in logs), the original maturity of the loan (in years), and dummy variable on whether or not the loan is secured by collateral (takes value 1 for secured loans, and 0 otherwise). For the purpose of our study, loans with co-credit borrower or where endorser is appointed and/or are secured by a bill of exchange only (and none of the other types of collateral) are considered as unsecured.

Bank specific variables

We complement data from the Credit Registry with balance sheet information[9] on banks' total assets (measured in logs) and their capital positions. As for the latter, regulatory capital ratio is employed (the Tier 1 ratio), calculated as a share of banks' Tier 1 regulatory capital in risk weighted assets[10]. Alternatively, in some of the specifications, the capitalization ratio is used- calculated as a share of banks' equity and reserves in total assets.

[7] More precisely, banks do not report the risk category of a particular loan, but the percentage of impairment losses determined for that particular loan. Depending on the reported percentage of impairment losses, the risk category of each particular loan can be obtained (from A to E), as prescribed in the regulation on credit risk management.

[8] According to our regulation, loans classified in D and E are considered as non-performing, as well as loans classified in risk category C, which, on any basis, have not been collected in more than 90 days from the date of maturity. Potentially useful information with reference to our study is the fact that banks are obliged to classify restructured loans, at least, in risk category C, or even higher (D or E). The regulation on credit risk management provides a list of criteria upon which, individual credit exposures should be classified by banks, in the respective risk category (Decision on credit risk management, available at: http://www.nbrm.mk/ns-newsarticle-decision_credit_risk_2013.nspx.

[9] As reported by banks according to Decision on submitting data on the accounts balances and value entries in banks' general ledger and financial statements (Official Gazette of the Republic of Macedonia No. 126/11), available at (in Macedonian only): http://www.nbrm.mk/ns-newsarticle-odluka_za_dostavuvanjie_podatotsi_za_sostojbata_i_promietot_na_smietkitie_od_smietkovniot_plan_na_bankitie_i_finansiskitie_izvieshtai.nspx.

[10] As reported by banks according to Decision on the methodology for determining the capital adequacy (Official Gazette of the Republic of Macedonia No. 47/12, 50/13, 71/14, 223/15, 218/16), available at: http://www.nbrm.mk/ns-newsarticle-decision_capital_adequacy_2012.nspx.

Time specific variables

Within the study, the main policy rate of the central bank should be used as a relevant short-term rate in the economy. In the Macedonian case, the interest rate on the one-month Central Bank bills (CB bills) is the key rate, which reflects the monetary policy stance. Yet, in April 2012, the portfolio of monetary instruments was enriched with the introduction of the overnight deposits and seven-day deposits that are also relevant for banks' decisions. Hence, for the purpose of the study, until April 2012 we do use the CB bills rate, but as of April 2012 we calculate an effective interest rate. It is a volume-weighted average of the interest rates on all three instruments.

In some of the specifications we also try to control for the specifics of the economy, throughout the time horizon used in the estimates. For this purpose we use a variable which should broadly capture these effects, i.e. the real GDP growth.

5. Methodology and empirical results

In this section we present the methodology used for the estimation and the empirical findings from the estimated model. Our main interest is focused on the reaction of the ex-ante credit rating of newly granted loans to the changes in the key policy rate. This will allow us to draw conclusions on whether a new, risk-taking channel of monetary policy exists in Macedonia, apart from the more traditional channels.

In the search for the appropriate estimator we have to take into account the specifics of our sample. Namely, as mentioned previously, we are dealing with a dataset which consists of time-specific, bank-specific and loan-specific variables. Although the time and bank-specific variables can be dynamically tracked, this is not the case with the loan-specific variables (including most importantly the dependent variable) because each new loan occurs only once, at the date of approval and is not followed afterwards. By construction, this means that there are many loans per period, per bank, which makes our dataset non-longitudinal, so typical panel analysis exploiting the time dimension, cannot be conducted. However, given that the research question that we try to address does not require use of any time series operators or autoregressive panel models, we can still use static panel models even on the series of cross-sections in our sample. The reason why we opt to follow this approach is in order to control for the bank-level fixed effects and thus to alleviate the potential omitted variable bias. Namely, it is presumable that there are some fixed effects, specific to each individual bank that impact the bank's risk behaviour, and which are not captured in the fully unrestricted model. This is also known as unobserved heterogeneity, which is one of the many sources of endogeneity. However, by applying this estimator, the diagnostics tests show that the model suffers from considerable heteroscedasticity which influences the inference. Due to the fact that our number of clusters is very small (in our case we have only 7 banks and 15 separate time periods), we cannot use cluster robust standard errors to correct for the problem of heteroscedasticity of the error structure. Namely, in the case of few clusters, cluster-robust standard errors are no longer valid, as their derivation relies on asymptotic results. Not just that this would not be an improvement over the non-robust standard errors, in fact it might make matters worse. For that reason, we opt to using the pooled OLS

(POLS) estimator as an alternative approach, with heteroscedasticity-consistent standard errors. In addition, mimicking the fixed effects estimator, a full set of bank dummy variables is also included in the model to control for the unobserved bank-level heterogeneity. We expect this to capture some of the effects from omitted variables that vary across banks, but not time. The inclusion of bank dummy variables is also supported by the joint significance of the fixed effects in the standard fixed-effects model and by the significance of the general F-test in the OLS regressions.

Loan risk ratings, the CB bills rate and bank and loan characteristics

Dependent variable: risk rating of individual loans Table 1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
CB bills rate	-0.015***	-0.012***	-0.012***	-0.012***	-0.012***	-0.013***	-0.011**
	[0.002]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]
Tier 1 capital ratio		0.266**	0.264**	0.264**	0.253**	0.246**	0.316**
		[0.123]	[0.123]	[0.123]	[0.123]	[0.123]	[0.127]
Bank size		0.014	0.014	0.014	0.013	0.011	0.023
		[0.023]	[0.023]	[0.023]	[0.023]	[0.023]	[0.023]
Loan size			0.003			-0.002	-0.002
			[0.003]			[0.003]	[0.003]
Dummy for loans with collateral				-0.004		-0.012**	-0.011*
				[0.006]		[0.006]	[0.006]
Loan maturity					0.010***	0.010***	0.010***
					[0.001]	[0.001]	[0.001]
GDP growth							0.007***
							[0.001]
Constant	1.185***	0.874**	0.865**	0.894**	0.888**	0.957**	0.693
	[0.010]	[0.438]	[0.438]	[0.437]	[0.439]	[0.437]	[0.448]
Observations	29,074	29,074	29,074	29,074	29,074	29,074	29,074
Number of banks	7	7	7	7	7	7	7
Bank dummy variables	YES	YES	YES	YES	YES	YES	YES
R-squared	0.137	0.137	0.137	0.137	0.140	0.140	0.140

Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1

Source: Authors' calculations.

In line with the expectations, the results show that the short-term interest rate has a negative and significant effect on ex-ante bank risk-taking, which is a finding akin to studies in other countries (Dell'Ariccia et al. (2013), Ioannidou et al. (2014), Jimenez et al. (2014)). This provides evidence of a potential risk-taking channel of the monetary policy in Macedonia, indicating that monetary policy actions may affect not only the quantity, but also the quality of banks' lending. As it can be seen from the table, the interest rate maintains its significant negative effect even after controlling for bank-specific (column 2) and loan-specific variables (columns 3-6). Moreover, the coefficient on interest rate is fairly stable in magnitude and varies between -0.011 and -0.015. The estimation results in column 2, where we control for the different bank characteristics suggest that a reduction of the interest rate of one standard deviation (1.025) is associated with an increase in loan risk ratings of 0.012. However, compared with the standard deviation of loan risk ratings of 0.46, albeit statistically significant, this appears to be a very small economic effect.

In order to extend the analysis of the relationship between monetary policy and bank risk-taking, in columns 3-6 we control for the distinct loan characteristics that are most likely to affect risk ratings, such as loan amount, maturity and collateral, by including them first successively, and then jointly in the estimation. The results show that the economic and statistical significance of the interest rate in the specification using the full set of independent variables (column 6) is very similar to the estimation which controlled only for the bank-specific variables. The effect of the other bank-specific variables on the risk rating is also similar. Namely, we find that the coefficient on Tier 1 capital ratio is positive and significant in all regressions, implying that the increase in the level of capitalization of banks leads to increase in their risk appetite. The literature offers contradictory results as to the effects of bank capital on banks' risk appetite. On the one hand, some authors find that better capitalized banks are safer and have a lower risk exposure (Dell'Ariccia et al., 2013), while other authors report opposite results (Ioannidou et al., 2014, Bonfim and Soares, 2013). Our results are consistent with the latter line of research. One explanation might be that banks with higher capital might tolerate higher losses, and therefore take higher risk. Regarding the loan-specific variables, we find that although the amount of the loan has no significant implications for the credit rating, there is a positive and significant relationship between the rating and the loan maturity, meaning that loans with longer maturity tend to have poorer ex-ante credit ratings. Similarly, whether a loan is secured by collateral or not also plays a significant role for the ex-ante credit rating. However, this relationship is negative, with collateralized loans reducing banks' risk-taking, since ex ante they are assigned better credit ratings on average than non-collateralized loans. Also, when we include GDP growth in order to control for the effects of the macroeconomic environment on the demand for loans that might be related with the dependent variable, results remain broadly unaltered (column 7). Moreover, the relationship between GDP growth and risk-taking is positive, indicating a certain pro-cyclicality in the banks' risk behaviour. The explanation might be that higher growth rates lead to a rise in banks' optimism and tolerance to risk which, in turn, results in approval of ex-ante riskier loans.

Next, we test whether the strength of the interest rate effect on banks' risk-taking depends on their levels of capitalization. This hypothesis is developed in the simple model of Dell'Ariccia et al. (2013), according to which low interest rates increase banks' risk-taking, especially for banks with relatively high capital (low leverage). For that reason, in specification (2) of Table 2 we include the interaction term between the Central bank bills rate and the Tier 1 capital ratio, among the other regressors[11]. It is expected a priori the coefficient on the interaction term to be negative, which would indicate a stronger effect of interest rate cuts on risk-taking of highly capitalized banks (Dell'Ariccia et al., 2013).

[11] Similar estimation is also done by including the interaction term between the bank assets and the interest rate, to investigate whether there is a differential effect of bank size on the link between the interest rate and risk taking. However, the results show that both bank size and the interaction term are not statistically significant and for the sake of brevity they are not reported.

Loan risk ratings and the interaction between the CB bills rate and bank capital

Dependent variable: risk rating of individual loans — Table 2

	(1)	(2)	(3)
CB bills rate	-0.013***	-0.027***	-0.035***
	[0.004]	[0.007]	[0.008]
Tier 1 capital ratio	0.246**	-0.177	
	[0.123]	[0.240]	
Tier 1 capital ratio x CB bills rate		0.116***	
		[0.044]	
Equity-assets ratio			-0.220
			[0.384]
Equity-assets ratio x CB bills rate			0.277***
			[0.073]
Bank size	0.011	0.019	0.049**
	[0.023]	[0.022]	[0.021]
Loan size	-0.002	-0.002	-0.002
	[0.003]	[0.003]	[0.003]
Dummy for loans with collateral	-0.012**	-0.012**	-0.012*
	[0.006]	[0.006]	[0.006]
Loan maturity	0.010***	0.010***	0.010***
	[0.001]	[0.001]	[0.001]
Constant	0.957**	0.867**	0.283
	[0.437]	[0.431]	[0.407]
Observations	29,074	29,074	29,074
Number of banks	7	7	7
Bank dummy variables	YES	YES	YES
R-squared	0.140	0.140	0.141

Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1

Source: Authors' calculations.

The results from this specification confirm in general the ones without the interaction term[12]. As it can be seen, we again obtain a statistically significant, negative coefficient on the short-term interest rate, which appears to be somewhat larger in magnitude. However, opposite to the theoretical suggestions in Dell'Ariccia et al. (2013), we find that the coefficient on the interaction term between bank capital and the interest rate is positive and significant. Given the negative coefficient on the interest rate, the interpretation in the model with the interaction term is not straightforward, and requires an additional calculation of the marginal effect of the interest rate on risk rating, while holding the capital ratio constant at representative values. Indeed, the calculation points to a negative marginal effect, but with minimal economic significance. Namely, based on the estimation results presented in column 2 of Table 2, when evaluated at one standard deviation below the mean of

[12] Note that in this case the coefficient on Tier 1 capital ratio changes signs and becomes statistically not significant. However, the tests of the main effects in this model do not test the same hypotheses that they do when carried out in the model without interaction. Instead, when we test for the overall significance of Tier 1 ratio in the interaction model, we find that it statistically significant. This means that the main effects of the variables that are used to compute the interaction terms should still be included in the model, even if they are not significant. Otherwise, main effects and interaction effects can get confounded.

the Tier 1 capital ratio, a one standard deviation reduction in interest rates results in worsening of loan risk ratings by 0.02, which is a small effect taking into account that the standard deviation of the risk rating variable equals 0.46. The effect of a one standard deviation decrease in interest rates is even smaller when we hold the capital ratio constant at one standard deviation above the mean, amounting only to 0.01. This finding suggests that interest rate cuts encourage marginally larger risk-taking for banks with lower capital ratios, while the negative relationship for better capitalized banks is slightly weaker, given that the internal loan risk ratings assigned by these banks tend to worsen by a bit less than those assigned by lower capitalized banks. This goes against the aforementioned proposition that the effect of lower interest rates on bank risk-taking should be stronger for well-capitalized banks, compared to lower capitalized banks. However, similar result is also found in the research of Ioannidou et al. (2014) for the case of Bolivia, Jimenez et al. (2014) for the case of Spain, Özşuca and Akbostancı (2016) for the case of Turkey and Lopez et al. (2010) for the case of Colombia. The results in column 3, where we use a different proxy for bank capitalization, i.e. the equity-assets ratio, also broadly support these conclusions, albeit the economic relevance becomes even smaller, and the statistical significance actually disappears when evaluated at one standard deviation above the mean.

Table 3 reports the estimation results obtained by splitting the sample by bank capital. The evidence suggests that the interest rate has the same encouraging effect on risk-taking, regardless whether we analyse separately the banks with capital ratios higher or lower than the median.

Subsampling by bank capital

Dependent variable: risk rating of individual loans — Table 3

	(1) Banks with Tier 1 capital ratio above median	(2) Banks with Tier 1 capital ratio below median
CB bills rate	-0.016**	-0.010*
	[0.007]	[0.005]
Tier 1 capital ratio	-0.002	0.033***
	[0.001]	[0.004]
Bank size	-0.061**	0.093***
	[0.029]	[0.036]
Loan size	-0.007*	0.006
	[0.004]	[0.005]
Dummy for loans with collateral	0.024***	-0.049***
	[0.009]	[0.009]
Loan maturity	-0.004***	0.023***
	[0.001]	[0.002]
Constant	2.373***	-0.852
	[0.559]	[0.700]
Observations	14,299	14,775
Number of banks	7	7
Bank dummy variables	YES	YES
R-squared	0.015	0.213

Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1

Source: Authors' calculations.

6. Robustness checks

Table A in Annex 1 reports the results from the estimation when splitting the sample by different loan characteristics. In this case, the results are mixed. For example, we continue to find negative and significant relationship between the interest rate and the risk rating only for the loans with maturity longer than median and the loans that are secured by collateral. Opposite to this, the coefficient on the interest rate becomes positive in the subsamples of shorter-term and non-secured loans. This implies that in these cases other factors might be at play in the banks' decisions to undertake risk.

Table B in Annex 1 presents an alternative specification, in which we include time dummy variables in the model[13]. These variables should capture changes in economy-wide conditions that are not captured by the interest rate. In this case, the interest rate variable is dropped because it varies over time, but not across banks, and will therefore be captured with the time dummies. This will enable us to check the robustness of the estimated interaction between the interest rate and banks' capitalization levels. The comparison shows that the coefficients on the interaction term between the two proxies for bank capitalization and the interest rate are similar, which lends support to the robustness of the results in our main specification.

As an additional robustness check we include an interaction between the Central bank bills interest rate and the real growth of GDP in the model, in order to control directly for the potential dependence of risk ratings on the economy-wide conditions. As shown in Table C in the Annex, the results again support the conclusion that there is an increasing effect of lower interest rates on bank risk-taking. Furthermore, the coefficients on the interactions between the capital ratios and the short-term interest rate do not change very much in this specification of the model.

Finally, in order to examine the effect of past interest rate decisions on credit risk on the date of loan origination, we use the six-month lag of the interest rate as an explanatory variable. This might also help us to tackle the possible problem of reversed causality between interest rates and risk-taking. As shown in Table D in Annex 1, the results do not change the conclusions drawn so far in our analysis.

7. Conclusion

The monetary policy risk-taking channel became particularly topical issue after the outburst of the global financial crisis. The risk-taking approach, suggests that accommodative monetary policy impacts not only the quantity, but the quality of credits, as well, through its effect on banks' perceptions and risk pricing.

In the paper we made an effort to empirically test the presence of the risk-taking channel on the Macedonian case. For this purpose we followed an approach,

[13] The results from the F-test show that the time dummies are strongly statistically significant. However, in order to save space, we do not report them in the table.

commonly employed in the empirical literature on this matter, using micro, or individual data on newly extended loans. The database was extracted from the Credit Registry of the National bank, and covered the seven largest banks and their newly extended loans in the corporate credit portfolio for the 2010 -2017 period. We used the pooled OLS estimation to test the linkage between the policy rate and the ex-ante risk rating assigned by banks to each individual loan. Our study revealed inverse relationship between the two, supporting the existence of the risk-taking channel in Macedonia. The results proved to be robust after controlling for several bank, loan and time specific variables. Yet, the magnitude of the coefficient was rather small, indicative for small economic significance.

The findings of the paper are policy-relevant, as they are indicative for the presence of the risk-taking monetary policy channel in Macedonia and the need to take financial stability and banks' risk pricing into consideration when deciding on the policy rate, and/or on the need to complement it with targeted macro-prudential measures. The paper is also meaningful from the pure research perspective, since to the best knowledge of our knowledge it is the first effort to estimate this alternative monetary policy channel in the region, and the first effort to use the Credit Registry database for research purposes. Future research in this area might try to tackle more thoroughly the definition of the ex-ante risk rating, by compiling alternative indicators, and testing whether the risk-taking channel exists after controlling for the different risk measures. In addition, the risk-taking channel could be assessed on the household credit portfolio, as well.

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Annex 1

Subsampling by loan characteristics

Dependent variable: risk rating of individual loans — Table A

	(1) Loans with maturity longer than median	(2) Loans with maturity shorter than median	(3) Loans secured by collateral	(4) Loans not secured by collateral
CB bills rate	-0.037***	0.010*	-0.025***	0.016*
	[0.006]	[0.006]	[0.005]	[0.009]
Tier 1 capital ratio	-0.005***	0.011***	0.003**	0.001
	[0.002]	[0.002]	[0.001]	[0.003]
Bank size	-0.154***	0.180***	-0.023	0.091*
	[0.031]	[0.033]	[0.025]	[0.049]
Constant	4.080***	-2.310***	1.601***	-0.609
	[0.592]	[0.640]	[0.481]	[0.941]
Observations	12,827	16,247	23,141	5,933
Number of banks	7	7	7	7
Bank dummy variables	YES	YES	YES	YES
R-squared	0.177	0.114	0.144	0.115

Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1

Source: Authors' calculations.

Regressions including time dummy variables

Dependent variable: risk rating of individual loans — Table B

	(1)	(2)
Tier 1 capital ratio	-0.882***	
	[0.260]	
Tier 1 capital ratio x CB bills rate	0.158***	
	[0.046]	
Equity-assets ratio		-1.403***
		[0.411]
Equity-assets ratio x CB bills rate		0.352***
		[0.077]
Bank size	-0.118***	-0.059
	[0.044]	[0.038]
Loan size	-0.003	-0.003
	[0.003]	[0.003]
Dummy for loans with collateral	-0.015**	-0.013**
	[0.006]	[0.006]
Loan maturity	0.010***	0.010***
	[0.001]	[0.001]
Constant	3.236***	2.096***
	[0.810]	[0.702]
Observations	29,074	29,074
Number of banks	7	7
Bank dummy variables	YES	YES
Time dummy variables	YES	YES
R-squared	0.144	0.144

Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1

Source: Authors' calculations.

Loan risk ratings, the CB bills rate, bank capital and GDP

Dependent variable: risk rating of individual loans Table C

	(1)	(2)	(3)
CB bills rate	-0.038***	-0.056***	-0.063***
	[0.009]	[0.011]	[0.011]
CB bills rate x GDP growth	0.007***	0.007***	0.007***
	[0.002]	[0.002]	[0.002]
Tier 1 capital ratio	0.258**	-0.310	
	[0.126]	[0.239]	
Tier 1 capital ratio x CB bills rate		0.156***	
		[0.045]	
Equity-assets ratio			-0.406
			[0.382]
Equity-assets ratio x CB bills rate			0.327***
			[0.074]
Bank size	-0.000	0.010	0.040*
	[0.024]	[0.024]	[0.021]
Loan size	-0.002	-0.002	-0.002
	[0.003]	[0.003]	[0.003]
Dummy for loans with collateral	-0.010	-0.010	-0.010
	[0.006]	[0.006]	[0.006]
Loan maturity	0.010***	0.010***	0.010***
	[0.001]	[0.001]	[0.001]
GDP growth	-0.016**	-0.016**	-0.014**
	[0.007]	[0.007]	[0.007]
Constant	1.221***	1.098**	0.522
	[0.466]	[0.461]	[0.424]
Observations	29,074	29,074	29,074
Number of banks	7	7	7
Bank dummy variables	YES	YES	YES
R-squared	0.141	0.141	0.142

Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1

Source: Authors' calculations.

Regressions with the lag of CB bills rate

Dependent variable: risk rating of individual loans Table D

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
CB bills rate (t-1)	-0.009***	-0.007***	-0.007***	-0.007***	-0.007***	-0.008***	-0.007***
	[0.002]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
Tier 1 capital ratio		0.275**	0.274**	0.272**	0.262**	0.255**	0.300**
		[0.129]	[0.129]	[0.129]	[0.129]	[0.129]	[0.131]
Bank size		0.018	0.017	0.017	0.017	0.015	0.021
		[0.023]	[0.023]	[0.023]	[0.023]	[0.023]	[0.024]
Loan size			0.003			-0.002	-0.002
			[0.003]			[0.003]	[0.003]
Dummy for loans with collateral				-0.004		-0.012*	-0.011*
				[0.006]		[0.006]	[0.006]
Loan maturity					0.010***	0.010***	0.010***
					[0.001]	[0.001]	[0.001]
GDP growth							0.007***
							[0.001]
Constant	1.170***	0.796*	0.784*	0.813*	0.806*	0.874*	0.736
	[0.008]	[0.449]	[0.448]	[0.448]	[0.449]	[0.448]	[0.453]
Observations	29,074	29,074	29,074	29,074	29,074	29,074	29,074
Number of banks	7	7	7	7	7	7	7
Bank dummy variables	YES	YES	YES	YES	YES	YES	YES
R-squared	0.137	0.137	0.137	0.137	0.140	0.140	0.141

Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1

Source: Authors' calculations.

Annex 2

List of input data in the Credit Registry of the National Bank of the Republic of Macedonia

No.	Data on clients identification and characteristics	Data on maturity and other dates related to the agreement	Data on the amounts of credit exposure	Data on the collateral (if any) provided by the client	Data on other characteristics of the credit agreement	Other data on the credit quality	Data on written-off claims
1.	Type of client (legal entity, individual, retailer, bank, etc.)	Date of the first cash outflow on the basis of the credit agreement	Total approved exposure amount	Type of collateral (residential or commercial real estate, automobile, guarantees, securities, endorser, co-borrower, etc.)	Number of credit agreement (according to bank own format)	Amount and percentage (as share in total credit exposure) of impairment losses and/or special reserves determined by the bank	Outstanding amount of written-off principal
2.	Residency status and name of country	Final maturity date of the credit agreement	Amount of undue principal of the credit agreement as of the end of the reporting month	Amount of collateral	Type of debt repayment (in annuities, bullet loans or credit cards/overdrafts)	Scope of the impairment losses determined by the bank (calculated for individual credit exposure or for group of exposures on aggregate basis)	Outstanding amount of written-off interest
3.	Code for unique identification in Macedonia	Date of first maturity of the credit agreement principal	Amount of due principal of the credit agreement as of the end of the reporting month	Lien over collateral (primary, secondary, etc.)	Interest rate type (fixed, variable or adjustable according to decision of authorized body in the bank)	Identification of credit agreements where restructuring or extension of the final maturity date was made	Outstanding amount of the other written-off claims
4.	Title of the legal entity and tax number for legal entities - residents	Date of restructuring or extension (if any) of the final maturity date	Amount of interest as of the end of the reporting month	Endorser/co-borrower information: - national ID - tax number - title of the legal entity - name of surname of the individual	Currency (EUR, USD, MKD, etc.)*	Number of restructurings / extensions of the final maturing date (if any)	
5.	Name and surname of the individual	New exposure maturity date (due to restructuring or extension of final maturity date)	Amount of non-performing principal of the credit agreement as of the end of the reporting month		Purpose of the foreign currency credit	Identification of credit agreements that are repayed by endorser or another entity due to default of original borrower	
6.	Municipality for residents from Macedonia		Amount of non-performing interest as of the end of the reporting month		Purpose of the credit approved to individuals (consumer loan, mortgage loan, automobile loans, etc.)	Maximum noted delay in repayment over entire duration of the agreement (in number of days)	
7.	Prevailing activity of legal entities		Amount of other claims according to the agreement as of the end of the reporting month		Agreed annual nominal interest rate	Amount to which the maximum noted delay in repayment pertains	
8.	Client with matched foreign currency position		Amount of off-balance sheet items (if any related to the agreement) as of the end of the reporting month				
9.			Total credit exposure deriving from the credit agreement as of the end of the reporting month				
10.			Annuity amount				
11.			Amount approved in the restructuring or extension (if any) of the final maturity date				

* Agreements in Denars with FX clause are separately identified by reporting the currency of the FX clause.

Source: Instructions for implementation of the Decision on the contents and the manner of functioning of the Credit Registry (Official Gazette of the Republic of Macedonia No. 14/14, 83/15 and 225/15), Available at: http://www.nbrm.mk/ns-newsarticle-instructions_credit_registry_n.nspx.

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The risk-taking channel of monetary policy in Macedonia: evidence from credit registry data[1]

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[1] This presentation was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

The Risk-Taking Channel of Monetary Policy in Macedonia: Evidence from Credit Registry Data

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Disclaimer: The opinions and views expressed in this paper are only those of the authors and do not necessarily reflect the position and views of the National Bank of the Republic of Macedonia. Any errors or omissions are the responsibility of the authors.

Motivation

- Increasing interest on the link between monetary policy and banks' risk-taking in recent years
  - the "Great Recession" sawn by the low rates environment prior to its emergence
- The risk-taking channel: accommodative monetary policy impacts not only the quantity, but the quality of banks' credits as well, through its effect on banks' perceptions and risk pricing
- Research objectives:
  - to empirically test the presence of the risk-taking channel in Macedonia
  - to analyze the impact of banks' leverage on the risk-taking behavior
- Our contribution:
  - to the best of our knowledge, this is a first attempt to explore the risk-taking monetary police channel for Macedonia
  - also, first-time utilization of the confidential micro database from the Credit Registry of NBRM for research purposes

Econometric methodology

- Following the specification of Dell'Ariccia et al.:

(1) $$LRR_{kit} = \lambda_i + \beta r_t + \eta K_{it} + \mu L_{kit} + \Omega B_{it} + \varepsilon_{kit}$$

(2) $$LRR_{kit} = \lambda_i + \beta r_t + \eta K_{it} + \nu K_{it} r_t + \mu L_{kit} + \Omega B_{it} + \varepsilon_{kit}$$

where

LRR_{kit} is the risk rating of loan k, extended by bank i during the semester t

λ_i are bank-specific effects

r_t is the Central bank's effective interest rate

K_{it} is a measure of bank's capitalisation

L_{kit} is a set of loan specific variables

B_{it} is a measure of bank size

$K_{it}r_t$ is interaction term between interest rate and bank capital

- Estimation method: POLS with robust s.e. and bank dummy variables to control for the likely presence of unobserved heterogeneity (bank-level fixed effects related to banks' ownership, management, clients etc.)

Data description

- The Credit Registry of NBRM: electronic base of data and information on the credit exposures of deposit-taking financial institutions to their clients, the main purpose of which is to contribute to improvement of the credit risk management and the maintenance of the financial stability of Macedonia
- Biannual data on individual new loans extended to non-financial companies, for the period 2010:H1-2017:H1
- 7 largest banks, with market share of around 90%

Dependent variable	Loan specific variables	Bank specific variables	Time specific variables
Risk rating assigned by the bank to a given loan classified in one of the five risk categories (A=1, B=2, C=3, D=4 and E=5)	loan size (in log)	total assets (in log)	NBRM's effective interest rate
	loan original maturity (in years)	Tier 1 capital ratio	real GDP growth
	dummy variable for collateral (1 for secured loans, and 0 otherwise)	equity-total assets ratio (alt.)	
Source: Credit Registry of NBRM		Source: Banks' balance sheets	Source: NBRM, SSO

Main results

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
CB bills rate	-0.015***	-0.012***	-0.012***	-0.012***	-0.012***	-0.013***	-0.011**
	[0.002]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]
Tier 1 capital ratio		0.266**	0.264**	0.264**	0.253**	0.246**	0.316**
		[0.123]	[0.123]	[0.123]	[0.123]	[0.123]	[0.127]
Bank size		0.014	0.014	0.014	0.013	0.011	0.023
		[0.023]	[0.023]	[0.023]	[0.023]	[0.023]	[0.023]
Loan size			0.003			-0.002	-0.002
			[0.003]			[0.003]	[0.003]
Dummy for loans with collateral				-0.004		-0.012**	-0.011*
				[0.006]		[0.006]	[0.006]
Loan maturity					0.010***	0.010***	0.010***
					[0.001]	[0.001]	[0.001]
GDP growth							0.007***
							[0.001]
Constant	1.185***	0.874**	0.865**	0.894**	0.888**	0.957**	0.693
	[0.010]	[0.438]	[0.438]	[0.437]	[0.439]	[0.437]	[0.448]
Observations	29,074	29,074	29,074	29,074	29,074	29,074	29,074
Number of banks	7	7	7	7	7	7	7
Bank dummy variables	YES	YES	YES	YES	YES	YES	YES
R-squared	0.137	0.137	0.137	0.137	0.140	0.140	0.140

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Main results

VARIABLES	(1)	(2)	(3)
CB bills rate	-0.013***	-0.027***	-0.035***
	[0.004]	[0.007]	[0.008]
Tier 1 capital ratio	0.246**	-0.177	
	[0.123]	[0.240]	
Tier 1 capital ratio x CB bills rate		0.116***	
		[0.044]	
Equity-assets ratio			-0.220
			[0.384]
Equity-assets ratio x CB bills rate			0.277***
			[0.073]
Bank size	0.011	0.019	0.049**
	[0.023]	[0.022]	[0.021]
Loan size	-0.002	-0.002	-0.002
	[0.003]	[0.003]	[0.003]
Dummy for loans with collateral	-0.012**	-0.012**	-0.012*
	[0.006]	[0.006]	[0.006]
Loan maturity	0.010***	0.010***	0.010***
	[0.001]	[0.001]	[0.001]
Constant	0.957**	0.867**	0.283
	[0.437]	[0.431]	[0.407]
Observations	29,074	29,074	29,074
Number of banks	7	7	7
Bank dummy variables	YES	YES	YES
R-squared	0.140	0.140	0.141

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Alternative specifications

- Subsampling by bank capital
- Subsampling by loan characteristics
- Regressions including time dummy variables
- Regressions with the interaction between Central bank bills interest rate and real GDP growth
- Regressions with the lag of CB bills rate

➢ The results broadly in line with the ones from the baseline specification

Conclusion

- Our study reveals inverse relationship between the policy rate and the ex-ante risk rating assigned by banks, supporting the existence of the risk-taking channel in Macedonia.
- The results prove to be robust after controlling for several bank, loan and time specific variables, but the economic significance is rather small.
- Regarding the impact of leverage on risk-taking, we find a lower risk-taking for better capitalized banks, although the degree of difference between banks with higher and lower capitalization is marginal.
- The findings of the paper are policy-relevant, as they are indicative for the presence of the risk-taking monetary policy channel in Macedonia and point to the need to take financial stability and banks' risk pricing into consideration when deciding on the policy rate.
- This is just a beginning - future research focused on assessment of the risk-taking channel in view of some alternative risk indicators, as well as on conducting a similar analysis for the household lending segment.

Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

The impact of macroprudential policies and their interaction with monetary policy: an empirical analysis using credit registry data[1]

Leonardo Gambacorta and Andrés Murcia,

Bank for International Settlements

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[1] This paper was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

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The impact of macroprudential policies and their interaction with monetary policy: an empirical analysis using credit registry data

by Leonardo Gambacorta and Andrés Murcia

Monetary and Economic Department

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The impact of macroprudential policies and their interaction with monetary policy: an empirical analysis using credit registry data

Leonardo Gambacorta and Andrés Murcia[1]

Abstract

This paper summarises the results of a joint research project by eight central banks in the Americas region to evaluate the effectiveness of macroprudential tools and their interaction with monetary policy. In particular, using meta-analysis techniques, we summarise the results for five Latin American countries (Argentina, Brazil, Colombia, Mexico and Peru) that use confidential bank-loan data. The use of granular credit registry data helps us to disentangle loan demand from loan supply effects without making strong assumptions. Results from another three countries (Canada, Chile and the United States) corroborate the analysis using data for credit origination and borrower characteristics. The main conclusions are that (i) macroprudential policies have been quite effective in stabilising credit cycles. The propagation of the effects to credit growth is more rapid (they materialise after one quarter) for policies aimed at curbing the cycle than for policies aimed at fostering resilience (which take effect within a year); and (ii) macroprudential tools have a greater effect on credit growth when reinforced by the use of monetary policy to push in the same direction.

Keywords: macroprudential policies, bank lending, credit registry data, meta-analysis.

JEL classification: E43, E58, G18, G28.

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1. Introduction

The recent Global Financial Crisis (GFC) has made it clear that the systemic dimension of financial stability cannot be ignored. Treating the financial system as merely the sum of its parts leads one to overlook the historical tendency for credit to swing from boom to bust. We have gained valuable experience in the use of macroprudential policies but their implementation still raises a number of issues. One is how to evaluate the impact of macroprudential policies, especially when more than one tool is activated. Another is the interaction of these tools with other instruments such as monetary policy. Bearing those caveats in mind, the effectiveness of macroprudential policies should be analysed with respect to the specific goals they are designed to achieve, that is, to increase the resilience of the financial system or, more ambitiously, to tame financial booms and busts.

Evidence for the effectiveness of macroprudential policies is mixed and more work is needed. Part of the explanation could be that most of the evidence gathered so far is based on aggregate data at either the country level or the bank level. Very limited use has been made of credit registry data with the notable exceptions of a study on the activation of dynamic provisioning in Spain (Jimenez et al (2016)) and a study on the effects of reserve requirements in Uruguay (Camors et al (2016)).

To study the impact of macroprudential policies and their interaction with monetary policy, we initiated (under the auspices of the Consultative Council for the Americas (CCA)) a joint project covering the eight countries that are BIS shareholders (Argentina, Brazil, Canada, Chile, Colombia, Mexico, Peru and the United States). Five of these countries (Argentina, Brazil, Colombia, Mexico and Peru) made use of credit registry data and followed a common approach in which the impact of macroprudential tools on lending growth was estimated using the same methodology and data. The use of granular credit registry data helps us to disentangle loan demand from loan supply effects without making strong assumptions. The analysis from this exercise was then complemented by work conducted in the three other CCA countries (Canada, Chile and the United States) on the effects of specific policies using information on credit origination and borrower characteristics.

Latin America is a good laboratory for the evaluation of the effectiveness of macroprudential tools, given that their use has had a relatively long history there (Jara et al (2009), Tovar et al (2012), Agénor and Pereira da Silva (2016)).[2] Graph 1 shows that the vast majority (around 80%) of existing macroprudential tools have been applied in EMEs (see also Altunbas et al (2017)). Moreover, five of the eight countries involved in the project have well developed credit registry frameworks and data that allow for an estimation of the transmission from macroprudential impulses to the given policy objective without making too many assumptions.

The confidentiality of credit registry data meant that we were unable to combine our data into a unique data set. This means that we had to run separate country-by-country regressions and compare them. In order to ensure that results were comparable, we implemented a common empirical strategy. Great attention was paid to limiting differences in the definition of variables and the treatment of data. In spite of our standardised approach, we faced a major issue in comparing macroprudential

[2] Annex A gives details of the macroprudential tools for the eight CCA countries involved in the project.

policies that can be very different in nature. To tackle this, we used meta-analysis techniques that helped summarise the results of different country estimates. This type of analysis also let us estimate the relevance of different policy characteristics (or tools) in explaining the heterogeneity of policy effects. Given the nature of the data set at the bank-borrower level, it is important to bear in mind that each coefficient used as an input in the meta-analysis is obtained using a huge number of observations (up to 20 million in some cases) and typically associated with a low standard error. This improves the precision of the calculation of the semi-elasticity of lending to the various macroprudential policies. As usual, when we use meta-analysis techniques to summarise results, there is a challenge with inference, as the number of coefficients tends to be small, reducing the degrees of freedom.

Table 1 describes the different types of macroprudential tool used in the region of the Americas using the categorisation presented in Claessens et al (2013). In particular, only 22% of the policy actions had the direct objective of increasing the resilience of the financial sector, using capital liquidity or provisioning requirements, while 78% had the main purpose of dampening the cycle – ie were used by authorities to dampen an expected credit boom or credit crunch. In particular, the use of reserve requirements has been particularly active in the region. It is also noticeable that more episodes of tightening have taken place than of easing. As it has been extensively documented (Igan and Tan (2015)), credit behaviour in Latin America tends to be highly correlated with the dynamics of external capital flows. In that sense, the use of macroprudential policies has been accompanied in many cases by capital flow management tools.

The main novelty of this paper is that we compare the effectiveness of macroprudential policies by using highly granular data. The richness of our data helps us disentangle shifts in loan demand and those in loan supply, and isolate the impact of macroprudential tools on credit dynamics and that on banking sector risks. We also shed some light on the link between monetary and macroprudential policies, by studying whether responses to changes in macroprudential tools vary with monetary policy conditions. Our initiative complements that undertaken by the International Banking Research Network (IBRN), where researchers from 15 central banks and two international organisations use confidential bank-level data to analyse the existence of cross-border prudential policy spillovers (Buch and Goldberg (2017)). By focusing on domestic credit, our paper complements to some extent the IBRN analysis.

Using information from the five countries that reported information for the meta-analysis, our main results can be summarised in the following way. First, the macroprudential policies implemented by our sample of countries have been effective in dampening credit cycles. In particular, macroprudential policies used with the main purpose of curbing the cycle have been particularly successful in reducing credit growth, even in the short term (within three months). The manifestation of the effects of capital-based requirements is less rapid, taking place within a year. Second, the effectiveness of macroprudential tools is affected by the contemporaneous use of monetary policy. Macroprudential tools that acted as a complement to monetary policies (ie pushing in the same direction) were more effective than those that acted as a substitute for monetary policies (ie pushing in the opposite direction).

Related literature. The evidence for the impact of macroprudential policies is still mixed and additional work is required before solid conclusions can be reached. For instance, recent evidence suggests that debt-service-to-income ratio (DSTI) caps and, probably to a lesser extent, loan-to-value ratio (LTV) caps are more effective than capital requirements in containing asset growth (Claessens et al (2013)). Indeed, the recent activation of the Basel III countercyclical capital buffers on risk-weighted domestic residential mortgages in Switzerland seems to have had little impact on credit extension (Basten and Koch (2015)), although it had some effect on mortgage pricing. But the main goal of the Basel III countercyclical capital buffers is to increase the banking sector's resilience, not to smooth the credit cycle. Restraining a boom is perhaps no more than a welcome side effect of capital-related macroprudential tools (Drehmann and Gambacorta (2012)).

A second issue pertains to the different nature of macroprudential objectives and instruments. In this area, there is no one-size-fits-all approach. Which tools to use, how to calibrate them and when to deploy them will depend on how the authorities view the vulnerabilities involved, and how confident they are in their analysis. The legal and institutional setup will also be relevant. Moreover, a given instrument's effects will depend on a variety of other factors that need to be assessed against the chosen objective. Some instruments may work better in achieving the narrow objective of strengthening financial system resilience rather than the broader one of constraining the cycle. For instance, countercyclical capital buffers aim at building cushions against banks' total credit exposures, whereas LTV caps only affect a targeted set of new borrowers (and usually only those who are highly leveraged). This argues in favour of capital buffers when the objective is to improve overall resilience. But LTV caps may work better if the aim is to curb specific types of credit extension.

The literature suggests that some instruments may work better to achieve the narrow aim of increasing financial system resilience than the broader aim of constraining the cycle. Some cross-country studies using country-level data point to their effectiveness in limiting excessive credit growth (Cerutti et al (2017), Bruno et al (2017)), especially in the housing sector (Akinci and Olmstead-Rumsey (2015)). There is also evidence that the effects appear to be smaller in financially more developed and open economies (Cerutti et al (2017)).

There is also a need to shed more light on the interaction between monetary and macroprudential policies. For example, there is considerable, although not undisputed, evidence supporting the view that search for yield in a low interest rate environment contributed to the build-up of the GFC through the so-called risk-taking channel of monetary policy (Borio and Zhu (2014), Adrian and Shin (2014), Altunbas et al (2014)). This channel could be particularly relevant when economic agents anticipate that low rates will persist or that monetary policy will always be eased in case of market turmoil – a type of put option offered by the central bank to financial markets. But macroprudential policies could also influence the transmission of monetary policy. For example, changes in LTV or DSTI caps could alter lending conditions and, therefore, consumption decisions. Moreover, by influencing credit conditions, macroprudential policies could also affect real interest rates, indirectly modifying the monetary policy stance, even in the absence of any direct changes to policy rates.

The interaction between these types of policy could have additional implications, in which credit behaviour is often strongly correlated with international capital inflows. An increase in monetary policy rates in reaction to financial stability concerns could have the adverse effect of a sudden increase in capital inflows, which could exacerbate domestic credit and asset price bubbles. In this case, the use of macroprudential policies or capital flow management policies would be critical (Freixas et al (2015)).

On the interaction of monetary and macroprudential polices, evidence obtained from DSGE models[3] and empirical analyses suggests that both policies are complements rather than substitutes, although the results vary by type of shock. Some of these models predict that in the wake of a financial shock, even if the reaction in terms of macroprudential policy should be larger, both types of policy should work in the same direction (Agénor et al (2012, 2016)). In the presence of productivity and demand shocks, the policy responses could differ depending on the size and nature of the shocks (IMF (2013a)). In particular, according to some models with endogenous financial distortions, macroprudential policies must react to credit cycles and the optimal monetary policy response will depend on the size of the respective shocks and the riskiness of balance sheets, including capital buffers and bank leverage (Brunnermeier and Sannikov (2014)).

Recent empirical evidence for Asian economies suggests that macroprudential policies tend to be more successful when they complement monetary policy by reinforcing monetary tightening rather than when they act in the opposite direction (Bruno et al (2017)). IMF (2013b) discusses a number of episodes in which macroprudential tools have been used in conjunction with monetary policy to produce successful outcomes in terms of financial and monetary stability objectives. In addition, some authors have argued that it would be imprudent to rely exclusively on monetary policy frameworks when seeking to tame financial booms and busts. Since some financial cycles, such as credit cycles, are very powerful, monetary and fiscal policies should also play a role (Borio (2014)).

Finally, some studies analyse the effectiveness in a cross-country setup. Cerutti et al (2017) find that the effectiveness of macroprudential policies on credit growth, other things being equal, is lower in advanced economies, which tend to have deep and sophisticated markets that offer alternative sources of non-bank finance, and in open economies that tend to allow borrowers to obtain funds from across the border. Cizel et al (2016) document shifting of credit provision to the shadow banking sector following the adoption of macroprudential measures, with stronger substitution effects found for advanced economies. Reinhardt and Sowerbutts (2015) show further evidence of cross-border leakages for capital requirements, but do not find such effects for loan restriction tools, such as LTV and DSTI caps. Aiyar et al (2014) analyse the experience for the United Kingdom and find that capital requirements can be circumvented by foreign bank branches that are not affected by regulation, or by the shadow banking sector. The recent multi-study initiative of the IBRN (Buch and Goldberg (2017)) confirms this finding and shows that the effects of prudential instruments sometimes spill over borders through bank lending, but also shows that such effects have not been large on average. Interestingly, international spillovers vary across prudential instruments and across banks. Bank-specific factors such as balance sheet conditions and business models drive the amplitude and direction of spillovers to lending growth rates.

Outline. The remainder of the paper is organised as follows. The next section describes the empirical strategy and how we used the credit registry data. Section III discusses the main findings of country papers. Section IV presents the country-by-country results using meta-analysis techniques. The last section contains our main conclusions.

[3] See, for instance, Angelini et al (2012), Alpanda et al (2014) and Lambertini et al (2013).

2. Empirical strategy

Credit register data are typically highly confidential. This means that it is not possible to pool country-level data. Instead, it is necessary to run regressions at a country level and compare results. This does not allow the cross-sectional variability at the country level to be exploited; however, it does let us tackle the potential existence of national differences in the transmission mechanism, allowing each regression to be tailored to take into account different institutional characteristics and/or financial structures. To make comparisons possible, the country level analysis has to use the same modelling strategy and data definition (as far as data sources allow in terms of coverage, collection methods and definitions). In other words, the policy experiment has to be coordinated by using a baseline model specification and by running similar tests.

In order to implement a common approach for the countries participating in the project, we prepared a research protocol in which the equations and the definition of variables was initially discussed and agreed. Country teams complemented the analysis in their respective papers checking the robustness of the results by modifying the baseline models to take into account of country specific characteristics.

Impact of macroprudential tools on bank lending

The first step is to evaluate the impact of a change in macroprudential tools on credit availability using a panel methodology. To this end, we use four different specifications. In the first, we use controls for bank-specific characteristics and their interaction with macroprudential tools (Equation 1). In the second specification, we control for the interaction between macroprudential tools with changes in monetary policy (Equation 2). The third equation controls for the interaction of macroprudential policies with business cycle conditions (Equation 3). These three equations aim at answering the following questions:

(i) Are macroprudential tools effective in altering credit growth?

(ii) How is the effectiveness of macroprudential policies affected by monetary policy conditions?

(iii) How is the effectiveness of macroprudential policies altered by business cycle conditions?

Macroprudential tools and loan supply shifts

As a first step, we evaluate the impact of macroprudential tools at the loan level using the following regression:[4]

$$\Delta Log\ Credit_{bft} = \delta_f + \sum_{j=1}^{4} \beta_j \Delta \mathrm{Macropru}_{t-j} + \sum_{j=1}^{4} \beta'_j \Delta \mathrm{Macropru}_{t-j} * \tilde{X}_{bt-j} + \\ + controls_{bft} + quarter_t + \varepsilon_{bft} \qquad (1)$$

4 The regression is similar to that used in Jimenez et al (2014) to study the impact of monetary policy changes on bank lending by means of credit registry data. For the sake of simplicity, here we consider the case of only one macroprudential tool. However, in many cases, more than one macroprudential tool could be in place at any one time.

where $\Delta Log\ Credit_{bft}$ is the first difference of the logarithm of actual value of loans by bank b to firm f at time t. We include as explanatory variables the change in the macroprudential tool lagged four periods ($\Delta \mathrm{Macropru}_{t-j}$) and its interaction with a vector of bank-specific characteristics (X_{bt-j}). We also include a complete set of firm fixed effects (δ_f), quarterly dummies to control for seasonal effects (θ_t) and control variables ($controls_{bft}$) that include bank-specific and loan characteristics.[5] Our main coefficients of interest are the vectors β and β' that indicate the change of credit induced by the specific macroprudential tool and its interactions with bank-specific characteristics.[6] The test is on the overall significance of $\sum_{j=1}^{4} \beta_j$ and $\sum_{j=1}^{4} \beta'_j$.

The inclusion of interaction terms between macroprudential tools and bank-specific characteristics ($\Delta \mathrm{Macropru}_{t-j} * X_{bt-j}$) is essential for evaluating whether responses to macroprudential shock differ by type of bank (ie strongly capitalised vs weakly capitalised banks; large vs small banks; highly liquid vs less liquid banks etc). In the vector X of bank-specific characteristics, we include indicators of capital, liquidity, size and funding structure. Bank balance-sheet data are demeaned so that we can interpret $\sum_{j=1}^{4} \beta_j$ as the effect on the average bank. We employ lagged values of macroprudential and monetary policy changes as the latter may be influenced by lending conditions. A model with interaction terms was also used in Buch and Goldberg (2017) for evaluating whether spillovers effects of prudential tools depend on bank specific characteristics.

The approach underlying equation (1) builds on the bank lending channel literature. In order to discriminate between loan supply and loan demand movements, the literature has focused on cross-sectional differences between banks.[7] This strategy relies on the hypothesis that certain bank-specific characteristics (for example size, liquidity and capitalisation) influence only loan supply movements, while demand for bank loans is independent of these characteristics. Broadly speaking, this approach assumes that, after a monetary tightening (macroprudential tightening in our case), banks differ in their ability to shield their loan portfolios. In particular, smaller and less well capitalised banks, which suffer a high degree of informational frictions in financial markets, face a higher cost in raising non-secured deposits and are constrained to reduce their lending by more. For their part, illiquid banks are less able to shield themselves from the effect of a policy tightening on lending simply by drawing down cash and securities. This literature does not analyse the macroeconomic impact of the "bank lending channel" on loans but predicates the existence of such channel upon the evident fact that banks respond differently to changes in monetary policy conditions.

5 Loan characteristics differ among country regressions depending on the availability of information. In particular some country team included controls to identify whether the loans are collateralized (Argentina, Brazil and Colombia) and have a different remaining maturity (Colombia). Some country teams also included credit risk variables at the firm level to identify those debtors that presented payment delays in specific loan contracts (Brazil and Colombia) and others some dummies for identifying different types of credit lines (Argentina).

6 In the baseline, we assume fixed effects by debtors and standard error clustered at the bank level. However, country teams have checked the robustness of the results by using alternative clustering approaches. For a general discussion on different approaches used to estimating standard errors in finance panel data sets, see Petersen (2009).

7 For a review of the literature on the distributional effects of the "bank lending channel" see, among others, Gambacorta (2005).

It is worth stressing that the use of granular data allows us to take crucial steps in addressing the identification challenge to disentangle loan demand from loan supply shifts. In particular, we analyse the effects of macroprudential and monetary conditions and economic activity on the granting of loans with individual firm records depending on the strength of bank balance sheets measured by bank capital and liquidity ratios, controlling for time-varying observed and unobserved firm heterogeneity with firm- fixed effects.

One limit of the above described panel approach is that the results obtained indicate the effects for the average bank-firm loan. If the average loan is relatively small, it could be difficult to derive any implication for the macro relevance of the result. To tackle this issue country teams performed as a robustness check a weighted OLS regression by firm relevance (by size of loan).

Interaction between monetary and macroprudential policies

In the second step of the analysis, we aim at evaluating whether responses to macroprudential policies vary with monetary policy conditions. We test this by introducing in equation (1) interaction terms between our macroprudential tool variable and a monetary policy indicator (ie changes in the real money rate, Δr_t,):

$$\Delta Log\ Credit_{bft} = \delta_f + \sum_{j=1}^{4} \beta_j \Delta \mathrm{Macropru}_{t-j} + \sum_{j=1}^{4} \delta_j \Delta \mathrm{r}_{t-j} + \sum_{j=1}^{4} \gamma_j \Delta \mathrm{Macropru}_{t-j} * \Delta \mathrm{r}_{t-j} + controls_{bft} + quarter_t + \varepsilon_{bft} \qquad (2)$$

The reason for this test is to verify the effectiveness of macroprudential tools when monetary policy pushes in the same or opposite direction. The main test is on the significance of $\sum_{j=1}^{4} \gamma_j$. In particular, we can construct a test taking the first derivative of equation (2) with respect to changes in macro policy and monetary policy, respectively:

$$\frac{\partial \Delta Log\ Credit_{bft}}{\partial \Delta \mathrm{Macropru}_{t-1}} = \sum_{j=1}^{4} \beta_j + \sum_{j=1}^{4} \gamma_j\, \Delta r_t$$

$$\frac{\partial \Delta Log\ Credit_{bft}}{\partial \Delta r_t} = \sum_{j=1}^{4} \delta_j + \sum_{j=1}^{4} \gamma_j\, \Delta \mathrm{Macropru}_{t-1}$$

Since $\sum_{j=1}^{4} \beta_j$ and $\sum_{j=1}^{4} \delta_j$ are expected to be negative (both monetary and macroprudential policies tightening reduce bank lending), the effect of a change of one policy on the other will depend on the sign of the cross derivative $\frac{\partial^2 \Delta Log\ Credit_{bft}}{\partial \Delta \mathrm{Macropru}_{t-1} \partial \Delta r_t} = \sum_{j=1}^{4} \gamma_j$. Each policy will reinforce the other if $\sum_{j=1}^{4} \gamma_j < 0$. By contrast, if a macroprudential policy tightening reduces the effectiveness of a monetary policy tightening and vice versa then we should observe $\sum_{j=1}^{4} \gamma_j > 0$. [8]

[8] This analysis could be seen as analogous to the study of the interaction between fiscal and monetary policy. For example, with monetary policy, both conventional and unconventional, having reached the limits of its effectiveness, fiscal policy may be more effective, so the cross-derivative between the two policies should be positive (Buiter (2010)). For Woodford (2011), a fiscal multiplier well in excess of one is possible when monetary policy is constrained by the zero lower bound and, in this case, welfare increases if government purchases expand to partially fill the output gap that arises from the inability to lower interest rates. In our paper, we abstract from welfare criteria and we simply judge whether the effectiveness of the macroprudential tools in modifying bank lending is influenced by monetary policy conditions.

Macroprudential policies over the cycle

The third step of the analysis is to evaluate whether the effectiveness of macroprudential policies varies over the business cycle. For this, we have included in the baseline equation interaction terms between macroprudential tool indicators and real GDP growth:

$$\Delta Log\ Credit_{bft} = \delta_f + \sum_{j=1}^{4} \beta_j \Delta \text{Macropru}_{t-j} + \sum_{j=1}^{4} \eta_j \Delta \text{Macropru}_{t-j} * \Delta LogGDP_{t-j} + controls_{bft} + quarter_t + \varepsilon_{bft} \quad (3)$$

To identify whether the effectiveness of the macroprudential policies varies over the business cycle, the test is on the overall significance of $\sum_{j=1}^{4} \eta_j$. Even in this case, we can explain the test taking the first derivative of equation (3) with respect to changes in macroprudential policy:

$$\frac{\partial \Delta Log\ Credit_{bft}}{\partial \Delta \text{Macropru}_{t-1}} = \sum_{j=1}^{4} \beta_j + \sum_{j=1}^{4} \eta_j * \Delta LogGDP_{t-j}$$

Since $\sum_{j=1}^{4} \beta_j$ is expected to be negative (macroprudential policies tightening reduce bank lending), the effect of a macroprudential tightening/easing on lending growth will depend upon the sign of the cross derivative $\sum_{j=1}^{4} \eta_j$. For example, a macroprudential policy tightening will be stronger in an economic expansion ($\Delta LogGDP_{t-j} > 0$) if $\sum_{j=1}^{4} \eta_j < 0$ and vice versa. Buch and Goldberg (2017) propose a similar specification with a measure of the output gap and Credit to GDP ratio as a proxy of the financial cycle.

Intensive vs extensive margins

The econometric strategy presented above was mainly focused on the evaluation of the effects of macroprudential policies at the intensive margin (changes of lending relationships already in place between a firm and a given bank). However, firms could also start new credit lines or use some existing credit lines more than others. Indeed, the effects of macroprudential policies could be mitigated if firms can obtain credit from the less affected banks. In order to analyse the effects at the extensive margin (the overall effect for the firm), we estimated an equation at the firm level. Hence, to assess the macro relevance of changes in the macroprudential tool, we need to turn from bank-firm to firm-level estimation. More specifically we estimated the following model:

$$\Delta Log\ Credit_{ft} = \delta_p + \delta_i + \beta^* \Delta \text{Macropru}_{t-1} + controls_{ft} + quarter_t + \varepsilon_{ft} \quad (4)$$

where $\Delta Log\ Credit_{bft}$ is the change in the logarithm of actual credit by all banks to firm f over a given period after the introduction or change in a macroprudential tool, $\delta_p\ and\ \delta_i$ are the province and industry fixed effects.

Meta-analysis techniques

In order to summarise the results obtained at the country level, we use meta-analysis techniques. This approach is very helpful when studies are not perfectly comparable but evaluate the same or a closely related question. This technique allows the results of different studies to be combined and summarised and an overall significance to be estimated. In financial economics, the applications of meta-analysis are still limited. One example is provided by Buch and Goldberg (2014), who summarise the magnitude and transmission of liquidity shocks on global banks across countries; Arnold et al (2014) explored the reasons for corporate hedging, combining different estimations in the literature. More recently, Buch and Goldberg (2017) summarise by means of meta-analysis the results of a multi-study initiative of the IBRN to study cross-border prudential policy spillovers.

In our analysis, each observation is represented by the evaluation of the effects of a macroprudential policy on credit growth by means of one of the equations (1)–(3) discussed above. In Table 2, we report the characteristics of the macroprudential tools evaluated by country teams using the common approach. In particular, we have analysed eight different macroprudential tools. Following the classification in Claessens et al (2013), we have four types of policies with the main objective of enhancing the financial sector's resilience and four types of policies aimed at dampening the credit cycle. We analysed a total of 15 episodes of introduction/changes of such tools (twelve tightening and three easing).

We conduct the analysis in two separate steps. In a first step using *meta-analysis*, we are able to estimate a range of the effect of macroprudential policies on credit growth. In a second step, using *meta-regressions*, we look to identify some variables that help to explain the differences among the coefficients reported by country studies. This second step is particularly relevant in our case since the reported coefficients present a large level of heterogeneity. This is, in some sense, expected, since the macroprudential policies and populations were diverse. For a more detailed explanation of meta-analysis techniques, see Annex B.

Difference-in-difference analysis

The effects of macroprudential policies on credit supply were also tested using a difference-in-difference analysis, which identifies a causal relationship pre and post the introduction of a macroprudential policy by using a counterfactual. In particular, following Khwaja and Mian (2008) we evaluate whether the same firm borrowing from two different banks (affected and not affected by the regulation) experienced a different change in lending.[9] Since the comparison is across banks for the same firm, firm-specific demand shocks are absorbed by firm fixed effects, and in this way it is possible to insulate the effects of an unanticipated shock on credit supply.

For evaluating the responses of the supply of credit to changes in specific macroprudential policies, we estimated a similar equation to the one presented in Jimenez et al (2016), in which they estimate the effects of changes in provision requirements in Spain on credit commitments. In particular, we use the following specification:

$$\Delta Log\ Credit_{bf}(Impact\ period) = \delta_f + \beta Macropru\ (Counterfactual)_b + \\ +controls_{bf} + \varepsilon_{bf} \qquad (5)$$

where $\Delta Log\ Credit_{bf}(Impact\ period)$ refers to the change in log of the credit from bank b to the firm f in the window after the implementation of the macroprudential policy. We can consider a one-year window after the macroprudential tool started to

[9] The counterfactual was defined in different ways by country teams. Some of them (Brazil, Colombia) used the information from a period in which the policy was not employed. Other country teams (Argentina, Mexico) defined the counterfactual also using information from banks or institutions to which the new rule does not apply.

be in place. δ_f are firm fixed effects and $controls_b$ are the same variables at the bank level that are employed in the previous equations. All these controls were taken one quarter before the introduction of the macroprudential tool. $Macropru\ (Counterfactual)_b$ represents the evaluation of a specific macroprudential policy to a set of credits that are not subject to the specific regulation.

The advantage of this setting is that β can be interpreted as the additional annual change of credit growth with respect to the referenced group (counterfactual). In other words, it can be interpreted as a semi-elasticity in the sense that it represents the change of the credit growth to the average firm in response to the increase of one unit in the macroprudential requirement.

Data issues

In the shared approach, we used a common definition of variables and the same frequency. In particular, we used bank-level data at the quarterly frequency and matched them with macro controls (GDP, current account deficit, etc). We have controlled for the presence of possible outliers by winsorising all the variables used in the regression at 1%.

As for the definition of the change in macroprudential variable, we used a dummy $\Delta Macropru_t$) that takes the value of +1 if the macroprudential tool has been tightened in a given quarter and –1 if it has been eased. It is zero if no changes have occurred during that quarter. This approach has been widely applied (Kuttner and Shim (2012); Altunbas et al (2017); Akinci and Olmstead-Rumsey (2015); Buch and Goldberg (2017). It does not weight for the size of the change of the macroprudential tool (or whether it represents a binding constraint for firms/individuals) but it simplifies the comparison of the effectiveness of different macroprudential policies.

Indeed, the macroprudential tools analysed in this paper are of different types and they are not straightforward to compare in terms of their potential effects. Certainly one natural source of heterogeneity in the effects of macroprudential tools along the different dimensions of credit emerges from the types of policy that are implemented. Some countries such as Argentina, Brazil, Colombia and Peru present a mix of policies (capital-based instruments, provisioning, changes in reserve requirements, establishment of liquidity ratios and, in some cases, modifications in dividend distribution rules, or the establishment or changes in LTV and DTI ratios). Meanwhile, Mexico focuses on a specific change in its rules for provisioning. More details of the different policies employed in the Americas are provided in Table 1.[10]

The macroprudential toolkit tends to be large, combining an array of different instruments. As one might expect, the purpose of various policies can differ. For instance, some instruments are intended to increase the financial sector's resilience, while others focus on dampening the cycle. In that respect, the effects of specific macroprudential tools on credit growth can differ. Claessens et al (2013) distinguish

[10] Inside the CCA-CGDFS working group, even countries which have not been too active in the use of macroprudential policies (Canada, Chile and the United States) identified some relevant measures to evaluate. Calem et al (2017) aim at evaluating recent changes introduced by the CCAR and Dodd-Frank stress tests and Leveraged Lending Guidance. Allen et al (2017), using information at the borrower level, focus on the evaluation of policies in the housing market related to changes in LTV ratios in Canada and, finally, Alegría et al (2017) estimate the effect of loan-to-value ratios in the housing loan market originating from an unexpected Chilean central bank statement concerning housing price dynamics.

between the goals and the types of policy that are commonly used. Macroprudential tools with the main objective of enhancing the financial sector's resilience include countercyclical capital requirements, leverage restrictions, general or dynamic provisioning, the establishment of liquidity requirements, among others. Within the category of macroprudential tools aimed at dampening the credit cycle, Claessens et al (2013) include changes in reserve requirements, variations in limits on foreign currency exchange mismatches, and cyclical adjustments to loan-loss provisioning, margins or haircuts. Other macroprudential policy aims include reducing the effects of contagion or shock propagation from systemically important financial institutions (SIFIs) or networks. In this group might also be included policies such as capital surcharges linked to systemic risk, restrictions on asset composition or activities, among others.

Using the categorisation presented in Claessens et al (2013), we classify policies according to their purpose. In particular, policies with the purpose of dampening the cycle – ie those used by authorities to dampen an expected credit boom or credit crunch[11]– are identified with the term *cyclical*. Macroprudential tools which are intended to increase the resilience of the financial sector, using capital or provisioning requirements, are identified with the term *capital*.[12]

For consistency, all variables have been expressed in real terms. In the case of Argentina (Aguirre and Repetto, 2017) and Mexico (Levin et al, 2017) results have been carefully checked by taking into account different model specifications for loans expressed in different currencies. In particular, Levin et al (2017) find that changes in provisioning had more effect on loans denominated in local currency than it did on credits denominated in foreign currency.

The vector of controls $(controls_{bft})$ includes macro variables, bank-specific characteristics and bank-firm relationship characteristics. In particular:

Macro controls: change in real GDP, change in monetary policy rate, effective exchange rate and current account deficit. All the variables are expressed in constant prices (base 2012).

Bank-specific characteristics: size (log of total assets); liquidity ratio (cash and securities over total assets), capital ratio (Tier 1 to total assets); funding composition (deposits over total liabilities). The Colombian team also included a securitisation activity dummy (equal to 1 if the bank is active in the securitisation market); and return on assets (ROA). Specific effects on credit could originate from regulation. Gomez et al (2017) also evaluate if a prudential instrument (such as capital) is binding or not by including specific indicators signalling whether a bank is close to the regulatory threshold (changes in macroprudential policies could more strongly affect banks that are more constrained by capital policies). In fact, they found that institutions with

[11] We included in this group the following instruments: (i) deposit requirement on external loans and (ii) the marginal reserve requirement on banking deposits, both in Colombia; (iii) tightening of the capital buffer and profit reinvestment requirement that took place in 2012; (iv) tightening in the foreign currency net global position, both in Argentina and (v) the changes in reserve requirements used in Brazil.

[12] We included the following policies in this group: (i) the introduction of dynamic provisions systems in Colombia; (ii) the introduction of a new provisioning system in Peru; (iii) the change of methodology for the calculation of banking provisions in Mexico; and (iv) the introduction and the tightening of a capital buffer and profit reinvestment mechanism in Argentina.

lower capital buffers tend to restrict their credit supply to a greater extent. The estimations provided for the meta-analysis by the Colombian group used a measure of the capital target for each financial institution as opposed to directly using the capital ratio.[13] All the studies consider individual banks including both domestic and foreign institutions (subsidiaries and branches).

One statistical issue is related to the potential endogeneity problem between changes in macroprudential policies and the evolution of credit and other business cycle indicators (that are included in the specification to control for loan demand effects). As for the relationship between macroprudential tools and credit, the use of micro data rules out the problem: using credit register data at the loan level excludes the possibility that macroprudential tools are influenced by the single borrower condition. Regarding the interaction between macroprudential tools and business conditions, we mitigate the problem by including time dummies and/or sector*time dummies. Some papers (eg Barroso et al (2017)) control for different types of fixed effects by firm and by bank. Levin et al (2017) and Aguirre and Repetto (2017) also use random effects to evaluate if their results are robust and do not find significant differences.

3. Summary of country papers

This section summarises the main results of the nine country papers prepared by the research project.

Argentina. Aguirre and Repetto (2017) evaluate the effects of two macroprudential policies in place in Argentina over the period 2009–14: (i) introduction and tightening of a capital buffer (CB) through a limit on dividend distribution; (ii) two changes in limits on foreign currency net global position (FGP) of financial institutions. The results indicate that both changes in CB and FGP are effective in smoothing credit cycles (measured as quarterly growth rates of the outstanding credit stock at the firm-bank level). In addition, the introduction and tightening of these policies appear to have had significant effect on the behaviour of non-performing loans.

Brazil. The Brazilian case was analysed by means of two different papers. One on the effects of reserve requirements as a countercyclical tool and the second on the role of changes in LTV on the mortgage market. Barroso et al (2017) found that reserve requirements tightening had a negative effect on credit. The effectiveness of reserve requirements falls as the liquidity of banks increases. On the other hand, and in contrast to the functioning of the risk-taking channel of monetary policy, the authors

13 The capital ratio itself is not informative of how tight or easy bank capital may be for an individual bank. For example, a capital ratio of 2% above the minimum requirement could be perfectly adequate for most intermediaries but not for a bank that is particularly risk-averse. Moreover, there could be differences among bank businesses and capital management policies that could affect target bank capital levels. A way to overcome this problem is to use a measure of bank capital deviation from a desired or benchmark level. For this, it is necessary first to estimate a bank capital equation and then to calculate the deviation of the actual level of the bank capital ratio from the fitted value (residual). In this case a negative (positive) value of the residual indicates a capital level that is lower (higher) than the target/desired level. With this in mind, one can use the residual instead of the simple ratio in the previous equations. A possible reference for the bank capital equation is presented in Ayuso et al (2004). Brei and Gambacorta (2014; equation 1) extend this model to take into account the possible presence of a break during the crisis.

find that, during easing, less credit is provided in riskier loans. They also found evidence that the effects of reserve requirements on monetary policy were reinforced: the tightening in reserve requirements increases the effectiveness of monetary policy actions. Araujo et al (2017) estimate the impact of the specific case of the introduction of LTV limits for a set of subsidised loans between 2012 and 2014. They find that the LTV cap caused individuals more likely to borrow with a high LTV to make higher down payments, purchase cheaper houses, and default less. No similar effects are found on the, less affected, control group.

Canada. Allen et al (2017) combine loan-level administrative data with household-level survey data to analyse the impact of recent macroprudential policy changes in Canada using a micro-simulation model for the mortgage demand from first-time homebuyers. They find that policies targeting the LTV ratio are found to have a larger impact than policies targeting the DSTI ratio, such as amortisation. This is because there are more wealth-constrained borrowers than income-constrained borrowers entering the housing market.

Chile. Alegría et al (2017) document how specific warnings about real-estate markets, published in the Central Bank of Chile Financial Stability Report between June and December of 2012, affected bank lending policies. They found that warnings had a statistically significant effect reshaping the distribution of LTV ratios for granted loans. There is evidence of a shift out of mortgages with high LTV values, and into lower ratios during the period. They also reported different responses between private and state owned banks.

Colombia. Gómez et al (2017) analysed the impact of two macroprudential policies in the period 2006–09. In particular they evaluated the effects of the introduction of: (i) a *dynamic provisioning scheme for commercial loans* (DP); ii) *a countercyclical reserve requirement* (CRR) implemented in 2007 to control for excessive credit growth. The results indicate that DP and CRR had a negative effect on credit growth curbing excesses in the credit supply. A measure of the aggregate macroprudential policy stance suggests that the use of these policies has worked as an effective stabiliser of credit cycles and bank risk-taking. They also found that use of monetary policy and macroprudential policies have been used in the same direction, suggesting certain level of complementarities among policies.

Mexico. Using detailed credit register information, Levin et al (2017) evaluated the effects of a change in the calculation procedure for banking provisions (from a backward-looking to a forward-looking scheme). They found that a system of banking provisions based on expected losses reduced credit growth between 2009 and 2015. The effect is larger for loans denominated in local currency than for dollar-denominated credits. They also found that the use of internal methodologies for calculating banking provisions reduces the impact of that policy on credit growth.

Peru. Cabello et al (2017) analysed the effects on credit growth of two different macroprudential policies: (i) a new dynamic provisioning system (DP) and; (ii) the introduction of conditional reserve requirements on foreign currency liabilities that penalize banks that do not reduce their loans in foreign currency (CR). The authors found that DP had a significant effect on credit growth and CR had a significant effect on the share of loans denominated in foreign currency, which helped to stimulate the de-dollarisation process in Peru.

United States. Calem et al (2017) analyse how two types of recently used prudential policy affected credit supply in the United States. First, they test whether the US bank stress tests had any impact on the supply of mortgage credit. They find that the initiation of the Comprehensive Capital Analysis and Review (CCAR) stress tests in 2011 had a negative effect on the share of jumbo mortgage originations and approval rates at stress-tested banks – banks with worse capital positions were impacted more negatively. Second, they analyse the impact of the 2013 Supervisory Guidance on Leveraged Lending and the subsequent 2014 FAQ notice, which clarified expectations on the Guidance. They find that the share of speculative-grade term-loan originations decreased notably at regulated banks after the FAQ notice.

4. Summary of results using meta-analysis techniques

In order to detect evidence of the impact of macroprudential policies on credit growth, we employed meta-analysis techniques to summarise the results of the five country papers that used credit registry data. In particular, we used the coefficients obtained by the papers from Argentina, Brazil, Colombia, Mexico and Peru from the regressions (1)–(3) described in Section 2. These models could differ slightly from those used in the specific papers but are directly comparable between countries. For each equation, we have 13 observations (ie coefficients). Four of these observations correspond to the coefficients reported by Argentina (four policies,[14] one type of loan), one for Brazil (one policy, one type of loan), six coefficients reported by Colombia (three policies for two types of loan[15]), one for Mexico (one policy, one type of loan) and finally one for Peru (one policy, one type of loan). The estimated range of the effect of macroprudential tools combines the information of the reported coefficients and their respective standard error. As country teams evaluated different types of policies such as changes in reserve requirements (Colombia and Brazil), the introduction of additional capital buffers (Argentina), variations in provisioning systems (Colombia, Mexico and Peru) and restrictions on currency mismatching (Argentina) results can be compared using a meta-analysis technique. The full characteristics of the macroprudential policies summarised in the meta-analysis are reported in Table 2. In our commentary, for simplicity, we will refer to the papers by country name instead of author.

Due to the wide variety of macroprudential tools used and the different institutional characteristics of the countries analysed, we used a random effect estimation for the meta-analysis. This method allows us to estimate an expected range for the effectiveness of macroprudential policies on different dimensions of credit, taking into account not only the level of variation for each specific estimated coefficient, but also the level of variability of estimated coefficients among country estimations (see Annex B).

We anticipate that the way in which macroprudential policies are differentiated is quite relevant when explaining the differences among the estimated effects. In particular, as discussed above, we differentiate policies with the clear aim of dampening the cycle (*cyclical*) from those with the aim of increasing the financial

[14] The paper for Argentina separately evaluates the impact of the introduction of both policies and the tightening periods of them. This is the reason for reporting four different observations.

[15] A group of estimations for credit to firms and other for credit to individuals.

sector's resilience using capital or provisioning requirements (*capital)*. It is important to highlight that there are other possible ways of classifying the policies (see Claessens et al (2013)). For instance, one possibility is to draw a line between policies directed at financial institutions and those that are focused more on borrowers. However, this type of classification does not apply for the evaluated tools since all the policies considered in the common approach were supply-oriented. We don't analyse, for instance, cases of changes in LTV or DTI caps.

Another relevant distinction is related to the interaction of the specific macroprudential tools with monetary policy (see equation 2) and with business cycle conditions (see equation 3). With respect to the interaction of macroprudential policy with monetary policy (equation 2), we identified policies that reinforce the effects of monetary policy if the sign of the interaction terms between the policies (detected by the sum of the coefficient $\sum_{j=1}^{4} \gamma_j$ in equation 2) is negative and therefore the effect of the specific macroprudential policy on credit growth goes in the same direction as changes in monetary policy.

Effects of macroprudential policies on lending

We first analyse the impact of macroprudential policies on credit growth using random effects meta-analysis of the coefficients for equations 1, 2 and 3 and the combination of all the estimates. We compare the effects of macroprudential policies in the short term (ie after three months, by imposing j=1 in equation (1)-(3)) with effects after one year (j=1,…,4).

Tables 3 and 4 present the effects of macroprudential policies after three months and one year, respectively. When we combine all the observations together, we find that a tightening in macroprudential policy is associated with a reduction in annual credit growth of 4.2% after three months and 7.2% after one year.

Graph 2 presents "forest plots" of the coefficients for the different country studies and equations. The aggregate estimated effect is represented by a red line accompanied by the respective confidence interval (blue rhombus). The effect after three months (upper panel) is more heterogeneous than the effect after one year (lower panel). In particular, after three months, we do not always detect a clear negative correlation between macroprudential policies and credit growth. In particular, the correlation with bank lending growth is weaker for those policies aimed at increasing resilience. However, the weaker effect vanishes considering the impact through longer horizons (after one year). In this case the effects of policies directed at increasing capital buffers are always significant (see lower panel). A tightening in this type of policy is associated with a decrease in annual credit growth of 3–6% depending on the model used (see Table 4). All in all, this indicates that prudential policies aimed at raising additional buffers through capital requirements or provisioning (*capital*) take more time to manifest their effects.

The analysis of the forest plots aggregates country team results without controlling for specific institutional characteristics that could differ across jurisdictions. To this end, as a second step in the meta-analysis, we corroborate the above results by means of meta-regressions that allow us to control for time-invariant country characteristics (see Annex B for details). The results are presented in Table 5. The overall findings confirm that tools employed to curb the cycle (*cyclical*) have a significant negative effect on lending supply after one year. By contrast, also in this case we find that policies that directly affect the capital levels (*capital*) of financial institutions tend to have a non-significant effect in some specifications. When we combine all the observations together, both types of macroprudential tool have a significant impact on lending growth, but policies aimed at curbing the cycle (*cyclical*) have twice the effect of policies directed at increasing capital buffers.

All the above results are relatively robust and are confirmed in the individual country papers for Argentina, Brazil, Colombia, Mexico and Peru, even when alternative specifications or additional institutional characteristics are controlled for. Moreover, some of the country papers were able to shed some light on a possible differential impact of macroprudential tools among banks with different characteristics. In particular, there is some evidence that lending supply reacts differently for banks with a different level of risk and capitalisation (Brazil and Colombia).[16] However, there is limited significance of the standard indicators used in the bank lending channel literature (such as the capital and liquidity ratio) and this could be due to the fact that most Latin American banks maintain high levels of capital and liquidity buffer to protect themselves against external shocks. Indeed, significant effects of capitalisation are detected only when the capital buffer is calculated with respect to bank-specific targets, as banks can have different levels of risk-aversion.[17]

The interaction of macroprudential policies with monetary policy and the business cycle

The second step of the analysis described in Section 3 is to evaluate whether responses to macroprudential policies vary with monetary policy conditions. In particular, we analyse the sign of the sum of the coefficient $\sum_{j=1}^{4}\gamma_j$ in equation (2) reported by the five country teams that have access to credit registry data. Each policy reinforces the other if $\sum_{j=1}^{4}\gamma_j < 0$. By contrast, if a macroprudential policy tightening reduces the effectiveness of a monetary policy tightening and vice versa then we should observe $\sum_{j=1}^{4}\gamma_j > 0$.

The forest plot in Graph 3 indicates that, on average, the sum of the interaction term is negative and significant (see the blue rhombus that represents the estimated range of the interactions using a random effect analysis). Only for two out of the 13 episodes is the sum of the interaction terms non-statistically different from zero: the introduction in Argentina of a capital buffer regulation; and a tightening in requirement on external borrowing in Colombia. These results are confirmed in the meta-regression, where we also control for country-specific fixed effects (see the first

16 In particular, the Colombian paper finds that a tightening in a macroprudential policy index (as a measure of the macroprudential policy stance) affects the supply of credit at less stable financial institutions (those that exhibit low levels in the Z-score indicator). Similarly, Calem et al (2017) find that the CCAR stress tests had a greater effect on the credit supply of less well capitalised banks.

17 A way to overcome the uninformative content of the capital ratio is to use an alternative measure based on the deviation of bank capital from a desired or benchmark level. For example, the information reported by Colombia for the meta-analysis uses the specification proposed by Ayuso et al (2004) and Brei and Gambacorta (2014) for estimating a bank capital equation and calculating the deviation of the actual bank capital ratio from the fitted value (residual).

panel of Table 6). In particular, we don't find evidence that different types of policy (eg capital-based and cyclical) had differential levels of $\sum_{j=1}^{4}\gamma_j$.[18]

All in all, these results support the view that prudential policies and monetary policy reinforce each other. When these policies push in the same direction as monetary policy (ie both policies are tightened or both are eased) the effects have a larger impact on credit growth. In other words, macroprudential policies tend to be more effective in tackling credit cycles when they are accompanied by the use of countercyclical monetary policy.

The third step of the analysis is to evaluate whether the effectiveness of macroprudential policies varies over the business cycle. For this, we need to analyse the sign of the coefficients $\sum_{j=1}^{4}\eta_j$. For example, a macroprudential policy tightening will be stronger in an economic expansion ($\Delta LogGDP_{t-j} > 0$) if $\sum_{j=1}^{4}\eta_j < 0$ and vice versa. From the forest plot in Graph 4, we can see that the signs of the sum of the interaction terms tend to be positive but the overall effect is not statistically different from zero. Interestingly, the meta-regression analysis reported in the second panel of Table 6 indicate that, once country-specific (and invariant) institutional factors are controlled for, policies directed at increasing the resilience of banking sector (*capital*) exhibit larger negative levels of $\sum_{j=1}^{4}\eta_j$, suggesting that a tightening in those policies tends to have larger effects on credit growth during an economic expansion.

Intensive vs extensive margins

The results obtained estimating a credit growth equation at the firm level (see equation 4) showed that the macroprudential rule has a negative and significant effect on the growth of total firm credit. According to the information provided by country teams for Colombia, Peru and Mexico, there are no statistical differences between the coefficients reported at the loan level and the ones reported at the firm level. This test is particularly important for the validity of the previous results (based on the intensive margin) because the effects of macroprudential policies could be mitigated if firms obtain additional credit from new banks instead than simply relying on existing credit lines.

The Brazilian team (Barroso et al (2017)) analysed the intensive vs extensive margin, running some additional tests. In particular, they investigated the possible existence of asymmetric effects between easing and tightening of reserve requirements. In contrast with the "pushing on a string" results for monetary policy, the authors find that reserve requirements are more effective in an easing than in a tightening episode. In particular, their results indicate that in case of an easing the elasticity for the intensive margin is substantially higher than for the extensive margin (1.27% vs 0.36%). This implies that, in the case of a reduction of reserve requirements,

[18] Our paper does not evaluate how macroprudential policies interact with fiscal policies. Martin and Philippon (2015) model a currency union and evaluate how the countries would have fared if they had conducted macroprudential policies to limit the increase in private debt. They find that this policy stabilises private demand and therefore employment, and it reduces the need for bank recapitalisation, leading to lower spreads and more room for countercyclical fiscal policy. Their experiment also uncovers a new interaction between macroprudential and fiscal policies. A biased government substitutes public debt for private debt in response to restrictive macroprudential policy, thereby undoing some of the macroprudential benefits. This suggests a complementarity between fiscal rules and macroprudential rules.

firms tend to obtain additional credit mainly through banks with which they had already a stable relationship.

The above results are also corroborated by Aguirre and Repetto (2017), who followed an alternative approach that considers the intensive vs the extensive margin at the bank level. In particular, they first run the baseline equation for a subsample of firms with loans over the whole period of analysis. The effect of macroprudential tools on credit growth for this subsample was then compared with the results obtained when considering all the firms in the sample (including the new and closed banking relationships). They find that macroprudential policy measures reduced credit growth in both samples, but more by cutting off lending to the larger sample (extensive margin) than by providing less credit to the same set of firms (intensive margin). This result is also in line with the evidence that in the case of shocks banks tend to modify their lending supply by less to firms with which they have a stable relationship (Bolton et al (2016)).

Macro relevance of the results

The results obtained using the panel approach indicate the effects for the average bank. If the average bank is small, it is difficult to derive any implication for the macro relevance of the result. To deal with this issue, country teams have also estimated OLS weighted by firm relevance (total amount of loans) for equation (1). The results reported in Table 7 indicate that the reported coefficients under both approaches (panel and weighted OLS) have in all case but one, the same sign and a similar magnitude. In other words, a tightening in a macroprudential policy predicts negative effects on credit supply at the micro level (effects on the average bank) but also at the macro level (aggregate dynamics of credit), which indicates the relevance of the results from a macroprudential perspective.

The only noticeable exception is the result from Brazil in which the panel estimation indicates a drop in lending supply by 2.1% for the average bank, while the weighted OLS reports an aggregate drop of 0.4%. As explained in Barroso et al (2017) the difference in the coefficient could be due to the fact that the biggest firms were better able to mitigate the effects of the tightening of reserve requirements by resorting to unaffected banks (three quarters of Brazilian banks were unaffected by reserve requirement policies even though the affected ones detain a large portion of the loan market share).

Difference-in-difference analysis

The results discussed above using panel data estimations were confirmed through the difference-in difference analysis discussed in Section 3. This test is particularly important as a significant effect of changes in macroprudential tools on credit growth could be related to other events occurring at the same time as the policies were implemented. To solve this problem, the effects of some macroprudential policies were evaluated using a counterfactual (difference-in difference) analysis in specific episodes (see Table 8 for a sum up of the tests).

Gomez et al (2017) confirmed that both macroprudential policies evaluated for Colombia had significant effects on credit supply. Using an identification strategy that stems in the time dimension (ie evaluating the effects before and after the policy shock) they found that a 1 percentage point increase in the provisioning to commercial loans portfolio (as it was observed in the period evaluated) led to a decrease of 0.97 percentage points in credit growth after one year. In the case of the countercyclical reserve requirement, an increase of 10 basis points in the marginal reserve requirement to total liabilities ratio (as was observed in the period of analysis) leads to a decrease of 0.8 percentage points. These results are comparable with Jimenez et al (2016), who find that an increase of 14 basis points (equivalent to one standard deviation) in the ratio between provisions and total loans in Spain led to a decrease in committed lending by 2%.

Using a similar approach, Barroso et al (2017) estimate that the easing of reserve requirements in November 2008 generated an additional increase in monthly credit growth of 1.5%. The tightening in such requirements in March 2010 led to a decrease of 0.4% on average. Both results confirmed that reserve requirements had a significant impact on the credit cycle in Brazil. These results are in line with the findings in the literature. Analysing the case of Uruguay, Camors et al (2016) found that a 1 percentage point increase in total reserve requirements translated into an average fall in committed lending of 0.35%.

Aguirre and Repetto (2017) used a slightly different definition for the counterfactual experiment, based on the comparison between those institutions affected by the regulation vis a vis the unaffected. The results indicate that both the introduction of the countercyclical buffer and the reintroduction of the limit on the foreign currency position had a significant and negative effect on credit growth in Argentina. In particular, they found that the introduction of the limit on foreign currency generated an average decrease of 4.8% in credit growth. Moreover, the introduction of the countercyclical capital buffer is associated with a decrease in credit growth of 3.4%. In a similar way Aiyar et al (2014) analyse the experience of UK banks and find that an increase in the capital requirement ratio of 100 basis points induces, on average, a cumulative fall in lending growth of 6.5–7.5%.

5. Conclusions

The impact of macroprudential policies on credit growth remains an open issue. Most of the academic work on the subject has been based on aggregate- or bank-level information and has failed to reach conclusive results. This paper summarises the results of a joint project commissioned by the Consultative Council for the Americas that evaluates the effectiveness of macroprudential tools and their interaction with monetary policy. In particular, we used loan-level data and a common protocol for five Latin American countries (Argentina, Brazil, Colombia, Mexico and Peru) and corroborated the analysis using data on credit origination and borrower characteristics for other three countries (Canada, Chile and the United States). Given that, for confidentiality reasons, it was not possible to pool credit registry data sets, we used meta-analysis techniques to compare the results.

The main takeaways of the joint project are, first, that macroprudential policies have been successful in dampening credit cycles and reducing banking sector risk. In particular, macroprudential policies mainly aimed at curbing the cycle have been demonstrably effective in reducing credit growth even in the short term (within three months). The propagation of the effects for capital-based requirements is less rapid, taking place within a year. Country papers corroborated this result and suggested that bank-specific characteristics also influenced the impact of macroprudential policies on credit. In particular, some of the contributions showed that the effects of macroprudential policies were more pronounced for less stable financial institutions (eg Colombia), less strongly capitalised banks (eg the United States and Brazil) and less liquid intermediaries (Brazil).

Second, the effectiveness of macroprudential tools is reinforced by the use of monetary policy and vice versa. Macroprudential tools that acted as a complement to monetary policies (ie pushed in the same direction) were relatively more effective.

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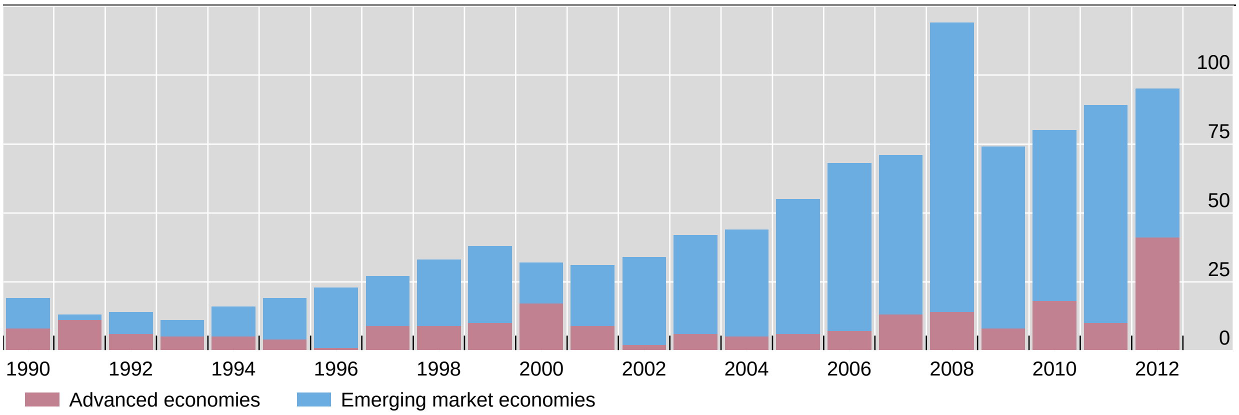
Graphs and tables

Use of macroprudential measures over time[1]

Number of macroprudential policy actions Graph 1

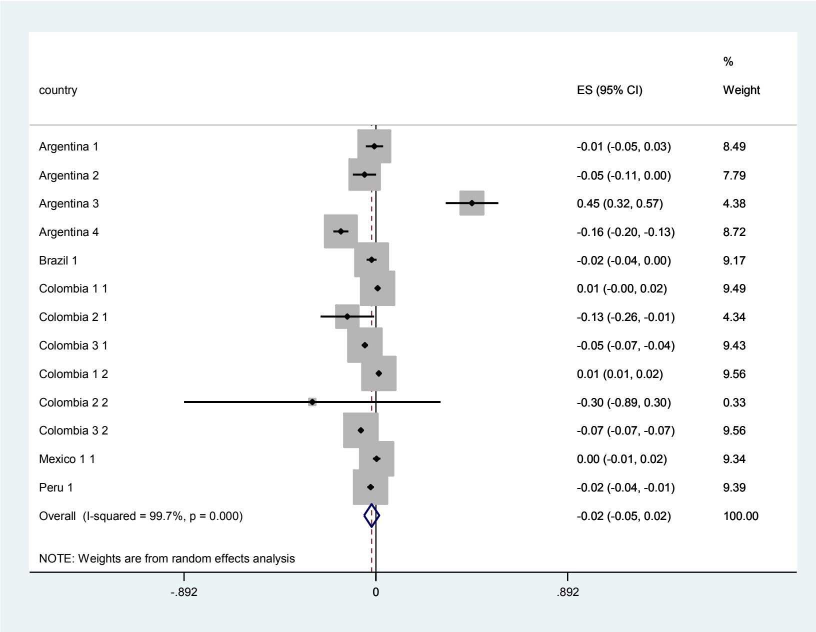


[1] The sample covers 1,047 macroprudential policy actions adopted in 64 countries (29 advanced and 35 emerging market economies). The database has been constructed using information in Kuttner and Shim (2016) and Lim et al (2013).

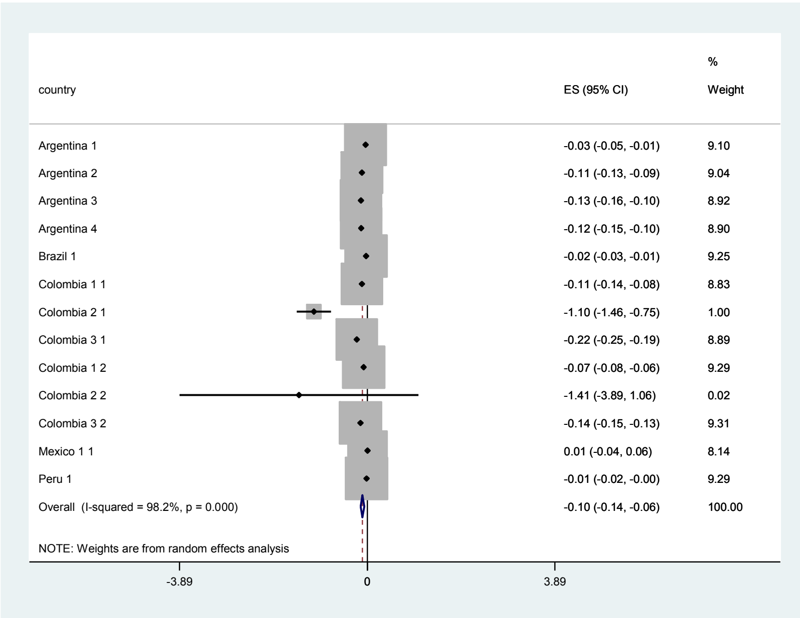
Sources: IMF; BIS.

Forest plot of the effects of MPP on credit growth controlling for bank characteristics (Equation 1) Graph 2

(a) Effect after three months



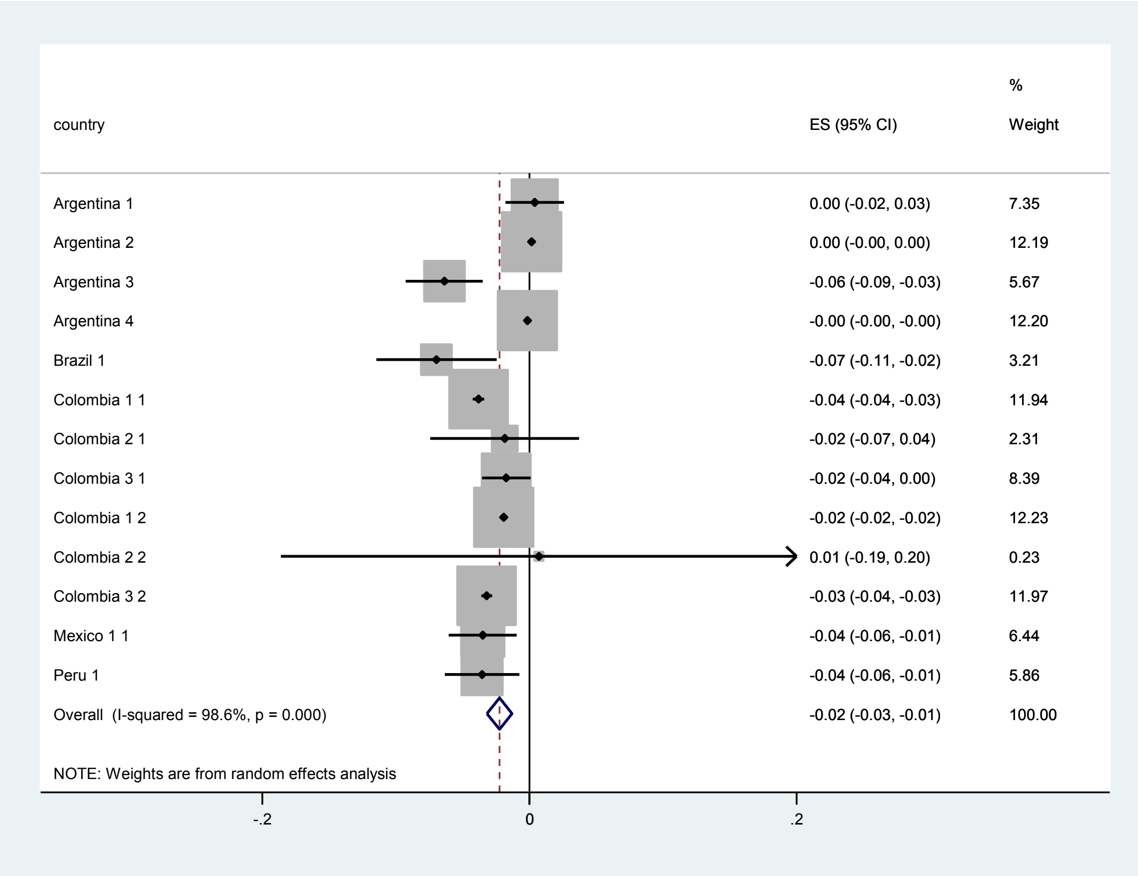
(b) Effect after one year



Note: The rows correspond to the analysed policies and the size of the grey squares represents the weights of each country observation. The x-axis represents the level of the coefficient and the country coefficients are embodied by black dots. Each point is crossed by a line which represents the confidence interval of the estimated value. The blue rhombus represents the estimated range of the effect using random effects analysis. Convention of policies evaluated: Argentina 1: Introduction of capital buffer; Argentina 2: tightening of capital buffer; Argentina 3: Introduction of limits on net global position; Argentina 4: tightening in the limits on net global position; Brazil 1: Use of reserve requirements; Colombia 1 1 introduction of dynamic provisioning system. Evaluation made on loans to firms; Colombia 2 1: requirement on external borrowing. Evaluation made on loans to firms; Colombia 3 1 Marginal reserve requirements. Evaluation made on loans to firms; Colombia 1 2 : introduction of dynamic provisioning. Evaluation made on loans to individuals; Colombia 2 2 requirement on external borrowing. Evaluation made on loans to individuals; Colombia 3 2 Marginal reserve requirements. Evaluation made on loans to individuals; Mexico 1: Provisions on expected losses Peru 1: Introduction of dynamic provisioning system.

Forest plot of the sum of the interaction terms between monetary and macroprudential policies ($\sum_{j=1}^{4} \gamma_j$ in Equation 2)

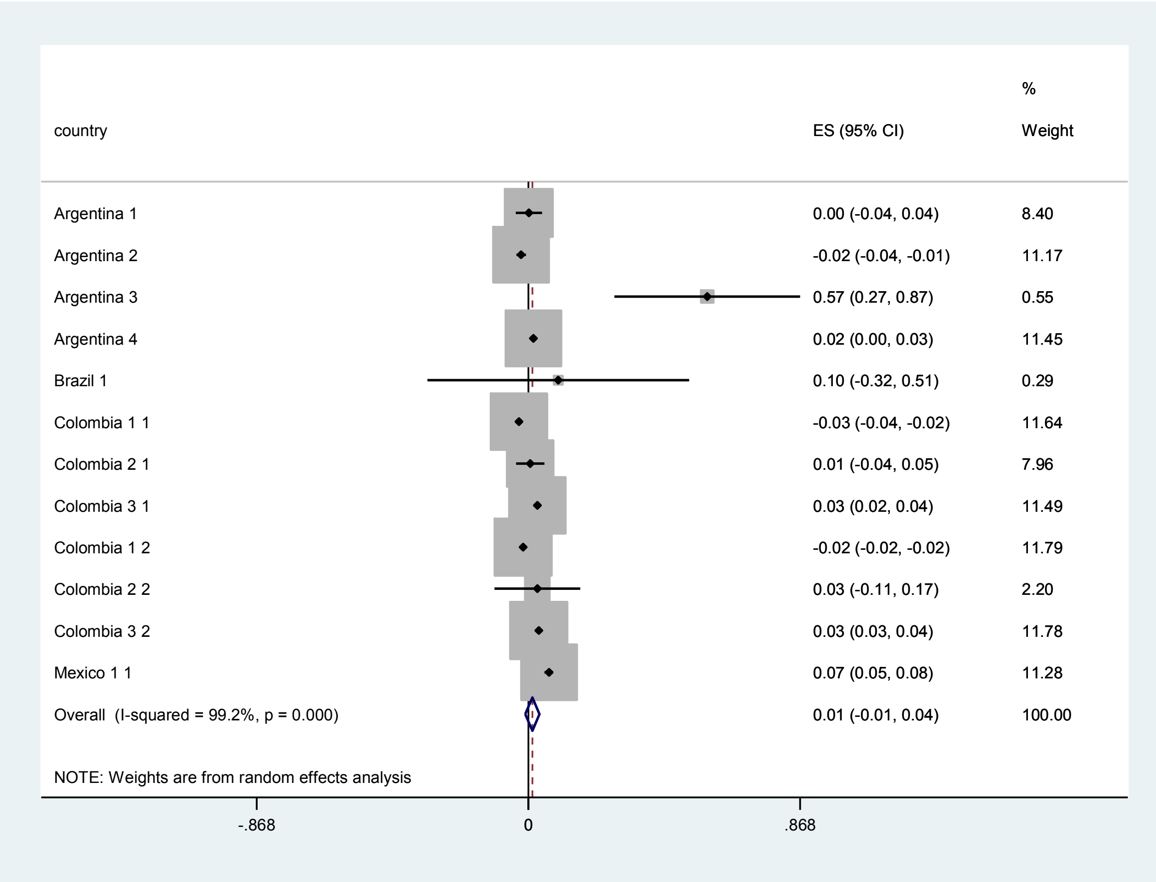
Graph 3



Note: The rows correspond to the analysed policies and the size of the grey squares represents the weights of each country observation. The x-axis represents the level of the coefficient and the country coefficients are embodied by black dots. Each point is crossed by a line which represents the confidence interval of the estimated value. The blue rhombus represents the estimated range of the sum of interactions using random effects analysis. Convention of policies evaluated: Argentina 1: Introduction of capital buffer; Argentina 2: tightening of capital buffer; Argentina 3: Introduction of limits on net global position; Argentina 4: tightening in the limits on net global position; Brazil 1: Use of reserve requirements; Colombia 1 1 introduction of dynamic provisioning system. Evaluation made on loans to firms; Colombia 2 1: requirement on external borrowing. Evaluation made on loans to firms; Colombia 3 1 Marginal reserve requirements. Evaluation made on loans to firms; Colombia 1 2: introduction of dynamic provisioning. Evaluation made on loans to individuals; Colombia 2 2 requirement on external borrowing. Evaluation made on loans to individuals; Colombia 3 2 Marginal reserve requirements. Evaluation made on loans to individuals; Mexico 1: Provisions on expected losses. Peru 1: Introduction of dynamic provisioning system.

Forest plot of the interaction between macroprudential policy and business cycle conditions ($\sum_{j=1}^{4}\eta_j$ in Equation 3)

Graph 4



Note: The rows correspond to the analysed policies and the size of the grey squares represents the weights of each country observation. The x-axis represents the level of the coefficient and the country coefficients are embodied by black dots. Each point is crossed by a line which represents the confidence interval of the estimated value. The blue rhombus represents the estimated range of the effect using random effects analysis. Convention of policies evaluated: Argentina 1: Introduction of capital buffer; Argentina 2: tightening of capital buffer; Argentina 3: Introduction of limits on net global position; Argentina 4: tightening in the limits on net global position; Brazil 1: Use of reserve requirements; Colombia 1 1 introduction of dynamic provisioning system. Evaluation made on loans to firms; Colombia 2 1: requirement on external borrowing. Evaluation made on loans to firms; Colombia 3 1 Marginal reserve requirements. Evaluation made on loans to firms; Colombia 1 2: introduction of dynamic provisioning. Evaluation made on loans to individuals; Colombia 2 2 requirement on external borrowing. Evaluation made on loans to individuals; Colombia 3 2 Marginal reserve requirements. Evaluation made on loans to firms; Mexico 1: Provisions on expected losses. Peru 1: Introduction of dynamic provisioning system.

Different types of macroprudential tool in the Americas

Table 1

Type of instrument	Measures	Frequency of use (percent)	Tightening measures	Loosening measures
	(1)	(2)	(3)	(4)
a. Enhancing Resilience (1)	38	22		
Capital requirement/Risk weights (RW)/ Limits on dividend distribution	21	12.1	17	4
Provisioning requirement (Prov)	9	5.2	9	0
Liquidity ratios	8	4.6	7	1
b. Dampening the cycle (2)	135	78		
Changes in reserve requirement (RR)	108	62.4	53	55
Net open position (NOP)	9	5.2	4	5
Changes in LTV, DTI limits	13	7.5	9	4
Limits on credit growth or lending to specific sectors	2	1.2	1	1
Foreign currency lending limits	3	1.7	3	0
Total	***173***	***100***	***45***	***16***

Note: (1) We follow the classification in Claessens et al (2013) with respect to the objectives of macroprudential policies. According to them, in reviewing the goals of various types of macroprudential policies, it is useful to classify measures in four groups. The first two groups are aimed at reducing the occurrence and consequences of cyclical financial risks, by respectively either (1) dampening the expansionary phase of the cycle, or (2) reinforcing the resilience of the financial sector to the adverse phases of the cycle. The database has been constructed using information in Kuttner and Shim (2016) and Lim et al (2013). The information includes the following countries: Argentina, Brazil, Canada, Chile, Colombia, Mexico, Peru, United States and Uruguay.

Macroprudential policies reported for meta-analysis by country groups

Table 2

Instrument	Country	Description	Authority responsible for the measure	Objective of the policy (classification used by Claessens et al (2013))*
1. Capital buffer and profit reinvestment	Argentina	Authorities established that any financial institution could redistribute profits through dividends as long as its regulatory capital after dividends are paid is at least 75% above the regulatory minimum capital requirement. This measure was introduced in 2010, with 30% threshold of regulatory capital requirement over which profits may be distributed; it was further increased to 75% in 2012.	Central bank	Enhancing resilience (introduction) and dampening the cycle (tightening)
2. Foreign currency net global position	Argentina	To limit currency mismatches of banking institutions, a limit in the difference between assets and liabilities denominated in foreign currency was introduced in 2014, with a 30% threshold of regulatory capital and then lowered (tightened) to 20% in September that year.	Central bank	Dampening the cycle (tightening)
3.Reserve requirements	Brazil	Brazil has been active in the use of reserve requirements. Different scenarios are considered (i) the release of reserves in 2008–09 in response to the liquidity squeeze following the global financial crisis; (ii) the reversal of the policies in 2010–11 in the context of high capital inflows and associated credit growth; and (iii) the renewal of stimulus during 2012–14 in response to perceived weakness of economic activity and credit growth.	Central bank	Dampening the cycle
4.Dynamic provisioning regime	Colombia	Inspired by the Spanish system, a new provisioning regime with countercyclical considerations for commercial loans began in July 2007.	Supervisor	Enhancing resilience
5.Deposit requirement on external loans	Colombia	Almost simultaneously with the establishment of a marginal reserve requirement on deposits, the central bank adopted a requirement on short term external loans of 40% with a holding period of six months.	Central Bank	Dampening the cycle
6.Marginal reserve requirement on banking deposits	Colombia	In response to an episode of excessive credit growth, in May 2007 the central bank established a marginal reserve requirement of 27% on current accounts, 12.5% for saving accounts and 5% for term deposits with a maturity lower than 18 months.	Central bank	Dampening the cycle
7.Changes in provisioning	Mexico	From a backward-looking scheme of provisions, the authorities introduced a new provisioning methodology designed to increase the accuracy of provisions including expected losses considerations. It was introduced in 2009, 2011 and 2014 for different types of loan.	Supervisor	Enhancing resilience
8.Dynamic provisioning	Peru	To reduce the procyclical behaviour of credit, a dynamic provisioning scheme was introduced in 2008.	Supervisor	Enhancing resilience

* According to this paper, in reviewing the goals of various types of macroprudential policies, it is useful to classify measures in four groups. The first two groups are aimed at reducing the occurrence and consequences of cyclical financial risks, by respectively either (1) dampening the expansionary phase of the cycle, or (2) reinforcing the resilience of the financial sector to the adverse phases of the cycle. The paper also considers a third group that includes those prudential policies directed to dispelling the gestation of cycles and a fourth group of policies which is aimed at risks arising from interconnectedness and tries to ensure the internalisation of spillovers. These two types of policies are not analysed in this paper.

Effects of macroprudential policies on credit growth after three months. Meta-analysis of estimated coefficient of MPP on credit growth

Table 3

	Eq.1	Eq.1 cyclical	Eq1 capital	Eq.2	Eq.2 cyclical	Eq.2 capital	Eq.3	Eq.3 cyclical	Eq.3 capital	ALL	ALL cyclical	ALL capital
Q (1)	1033***	105.3***	94.87	4415***	53.6***	32.9***	241.5***	37.2***	24.85***	5691.0***	1273***	333.15***
Degrees of freedom	12	6	5	12	6	5	12	6	5	37	20	16
I^2 (2) (%)	98.8	99.2	94.7	99.7	88.8	84.8	95.4	66.7	85.5	99.3	99.7	92.3
τ^2 (3)	0.0014	0.0015	0.0010	0.0034	0.0006	0.0002	0.0035	0.0069	0.004	0.0019	0.0008	0.0011
Random-effects mean (4)	**-0.057*** **	**-0.094*** **	**-0.027* **	-0.020	**-0.072*** **	-0.002	**-0.036* **	**-0.108*** **	-0.021	**-0.042*** **	**-0.084*** **	-0.019
95% conf.int	-0.081 to -0.0034	-0.129 to -0.060	-0.055 to 0.001	-0.055 to 0.015	-0.099 to -0.046	-0.017 to 0.012	-0.077 to 0.006	-0.189 to -0.027	-0.053 to 0.004	-0.058 to -0.025	-0.101 to -0.067	-0.054 to 0.010

Notes: (1) The *Q* Measure evaluates the level of homogeneity/heterogeneity among studies. It is calculated as the weighted squared difference of the estimated effects with respect to the mean. The statistical distribution of this measure follows a χ^2 distribution. The null hypothesis of the test assumes homogeneity in the effect sizes. (2) This percentage represents the magnitude of the level of heterogeneity in effect sizes and it is defined as the percentage of the residual variation that it is attributable to between study heterogeneity. It is defined as the difference between the Q measure and the degrees of freedom divided by the *Q* measure. Although there can be no absolute rule for when heterogeneity becomes important, Harbor and Higgins (2008) tentatively suggest adjectives of low for I^2 values between 25% and 50%, moderate for 50%-75% and high for values larger than 75%. (3) τ^2 is a measure of population variability in effect sizes. It depends positively on the observed heterogeneity (Q measure) and its difference with respect to the degrees of freedom. Given the expected value of Q measure under the null hypothesis of homogeneity is equal to the degrees of freedom; a homogeneous set of studies will result in this statistic equal to cero. Under the presence of heterogeneity this estimate should be different from cero. (4) It corresponds to the weighted average of coefficients reported in different estimations. The weights are calculated considering the sampling fluctuation of each effect size (standard error per reported coefficient) and estimated population variance of effect sizes (τ^2). ***,** and * denote significance at the 1%,5% and 10%, respectively.

Effects after one year of macroprudential policies on credit growth. Meta-analysis of estimated coefficient of MPP on credit growth

Table 4

	Eq.1	Eq.1 cyclical	Eq1 capital	Eq.2	Eq.2 cyclical	Eq.2 capital	Eq.3	Eq.3 cyclical	Eq.3 capital	ALL	ALL cyclical	ALL capital
Q (1)	663***	61.8***	123.01***	200.4***	86.5***	31.1***	99.5***	26.3***	39.84***	1784***	434***	573.5***
Degrees of freedom	12	6	5	12	6	5	12	6	4	37	20	16
I^2 (2) (%)	98.2	98.2	95.9	94	93.1	83.9	88.9	77.2	90	97.9	95.4	98.8
τ^2 (3)	0.0039	0.0054	0.0017	0.0008	0.0017	0.0002	0.0010	0.0029	0.0005	0.0024	0.0033	0.0010
Random-effects mean (4)	**-0.098*** **	**-0.150*** **	**-0.056*** **	**-0.042*** **	**-0.068*** **	**-0.031*** **	**-0.065*** **	**-0.115*** **	**-0.054*** **	**-0.072*** **	**-0.125*** **	**-0.047*** **
95% conf.int	-0.149 to -0.072	-0.215 to -0.086	-0.090 to -0.021	-0.060 to -0.024	-0.105 to -0.032	-0.043 to -0.018	-0.091 to -0.040	-0.178 to -0.053	-0.075 to -0.033	-0.114 to -0.060	-0.158 to -0.091	-0.063 to -0.031

Notes: (1) The *Q* Measure evaluates the level of homogeneity/heterogeneity among studies. It is calculated as the weighted squared difference of the estimated effects with respect to the mean. The statistical distribution of this measure follows a χ^2 distribution. The null hypothesis of the test assumes homogeneity in the effect sizes. (2) This percentage represents the magnitude of the level of heterogeneity in effect sizes and it is defined as the percentage of the residual variation that it is attributable to between study heterogeneity. It is defined as the difference between the *Q* measure and the degrees of freedom divided by the Q measure. Although there can be no absolute rule for when heterogeneity becomes important, Harbor and Higgins (2008) tentatively suggest adjectives of low for I^2 values between 25% and 50%, moderate for 50%-75% and high for values larger than 75%. (3) τ^2 is a measure of population variability in effect sizes. It depends positively on the observed heterogeneity (Q measure) and its difference with respect to the degrees of freedom. Given the expected value of Q measure under the null hypothesis of homogeneity is equal to the degrees of freedom; a homogeneous set of studies will result in this statistic equal to cero. Under the presence of heterogeneity this estimate should be different from cero. (4) It corresponds to the weighted average of coefficients reported in different estimations. The weights are calculated considering the sampling fluctuation of each effect size (standard error per reported coefficient) and estimated population variance of effect sizes (τ^2). ***,** and * denote significance at the 1%,5% and 10%, respectively.

Effects of macroprudential policies on credit growth. Meta-regression

Table 5

Explanatory variables:	Dependent variable: Estimated effect of macroprudential policy on credit growth							
	Eq 1	Eq 1	Eq 2	Eq 2	Eq3	Eq3	ALL	ALL
Countercyclical instrument (1)	-0.0712 (0.0640)	**-0.0791*** **(0.0347)**	**-0.2631**** **(0.0869)**	**-0.2949**** **(0.1032)**	**-0.3616**** **(0.1417)**	**-0.3848***** **(0.1385)**	**-0.2251***** **(0.0577)**	**-0.2450***** **(0.0617)**
Capital instrument (2)	0.0163 (0.0639)	0.01814 (0.0351)	**-0.1777*** **(0.08391)**	-0.1766 (0.1032)	**-0.2911*** **(0.1481)**	-0.2911 (0.1540)	**-0.1381***** **(0.0573)**	**-0.1257***** **(0.0605)**
Country effects	No	Yes	No	Yes	No	Yes	No	Yes
Adjusted R^2 (percent)	9.16	91.7	46.7	12.4	33.1	38.0	31.7	25.1
Joint test for significance of all variables	1.58	5.09**	4.94**	1.54	3.43*	2.53	7.74***	3.05***
Number of observations	13	13	13	13	13	13	39	39

Note: (1) We identified with a dummy variable the policies employed with countercyclical purposes. To this group we included: (i) the increase in capital buffers requirements requirement, (ii) the increase in the limits on external borrowing position, both employed in Argentina in 2012; (iii) the imposition of marginal reserve requirements; and iv) the obligation of a deposit requirement on external loans, both employed in Colombia in 2007. (2) We identified with a dummy variable those instruments that have effects on the capital of banking institutions. To this group belong the following policies: (i) the establishment and (ii) the tightening in capital buffers that took place in Argentina in 2010 and 2012, respectively; iii) the introduction of a dynamic provisioning system in Colombia and (iv) in Peru and finally (v) the changes in provisioning requirements that took place in Mexico. (***,** and * denote significance at the 1%,5% and 10%, respectively.

Effectiveness of macroprudential policy conditional on monetary policy and business cycle. Meta-regression

Table 6

Explanatory variables:	Dependent variable: Sum of coefficients of the interaction terms between macroprudential and monetary policy		Dependent variable: Sum of coefficients of the interaction terms between macroprudential policy and changes in GDP	
Countercyclical instrument (1)	-0.0127 (0.0120)	-0.0095 (0.0125)	-0.0656 (0.0186)	-0.0880 (0.0298)
Capital instrument (2)	-0.0096 (0.0129)	-0.0098 (0.0121)	-0.0769 (0.0494)	**-0.0546*** **(0.0272)**
Country effects	No	Yes	No	Yes
Adjusted R^2 (percent)	6.4	7.1	90.1	84.3
Joint test for significance of all variables	0.8	1.07	10.56***	2.44
Number of observations	13	13	13	13

Note: (1) We identified with a dummy variable the policies employed with countercyclical purposes. To this group we included: (i) the increase in capital buffers requirements requirement, (ii) the increase in the limits on external borrowing position, both employed in Argentina in 2012; (iii) the imposition of marginal reserve requirements; and (iv) the obligation of a deposit requirement on external loans, both employed in Colombia in 2007. (2) We identified with a dummy variable those instruments that have effects on the capital of banking institutions. To this group belong the following policies: (i) the establishment and (ii) the tightening in capital buffers that took place in Argentina in 2010 and 2012, respectively; (iii) the introduction of a dynamic provisioning system in Colombia and (iv) in Peru and finally (v) the changes in provisioning requirements that took place in Mexico. (***,** and * denote significance at the 1%,5% and 10%, respectively.

Panel estimation vs weighted OLS. Effects after one year

Table 7

Instrument	Country	Panel estimation	Weighted OLS
1. Capital buffer and profit reinvestment	Argentina	-0.1086*** (0.0115)	-0.0546* (0.0319)
2. Foreign currency net global position	Argentina	-0.1244*** (0.0141)	-0.2559*** (0.0893)
3.Reserve requirements	Brazil	-0.0209** (0.0064)	-0.0039 (0.0062)
4.Dynamic Provisioning regime	Colombia	-0.1068*** (0.015)	-0.3683*** (0.0714)
5.Deposit requirement on external loans	Colombia	-1.1044*** (0.1813)	-0.9769*** (0.5172)
6.Marginal reserve requirement on banking deposits	Colombia	-0.2173*** (0.01421)	-0.2006** (0.018)
7.Changes in provisioning	Mexico	-0.0508*** (0.0076)	-0.1356* (0.0812)
8.Dynamic Provisioning	Peru	-0.0122*** (0.0052)	-0.0484** (0.0196)

Note: ***,** and * denote significance at the 1%,5% and 10%, respectively.

Estimated effect of macroprudential polices on credit growth using difference in difference analysis

Table 8

Country	Instrument	Counterfactual used	Effect on credit growth	Comments
Argentina	Introduction of the capital buffer and the limit on foreign currency holdings.	The evaluated policies did not apply to all the intermediaries. The counterfactual is based on this categorisation.	-3.4% for the capital buffer and -4.8% for the introduction of the limit on foreign currency holdings	Time window of six months before and after the implementation of each rule.
Brazil	Changes in reserve requirements	Based on the levels of reserve requirements that banks would have constituted assuming that each requirement was enacted one month before.	For the intensive margin the impact is -0.77% (November 2008) and -1.32% (March 2010). For the extensive margin the effect is -0.54 and -0.67%, respectively.	Monthly data. They evaluated an easing in reserve requirements in November 2008 and a tightening in such requirements in March 2010
Colombia	Introduction of dynamic provisioning system and the marginal reserve requirement.	Based on the levels of provisions and reserve requirements that banks would have constituted assuming that each requirement was enacted one year before.	-0.97% for provisioning and -0.80% for reserve requirements	The values of the elasticities are calculated assuming an increase in 1% in the ratio between provisions for the introduction of dynamic provisions, and an increase of 10bp in the ratio between reserve and total liabilities. One-year window was employed

Note: Country teams of Mexico and Peru did not report this analysis.

Annex A: Macroprudential instruments in CCA countries

Instrument	Argentina	Brazil	Canada	Chile	Colombia	Mexico	Peru	United States
Capital-based instruments								
Countercyclical capital buffers	No	No	No	No	No	No	No	No
Limits on Leverage	No	No	No	No	No	No	No	No
Dynamic Provisioning	No	No	No	No	**Yes (2007)**	**Yes (2011) (provision on expected losses)**	**Yes (2008)**	No
Limits on dividend distribution	**Yes (2010, 2012 conservation buffer)**	No	No	No	*Yes (2008)*	No	No	*Yes, CCAR (2011, 2012, 2013, 2014)*
Other capital-based tools	*Yes (2004, 2007, 2012 changes in risk weights for specific operations)*	**Yes (Change of risk weights for some housing loans and some auto and payroll loans)**	No	No	*Yes (increase in the LGD of some consumer loans in 2011 and temporary provision for entities with high NPL growth in 2012).*	No	*Yes (on specific operations 2010, 2012)*	**Yes, SCAP (2009), DFA Stress tests (2013, 2014)**
Liquidity-based instruments								
Countercyclical reserve requirements	*Yes (but not countercyclical)*	**Yes (2008, 2009, 2011, 2012)**	No	No	**Yes (2007)**	No	**Yes. (2010, 2011)**	No
Liquidity ratios	*Yes (2008)*	*Yes. Liquidity measures and capital flow tax to ease funding problems of banks that lend to firms.*	No	*Yes*	*Yes (2008)*	*Yes*	*Yes (1997, 2012)*	No
Limits on non-core liabilities	No	No	No	No	No	No	No	No
Asset-based instruments								
LTV and DTI limits	*Yes (LTV for mortgages)*	**Yes. Establishment of LTV caps for some housing loans.**	**Yes (2004, 2007, 2008, 2010, 2011, 2012)**	No	*Yes (1999)*	No	*Yes*	*Yes (2014) (Dodd Frank)*
Limits on credit growth	No	No	No	No	*Yes*	No	No	No
Limits on exchange rate risk	**Yes (limits on net foreign currency position of FI)**	*Yes (2007)*	No	*Yes*	*Yes (2005)*	*Yes (1997)*	*Yes (2010-2011)*	No
Limits on derivatives	*Yes*	*Yes (2011)*	No	No	*Yes (2007)*	*Yes (2001)*	*Yes (2011)*	No
Other asset-based instruments	No	No	No	No	No	No	No	**Yes (2013) (Leveraged Lending Guidance)**

Note: The number in brackets indicates the year of modification or use of macroprudential instrument. Macroprudential tools that have been evaluated in this project by country teams are indicated in bold.

Annex B: Meta-analysis techniques

Meta-analysis techniques are very helpful when studies are not perfectly comparable but evaluate the same or a closely related question. The main purpose of the meta-analysis is to better exploit the information of a set of estimations for a specific problem. These techniques are especially used in medical sciences for summarising the effect of specific treatments or policies on a population of individuals. The unit of analysis is commonly a study in which a specific coefficient is estimated. There are two usual approaches that are used depending on the type of information employed and also on the question to be answered: "fixed" and "random effects" estimations.

Under the presence of homogeneous effect sizes, which means that there is low level of variability in the estimated coefficients, we could employ a fixed effects approach in which the estimated effect of any policy corresponds to the average of coefficients weighted by their respective standard deviation. In the case of macroprudential policy evaluation, if we were evaluating the same policy with a similar population, we could employ this method. Nevertheless this is not the case here since we have different sources of heterogeneity.

We therefore employed a random effects methodology in which the objective is to try to model the unexplained heterogeneity of effects. Random effects models conceptualise the population of effect sizes as falling along a distribution with both mean and variance, but beyond variance due to sampling fluctuations of individual studies (Card (2016)). In other words, this type of estimation considers not only the level of variation for each specific estimated coefficient (as was done under the fixed-effect approach) but also the level of variability of estimated coefficients among the studies (or country estimations in our case).

The first step for performing a random effects meta-analysis is precisely to estimate the level of heterogeneity among effect sizes. This is constructed using the squared weighted sum of the difference between the estimates and its average. This statistic is commonly called the Q measure. In our case the value of this statistic is quite high, in many cases rejecting the null hypothesis of homogeneity under a χ^2 statistical distribution (Table 3), suggesting a large level of heterogeneity among estimates for the four considered equations.

The second step is to estimate the population variability in effect sizes (τ^2). There are different methodologies to estimate this parameter, but the simplest one uses the observed heterogeneity (total variability) and the expected variability given the standard errors of the coefficients. This statistic depends positively on Q and negatively on the number of studies (ie country estimations) or degrees of freedom.

The third step is to use this estimate of population variability to provide random-effects weights of effect sizes. This type of estimation considers two sources of imprecision of estimates: population variability and sampling fluctuation. The weights of each coefficient are defined as the inverse of the sum of the sampling standard error and the population variability.

All these elements together allow an expected range of different coefficients to be calculated. It is important to highlight that the purpose of a meta-analysis random effect calculation is not to estimate an expected value but a range.

More formally, given a certain level of variability of the country effects, we could expect that the true effects of a macroprudential policy, θ_i, varies between estimations by assuming that they have a normal distribution around a mean effect, θ. In that sense, the effect could be represented in the following way:

$y_i|\theta_i \sim N(\theta_i, \sigma_i^2)$, where $\theta_i \sim N(\theta, \tau^2)$

So, $y_i \sim N(\theta_i, \sigma_i^2 + \tau^2)$

As it was mentioned above, under this approach there are two sources of variance that are estimated: (i) the variance around the mean of the estimated effect and (ii) the between-study variance.

The main result of this estimation corresponds to a range in which the expected value of the effect of a macroprudential tool in which a specific dimension of credit (ie credit growth or bank risk) could be located.

It is common to observe in this type of estimation a great level of heterogeneity among studies, or as in our case, among country estimations. The country estimations in our exercise are no exception. It is natural to expect a higher level of heterogeneity since we are combining not only different countries but also different types of policy.

When the estimated coefficients are quite diverse, increasing the uncertainty of an average effect, one common alternative is to try to explain the differences in the results using statistical estimations. This approach is called meta-regression analysis. This type of analysis is commonly employed on study-level summary data that investigate the extent to which statistical heterogeneity between results of multiple studies can be related to one more characteristics of the studies.

The meta-regression allows for such residual heterogeneity (between-study variance) by assuming that the true effects follow a normal distribution around the linear predictor. In that line, the meta-regression can be formally defined in the following way:

$y_i|\theta_i \sim N(\theta_i, \sigma_i^2)$, where $\theta_i \sim N(x_i\beta, \tau^2)$

So, $y_i \sim N(x_i\beta, \sigma_i^2 + \tau^2)$

where β is the vector of estimated effects of study characteristics. This type of equation is estimated by weighted least-squares, in which the weight of each estimated coefficient depends inversely of its variance and corresponds to the inverse of the sum of two types of deviations (σ^2, τ^2).

Meta-regressions are similar in essence to OLS regressions, in which an outcome variable is predicted according to the values of one or more explanatory variables (Higgins and Green (2011)). In our case the dependent variable is the effect estimate of macroprudential tools on the different dimensions of credit and the explanatory variables are characteristics of studies that might influence the size of intervention effect.

The regression coefficient obtained from the meta-regression analysis describes how the outcome variable (the effect of macroprudential policy) changes with a unit increase in the explanatory variable. As some of our dependent variables are categorical variables in most cases (dummy variables), the regression coefficients estimate how the macroprudential effect in each subgroup differs from a nominated reference subgroup.

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BANK FOR INTERNATIONAL SETTLEMENTS

Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

The impact of macroprudential policies and their interaction with monetary policy: an empirical analysis using credit registry data[1]

Leonardo Gambacorta and Andrés Murcia,

Bank for International Settlements

[1] This presentation was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

BANK FOR INTERNATIONAL SETTLEMENTS

The impact of macroprudential policies and their interaction with monetary policy: An empirical analysis using credit registry data

Leonardo Gambacorta (BIS and CEPR)

9th biennial IFC Conference

“Are post-crisis statistical initiatives completed?”

BIS - Basel, 30 August 2018

The views expressed are the presenter only and not necessarily those of the BIS

Main characteristics of the research project

- Most of the studies use aggregate data or bank-level data. A very limited use has been done of credit registry data (some exceptions Jimenez et al, 2016; Camors et al, 2016)
- Joint project under the auspices of the Consultative Council for the Americas (CCA):
  - Credit register data for five countries Latin America countries: AR, BR, CO, MX, PE (good laboratory)
  - Not possible to pool the data (data highly confidential)
  - Research protocol (same modelling strategy and similar data definition)
  - Focus on domestic credit. Project wants to complement the analysis of the IBRN (cross-border spillover of MP tools)
  - 5 country paper and one summary paper (meta analysis techniques)

Macroprudential policies analyzed

Type of instrument	Episodes		Tightening episodes		Loosening episodes	
	Meta analysis	All studies	Meta analysis	All studies	Meta analysis	All studies
a. Enhancing resilience						
Capital requirement/Risk weights (RW)	0	1	0	1	0	0
Provisioning requirement (Prov)	4	4	4	4	0	0
Limits on dividend distribution	2	2	2	2	0	0
Liquidity ratios	0	0	0	0	0	0
Other capital based tools	0	3	0	3	0	0
b. Dampening the cycle						
Changes in reserve requirement (RR)	5	8	3	5	2	3
Changes in limits on net open position (NOP)	2	2	2	2	0	0
Changes in LTV, DTI limits	0	8	0	5	0	3
Limits on credit growth or lending to specific sectors	0	0	0	0	0	0
Requirement on external borrowing operations	2	2	1	1	1	1
Other asset based instrument	0	1	0	1	0	0
Total	**15**	**31**	**12**	**24**	**3**	**7**

Note: The classification is based on Claessens et al (2013).

Main questions

1. Are macroprudential tools effective in stabilising credit cycles?

2. How is the effectiveness of macroprudential policies on credit growth affected by monetary policy conditions?

1. Are MaPs effective in stabilising the credit cycle?

$$\Delta Log\ Credit_{bft} = \delta_f + \sum_{j=1}^{4} \beta_j \Delta \text{Macro tool}_{t-j} + \sum_{j=1}^{4} \beta'_j \Delta \text{Macro tool}_{t-j} * \tilde{X}_{bt-j} +$$
$$+ controls_{bft} + quarter_t + \varepsilon_{bft}$$

where:

$\Delta Log\ Credit_{bft}$ is the change in the logarithm of actual value of loans by bank *b* to debtor *f*

$\Delta \text{Macro tool}_{t-j}$: tightening +1; 0 invariant; easing -1.

$\tilde{X}_{bt-j}$ is a vector of bank specific characteristics (capital, liquidity, deposit ratio and size)

$controls_{bft}$ include macro variables, firms and contract characteristics

δ_f are bank fixed effects

$quarter_t$ are quarterly seasonal dummies

2. How the effectiveness of macroprudential policies on credit growth is affected by monetary policy conditions?

$$\Delta Log\ Credit_{bft} = \delta_f + \sum_{j=1}^{4}\beta_j \Delta \text{Macro tool}_{t-j} + \sum_{j=1}^{4}\delta_j \Delta \text{r}_{t-j} + \sum_{j=1}^{4}\gamma_j \Delta \text{Macro tool}_{t-j} * \Delta \text{r}_{t-j} + controls_{bft} + quarter_t + \varepsilon_{bft}$$

The main test is on the significance of $\sum_{j=1}^{4}\boldsymbol{\gamma_j}$

$$\frac{\partial \Delta Log\ Credit_{bft}}{\partial \Delta \text{Macro tool}_{t-j}} = \sum_{j=1}^{4}\beta_j + \sum_{\boldsymbol{j=1}}^{\boldsymbol{4}}\boldsymbol{\gamma_j}\, \Delta r_{t-j}$$

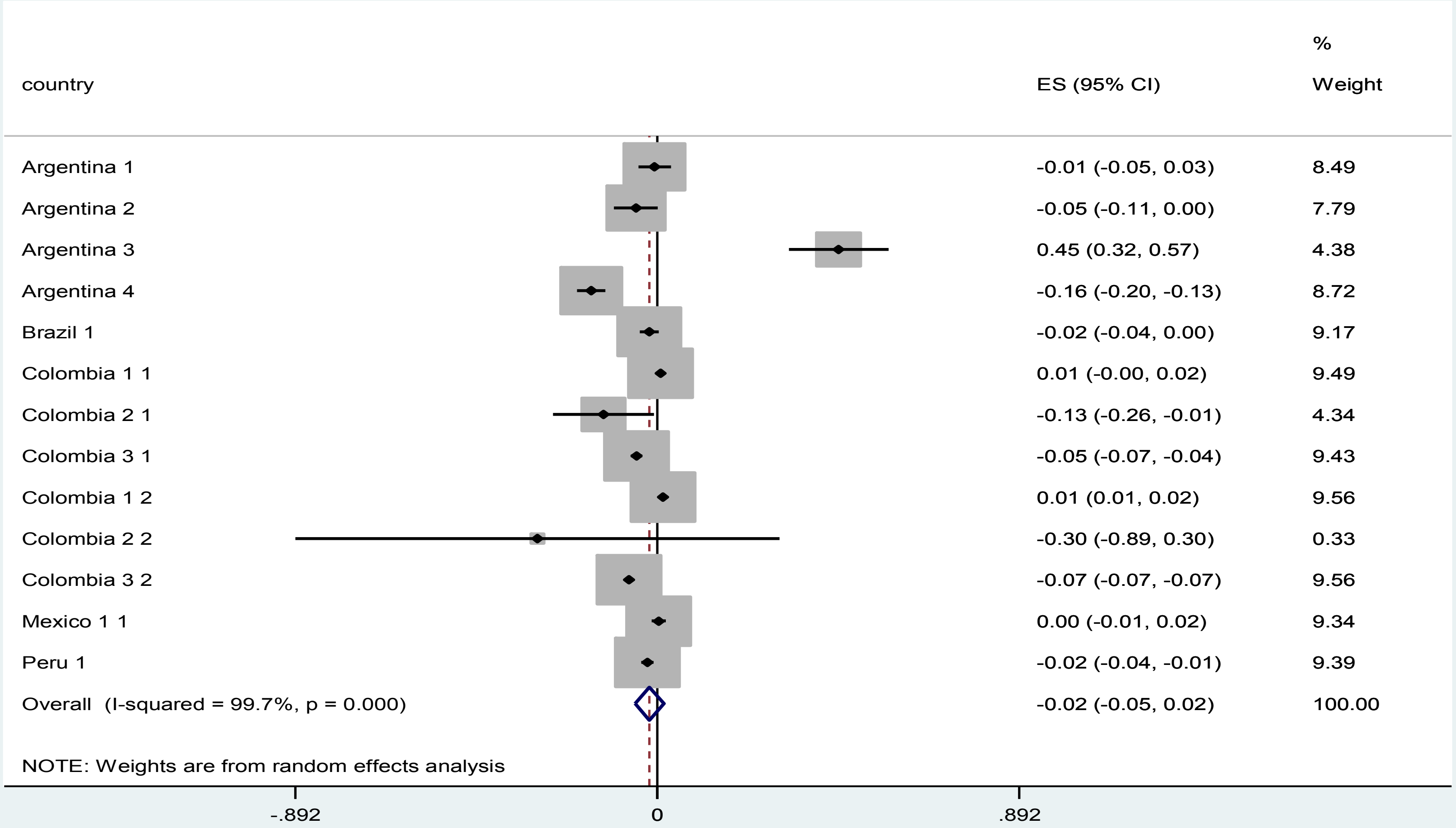
<0 **?**

- If $\sum_{j=1}^{4}\gamma_j < 0$ then each policy will reinforce the other
- By contrast, if $\sum_{j=1}^{4}\gamma_j > 0$, a monetary policy tightening reduces the effectiveness of a macroprudential tightening

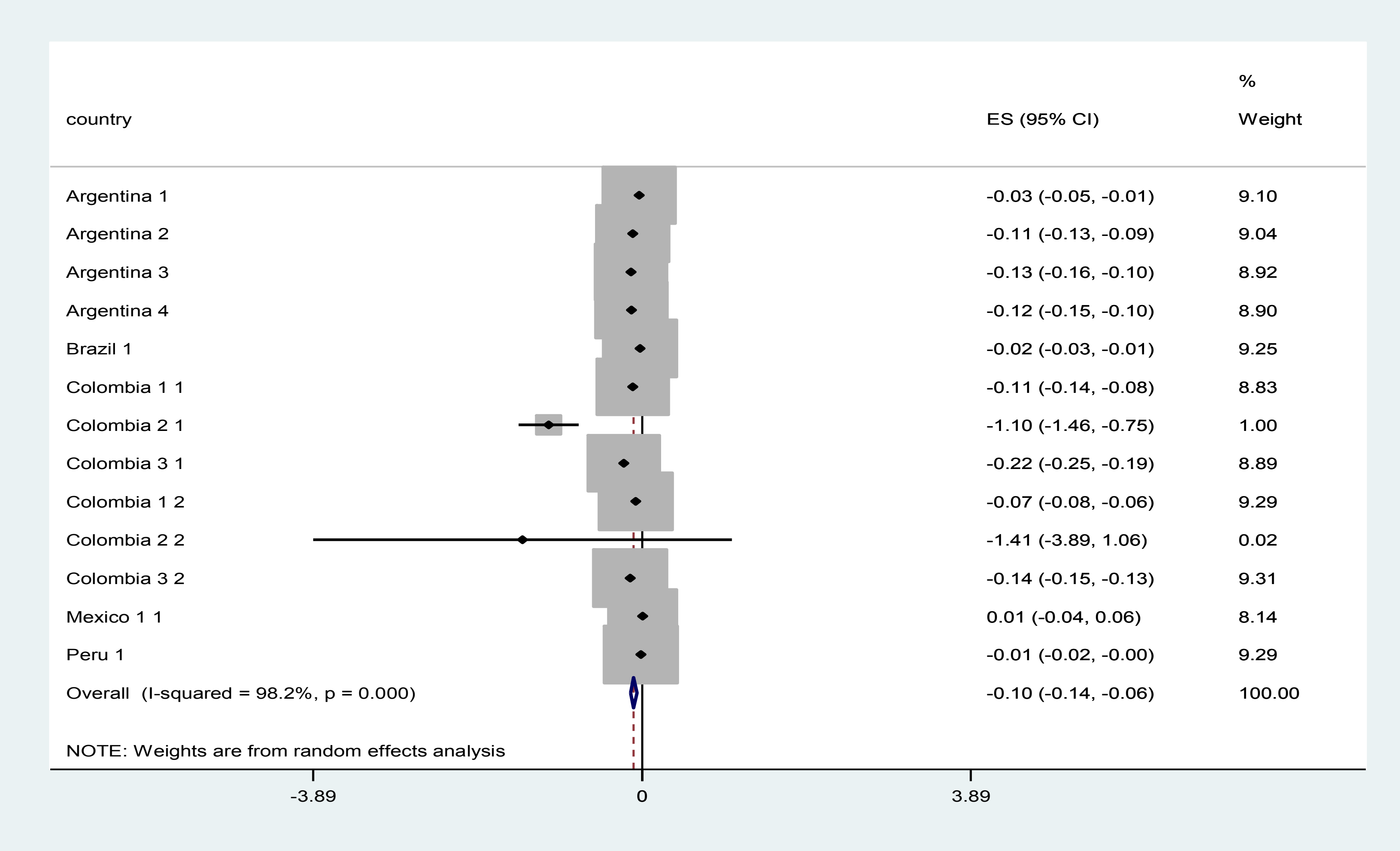
1. Effects of macroprudential policies on lending

- A tightening in macroprudential policies is associated with a reduction in credit growth of 4.2% after three months and 7.2% after one year
- Prudential policies aimed at raising additional buffers through capital requirements or provisioning take more time to manifest their effects
- There is evidence from country team papers that lending supply reacts differently for banks with a different level of risk and capitalization

Forest plot of the effects of MaPs on credit growth controlling for bank characteristics (after 3 months)



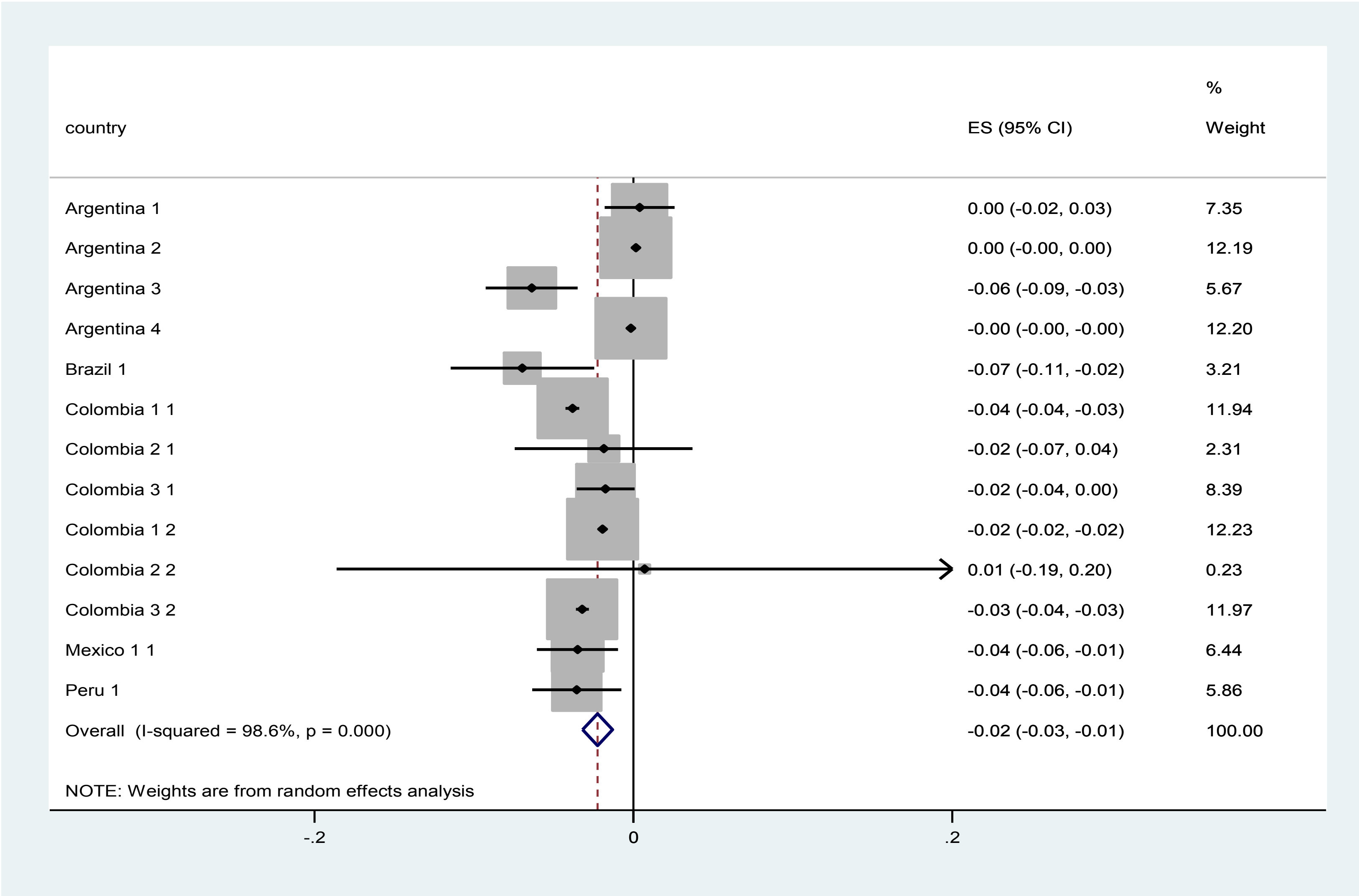
Forest plot of the effects of MaPs on credit growth controlling for bank characteristics (after one year)



2. Interaction of monetary and macroprudential policies

- The effectiveness of macroprudential tools on credit growth is affected by the contemporaneous use of monetary policy
- $\sum_{j=1}^{4} \gamma_j < 0$ so each policy reinforce the other
- Macroprudential tools that acted as a complement to monetary policies (ie pushed in the same direction) were relatively more effective

Forest plot of the sum of the interaction terms between monetary and macroprudential policies ($\sum_{j=1}^{4} \gamma_j$ in Equation 2)



Conclusions

1. *Are macroprudential tools effective in stabilising credit cycles?*

   - Yes. They have been effective in stabilising credit cycles
   - The propagation of the effects on credit growth is more rapid (after one quarter) for those policies with a purpose of dampening the cycle than for capital based requirements (within a year)

2. *How the effectiveness of macroprudential policies on credit growth is affected by monetary policy conditions?*

   - The effectiveness of macroprudential tools on credit growth is affected by the contemporaneous use of monetary policy
   - Macroprudential tools that acted as a complement to monetary policies (ie pushed in the same direction) were relatively more effective

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Credit statistics as a tool for assessing the effectiveness of policies aimed at reducing credit cost [1]

Marcia Fiorindo, Monica Une, Juliano Cavalheiro and Fernando Rocha,
Central Bank of Brazil

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Credit Statistics as a Tool for Assessing the Effectiveness of Policies Aimed at Reducing Credit Cost

Marcia Fiorindo, Monica Une, Juliano Cavalheiro and Fernando Rocha[1]

Abstract

In 2016, the Banco Central do Brasil (BCB) established a policy agenda, based on four pillars, to address structural issues of the domestic financial system. Identifying and overcoming the systems' shortcomings would bring long-lasting benefits to society. Lower Cost of Credit is one of these four pillars, and includes policies aiming at: reducing the cost of credit to the borrower; increasing competiveness and flexibility in the credit market; and fostering more efficient credit allocation. New credit statistics that have been developed by the BCB are instrumental in assessing the success of these policies.

Keywords: credit statistics, interest rates,

Contents

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Introduction

The objective of this paper is to present some recent challenges to the production of credit statistics by the Banco Central do Brasil (BCB), associated to the policy need for a more comprehensive evaluation of the cost of credit in Brazil, as well as the statistics developed for this purpose.

Interest rates practiced in the Brazilian credit market are historically high. For several years, the BCB has conducted efforts to understand this issue better, with important analytical results.[2] In order to deepen the knowledge and, in this regard, to contribute to the reduction of the cost of credit, the BCB implemented a set of short, medium and long-term actions, included in the BC+ Agenda. Among these actions is the creation of a set of complementary statistics for the measurement of the cost of credit in Brazil, which includes methodological revisions and compilation improvements of pre-existing statistics and the development of new statistics.

In order to analyze the efforts referred to in this introduction, this article begins with a panorama of the credit market in Brazil (Section 1) and continues with a brief description of the BC+ Agenda (Section 2) and a detailed presentation of the statistics being compiled in the BCB for the measurement of the cost of credit (Section 3). In the end, Section 4 summarizes the new challenges that can already be envisaged for the production of statistics for this purpose.

Overview of Credit Markets in Brazil

Credit markets in Brazil registered strong growth in the decade from the mid-2000s to the recession of 2014-16. As percentage of GDP, total credit outstanding went from 24%, as of March 2004, to 53.7% in December 2015. After a contraction in both credit supply and demand caused by the recession and the gradual economic recovery, the amount of banking credit in the Brazilian economy stabilized around 46.6% pf GDP in the first half of 2018.

Besides economic growth and inflation stabilization in the first period, institutional advances, especially those related to the strengthening of credit operations guarantees, have boosted the expansion of credit supply, in an environment of soundness of the financial system. In this context, the real estate credit market was particularly developed. Its share of GDP increased from about 2% in 2008 to around 9.5% ten years later. Other credit segments that expanded strongly were vehicle financing and payroll loans. The growth of these lines of credit justified the greater expansion of the market of credit to households, compared to the market of credit to corporations. Currently (June 2018), loans to households correspond to 54% of the total SFN portfolio (38% in December 2003).

The creation of longer-term instruments – such as financial bills – backed by credit agreements – like mortgage and agribusiness bills – improved funding conditions for credit. Fund raising through these securities increased significantly since 2010, further stimulated by tax exemptions and compulsory deposits.

Credit markets in Brazil are characterized by significant participation of directed lending operations, which comprise rural and real estate loans and financing with funds from the National Development Bank (BNDES). In such operations, the source of funds or the interest rate is determined by specific legislation that has the purpose of fomenting economic sectors or activities, by providing resources at subsidized costs and longer terms. In June 2018, directed lending accounted for 47.6% of total credit volume in Brazil.

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[2] See, for instance, the series of annual Reports on Banking Economics and Credit (only in Portuguese) at https://www.bcb.gov.br/?SPREAD.

BC+ Agenda

On December 2016, the BCB launched a policy agenda named BC+, aimed at addressing structural issues of the domestic financial system. The BC+ agenda listed short-, medium- and long-term actions to be implemented by the BCB, the National Monetary Council (CMN), or by new legislation divided in four pillars: financial citizenship, modern legislation, financial system efficiency, and lower cost of credit.

The high cost of banking credit in Brazil is a complex subject with many contributing causes, from subsidies in important amounts of banking credit, to competition issues and high administrative cost to banking intermediation. The Lower Cost of Credit pillar in the BC+ agenda gather actions aimed at reducing these cost to the borrower, reducing delinquency rates, fostering competitiveness and flexibility in credit operations, stimulating a more efficient credit allocation and revising reserve requirement rules.

One important aspect of improving the efficient allocation of banking credit in Brazil is to reduce the subsidies in credit operations. To achieve this objective, a new legislation was approved so the interest rates on BNDES funding and its credit operations are now defined accordingly to real market interest rates (treasury securities yields), inflation and a spread. Previously, these interest rates were fixed by administrative decisions. The same rationale was applied to the full set of credit operations with public funding (rural sector, development funds, etc.).

Reducing the high levels of reserve requirements in Brazil contributes to reducing the costs of financial intermediation. In this sense, the BCB has both reduced the levels of reserve requirements (for example, from 40% to 25% for sight deposits), by around USD12.4 billion, or 10.4% in the second quarter of this year, and also simplified its rules. This is an ongoing action. Competition in the banking sector is also likely to be fostered by some of the actions of the BC+ agenda. A new legislation to reinforce credit bureaus in Brazil is being discussed in Congress. Regarding collateral in credit operations, a legislation was approved for registering electronically financial assets received as collateral. In addition, a new regulation now rules the functioning of covered bonds market, aligned to international best practices, and the consolidation of this instrument is expected to create alternative sources of funding to the real estate credit market.

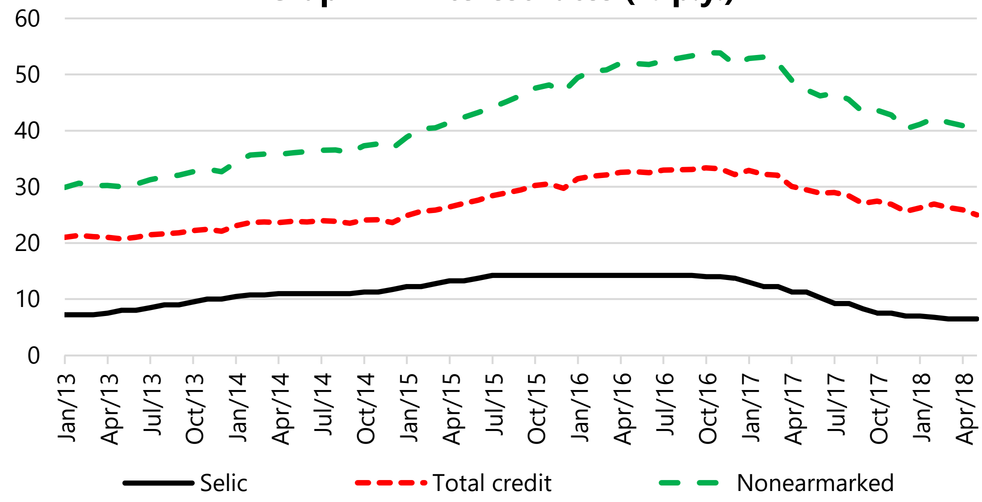
Looking at credit market segments, the BC+ agenda addresses market infrastructure issues in credit cards, which are likely to reduce costs and to improve competition. The initial impacts of these measures pointed to a significant reduction in credit card operation interest rates. The agenda also fosters research to better understand the composition of average banking spreads in Brazil and its causes.

All those measures demand good quality credit statistics as a tool to evaluate the effective impact of the agenda on the credit markets, both in the aggregate and in specific instruments or modalities. As such, the implementation of the BC+ agenda pushed forward a revision of available credit statistics, to complement the information set available for both policymakers, market analysts, financial institutions and society as a whole.

Measuring the Cost of Credit in Brazil

The cost of credit in Brazil remains high. Graph 1 presents the Brazilian monetary policy rate (Selic) and the average interest rates for the total banking credit and for the non-earmarked credit. As expected, banking rates move accordingly to the basic rate, but with a significant spread. As the Selic rate reached its minimum historical levels, the policy issue remains over the possibilities of more significant declines in banking rates. Those difficulties involve structural issues to be addressed by the BC+ agenda, such as high cost of revolving operations, but they also stimulate the development of a new set of credit statistics, as shown in the next items of this paper.

Graph 1 - Interest rates (% p.y.)



For the interest rate statistics, the characteristics of the banking credit markets represents a tradeoff, as it includes widely diversified operations in terms of maturities, interest rates, risks and collateral coverage. On one hand, the statistics try to synthetize this cost in a (single or a small number of) consolidated measure(s) but, on the other hand, there is the need to expand available information about the average cost of credit.

Statistics of new operations' interest rates

The BCB disseminates monthly statistics on the Brazilian credit market[3] with a one-month lag, including outstanding amounts, new operations, interest rates, spreads, maturities and non-performing loans. All these statistics are compiled based on daily information sent by the financial institutions, segmented by type of agreed charge (line of credit) and portfolio modality. The statistics of interest rates refer to the total effective cost of a banking loan to the final borrower, thus including the interest rates itself and tax and operating charges.[4]

The traditional measure of interest rates in Brazil considers the weighted average of interest rates of the new operations contracted in the reference month. Based on these data, the BCB compiles and disseminates the consolidated interest rates for each type of credit, as well as the rates of the large segments of this market (total, households, corporate, non-earmarked and direct resources).

These interest rates try to express the "price" of the credit contracted at the margin (i.e., in the last month) and fluctuate according to various conditions, such as the current monetary policy and the relations between the banking sector and the real sector of the economy, reflecting the agents' financial conditions and the consumer decisions and investment. Consolidated rates may also vary due to the composition effect, due to changes in the share of each institution in the modality`s lending, as well as changes in the representativeness of the outstanding amounts of each modality in the total portfolio.

Besides the aggregated interest rates, the BCB also publishes each financial institution interest rate by line of credit[5] on a daily basis, based on a moving average of the last five business days data, aiming to bring more transparency to clients and to stimulate competition.

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3 Press Release – Monetary and Credit Statistics (https://www.bcb.gov.br/ingles/notecon2-i.asp) and Time Series Management System (SGS, https://www3.bcb.gov.br/sgspub/localizarseries/localizarSeries.do?method=prepararTelaLocalizarSeries),

4 Operating charges: credit opening fees, insurances etc.

5 Only in Portuguese at https://www.bcb.gov.br/pt-br/#!/c/txjuros/.

Along with the statistics of the borrowers cost (interest rates), the BCB compiles statistics of the banks' funding costs and, thus, statistics on the banking lending spreads.

The BC+ agenda highlighted a gap in the then available set of interest rates statistics. Besides interest rates on the new monthly credit operations, there was a need for compiling an average interest rate that would represent the total outstanding credit. The objective was to capture the cost for households and corporations on a monthly basis due to credit operations contracted over time. This resulted in the Average Cost of Outstanding Loans indicator (ICC), published by the BCB since April 2017, with a time series beginning in January 2013.

Average Cost of Outstanding Loans (ICC)[6]

The first new credit cost statistic created by the BC+ agenda was the ICC. The ICC represents the average cost of all credit operations with amounts outstanding in the domestic financial system – from the borrower's perspective –, regardless of the credit operations' reference month. Therefore, it represents how much interest borrowers would pay, considering all the operations contracted in the past yet with instalments to be paid, as well as the new operations of the reference month. From the point of view of the financial system, it is an estimate of how much revenue the financial institutions would receive from their credit operations (assuming zero delinquency rate).

From the above definition, one can conclude that the ICC is relevant mostly in terms of the financial system totals or by credit modalities – and not by each financial institution total portfolio, which would not be comparable. Different institutions have different time distributions of their lending, mainly – but not only – due to the different composition of their portfolios, in terms of credit modalities.

In macroeconomic terms, the ICC aims to capture the different durations of credit operations and their effects on the rates borrowers pay each month. In longer-term contracts, such as real estate financing, for example, current interest rates tend to show a different evolution from that observed in the credit portfolio as a whole when changes in the monetary cycle occur. Conversely, this ability is limited when applied to revolving modalities because these operations balances are constantly restored, bringing the ICC too close to the lending rates of each month.

This aspect is better illustrated by comparing extremely different credit modalities in terms of maturities, amounts outstanding and monthly new operations. Let us consider real estate and revolving credit card loans to households. As the typical maturity of revolving credit card loans is less than two month, its amounts outstanding are R$35.1 billion, and monthly new operations, R$15.3 billion. For real estate, with maturity of 131 months, the values are R$576.1 billion and R$7.6 billion. The share of credit card loans in the traditional interest rate statistics therefore is the double of the real estate loans, as are the amounts of new operations. As for the ICC, the weight of real estate loans is significantly higher, as is the total amount outstanding.

The ICC's calculation takes into account the portfolio composition at the credit modality level, according to the contractual settlement dates and their respective interest rates[7]. The ICC for a credit modality, in a given reference month, corresponds to the average interest rate of the contracts that have outstanding amounts, weighted by the share of the amounts of the different vintage loans. In turn, the ICC of a portfolio composed of two or more modalities corresponds to the average of the ICCs of each modality, weighted by their respective outstanding amounts.

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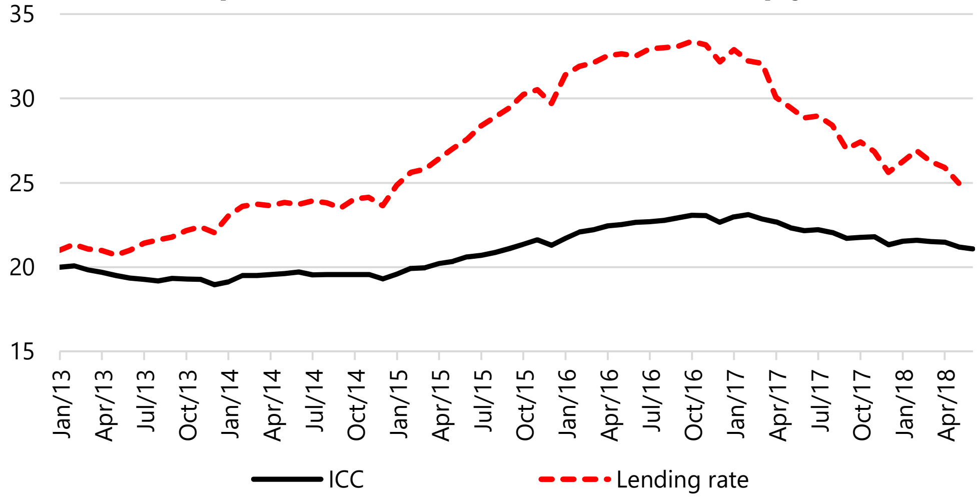
[6] BCB Technical Note 45 (only in Portuguese) presents further details on ICC methodology. Available at https://www.bcb.gov.br/conteudo/depec/NotasTecnicas/2018nt45custocred.pdf.

[7] In addition to the aggregated credit statistics, the ICC compilation also uses as data source the data available in the BCB`s Central Credit Risk System (SCR). The latter are provided to the BCB in a very disaggregated and detailed manner, on individual contracts level, with monthly frequency.

Graph 2 - Credit cost for total credit (% p.y.)

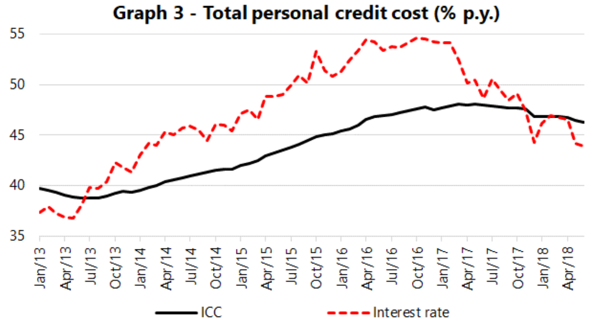


The statistics of ICC spread was also developed. Similarly to the spread of the new operations' interest rates, the ICC spread is the difference between the lending rate (the ICC itself) and the funding rate of the ICC. The latter is equal to the average of the funding rates that were estimated for each of the vintage loans, weighted by their respective shares in the remaining outstanding amounts of the portfolio.

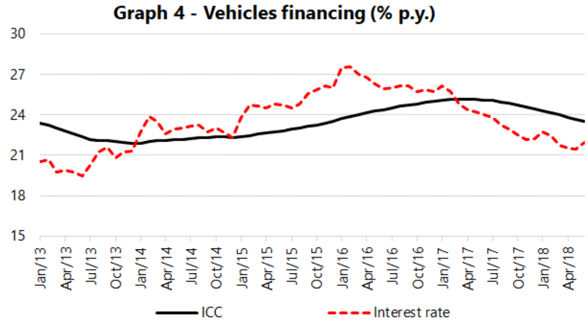
As can be seen in the above graph 2, at the margin, the ICC is much more stable than the interest rate, which is more heavily affected by factors like current trading conditions, seasonal factors or to the composition effect. In addition, the cost of total portfolio reflects monetary policy cycles more slowly, because it is compounded by the effect of past contracts in the current portfolio, which were contracted sometimes at different point in the monetary cycle as compared to the current Selic rate.

In addition to the ICC for total credit and its spread, ICC by credit modality was developed and published as of April 2018. The graphs below show examples of ICC and the interest rate trends for the main credit modalities.

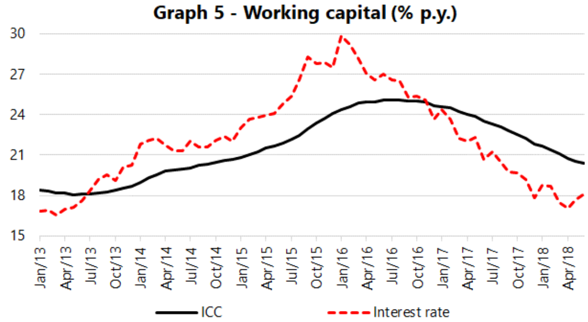
Graph 3 - Total personal credit cost (% p.y.)



Graph 4 - Vehicles financing (% p.y.)



Graph 5 - Working capital (% p.y.)



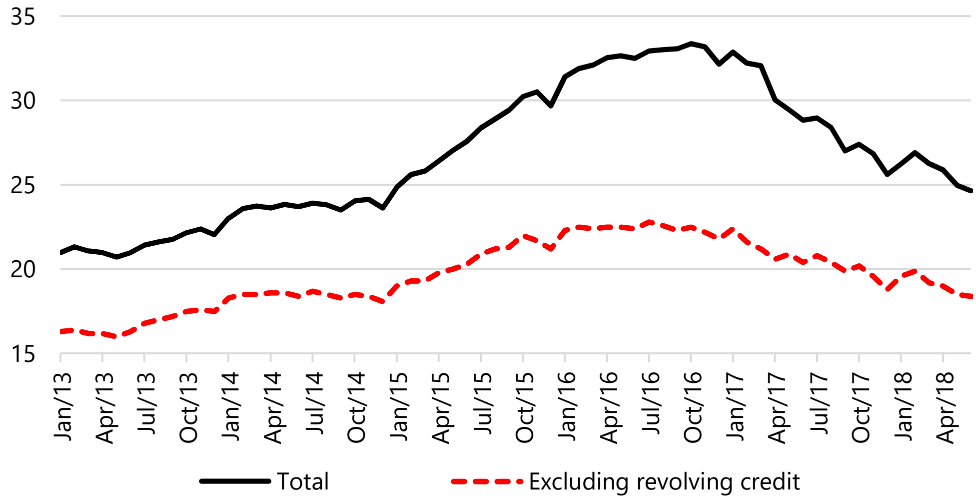
Interest rates and ICC excluding revolving credit

In addition to the ICC and interest rates for the total credit aggregates, it became increasingly relevant to compile and disseminate cost of credit statistics, excluding revolving credit operations. The revolving operations include the overdraft facility, credit card (revolving and on-demand) and guaranteed account (the latter, for corporates only). The main feature of revolving lines of credit is the complete absence of guarantees and the automatic and periodic renewal of the availability of resources, which are pre-approved. **Although not holding a significant share of the total credit outstanding[8] and usually having a duration from less than one month to two months – after which time they are renewed – these modalities have very high rates and contribute significantly to the high average cost of credit operations as a whole**.

In this respect, the compilation of a separate set of statistics for interest rates excluding revolving credit is relevant. It allows timely and clear monitoring of the pass through of monetary policy decisions through the credit channel, by removing the effects of operations that can be contracted and settled through months, at very high rates, and which often represent more a financial imbalance of the borrower than a consumption decision. Therefore, the reduction of the cost of the revolving credit modality is more closely related to actions towards financial education.

Graph 6 shows the trajectories of the interest rates, considering and excluding the revolving credit.

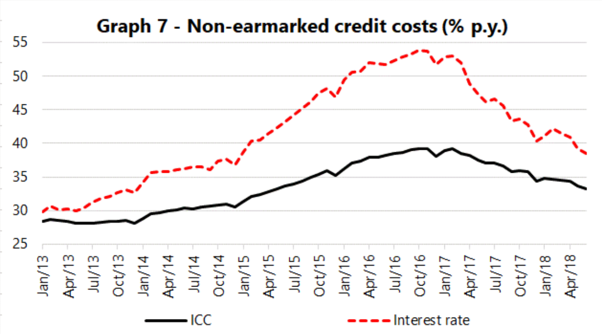
Graph 6 - Interest rates for total credit (% p.y.)

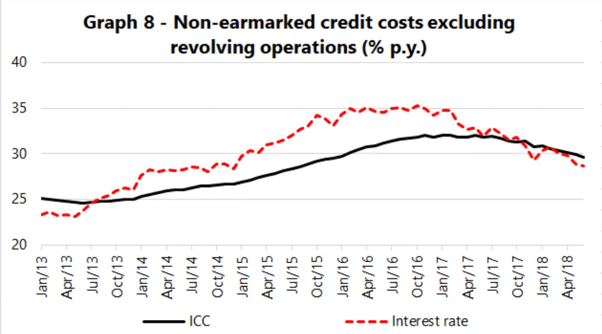


The interest rate excluding revolving credit shows, as expected, a more stable behavior when compared to the total rate. For example, from December 2015 to March 2017, the total rate rises 2.4 p.p., while the non-revolving rate remains stable. As of April 2017, a specific regulation for revolving credit card, detailed in item below, begins to apply and total rates fall considerably, capturing the effect of the new measure. The interest rate excluding revolving credit registers a downward movement, but follows the monetary policy easing that occurs in the period.

Moreover, the interest rate without the effect of the revolving credit presents a more coherent trajectory with the evolution of the ICC. Due to the changes of the monetary policy cycles and the larger gap between these changes and the ICC, the interest rate curve and the ICC curve are expected to cross over each other in some periods. This can only be verified when using the consolidated interest rate excluding the revolving modalities. Graphs 7 and 8 presents interest rates and the ICC with and without revolving credit for the non-earmarket credit and illustrate this difference.

8 Total revolving credit outstanding currently accounts for around 8% of total credit provided by the domestic financial system.





Changes in monetary policy tend to be translated more immediately into the interest rate, which in the case of the ICC occurs gradually, and with a certain lag, as it reflects the effect of past lending over time. The crossings of the above curves visually evidence these differences. At the beginning of 2013, when the ICC series began, the Selic began the upward cycle and the interest rate rose more rapidly, exceeding the ICC curve, which remained below contracted rates during the entire upward cycle and also at the beginning of the downward cycle, albeit on an upward trajectory. As of the end of 2016 – the beginning of the cycle of monetary policy easing –, the lending rate falls faster, while the ICC still reflects the operations contracted in the previous upward cycle. In this regard, the curves cross again at the end of 2017, when the lending rate sits below the ICC.

The cost of credit excluding revolving credit were calculated and disseminated in a historical series for interest rates, ICC, and respective spreads, thus completing the set of macroeconomic credit cost statistics that are used to evaluate the effects of actions on the Lower Credit Cost pillar of the BC+ agenda. It is worth noting that these new statistics are all produced from data already existing in the BCB's databases, regularly provided by financial institutions, and did not require any additional cost to information providers. The immediate availability of the data and its level of granularity allows the timely monitoring of the actions of the policy makers, whether macro or microeconomic issues.

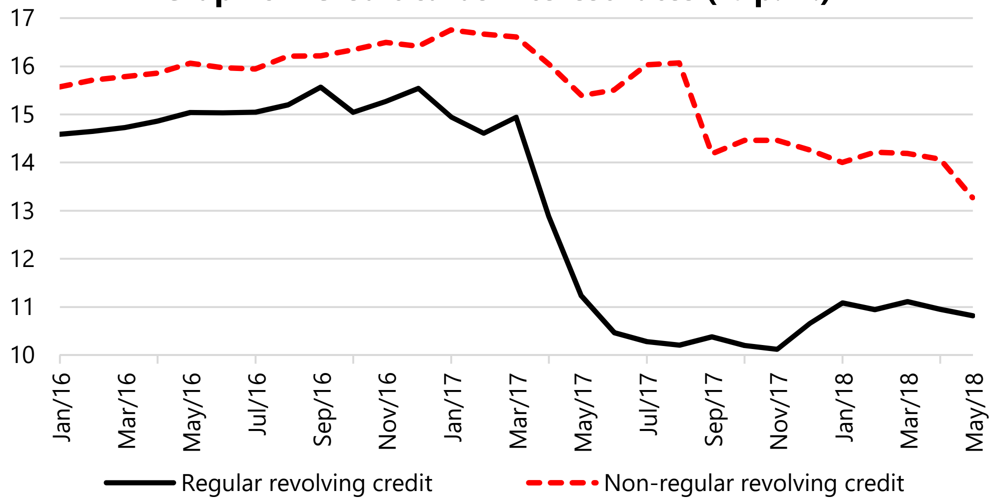
Credit cards revolving credit operations

Regarding credit cards operations, one specific measure of the BC+ agenda had a direct impact on available statistics implying the need for more disaggregate series. Resolution 4,549 – which entered into force in April 2017 – limited revolving financing of the credit card bill to around 30 days, restricting the use of this condition for an indefinite period. After this period, the financial institution is obliged to offer other line of credit in more advantage conditions to the borrower. The new rule favors the reduction of delinquency rates in these operations and, consequently, the reduction of provisioning, risks and interest rates, which were the highest of the Brazilian credit market.

In order to follow up on this measure, new statistical series were necessary, with segmentation by on-time and overdue revolving credit cards operations, which had different interest rates. The BCB requested the banks to send these decomposed series monthly, by outstanding amounts, new operations and interest rates. This was a necessary tool to monitor whether the new rule had the expected effect, which was to reduce interest rates, especially in the group of regular borrowers (the ones paying at least the minimum amount of 15% of the credit card bill), as well as to access the shift of balances from the revolving credit to cheaper lines of credit.

Graph 9 shows the evolution of interest rate indicators for regular and non-regular borrowers. Due to the new rules on revolving credit terms from April 2017 on, rates were significantly reduced, especially in the regular segment, which registered a drop from 14.9% per month in March to 10.7% p.m. in December 2017. There was also a reduction in the cost of credit for non-regular borrowers, (from 16.6% p.m. to 14.3% p.m. in the same period). The additional disclosure by the BCB of such data by each individual financial institutions is an important instrument to stimulate competition in the market.

Graph 9 - Credit cards interest rates (% p.m.)



Internal rate of return and the ICC

The Brazilian credit market is composed of a wide variety of operations and finance institutions, reflecting a significant range of modalities and lines of credit (types of costs), each with its interest rate and contracting period. In this context, summarizing in a single indicator the average interest rate of the financial system becomes a challenge. Therefore, the calculation of the consolidated rate and of large segments of this market also reflects the methodologies of weighting and capitalization of the indexes, as we have shown in this paper for the cases of interest rates of new operations and the ICC.

In financial terms, the average interest rate of total credit operations should correspond to the Internal Rate of Return (IRR). This rate, at a given moment, equates future cash inflows and outflows from the operations contracted. That is, it is the rate that makes the net present value of a cash flow from a credit operation equals to zero.

The credit databases currently available in the BCB do not provide access to the payments and receipts flows of each single transaction. The alternative to calculate the IRR of the outstanding amount of credit operations at each reference period is the calculation of an average interest rate in each period. This average rate of the credit portfolio may be calculated according to two criteria, which differ in the order of composition (or weighting) and of annualization of the rates.

The first criterion involves aggregation of the interest rates expressed on a monthly basis ("**monthlyzation**"). Firstly, the amount of interest due on each line of credit is calculated in a given month, which depends on the remaining balance of all past operations due in the reference month – or at a later date – and the respective interest rates. The total amount of such interest, when divided by the credit outstanding at the reference date, results in an average monthly interest rate which is then annualized. The average rate obtained this way corresponds to the ICC.

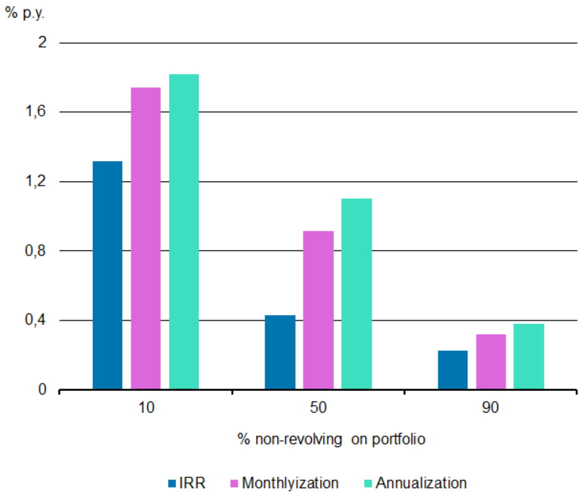
The interest rates aggregation can also be done directly from rates expressed as percentages per year ("**annualization**"). In this case, after obtaining the average interest rate of the remaining balances for a given modality, that rate is expressed on an annual basis. It is only after this procedure that these rates are weighted by the respective balances in the reference month[9].

[9] This is the annualization and weighting order adopted to calculate the interest rates of the new operations published monthly by the BCB.

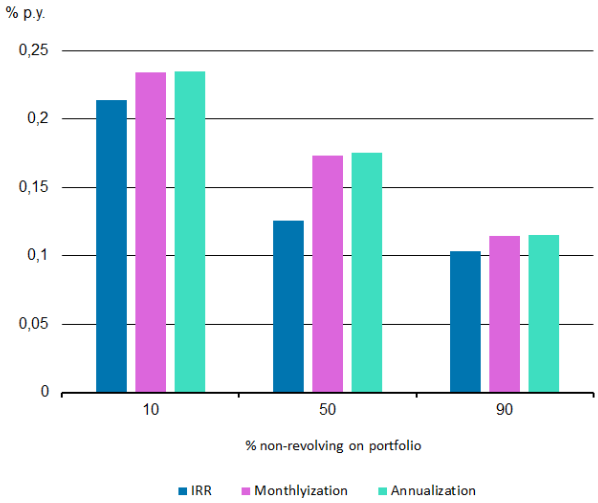
Simple simulations were used for the purposes of comparing these two forms of calculation with the theoretical calculation of the IRR,[10] considering only two credit modalities: revolving (one-month period) and non-revolving (twelve months), with uniform cash flow and portfolio with stable proportions for the two modalities after the twelve month period. These proportions corresponded to three scenarios: 10% non-revolving, balanced portfolio (50% for each modality) and 90% non-revolving (similar to the actual situation in Brazilian credit markets).

The two graphs below show the comparative results of aggregate portfolio rates with the IRR. The differences of the two exercises are in the rates used for revolving and non-revolving credit. The first figure shows a scenario of much higher rates[11].

Graph 10 - First simulation



Graph 11 - Second simulation



In all scenarios, the IRR is the lowest rate, and the rate consolidated by annualization, the highest, since the aggregation of rates already expressed on an annual basis enhances the effect on the average of the highest rates on the revolving credit. The rate obtained by monthlyzation gives intermediate numbers. In the third scenario – a portfolio with a non-revolving 90% share, which is the closest to reality –, the two forms of aggregation are closer to the IRR.

Although the IRR is conceptually the most appropriate methodology to express an average rate, operationally, it is not feasible to calculate it by the BCB. The exercise seems to show, in principle, that the rate obtained by monthlyzation, which is equivalent to the ICC, is a good approximation to the financial system credit portfolio IRR. In fact, the IRR corresponds to the return obtained by financial institutions, which is the counterpart for the cost incurred by households and corporations in its credit operations. **Nevertheless, further research on this matter is still necessary to reach the best operational proxy for an IRR to the Brazilian credit market borrowing costs**.

New banking spread decomposition

The BC+ agenda also pushed for a new methodology to calculate the composition of banking lending spreads, so that a more comprehensive and up-to-date overview of the structural causes of its high level can be obtained. The previous update of the methodology was made in 2008 and, since that time, important changes occurred in the financial system and credit markets, whether in

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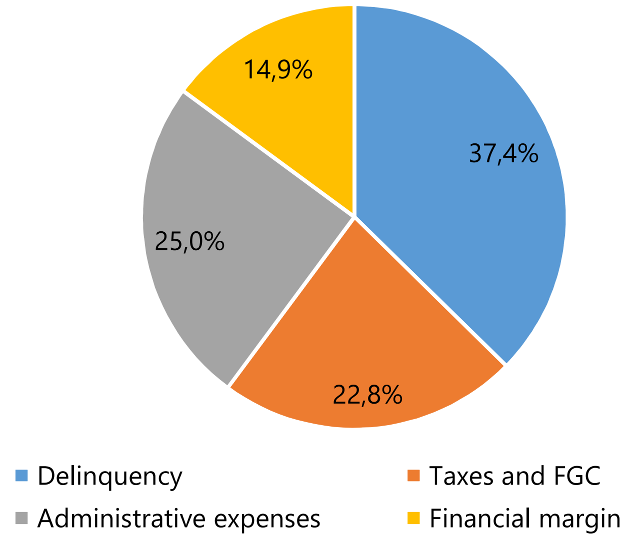
[10] See box 4, "Internal Rate of Return and ICC", of the 2018 Report of Banking Economy (Relatório de Economia Bancária), available only in Portuguese at https://www.bcb.gov.br/pec/depep/spread/REB_2017.pdf.

[11] In the first figure, 200% p.a. for revolving credit and 20% p.a. for non-revolving. In the second figure, 25% p.a. for revolving and 10% for non-revolving.

funding aspects and new products, or in the better coverage, timing and periodicity of the information provided by the financial institutions to the BCB.

In June 2018, the BCB published the results of the new methodology for estimating the components of banking spreads – shown in graph 12[12] –, with average data from 2015 to 2017.

Graph 12 - ICC spread components



As the graph indicates, the delinquency rate is the main determinant of the cost of the ultimate credit. Considering average values between 2015 and 2017, delinquency accounts for more than a third of the spread, followed by administrative expenses (25.0%), taxes and FGC[13] (22.8%) and, lastly, financial margin (14.9%).

Among the methodological updates in the spread decomposition, the rate paid by borrowers became the ICC and no longer the interest rate for the new operations contracted in the reference month. The ICC represents what effectively financial institutions would receive each month for their active credit operations.

Another relevant change is that the new methodology considers banking services as a product itself, assuming financial institutions allocate their resources proportionally to the average profitability of their main products: services provision, credit operations and treasury services. As a result, service revenues ceased to be deducted from administrative expenses and there was a significant increase in this cost factor in the spread calculation. Applying the new cost allocation procedure over the previous methodology – other things equal – one obtains an average participation of administrative costs of 23.98% for the years 2011 to 2016, as opposed to the 3.78% previously obtained. This change is compatible with the evolution of the financial system and the scope of its operations today.

Moreover, in the new methodology, the component "financial margin" corresponds to the spread of the ICC less the amounts of delinquency, administrative expenses and taxes and FGC, besides incorporating other factors not computed in the estimates. In view of the aforementioned significant increase in the share of administrative costs in the current methodology, the levels of the financial margin were negatively impacted compared to the net margin established in the previous versions.

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[12] The new methodology is described in the 2018 Report of Banking Economy, box 5: "Methodology of decomposition of the cost of credit and the spread"; and the results, in chapter 3: "Decomposition of the cost of credit and the spread".

[13] Customers and financial institutions pay taxes on credit operations. Borrowers pay on the contract date, while financial institutions pay taxes over the profit of their operations, besides other contributions. In addition, financial institutions contribute on a monthly basis to the Credit Guarantee Fund (FGC), to allow the coverage of deposits and other public investments in the event of insolvency of any financial institution.

Other Improvements in Credit Statistics from the BC+ Agenda

Macroeconomic statistics needs to be proactive in identifying possible gaps in its databases in order to anticipate the demands of policy makers and users in general. The BC+ agenda has been adopting a set of new measures aimed at reducing credit cost that may stress the need for creating new databases and new statistics. As recent potential examples can be mentioned credit FinTechs regulation[14], the use of a kind of covered bonds (Letras Imobiliarias Garantidas, LIG)[15] for funding of specific credit operations and the electronic register of receivables as guarantees in operations with corporations.

The guidelines of the BC+ Agenda also aim to improve conditions for small-sized companies to access credit. Since April 2018, the BCB has been releasing monthly series of credit statistics by company size, including the total credit, default rates (percentage of operations overdue for more than 90 days) and balance classified at the highest risk levels. As at May 2018, data accumulated in 12 months indicate that while large companies' portfolio grew 9%, the portfolio of micro, small and medium sized companies decreased by 21%. The absence of satisfactory guarantee mechanisms is among the difficulties that hinders the expansion of less costly credit supply to smaller companies.

Policy measures need to be constantly evaluated based on evidence, so they can be adjusted if necessary to try to achieve its planned results. Statistics plays an important role in providing the tools for a quantitative evaluation of policies, as the Brazilian case of the BC+ agenda and recent developments in credit statistics presented in this paper tried to illustrate.

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14 FinTechs authorized by the BCB are now able to lend directly to its borrowers without the need of a partner bank, a movement towards more competition in the credit markets. These credit operations must be reported to the BCB.

15 LIGs are similar to European Covered Bonds, which are debt securities issued by a bank or mortgage institution and collateralised against a pool of assets that, in case of failure of the issuer, can cover claims at any point of time. They are subject to specific legislation to protect bond holders and used as a source of long-term and more stable funding for real estate lending.

Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

Credit statistics as a tool for assessing the effectiveness of policies aimed at reducing credit cost [1]

Marcia Fiorindo, Monica Une, Juliano Cavalheiro and Fernando Rocha,
Central Bank of Brazil

[1] This presentation was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

9th Biennial IFC Conference:
Are Post-Crisis Statistical Initiatives Complete?

Credit Statistics as a Tool for Assessing the Effectiveness of Policies Aimed at Reducing Credit Cost

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Fernando Alberto Rocha
Department of Statistics (DSTAT)
Banco Central do Brasil (BCB)

Session 4.B – Data for policy assessment

BIS, Basel, 30 August 2018

BANCO CENTRAL DO BRASIL

Introduction

- Interest rates in the Brazilian credit market are historically high.
- BCB launched the **BC+ Agenda** in December 2016 among other, to contribute to the reduction of the cost of credit and to deepen the knowledge on Brazilian credit market.
- BC+ Agenda implied some **challenges to the production of credit statistics**, associated to the policy need for a more comprehensive evaluation of the cost of credit in Brazil.
- These challenges include the **creation of a set of complementary statistics for the measurement of the cost of credit**, including:
  - ➢ methodological revisions and compilation improvements of pre-existing statistics and
  - ➢ the development of new statistics.

BC+ Agenda

- BC+ Agenda is aimed at addressing structural issues of the domestic financial system by a combination of new legislation, regulatory measures and research about the credit market.

- The Agenda is structured in four pillars:

  - Financial citizenship,
  - Modern legislation,
  - Financial system efficiency, and
  - **Lower cost of credit**.

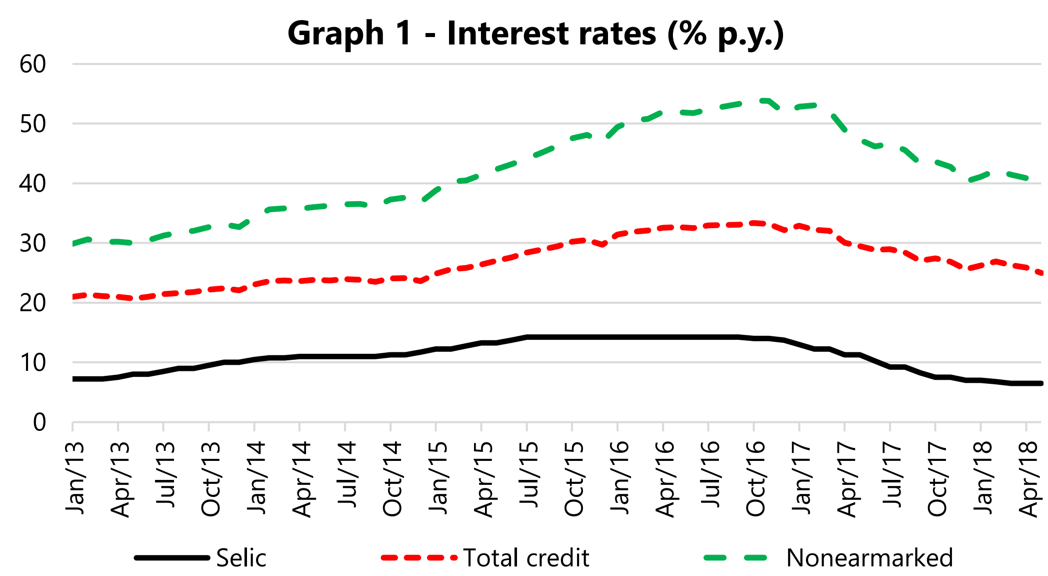
BC+ Agenda: Lower Cost of Credit

- High cost of credit in Brazil is a complex subject with many contributing causes, from subsidies in banking credit, to competition issues and high administrative cost to banking intermediation.
- BC+ Agenda tries to address all these subjects related to the costs of credit:
  - **Subsidies**: revision of the interest rates on directed lending, aligning them to market rates.
  - **Reserve requirements**: reduction of the high levels and simplification of rules.
  - **Competition**: new legislation for credit bureaus and electronic registering of financial assets (as collateral); improving covered bonds markets; revising the structure of credit card market; etc.

BC+ Agenda: Impact on Credit Statistics

- All those measures demand **good quality credit statistics as a tool to evaluate its effective impact**, both in the aggregate and in specific instruments or modalities.

- With the Selic rate at historical lows, how further can we go in the reduction of banking lending rates and banking spreads?



Statistics of new operations' interest rates

- The traditional measure of interest rates in Brazil considers the **weighted average of interest rates of the new operations contracted in the reference month**.
- These interest rates statistics try to express the **"price" of the credit contracted at the margin** (i.e., in the last month)
- Besides the aggregated interest rates (for the financial system or by modalities), the **BCB also publishes each financial institution interest rate by line of credit on a daily basis** (moving average of the last five business days data), aiming to bring more transparency to borrowers and to stimulate competition.
- BCB also compiles statistics of the banks' funding costs and, thus, statistics on the **banking spreads**.

Statistics of new operations’ interest rates

Pessoa Física - Crédito Pessoal Consignado Público

Classificadas por ordem crescente de taxa

Período: **07/08/2018 a 13/08/2018**

Modalidade: **Pessoa física - Crédito pessoal consignado público**

Tipo de encargo: **Pré-fixado**

		Taxas de juros	
Posição	**Instituição**	**% a.m.**	**% a.a.**
1	BCO DO NORDESTE DO BRASIL S.A.	0,06	0,74
2	BCO ALFA S.A.	1,43	18,52
3	FINANC ALFA S.A. CFI	1,51	19,70
4	BCO A.J. RENNER S.A.	1,57	20,61
5	BANCO INTER	1,58	20,72
6	BCO SANTANDER (BRASIL) S.A.	1,61	21,06
7	BCO BRADESCO S.A.	1,62	21,28
8	BCO DO ESTADO DO RS S.A.	1,64	21,56
9	BCO BRADESCO FINANC. S.A.	1,65	21,69
10	BCO SAFRA S.A.	1,66	21,88
11	BRB - CFI S/A	1,67	21,93
12	BARIGUI S.A. CFI	1,70	22,42
13	BCO DO BRASIL S.A.	1,71	22,50
14	BCO CCB BRASIL S.A.	1,71	22,55
15	CAIXA ECONOMICA FEDERAL	1,76	23,24
16	BANCO PAN	1,77	23,47
17	BCO BANESTES S.A.	1,80	23,81
18	BCO ARBI S.A.	1,83	24,30
19	BANCOOB	1,84	24,48
20	PARANA BCO S.A.	1,85	24,60
21	BCO CETELEM S.A.	1,85	24,64
22	BCO OLÉ BONSUCESSO CONSIGNADO S.A.	1,87	24,85
23	BANCO ITAÚ CONSIGNADO S.A.	1,92	25,69

Average Cost of Outstanding Loans (ICC)

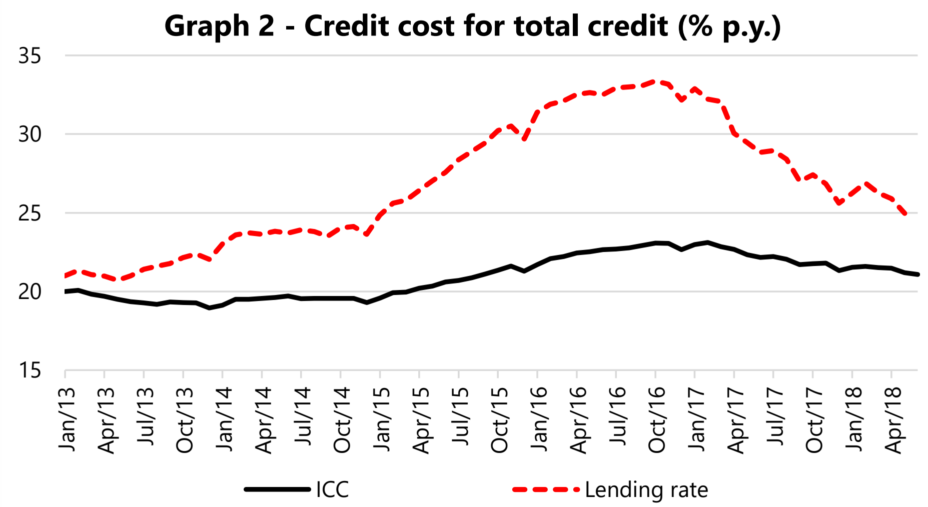
- **There were gaps in the then available set of interest rates statistics**. One of the most important was the need for a broader measure of interest rates, besides last month's average cost.
- **The first new statistic created by the BC+ agenda was the ICC**.
- **ICC represents the average cost of all credit operations with amounts outstanding**, regardless of the operations' reference month.
- ICC represents how much interest borrowers would pay, considering all the operations contracted in the past yet with instalments to be paid, as well as the new operations of the reference month.
- From the point of view of the financial system, it is an estimate of how much revenue financial institutions would receive from their credit operations (assuming zero delinquency rate).

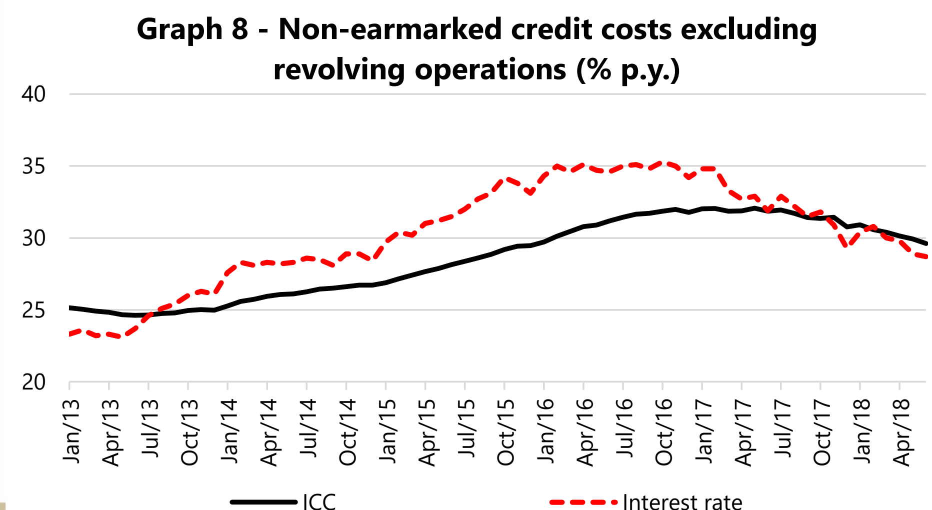
Average Cost of Outstanding Loans (ICC)

- Let us consider two extreme cases (**real estate lending and revolving credit card loans**) to clarify the differences between the ICC and "traditional" interest rates statistics.
  - As the typical maturity of revolving credit card loans is less than two month, its amounts outstanding are BRL35.1 billion, and monthly new operations, BRL15.3 billion.
  - For real estate, with average maturity of 131 months, the values are BRL576.1 billion and BRL7.6 billion.
- **The share of credit card in the "traditional" interest rate statistics is the double of the real estate loans** (amounts of new operations).
- As for the **ICC, the weight of real estate loans is significantly higher**, as is the total amount outstanding.

ICC and Interest Rate Statistics

- As expected, ICC is lower and more stable than "traditional" interest rates. But…
- … one should expect the lines in graph 2 to cross (average x margin), but they don't!
- Part of the answer lies on the role of revolving credit, with its three-digit interest rates per year.
- Considering credit cost without revolving operations, the lines do cross.





Internal Rate of Return (IRR) and the ICC

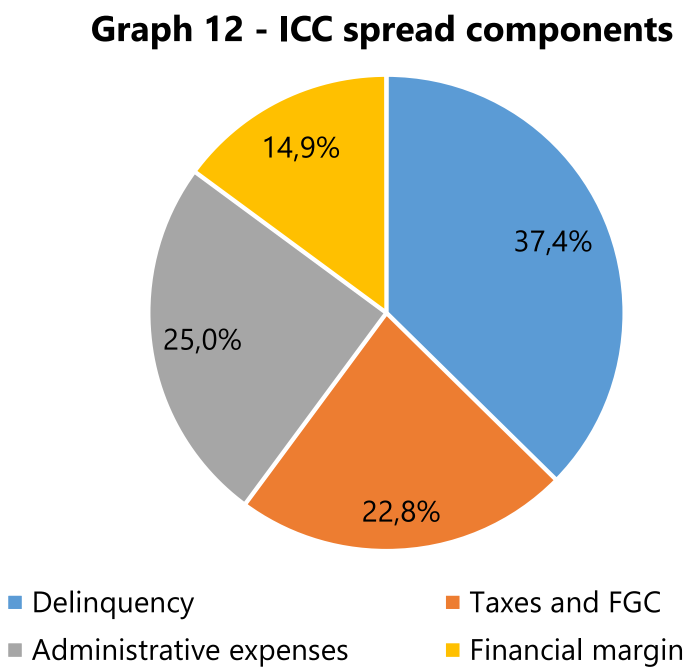
- The other part of the answer has to do with methodologies of weighting and capitalization of the interest rates.
- At high interest rates, it does make a significant difference whether:
  - the interest rates of each line of credit are calculated as rates per month (interest paid on the reference month divided by the total amount outstanding) and then aggregated as a weighted average and only after that, annualized; or
  - if the interest rates are, from the beginning, calculated as per year interest rates.
- Although preliminary tests with the first methodology seems to show better results, further research is still needed to define the best operational proxy for an IRR to the Brazilian credit costs.

New banking spread decomposition

- Besides providing users with a full set of credit cost measures, the BC+ Agenda also pushed for revising the decomposition of banking spreads, aiming at achieving a comprehensive and up-to-date overview of the structural causes of its high levels.

- As the graph summarizes, delinquency rates, taxes and administrative costs represents 85% of the total average banking spread.

- From these results, a series of measures were implemented to address the causes of high interest rates in Brazil.



BANCO CENTRAL DO BRASIL

Further Steps in Credit Statistics in Brazil

- As already mentioned, current research is trying to define the **best operational proxy for an IRR for the Brazilian credit market**. The results of the research have potential impacts for the current methodology of the ICC and possibly also the “traditional” interest rates.

- Other (permanent?) challenge is the communication of the new statistics, its methodologies and results, and the relation (differences!) with the traditional statistics. Some initiatives are:

  - A specific press conference for the ICC release;
  - ICC methodological note in the BCB’s website;
  - Publication of the Report on Banking Economics, with a press conference; and
  - Monthly credit press releases.

Thank you!

Questions, suggestions, critics and contributions are much welcome!

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Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

Estimating a country's currency circulation within a monetary union[1]

André Dias,

Bank of Portugal

[1] This paper was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

Estimating a country's currency circulation within a monetary union

André Dias[1,2] | Banco de Portugal

Abstract

We discuss the non-trivial problem of a country's currency circulation within a monetary union, focusing on an internationally relevant currency with significant intra monetary union cash flows: the euro. We compare the results currently published with a set of alternatives to estimate the Euros in circulation in some Euro area countries, based on different hypothesis, techniques and data. Although using a structural money demand model may be useful for some countries, our conclusions suggest that allocating a proportion of the Euros estimated to circulate in the Euro area to each country is more adoption ready and could offer relatively harmonized estimates.

Keywords: Currency union; Euro circulation; Structural money demand models

JEL classification: E41; E50

[1] The views expressed in this paper are those of the author and do not necessarily reflect the views of Banco de Portugal or the Eurosystem.

[2] The paper benefited from valuable contributions and insights by Mr. António Jorge Silva, Mr. Luís D'Aguiar and Ms. Filipa Lima, to whom I would like to express my sincere gratitude.

Contents

"The true currency of life is time, not money, and we've all got a limited stock of that."
Robert Harris

Introduction

Unlike time, money is a dimension of our world that can be controlled and which serves an instrumental role in the way we live. Indeed, the central bank usually has the power to control the supply of cash to the economy, which is used to fulfil different needs of the agents in such economy. Although recent technological advances, affecting especially the financial industry and involving innovative payments solutions, have built the narrative for a growing demise of the use of cash, recent studies for different jurisdictions and currencies have somewhat dispelled this belief and have shown that cash still holds a critical role in the way we make payments and store value.

Esselink & Hernández (2017) concluded, through a survey conducted in 2016, that 79% of the number of payments (and 54% of the value of payments) done in the Euro area were made in cash, whereas only 19% of the number (and 39% of the value) of payments in the same area were settled through cards. On a similar note, using data collected by the Bank of International Settlements' (BIS) Committee on Payments and Market Infrastructures (CPMI), Bech *et al.* (2018) argue that, although card payments have recorded a consistent increase over the last decade, cash in circulation also increased in CPMI countries[3], therefore curtailing the theory of a progressive move towards a cashless society[4]. From a different perspective, Judson (2017) also reports that, despite the increasing pressure for the fading out of cash, demand for U.S. Dollars keeps growing.

Against this backdrop, it is reasonable to argue that cash still holds an important role in modern economies and that it warrants the attention and study of its different stakeholders, spearheaded by central banks. In this domain, several topics can be approached with relevant insights for policy making. However, many of them depart from the assumption that the volume of cash in circulation is perfectly known. Yet, this assumption does not always hold for all economies and deserves scrutiny.

In fact, one of the most interesting topics concerning cash is the actual determination of the stock of cash in circulation in a given economy, which ultimately is available to fulfil the resident's needs. While it may appear as a straightforward computation, the international role of the concerned currency and/or the impact of intra-currency union cash flows can significantly affect this stock and, hence, complicate its calculation process. This is particularly the case of the U.S. Dollar and the Euro: since these currencies are typically accepted for international settlements and are used as a means of storage of value in countries outside of the currency's jurisdictions, the circulation of U.S. Dollar and Euro in such countries is not negligible and significantly reduces the amount of cash in circulation in the issuing

3 Australia, Belgium, Brazil, Canada, China, Euro area, France, Germany, Hong Kong SAR, India, Italy, Japan, Korea, Mexico, Netherlands, Russia, Saudi Arabia, Singapore, South Africa, Sweden, Switzerland, Turkey, United Kingdom and United States.

4 According to the same authors, the only countries where evidence of the substitution of cash for cards was found was in Russia and Sweden.

country/area[5]. Moreover, in the case of currency unions, such as the European Economic and Monetary Union (EMU), the intra-currency union cash migrations, due to, *inter alia*, tourism and the shadow economy, also increase the complexity of the computation of the amount of cash in circulation in each currency union country, given that such movements are typically not recorded directly at the central bank's cash counter and, therefore, need to be estimated.[6]

To this end, we opted to address the issue of the compilation of the stock of cash in circulation. For this endeavour, we opted to focus specifically on the Euro area countries (fixed 2002 composition)[7], given that they encompass arguably the most complex framing of this problem: the Euro is an internationally relevant currency and there are non-negligible intra-Euro Area cash flows.

In this paper, we present three methods that allow the computation of an estimate for the volume of cash in circulation for the 12 countries: Method 1 consists in a naïve forecast according to legacy currency data; Method 2 departs from the ECB's indirect estimation of the cash in circulation in the Euro area and allocates a proportion of such volume to each country according to *ad hoc* criteria; Method 3 leverages on the derivation of a structural money demand function for each country, taking a non-Euro area European Union country as reference, to determine the cash in circulation in each country. The results are benchmarked against the volume of cash in circulation currently shown in the financial accounts[8].

The goal of this paper is therefore to provide a further contribution for the discussion on the possible methods to estimate cash in circulation when a country participates in a currency union and/or when its currency has a relevant international role. By the same token, the objective is also to raise awareness to the potential of each of the techniques used in supporting, together with national practices and expertise in this field, the development of a methodology for the explanation of cash holdings in each country.

The paper is organized as follows: section 1 briefly presents the methodological guidelines adopted; sections 2 to 4 introduce and discuss the outcome of the methods used and section 5 concludes.

5 In fact, recent estimates by the European Central Bank point that 30% of the Euros put in circulation until the end of 2016 were actually circulating outside the Euro area while Judson (2012) estimates that about 50% of U.S. Dollars were held outside the United States. For a deeper discussion of this issue, please consult ECB (2017a), ECB (2017b) or Judson (2012).

6 For an introduction on the issue of tourism in the compilation of the national currency in circulation, check, for example, box 1 in Politronacci *et al.* (2017).

7 In 2002, the Euro Area comprised 12 countries: Belgium, Germany, Ireland, Greece, Spain, France, Italy, Luxembourg, Netherlands, Austria, Portugal and Finland.

8 For this purpose, we considered the stock of instrument F.21 (currency) held in the financial balance sheet of each country, which is reported by each country to Eurostat in the framework of the Quarterly Financial Accounts (according to ESA 2010).

1. Methodological principles

Throughout this study, we opted to resort exclusively to data publicly available, in order to ensure a level playing field between countries and to maximize the replicability of our exercises. The data shown are mostly available through the Eurostat's, the European Central Bank's (ECB) and/or through the National Central Banks' (NCB) websites.

We refer to the concepts of currency union and monetary union as synonyms and in line with the concepts defined in Appendix 3 of the International Monetary Fund's 6th edition of the Balance of Payments and International Investment Position Manual (BPM6).[9]

We interpret cash in circulation as the value of the legal tender in circulation in each Euro Area country, in the form of banknotes. Hence, we exclude from the scope of the term 'cash in circulation' the role of coins, due to their relatively low relevance in the Euro Area – as of March 2018, coins represented only 2,35% of the Euros put in circulation.

The estimations that we compute for Euro Area countries concern the period from 2002 to the end of 2017 and, when possible, are shown on a monthly basis. In all other cases, the data presented has a quarterly frequency.

For simplicity, we cover only the countries that first introduced the Euro at its inception in 2002: Belgium, Germany, Ireland, Greece, Spain, France, Italy, Luxembourg, Netherlands, Austria, Portugal and Finland. Countries who joined the Euro Area later on (Slovenia, Cyprus, Malta, Slovakia, Estonia, Latvia and Lithuania) are excluded, to avoid the impact of different changeover periods.

2. Method 1 – Extrapolating legacy currencies

As referenced previously, the impact of intra Euro Area cash flows and the international role of the Euro prompted Euro Area countries to develop complex estimation methods to determine the volume of cash in circulation after the adoption of the Euro. By contrast, during the legacy era[10], when no intra currency union flows were to be estimated and not all currencies had a relevant international role, the compilation of the cash in circulation was relatively simpler: in broad terms, it corresponded to the currency put into circulation by the central bank subtracted by the cash in the vaults of resident monetary and financial institutions.[11] Within this framework, the series yielded were generally relatively free of estimation uncertainty,

[9] "*For statistical purposes, a currency union is defined as a union to which two or more economies belong and that has a regional central decision making body, commonly a currency union central bank (CUCB), endowed with the legal authority to conduct a single monetary policy and issue the single currency of the union.*" BPM6, Appendix 3.9

[10] We refer to the era of currencies that immediately preceded the Euro in each country – *e.g.* the Deutsche Mark in Germany or the French Franc in France.

[11] This premise implies that the concerned currency is not internationally relevant. In case it is internationally relevant, a correction for the international circulation (transaction and hoarding motive) is due.

given that the core information necessary was typically known by the central bank with a high degree of accuracy.

Considering this, one method that can be constructed to provide an estimate of the cash in circulation in each Euro area country can be drawn from extrapolating legacy cash in circulation data. This is one of the approaches proposed in Politronacci *et al.* (2017)[12] and referred in Bartzsch *et al.* (2015) as part of the annual banknote production plan in Germany.

To this end, we have surveyed the information published by the NCBs of the countries under analysis and sought to extract historical time-series of cash in circulation, registered in the liabilities of the central bank. To maximize the utility of our analysis, we imposed that such series should be relatively long – over 5 years of legacy era data. We were able to retrieve information for Spain, Portugal, France, Italy and Greece, for the period spanning from 1980 to 2001 (monthly data – 264 observations). For all other countries, the series were either not published or not long enough.[13]

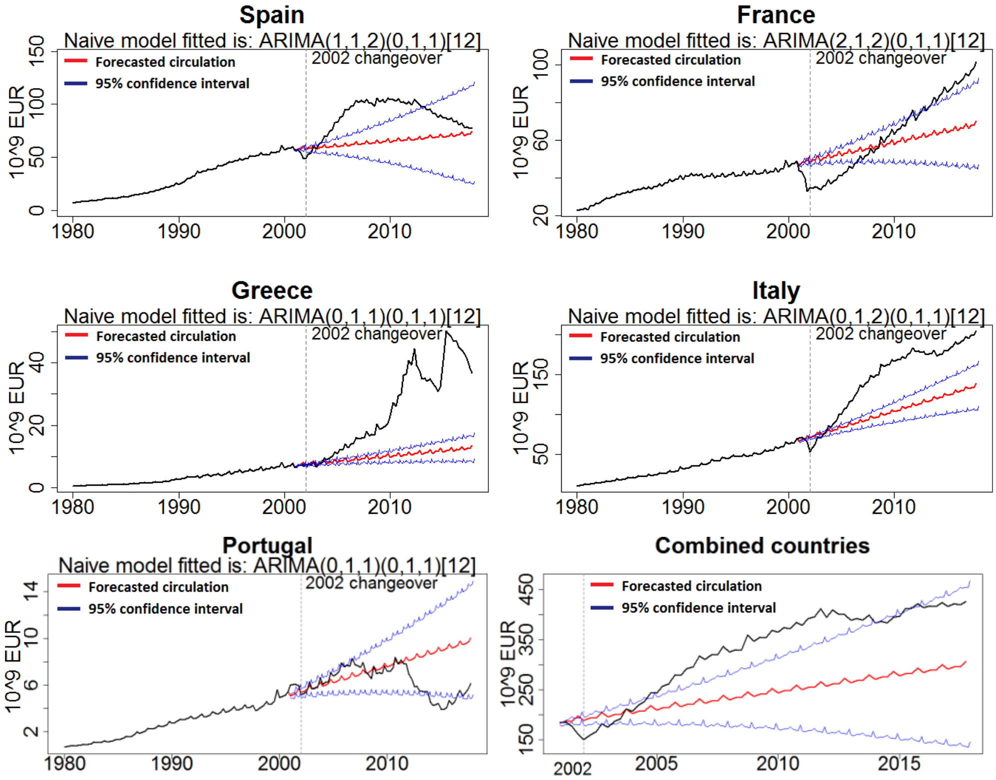
To produce the results of this method, we opted to automatically fit an ARIMA model to the historical cash in circulation series. In this exercise, we opted to estimate such model for the 1980-2000 period, to avoid the pre-cash changeover effect felt in 2001, which could somehow bias our parametric results. The candidate models were chosen according to the Bayesian information criteria presented in Schwarz (1978).[14] The forecasts for the cash in circulation during the Euro area were then obtained by using the parametric estimates yielded by the fitted model and are shown in figure 1 below, with a 95% confidence interval (blue lines).

12 To estimate the Euros in circulation in France for 2002-2017, the authors extrapolate the circulation of French Francs from 1979 to 2000 to the Euro era.

13 The ECB publishes the series "Currency in circulation" for all Euro area countries. However, this information only dates back to 1999, which does not fit our time-frame requirements.

14 To prevent that the selected model was over fitted, we restricted the maximum number of p and q auto-regressive and moving-average terms, respectively, to 3, the number of P and Q seasonal auto-regressive and moving-average terms, respectively, to 1. For further explanations and details on automatic ARIMA modelling, please consult, for example, Hyndman & Khandakar (2008).

Figure 1 – Method 1 estimation results | Reported circulation (black)[15] *vs* forecasted circulation (red)



Source: NCBs and author's calculations

The results shown project the model observed for legacy currencies to the Euro era. When compared to the stocks currently reported by each country, the method is able to produce a 95% confidence interval which includes the values currently reported by Portugal and Spain (and France in several periods). The estimations for Greece and Italy are below the reported stocks. However, when we combine the estimates produced for these 5 countries and compare them with the sum of the reported stocks of cash in circulation, it seems that method 1 underestimates the aggregated cash in circulation in such countries.

The methodology supporting this forecast implies assuming that the time-series structure determining such model holds in both the Euro and the legacy era. However, the changeover to the Euro in 2002 can arguably be interpreted as a structural change, as well as the impact of the developments in payment systems since the introduction of the Euro. Moreover, as Miller (2017) highlights, forecasting on historical data can be useful in the short-term, but if the structural factors underlying such forecast change significantly, then the model will most probably underperform over the long-run. This is the reason why the confidence intervals significantly expand over time and why we have named this estimate as 'naïve'.

Against this background, the estimates rendered through this method, derived through the time-series structures verified for the cash in circulation during the legacy era – which have, most likely, developed and changed significantly over the years –,

15 The series used until December of 2000 for each country correspond to the amount inscribed as cash in circulation in the respective central bank's liabilities. After that period, the values considered are those reported as the stock of instrument F.21 (currency) held in the financial balance sheet of each country.

should be taken with caution. Concurrently, they can be understood as a smoothened forecast of the Euros in circulation in each country – had the time-series structure of cash in circulation remained constant since the 1980-2000 era – and can be used to support the validation of the methods currently employed by each country to estimate cash in circulation.

3. Method 2 – Estimating the Euros held within the Euro area and allocating a proportion to each country

The European Central Bank, as the supranational central bank of the European currency union, is interested in studying and modelling the circulation of Euros within and outside the Euro area. That is why it develops regularly a report on the international role of the Euro and why it has recently been studying the methodological issue of estimating the circulation of Euros outside the Euro area. In ECB (2017a), the ECB published an upgrade to the method it used to estimate the Euros circulating outside the Euro area, which now includes an upper bound, based on a fixed coins to banknotes ratio, and a lower bound for this stock, derived from data on the shipments to non Euro area countries of Euro currency by denominations. These lower and upper bounds are used to calculate the point estimate of the Euros circulating outside the Euro area, which consists in the arithmetic average between such bounds.

Although the end-purpose of the ECB (2017a)'s method is different from ours, it can still be adapted as a tool to estimate the amount of Euros in circulation in each country. Indeed, if the ECB (2017a) defined a method to estimate the Euros circulating outside the Euro area, then, by difference, one can obtain the Euros circulating within the Euro area. Using this stock as a reference, it is possible to allocate a proportion to each country according to specific and harmonized criteria, which will then be used to obtain the point estimate of the circulation that we are seeking. This is the reasoning behind method 2.

To compute the ECB (2017a)'s estimate for the Euros circulating outside the Euro area, we need its two elements: the upper and the lower bounds. The upper bound is obtained by applying the ratio of coins to banknotes used in ECB (2017a)[16] to the Euro coins in circulation in the Euro area in each period. The lower bound is more complex and demands more in-depth data. Indeed, the ECB (2017a)'s lower bound relies on data on official shipments of Euro banknotes to non Euro area countries by denomination since 2013, which is then combined with the data on the issuance of banknotes by the Eurosystem since 2002[17]. However, the data on official shipments by denomination is not currently published and cannot be accessed by the public. For this reason, to proxy the lower bound amount, we opted to use a fixed proportion of the total Euros in circulation in each period, based on the lower bound published for December of 2016 in ECB (2017a). The lower bound was then proxied as follows:

$$Lower\ bound\ proxy_t = Total\ euros\ in\ circulation_t * fixed\ proportion^{18}$$

[16] The ECB (2017a) considers the ratio of coins to banknotes verified in 2002: 4,16%.

[17] For an explanation of how this combination is operated, please consult the ECB (2017a).

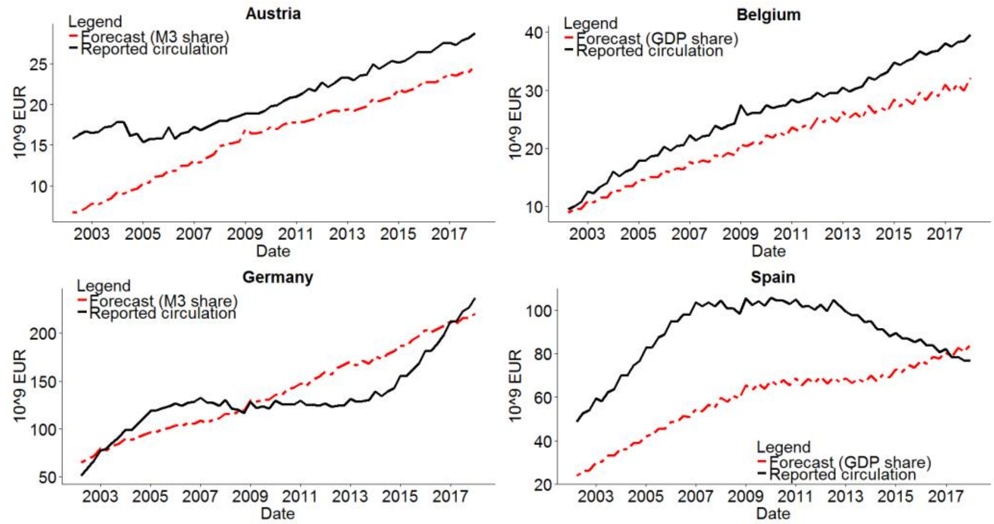
[18] $Fixed\ proportion = \frac{Lower\ bound\ in\ ECB(2017a)_{Dec.2016}}{Total\ euros\ in\ circulation_{Dec.2016}} = 25\%$

Having calculated the monthly point estimate for the Euros circulating outside the Euro area, in line with the ECB (2017a) methodology, we computed the estimate for the Euros circulating within the Euro area by subtracting the referred point estimate to the stock of Euros in circulation in each period. To complete this estimation method for the amount of Euros circulating in each country, we allocated a proportion of the Euros circulating in the Euro area according to two alternatives: the proportion of each country's GDP in the Euro area (fixed 2002 composition) and the relative weight of the contribution of each country to the collective contribution of the countries under analysis to the Euro Area's M3[19].

Using each of these keys will naturally reflect the rationale behind each one, and their underlying premises, which will therefore confer to the resulting allocation a harmonized distribution across countries. The reasoning behind the usage of each country's GDP share in the Euro area's GDP is that it allows to allocate the Euros circulating in the Euro area according to an objective, harmonized, measure of wealth, which seeks to portray economic activity, and thereby "linking" our estimate to this phenomenon. Concurrently, the argument for the usage of the relative weight of the contribution of each country to the collective contribution of the countries under analysis to the Euro Area's M3 is that it allows to understand and reflect the relative importance of each country in this important monetary aggregate.

The results generated by each allocation key are summarized as follows:

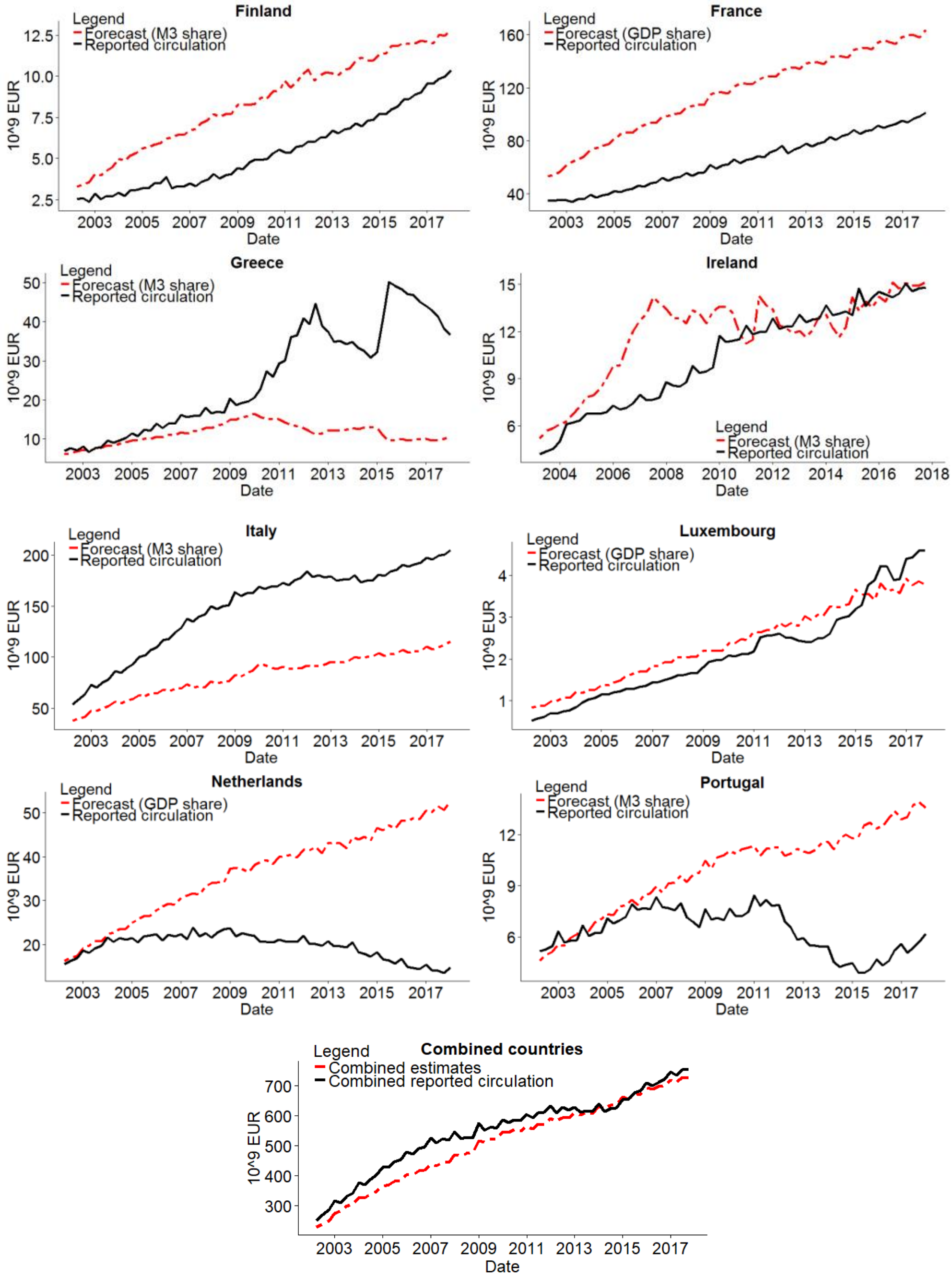
Figure 2 – Method 2 estimation results (2002-2017)



19 This was obtained as follows:

$$M3\ share\ Country\ X = \frac{Contribution\ to\ M3_{Country\ X_t}}{\sum_x^N Contribution\ to\ M3_{Country\ X_t}}$$

Where X are the countries Euro area countries under analysis (fixed 2002 composition)



Source: ECB, NCBs and author's calculations

The results presented in figure 2 show somewhat mixed results: it appears that in some countries the forecast consistently overestimates (Finland, France, Portugal and Netherlands) or underestimates (Austria, Belgium, Spain, Greece and Italy) the reported circulation, while in others it seems to be following closely the reported stocks (Germany, Ireland and Luxembourg). However, if one compares the combined estimates with the sum of cash in circulation reported by each country, it hints at the idea that, overall, method 2 follows closely the combined reported circulation. Note that, for all countries, we opted to show only the most conservative estimate by retaining the smallest estimates resulting from the M3 and GDP share allocations, to avoid that the forecasts are inflated by the particularities associated with the compilation of country's GDP or M3 contribution.

In any case, regardless of the allocation measures chosen, there are two key virtues worth highlighting. Firstly, method 2 estimates the Euros circulating in each country based on an ECB approved method to estimate the Euros circulating outside the Euro area. In that sense, the estimate rendered for the Euros circulating within the Euro area is one that stems from a commonly accepted and published method, which reinforces the quality of the end results. Secondly, by using relatively fair and impartial allocation keys, we are also ensuring a clear and objective estimation criterium for all countries, which can further promote the consistency of the different estimation methods currently used by each country.

4. Method 3 – Estimating a structural money demand function

To explore additional methods for estimating the Euros in circulation in each country, we have investigated the existing literature, with particular emphasis on structural models of money demand, given that they can incorporate short and long run dynamics between that aggregate and its selected determinants. Two good examples of such models are the Bundesbank (2009)'s model[20] and Bartzsch *et al.* (2015) model for explaining and forecasting the demand for Euro banknotes in Germany[21].

From this investigation, a possible solution to the estimation of the cash in circulation in each Euro area country was found in the estimation of a banknote demand function, in line with one of the proposals in Bartzsch *et al.* (2011b, section 2.2.4). In this study, the authors estimate foreign demand for Euro banknotes issued in Germany departing from the setup of a demand function for German banknotes without foreign demand, which is then applied to a country whose banknote demand is comparable to Germany, except for foreign demand.[22] The authors used the domestic circulation estimated for Germany via this banknote demand function to obtain, by difference of the total cumulated net issuance of German banknotes, a point estimate of the German banknotes in circulation abroad.

Although we do not intend to use this framework for the same purposes, we can adapt it to estimate the cash in circulation in each Euro area country. To do this, we need to apply the same reasoning as in Bartzsch *et al.* (2011b) and, for each Euro area country, find another country whose structural drivers for cash in circulation are

20 The Bundesbank (2009)'s model seeks to explain, through a vector error correction model, the demand for small, medium and large denominations via cash consumption, the opportunity cost to hold cash (proxied by the interest rate level), the demand from non-Euro area countries (proxied by the real exchange rate of the Euro *vis-à-vis* the Euro area's 22 most important trade partners), house prices (BIS housing price indicator), an estimate of the shadow economy, the unemployment rate and the preference for alternative payment methods (proxied by the number of settled payment cards). The model ends up by concluding that, in the long run, the demand for small denominations is mainly influenced by cash consumption, the demand from non-Euro area countries and the opportunity costs, whereas the demand for large denominations is mainly driven by house prices and the demand from non-Euro area countries.

21 Bartzsch *et al.* (2015) also approach the issue via an error correction model where the demand for Euro banknotes is regressed against a set of variables depicting the motives to hold cash (transactions motive, store of wealth, availability of alternative means of payment, size of shadow economy and demand by non-residents).

22 For this purpose, Bartzsch *et al.* (2011b) chose France.

relatively comparable. To avoid that the method becomes endogenous – Euro area countries predicting the cash in circulation in other Euro area countries –, we opted to consider as possible reference countries all European Union Member-States who currently do not belong to the Euro Area[23]. This guarantees that the time series of the circulation of national currency of such a benchmark country are relatively free of uncertainty (given that they have their own currency), and that all countries involved have strong economic connections and tend to share the economic cycle[24].

To allocate a reference country to each Euro area country, we decided to cluster European Union countries according to proxies for the level of transactions, wealth, degree of openness of the economy, dimension, importance of tourism, hoarding motive and role of cashless payment instruments. This implies assuming that the possible reference country/ies for each Euro area country will be the set of non-Euro area countries who are classified in the same cluster.

The variables that we used for this exercise are detailed in table 1 below:

Table 1 – Proxies used in clustering analysis

Variable	Proxy for	Source
Gross domestic product at market prices (Current prices, 10^6 €)	Transactions level	Eurostat
Final consumption expenditure of households (Current prices, 10^6 €)	Transactions level	Eurostat
Population	Dimension	Eurostat
GDP *per capita*	Wealth	Author's calculations
Consumption *per capita*	Wealth	Author's calculations
Percentage of exports and imports of goods and services in GDP	Openness of economy	Eurostat and author's calculations
Nights spent at tourist accommodation establishments	Importance of tourism	Eurostat
Nights spent at tourist accommodation establishments *per capita*	Importance of tourism	Eurostat
Balance of travel account in balance of payments	Importance of tourism	Eurostat
Long term government bond yields – Maastricht definition (average)	Hoarding motive	Eurostat
Unemployment rate	Hoarding motive	Eurostat
Value of ATM cash withdrawals with cards issued by resident PSPs – at terminals provided by resident PSPs – *per capita*	Importance of cashless payments	ECB, Eurostat, and author's calculations
Human Development Index (HDI)	Wealth	World Bank

To determine the cluster where each country fits, we applied Ward's (1963) agglomerative hierarchical method and MacQueen's (1967) non-hierarchical *k-means*

23 Bulgaria, Czech Republic, Denmark, Croatia, Hungary, Poland, Romania, Sweden and the United Kingdom.

24 The European Commission's publication "European Business Cycle Indicators" is a good source for an overview of the EU business cycle and for a primary assessment of the business cycle in each EU country.

approach. In both cases, we set the number of clusters to three, to maximize the possibility that at least one non-Euro area country fits each cluster. The methods were applied to data from 2015, given that HDI data was not available for later years. Denmark and Estonia were circumstantially excluded from the analysis due to data shortages in different variables.[25] The results that we obtained through this partitioning are as follows:

Figure 3 – Ward's method results – 3 clusters

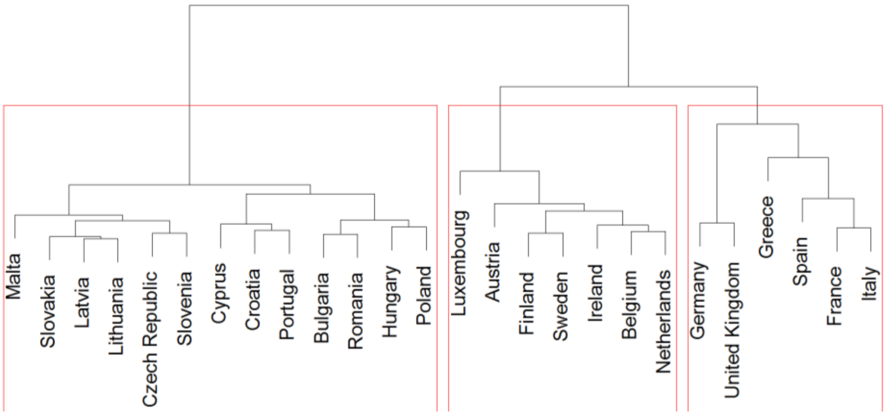
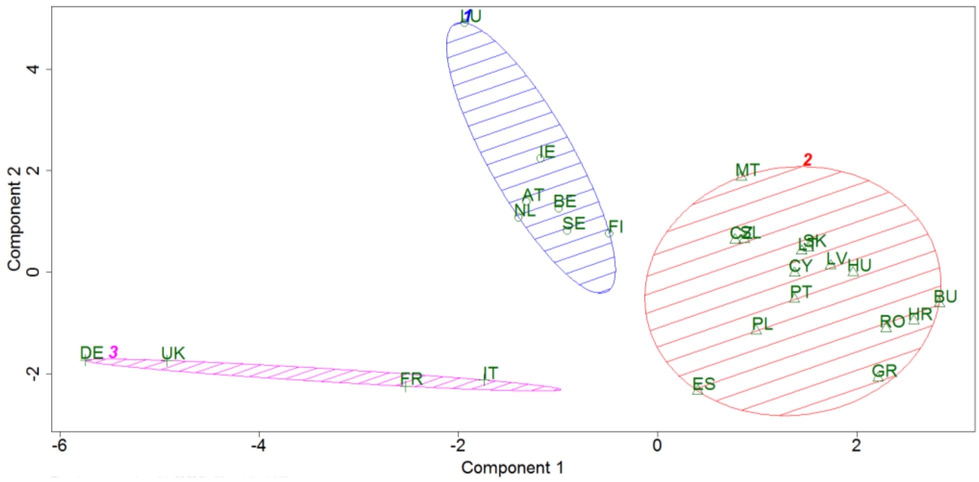


Figure 4 – K-means results[26] – 3 clusters



25 The data sources through which we extracted data for all countries did not include, for 2015, the proxy for the importance of cashless payments for Denmark and the long term government bond yields - Maastricht definition (average) – for Estonia.

26 We show the cluster representation against the score of each country in the two first principal components of the data used, which represent 66,33% of the variability of the data.

Table 2 – Ward's cluster descriptions

	Cluster 1	Cluster 2	Cluster 3
Population	-0.46	-0.44	1.12
GDP	-0.25	-0.53	0.84
Consumption	-0.31	-0.51	0.87
GDP_capita	1.20	-0.70	-0.12
cons_capita	1.04	-0.83	0.18
Openess	0.53	0.11	-0.89
Travel_exports	-0.18	0.08	1.29
10y_bond	-0.63	0.16	0.79
Unemployment	-0.43	-0.07	1.49
Card payment_capita	0.50	-0.50	0.05
HDI	0.92	-0.78	0.31

Table 3 – Summary of cluster results

	Ward's method	K-means	Non euro-area reference country
Austria	Cluster 1	Cluster 1	Sweden
Belgium	Cluster 1	Cluster 1	Sweden
Finland	Cluster 1	Cluster 1	Sweden
Ireland	Cluster 1	Cluster 1	Sweden
Luxembourg	Cluster 1	Cluster 1	Sweden
Netherlands	Cluster 1	Cluster 1	Sweden
Sweden	Cluster 1	Cluster 1	N/A
Bulgaria	Cluster 2	Cluster 2	N/A
Croatia	Cluster 2	Cluster 2	N/A
Cyprus	Cluster 2	Cluster 2	N/A
Czech Republic	Cluster 2	Cluster 2	N/A
Hungary	Cluster 2	Cluster 2	N/A
Latvia	Cluster 2	Cluster 2	N/A
Lithuania	Cluster 2	Cluster 2	N/A
Malta	Cluster 2	Cluster 2	N/A
Poland	Cluster 2	Cluster 2	N/A
Portugal	Cluster 2	Cluster 2	Bulgaria, Croatia, Czech Republic, Hungary, Poland, Romenia
Romania	Cluster 2	Cluster 2	N/A
Slovakia	Cluster 2	Cluster 2	N/A
Slovenia	Cluster 2	Cluster 2	N/A
France	Cluster 3	Cluster 3	United Kingdom
Germany	Cluster 3	Cluster 3	United Kingdom
Greece	Cluster 3	Cluster 2	United Kingdom, Bulgaria, Croatia, Czech Republic, Hungary, Poland, Romenia
Italy	Cluster 3	Cluster 3	United Kingdom
Spain	Cluster 3	Cluster 2	United Kingdom, Bulgaria, Croatia, Czech Republic, Hungary, Poland, Romenia
United Kingdom	Cluster 3	Cluster 3	N/A

As table 2 and 3 show, both Ward's method and the *k-means* procedure yielded approximately the same group configuration. Greece and Spain are the only countries that are classified in different clusters. Table 2 shows cluster means for each of the clusters computed through Ward's method. In a nutshell, one can describe cluster 1 as countries where wealth proxies stand out, and cluster 3 as countries where population, transactions and wealth proxies are most prominent.[27] Table 3 shows that cluster 2 is the one with the highest number of candidate reference countries and that Spain and Greece are the countries with the highest number of possible candidate countries, given that they are classified in clusters 2 and 3 in *k-means* and Ward's (1963) methods, respectively.

To apply the reasoning established in Bartzsch *et al.* (2011b) to each Euro area country, we have drawn a banknote demand function according to the following equation, where X is the respective reference country:

$$c_t^X = \beta_0 + \beta_1 P_t^X + \beta_2 Y_t^X + \beta_3 i_t^X + \varepsilon_t \qquad (1)$$

Equation 1 seeks to decompose the determinants of banknote demand and encompasses a set of key factors included in similar models.[28] In our model, the cash in circulation in the reference country (c_t^X) is regressed by the price level (P_t^X) and a transactions variable (Y_t^X) in the reference country, as well as the opportunity cost of holding money in (i_t^X). If we assume, as the core hypothesis for this estimation method, that the parameters yielded from the reference countries hold in all countries of the same cluster, then the volume of banknotes circulating in each Euro area country (represented by Z below) can be obtained by applying the parameters estimated in equation 1:

$$\hat{c}_t^Z = \hat{\beta}_0 + \hat{\beta}_1 P_t^Z + \hat{\beta}_2 Y_t^Z + \hat{\beta}_3 i_t^Z \qquad (2)$$

To proxy each of these regressors, we used as independent variables of our model the all-items harmonized index of consumer prices (to portray the fluctuation of prices in each economy), the final consumption expenditure of households (to mimic the overall behaviour of transactions in each economy) and the long term government bond yields – Maastricht definition (average) – to incorporate the effect of the opportunity cost of holding cash. All of this data is published by Eurostat. For this study, we considered a quarterly sample from 2002 to 2017 (64 observations), where all of the dependent and independent variables were not differenced, not seasonally adjusted and were considered in their logarithmic form, with the exception of bond yields.[29] Therefore, all parameters can be interpreted as a pure elasticities, except for the parameter associated with bond yields.

Using this set of variables, we applied the standard unit root, stationarity (Phillips & Perron (1988), Augmented Dickey-Fuller (1979, 1981) and Kwiatkowski *et al.* (1992)) and cointegration tests, which have shown that the vast majority of variables are I(1) and cointegrated.[30]

27 In cluster 2, the most comprehensive one, there is no clear-cut proxy deserving highlight in comparison with other clusters.

28 See, for example, the variables used by the Deutsche Bundesbank (2009), Rua (2017) and Bartzsch *et al.* (2015) in similar models for banknote demand.

29 This was due to the fact that in the latter end of our sample, bond yields drop to negative values for many countries, which jeopardizes the utilization of natural logarithms.

30 Results are available upon request to the author.

After concluding that their variables were also I(1) and cointegrated, Bartzsch *et al.* (2011b) consider 5 different estimation models[31] to compute their parametric estimates and conclude that, given their small sample size, the fully modified least squares (FM–OLS)[32] method with non-seasonally adjusted data would be the most robust method. Given that the characteristics of our data match those of Bartzsch *et al.* (2011b) and that our sample size (64 observations) is also not very large, we have also opted to use this estimation algorithm.

Applying this estimation method to our dataset, we have computed a set of regressions which considered the circulation in each possible reference country in national currency and in Euros and we have also tested the inclusion of seasonal dummies. After taking into account individual and global significance, the adjusted coefficient of determination in each regression and the Bayesian information criteria, we concluded that the best regressions for each cluster are the following:

Table 4 – Summary of estimation results

Cluster	Regression	Currency of y var.	Adj. R^2	σ Reg.
1	$\hat{c}_t^{SE} = 2{,}70P_t^{SE^{.}} - 0{,}14Y_t^{SE} + 0{,}24i_t^{SE^{***}}$	SEK	0.574	0.134
2	$\hat{c}_t^{CZ} = 1{,}88P_t^{CZ^{***}} + 0{,}44Y_t^{CZ^{***}} - 0{,}03i_t^{CZ^{***}}$	CZK	0.96	0.054
3	$\hat{c}_t^{UK} = 1{,}47P_t^{UK^{***}} + 0{,}35Y_t^{UK^{***}} - 0{,}04i_t^{UK^{*}}$	GBP	0.978	0.036
	$***$ 0,001 significance level (99,9% confidence) $**$ 0,01 significance level (99% confidence) $*$ 0,05 significance level (95% confidence) . 0,1 significance level (90% confidence)			

Note that in all but cluster 1, the regressions estimated are showing the expected signs, that is, an increase in prices and in transactions leads to an increase in the amount of cash in circulation, while an increase in the opportunity cost of holding money leads to a decrease of cash circulation. However, the regression estimated for Sweden has counterintuitive parameters (hoarding with positive sign, transactions with negative sign). This is mainly due to the fact that Sweden is one of the few countries were cash in circulation has been consistently decreasing, as was reported by Bech *et al.* (2018)[33]. For this reason, we opted to use the reference country of the nearest cluster (cluster 3 – United Kingdom) as a reference for countries belonging to cluster 1.

Hence, the estimates for the Euros in circulation in each Euro area country according to this method are calculated through equation 3 below, where the parameters are those drawn from the regressions in table 4 featuring the respective reference country and Z is the Euro area country.

31 The estimation methods considered were a static regression Engle and Granger (1987), dynamic ordinary least squares, fully modified ordinary least squares, canonical cointegration and Johansen (1995) system estimator.

32 In a nutshell, as Phillips (1995) describes, FM–OLS is an estimator developed by Phillips & Hansen (1990) that provides optimal estimates of cointegrating regressions, by modifying the traditional least squares estimation to take into account serial correlation effects and possible endogeneity in the independent variables stemming from the existing cointegration relationships.

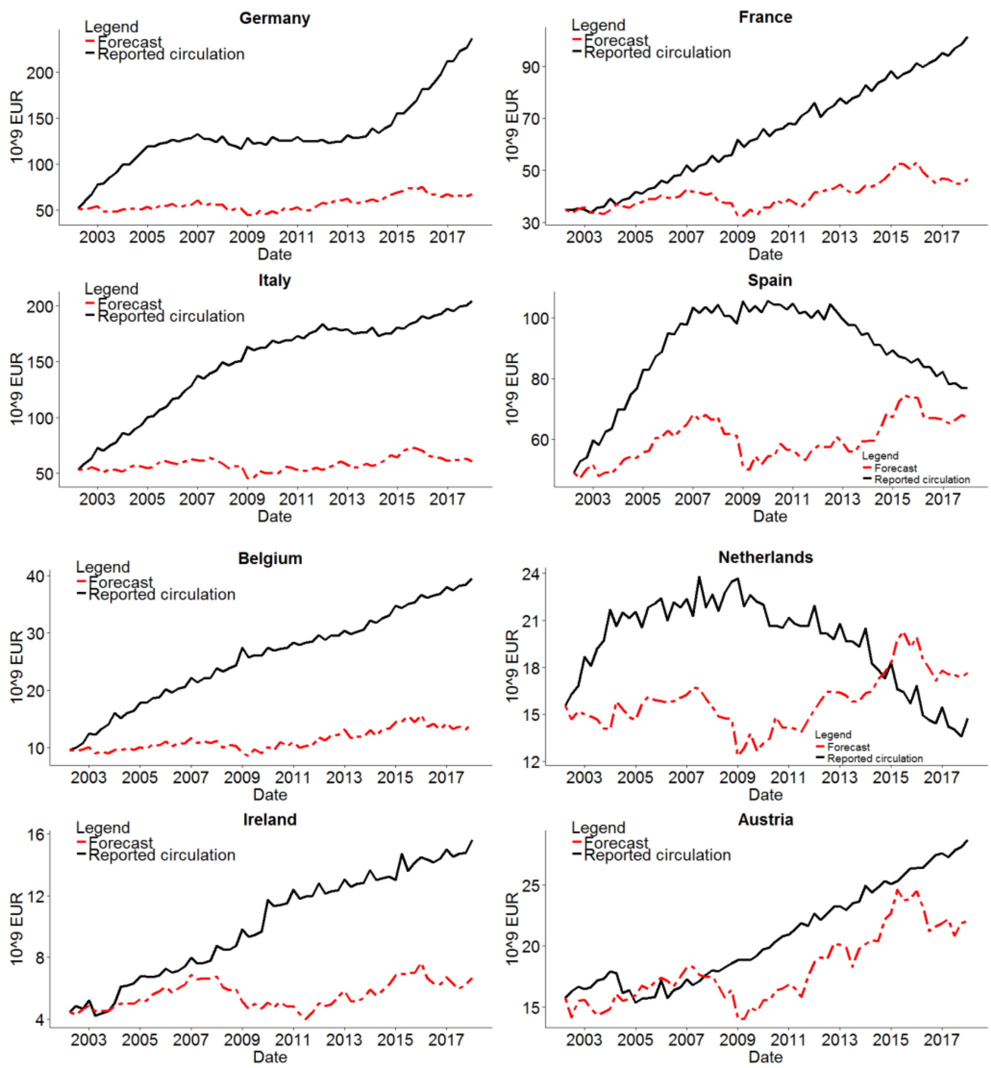
33 The Central Bank of Sweden (Sveriges Riksbank) reports that in January 2006 the amount of cash in circulation was 105.864 SEK, whereas in January of 2018 the same stock was 55.125 SEK.

$$\hat{c}_t^Z = \hat{\beta}_0 + \hat{\beta}_1 P_t^Z + \hat{\beta}_2 Y_t^Z + \hat{\beta}_3 i_t^Z \tag{3}$$

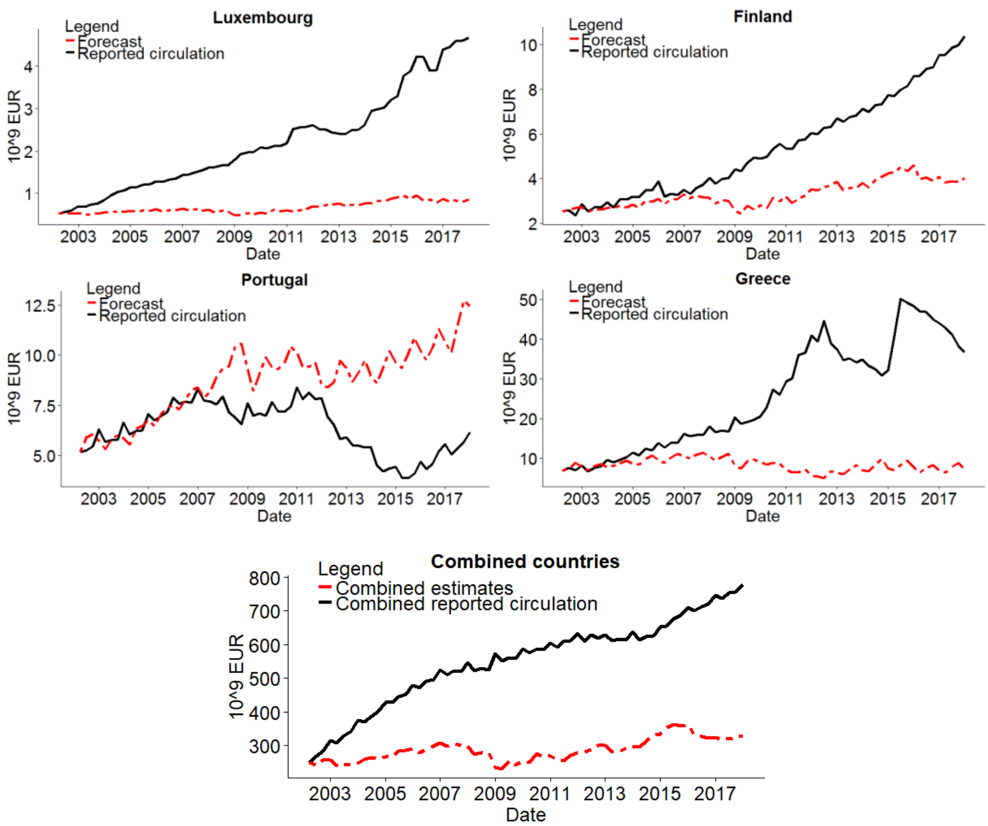
For Spain and Greece, the only countries that were classified in two different clusters, we used the parameters from the reference country whose regression showed the highest adjusted R^2 and lowest Bayesian information criteria: the United Kingdom.

Note that the resulting estimates ($\hat{c}_t^{XZ}$) are converted to Euros at the exchange rate prevailing in each period. Moreover, to ensure that both the forecasted and the reported series start from the same level[34], we have applied the annual rates of change derived from equation 3 to the level verified in the first quarter of 2002 to obtain the final forecast curve.

Figure 5 – Method 3 estimation results



[34] This is critical since, in many cases, there are important level differences between the reference country and the country being estimated (*e.g.* Luxembourg and United Kingdom).



Source: Eurostat, NCBs and author's calculations

The results of method 3, shown in figure 5, are somewhat mixed, but it appears that, in the majority of cases, it underestimates the stock of cash in circulation, especially when the stocks reported by each country show a strong upward trend (*e.g.* Germany, France, Italy, Belgium, Ireland, Luxembourg, Finland and Greece). A similar conclusion is also reached if one compares the combined estimates with the sum of the cash in circulation reported by each country. The method only overestimates the cash in circulation for Portugal and the Netherlands.

This can be due to the fact that the assumption of homogeneity of the structural impact of the variables chosen between countries might not hold in all pairs of reference and Euro area countries and that further investigation is needed. In fact, this is the risk one takes in applying a 'one-size fits all' technique such as method 3 and that calls for caution in the interpretation of the results.

Notwithstanding, unlike some of the estimation methods that we have formulated before, this design seems to be able to partially encompass the effect of the economic cycle, via the regressors it includes. Moreover, it also reflects the role of seasonality on the demand for Euro cash – due to the seasonality pattern embedded in the independent variables it includes –, which can be an interesting feature to explore for policy making.

All in all, the main merit of this model is that it departs from an hypothesis that can be reasonable in some specific pairs of reference and Euro area countries – similar structural impact of money demand factors and negligible foreign demand for the currency of the reference country – and incorporates such factors to obtain an estimate for money demand in each Euro area country. However, given that such assumptions might not always hold, these results must be taken carefully and as a further element to support the enhancement of the techniques currently used by each country.

5. Conclusions

The news about the demise of the use of cash seem somewhat exaggerated. Despite some punctual evidences of a shy decrease in its usage, cash still widely serves as a means of payment or of storage of value, regardless of the jurisdiction or of the currency concerned. Given its criticality, this paper focused on the issue of estimating the amount of cash in circulation in a given economy, under the special conditions introduced by the participation in a monetary union. For this purpose, all Euro area countries (fixed 2002 composition) were scrutinized.

Our goal was not one of persuading for the superiority of a specific technique, but rather to foster the discussion of this issue, particularly among central bank statisticians, with a view to propose practical solutions that may contribute to enhance current methods. Given the specificities of the estimation of cash in circulation in each economy/monetary union and since we are, in essence, trying to estimate a non-observable cross-border phenomenon, it should be underlined that there is no single method that can guarantee uncertainty-free results. Hence, any result of any estimation method must be duly validated from the theoretical point of view (e.g. the quality of the source data and the feasibility of the assumptions must be accurately factored in) and from the practical point of view (e.g. the results must be compared against the reality and idiosyncrasies of the countries under scrutiny).

In this spirit, this paper presents 3 possible estimation methods for the amount of Euros in circulation in each Euro area country, grounded on different data sources and statistical techniques.

Method 1 consists in the extrapolation, for the post 2002 period, of the time series structure of legacy currencies in the 1980-2000 period. The results of this method, which implies assuming no structural breaks in the cash in circulation series for the post 2002 era, appear to build confidence intervals that encompass the values currently reported by 3 of the 5 countries for which a forecast was possible.

Method 2 takes as starting point the method published by the ECB to estimate the Euros circulating outside the Euro area (published in ECB (2017a)) and takes as reference the estimate for the Euros circulating in the Euro area. A proportion of this stock was then allocated to each Euro area country according to harmonized criteria: (i) the share of each country’s GDP in the Euro area’s GDP; and (ii) the relative importance of the contribution of each country to the collective contribution of the countries under analysis to the Euro Area’s M3. The overall results of this method appear to be more in line with the stocks currently reported, although there are some cases of noticeable under/overestimation. Notwithstanding, this method has the virtue of being based on a publicly available (ESCB approved) estimation method and of producing estimates according to well-defined, harmonized criteria.

Finally, method 3 adapts one of the methods used by Bartzsch et al. (2011b) to estimate the “German euros” in circulation outside the Euro area and consists in estimating a structural money demand model for a country similar to the country for which we seek to estimate the cash in circulation. To determine the reference country for each Euro area country, hierarchical and non-hierarchical clustering was applied to a dataset containing proxies for the level of transactions, wealth, degree of openness of the economy, dimension, importance of tourism, hoarding motive and role of cashless payment instruments in each EU country. Through this technique, the United Kingdom, Czech Republic and Sweden were selected as reference countries for the estimation of a structural money demand model. The structural factors included in this regression were proxies for the evolution of prices, transactions and the opportunity cost of holding money. The results, which translate with greater emphasis the seasonality associated to each proxy, appear to underestimate the stock of cash in circulation in each Euro area country, especially when the stocks reported by each country show a strong upward trend. Hence, it must be highlighted that using this 'one-size fits-all' estimation approach carries the assumption that all pairs of reference and Euro area countries have similar structural money demand factors, which might not hold in all cases. Therefore, the results must be taken prudently and as a further element to support the development of the methods currently used by each country.

All in all, when the virtues and frailties of all three methods are considered, it is arguable that method 2 is seemingly more "adoption ready", given that it starts is grounded on an already approved and published methodology to estimate the Euros circulating outside the Euro area and employs relatively fair allocation criteria. Notwithstanding, the confidence interval yielded through method 1 can also be a useful reference to frame any future estimation experiments, and the structural model laid in method 3 can provide a basis for future country-specific adaptions that can prove important in supporting the methods currently used by each Euro area country. However, for future studies in this topic, new functional forms, techniques (e.g. country specific coins to banknotes ratio) and panels of variables can be tested to achieve a greater degree of accuracy in all countries. That said, any methodological changes arising from future refinements of the methods currently used must be duly contextualized and tested against the idiosyncrasies of each country.

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Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

Ninth IFC Conference on “Are post-crisis statistical initiatives completed?”

Basel, 30-31 August 2018

Estimating a country’s currency circulation within a monetary union[1]

André Dias,

Bank of Portugal

[1] This presentation was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

Estimating a country's currency circulation within a monetary union

9th biennial IFC Conference

André Cardoso Dias

BIS, Basel, 30-31 August 2018

Motivation

How many of us... carry cash when traveling abroad?

Over the last decade, cash in circulation **increased** in **CPMI countries***
(Bech *et al.*, 2018)

Despite **pressure** for the fading out of cash, demand for USD is **growing**
(Judson, 2017)

79% of the number of payments in the euro area **are settled in cash**
(Esselink & Hernández, 2017)

Cash is (still) king!

Stock of cash in circulation is an important input for central banks!

* The 24 CPMI jurisdictions are: AU, BE, BR, CA, CN, EA, FR, DE, HK, IN, IT, JP, KR, MX, NL, RU, SA, SG, ZA, SE, CH, TR, GB and US.

Objective

Address the issue of the compilation of the stock of cash in circulation

- Raise awareness to the complexity introduced by the participation in a monetary union and by the international relevance of the currency
- Discuss possible methods to consider such complexity in the techniques used to estimate currency in circulation
- Promote the debate within the central banking community on this issue

Methodology

Case-study: Cash in circulation in euro area countries (fixed 2002 composition)

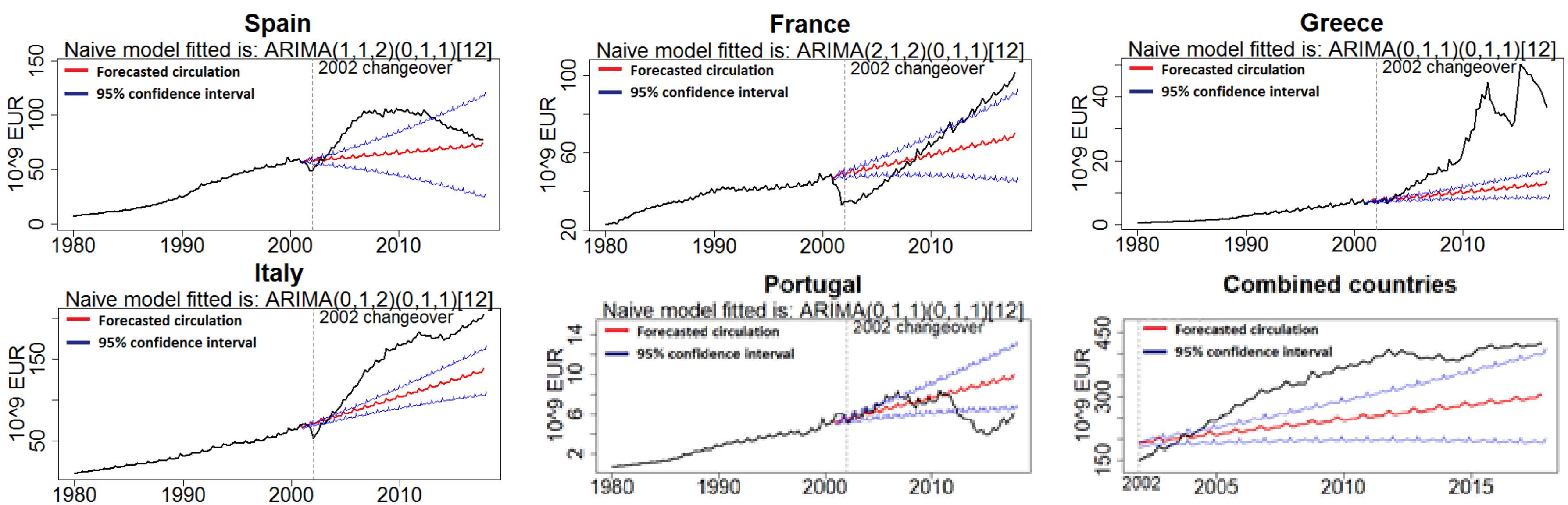
- All information used is publicly accessible
- Cash in circulation is considered net of coins, due to their low quantitative relevance
- Estimation period: 2002 to 2017
- 3 different methods tested:

Extrapolation of legacy currencies	Allocating a proportion of the circulation estimated for the euro area	Exploring a structural money demand model

Method 1 - Extrapolation of legacy currencies

Application of auto.ARIMA to legacy cash in circulation and forecast for euro era

- Imposed relatively long time-series (> 5 years, monthly) and overfit restrictions
- Data available only for 5 countries: France, Italy, Spain, Greece and Portugal



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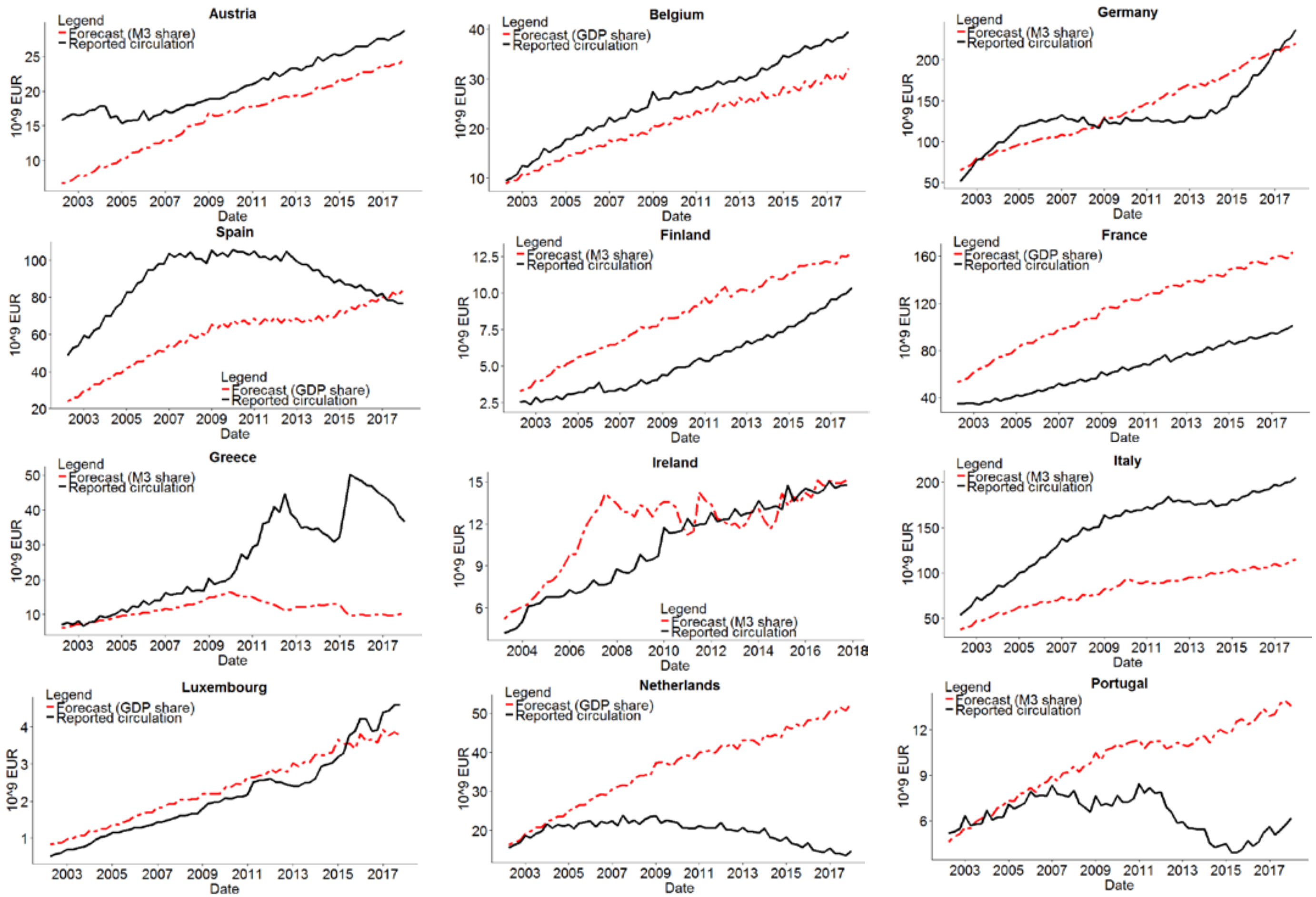
Method 2 - Allocating a proportion of the circulation estimated for the euro area

Based on ECB (2017a)'s estimate for cash in circulation outside the euro area

- Estimate of cash in circulation in euro area is obtained by difference
- 2 allocation keys considered: GDP share & contribution to M3 share

Method 2 - Allocating a proportion of the circulation estimated for the euro area



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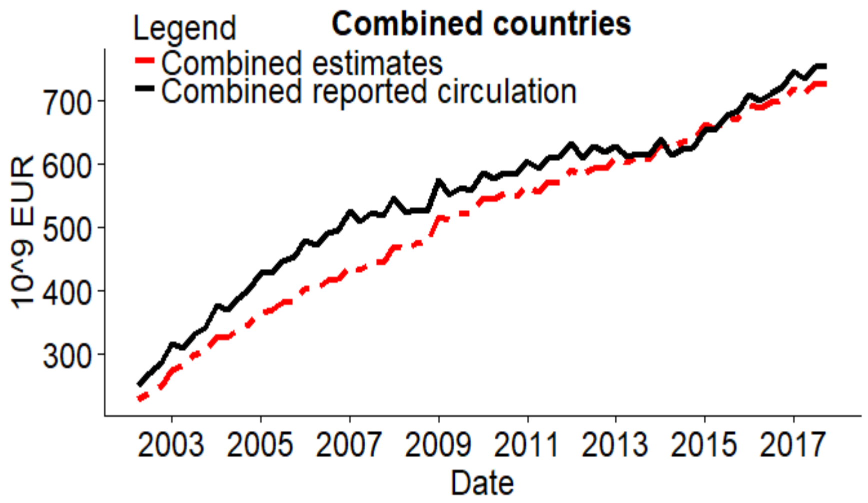
Method 2 - Allocating a proportion of the circulation estimated for the euro area



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Method 3 - Exploring a structural money demand model

Estimate structural money demand for EU countries outside the euro area and apply structural parameters for euro area countries

- Technique similar to proposal in Bartzsch *et al.* (2011b, section 2.2.4)
- Assume negligible foreign demand for non-euro EU currencies
- Include proxies for price level, transactions level and opportunity cost of holding cash

Reference countries X $\hat{c}_t^X = \hat{\beta}_0 + \hat{\beta}_1 P_t^X + \hat{\beta}_2 Y_t^X + \hat{\beta}_3 i_t^X$ (1)

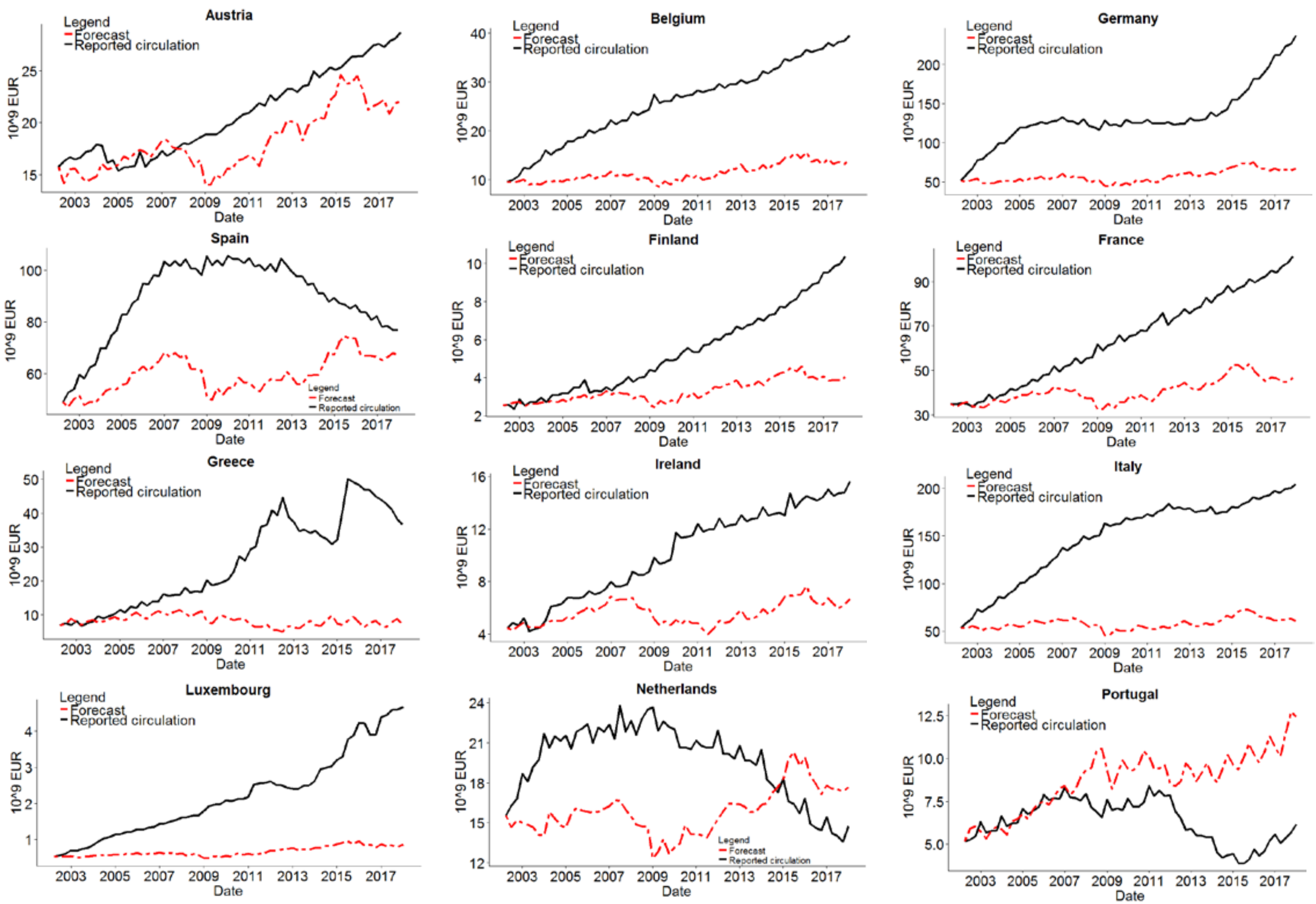
Euro area country Z $\hat{c}_t^Z = \hat{\beta}_0 + \hat{\beta}_1 P_t^Z + \hat{\beta}_2 Y_t^Z + \hat{\beta}_3 i_t^Z$ (2)

Method 3 - Exploring a structural money demand model

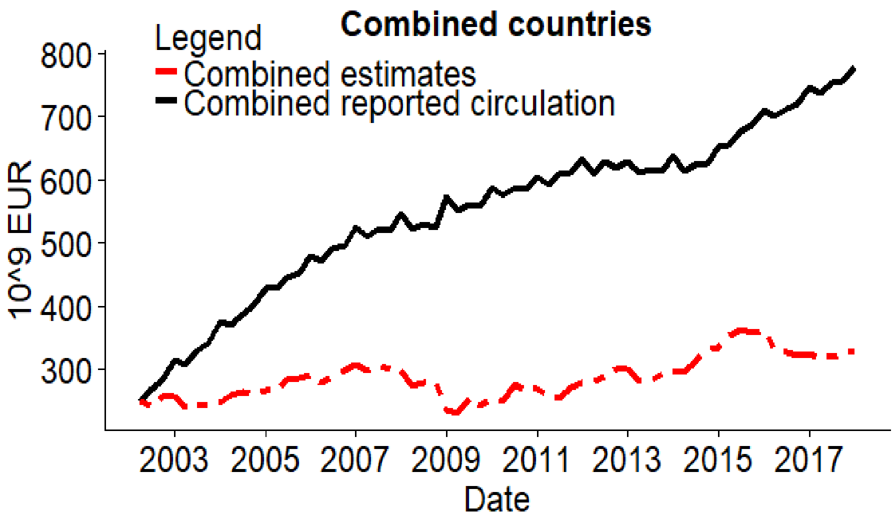
Pairs of non-euro & euro countries were determined according to Ward's (1963) and MacQueen's (1967) clustering methods

- Clustering based on dataset with proxies for transaction level, wealth, dimension, importance of tourism, hoarding motive, importance of cashless payments
- Non-euro countries in each cluster with best econometric performance were selected as reference

Method 3 - Exploring a structural money demand model



Method 3 - Exploring a structural money demand model



Conclusions

	Method	Merits	Limitations
1	Extrapolation of legacy currencies	Technically easy to implement	Assumes legacy time series structure holds in monetary union era
2	Allocating a proportion of the circulation estimated for the euro area	Enables the harmonization of the compilation of cash in circulation in the monetary union's countries	Assumes no differences between countries in the preference for cash
3	Exploring a structural money demand model	Proxies nearly all motives to hold cash and tracks their short & long run effects	Depends on structural resemblance between paired countries

- Cash still holds an instrumental role in the way we pay and 'save'
- Strong international role of currency & participation in a monetary union complexify the compilation of cash in circulation

There are no optimal answers to this issue...
further research & discussion are very much welcome!

Thank you!

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Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

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International financial flows and the Eurosystem's asset purchase programme: evidence from b.o.p and security by security data [1]

Katharina Bergant and Martin Schmitz,
European Central Bank

[1] This paper was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

International financial flows and the Eurosystem's asset purchase programme: evidence from b.o.p and security-by-security data

Katharina Bergant, Martin Schmitz[1]

Abstract

The growing complexity and interconnectedness of the international financial system as well as heterogeneity across sectors provide a strong case for incorporating micro data into policy analysis. In this paper, we use security-by-security data from the ESCB's securities holding statistics by sector (SHSS), which offers a comprehensive and granular dataset of the security holdings and transactions by euro area residents. With this information, we provide a detailed account of portfolio rebalancing in response to the Eurosystem's asset purchase programme (APP). The granular nature of the dataset enables us to complement the information available from b.o.p. statistics with security-specific information, such as the currency of denomination, yield and maturity of financial assets. This allows for instance to track euro area residents' investment behaviour in sovereign debt securities that are eligible to be bought by the Eurosystem under the APP, as well as in their closest substitutes, i.e. sovereign debt securities with the same characteristics issued by non-euro area advanced economies.

Keywords: Balance of payments, security-by-security data, portfolio rebalancing, capital flows, quantitative easing, micro data

JEL classification: F21, F34, E52, G15

Contents

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1. Introduction

Large scale asset purchase programmes (LSAPs) by central banks have become a popular tool of unconventional monetary policy since the global financial crisis to stimulate economic growth and fulfil inflation objectives in a zero lower bound environment. A major transmission channel of these policies to the real economy is portfolio rebalancing, induced by a decrease in long-term bond yields resulting from a scarcity of securities in the secondary market triggered by the central bank's purchases. Thereby, lower yields should lead investors to rebalance their portfolio towards higher yielding assets, both domestic and foreign.

The ECB's unconventional monetary policy measures, covering the large scale asset purchase programme (APP), a negative deposit rate, and targeted longer-term refinancing operations (TLTROs) reduced euro area long-term risk-free rates by around 80 basis points since June 2014 (ECB, 2017a). The resulting yield differentials between euro area and foreign government bonds have played an important role for euro area capital flows since then (ECB, 2017b). Evidence from the euro area balance of payments shows that the introduction of the main component of the APP in the first quarter of 2015 – namely the Public Sector Purchase Programme (PSPP) – was followed by significant net capital outflows in portfolio investment (Figure 1).[2]

This macro-based evidence confirms that LSAPs can trigger substantial cross-border capital flows by way of the portfolio rebalancing channel. In an integrated international financial system, monetary policy impacts both domestic investment patterns and international capital flows. The growing complexity and interconnectedness of the international financial system as well as sector heterogeneity provide a strong case for incorporating micro data for policy analysis (Lane, 2015). Limitations of macroeconomic statistics pertain for instance to the limited extent of sectoral information on holders and issuers of assets, both in a domestic and cross-border context. Data on country-level capital *flows* usually only offer a limited geographic breakdown, while bilateral data merely cover investment positions, are available at low frequencies, and do not include the holdings of domestic securities (e.g. the IMF's Coordinated Portfolio Investment Survey, CPIS).

Security-by-security data allow identifying important asset specific characteristics, such as the issuing entity, the yield of a debt security, market prices, as well as the currency denomination, maturity and rating. Such granular information – if consistent with macroeconomic statistics – enables data users and statisticians to drill down to specific dimensions of financial positions and transactions, both on an ad-hoc basis and to construct aggregate statistical indicators. Another benefit of security-by-security data relates to the possibility to analyse financial position and transactions on a who-to-whom basis at various layers of detail.

In this paper, security-by-security data from the European System of Central Banks (ESCB) securities holding statistics by sector (SHSS) is used, which offers a comprehensive, fully integrated, granular dataset of the security holdings and transactions of euro area residents. As such one is able to integrate the analysis of domestic and international sectoral portfolios. This dataset allows for providing a

[2] The PSPP accounts for approximately 80% of the entire asset purchase programme.

detailed account of euro area portfolio rebalancing – both at the aggregate and sector level, incorporating domestic, euro area and global capital financial transactions of euro area residents – in the period since the launch of the PSPP (2015Q1 to 2017Q4).

The remainder of this paper is organised as follows: Section 2 provides evidence on euro area cross-border portfolio rebalancing since the launch of the PSPP based on ECB balance of payments data. Section 3 presents the key features of the SHSS dataset which is subsequently used in Section 4 to present additional insights on euro area portfolio rebalancing. Section 5 concludes.

2. Evidence based on b.o.p. data

Figure 1: Breakdown of euro area net portfolio investment flows
(EUR bn)

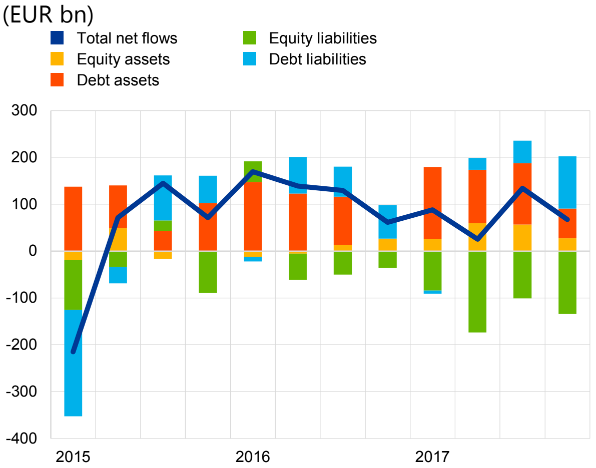
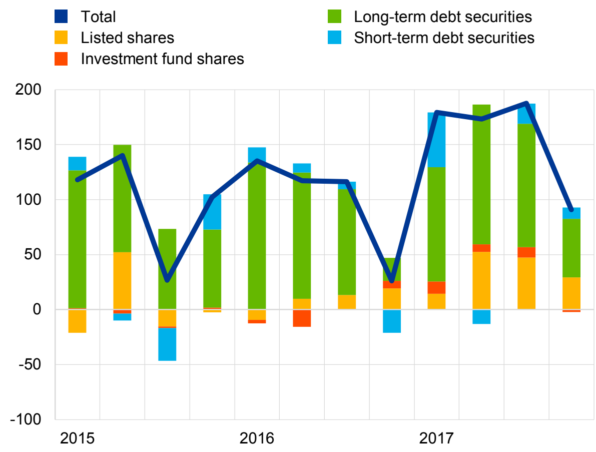


Figure 2: Euro area portfolio investment asset flows
(EUR bn)



Source: ECB.
Notes: For assets, a positive (negative) number indicates net purchases (sales) of non-euro area securities by euro area investors. For liabilities, a positive (negative) number indicates net sales (purchases) of euro area securities by non-euro area investors. For net flows, a positive (negative) number indicates net outflows (inflows) from (into) the euro area. Equity includes investment fund shares. The latest observation is for 2017Q4.

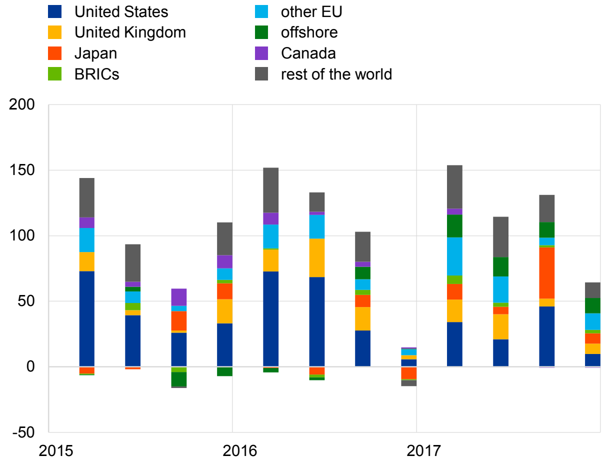
This section provides evidence from the ECB's b.o.p. statistics on developments in euro area portfolio investment since the announcement and launch of the PSPP in early 2015. Since then, the euro area has recorded net outflows (i.e. the net purchases of foreign asset by euro area residents exceeded the net purchases of euro area asset by foreign residents) in portfolio investment, owing to rebalancing towards non-euro area debt securities on the part of both euro area and non-euro area investors (Figure 1). While non-euro area residents account for a sizable share of bond sales to the Eurosystem as part of the PSPP, they have been large net buyers of euro area equity.[3] Euro area investors on the other hand were a major driving force behind the observed net outflows (Figure 2). Since the start of the

3 According to Cœuré (2017) the selling of euro area government bonds by non-residents in the PSPP is to some extent a mechanical feature of the programme due to the relatively large share of euro area government bonds held by non-residents. Moreover, the inflows to euro area equity by foreign investors partly reflected a confidence effect as the ECB's policy measures boosted investor confidence in the euro area's growth prospects.

PSPP, net purchases of foreign securities by euro area investors have largely consisted of debt securities – in particular long-term bonds – suggesting that domestic investors partly rebalanced their portfolios towards the closest substitute to PSPP eligible assets outside the euro area.

Zooming in on euro area investors' portfolio debt investment outside the euro area, one observes that since early 2015 net purchases were largely concentrated on securities issued by advanced economies outside the euro area (Figure 3). Almost two-thirds of cumulated net debt purchases went into securities issued by residents in the United States (37%), the United Kingdom (13%), Japan (6%), and Canada (5%). By contrast, there was only limited investment into the BRICs – Brazil, Russia, India and China (around 2%).

Figure 3: Geographical breakdown of euro area investors' net transactions of non-euro area portfolio debt securities (EUR bn)



Source: ECB.
Notes: "BRICs" comprises Brazil, Russia, India and China; "other EU" comprises EU Member States outside the euro area, excluding the United Kingdom. The latest observation is for 2017Q4.

3. The securities holdings statistics by sector (SHSS) dataset

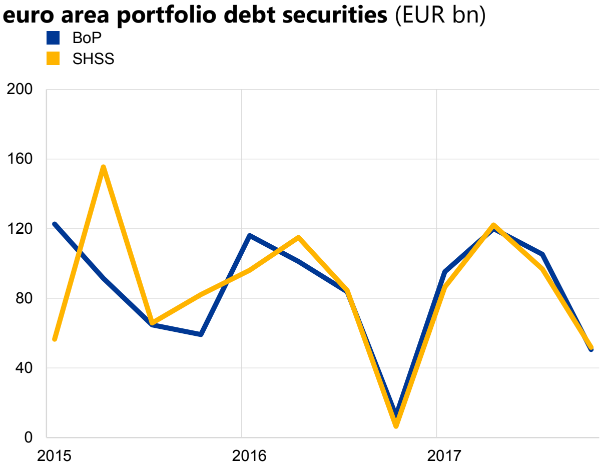
We use data on security-level portfolio transactions of all 19 euro area countries from the European System of Central Banks (ESCB) Sectoral Securities Holding Statistics (SSHS).[4] The data are collected by national central banks from (i) financial investors and (ii) custodians. The dataset covers short-term and long-term debt securities, listed shares as well as investment fund shares which are in most cases identified with a unique International Securities Identification Number (ISIN). The data are collected on a quarterly basis since 2013Q4; data released until 2017Q4 (reference quarter) have been used in this analysis. The SHSS data consist of *directly* and *indirectly* reported securities. A financial institution resident in the euro area is

[4] This dataset is collected according to Regulation ECB/2012/24, see http://www.ecb.europa.eu/ecb/legal/pdf/l_30520121101en00060024.pdf

obliged to report securities that it holds as its own investment ("direct reporting") as well as securities that it holds in custody ("indirect reporting"). Moreover, in some countries non-financial investors have direct reporting requirements. In the other countries, assets held in custody are included for non-financial investors in the SHSS.[5] Investors in the dataset are defined by their country of domicile and sector. We follow the European System of Accounts (2010) and aggregate the data to six sectors: monetary and financial institutions (MFI) excluding monetary authorities, insurance companies and pension funds (ICPF), other financial institutions (OFI),[6] non-financial corporations (NFCs), general government (GOV), and households (HH).

Using the ISIN for every security, SHSS data are merged with individual asset characteristics obtained from the ESCB's Centralised Securities Database (CSDB) which contains information on more than six million debt and equity securities issued globally (see ECB (2015) and Fache Rousová and Rodríguez Caloca (2018) for further details). Therefore, one can use information at the security-level, such as the instrument type, issuer country and institutional sector, currency of denomination, yield and maturity.

Figure 4: Euro area investors' net purchases of non-euro area portfolio debt securities (EUR bn)



Source: ECB.
Notes: The latest observation is for 2017Q4.

A priori b.o.p./i.i.p. and SHSS statistics are expected to provide rather consistent results, since the national portfolio investment assets of euro area residents should rely on SHSS (or data collected for SHSS purposes) as the primary data source. In particular, the ECB Guideline on external statistics defines that cross-border portfolio investment collection systems of euro area countries shall rely, as much as possible, on security-by-security information. Specifically, the Guideline defines that stocks of securities reported to national compiler on an aggregate basis, i.e. without

5 This approach prevents a double-counting of holdings which would happen if there are several intermediate financial institutions between the final non-financial investor and the financial institution holding assets in custody.

6 These include important intermediaries such as mutual funds which represent the largest subgroup of this sector.

standard (ISIN or similar) codes, should not exceed 15% of the total portfolio investment stocks of assets or liabilities.

The consistency between euro area b.o.p./i.i.p. statistics and SHSS has improved in recent years, especially for long-term debt securities (Figure 4). Over the period 2016Q1 to 2017Q4 the average ratio of SHSS to b.o.p./i.i.p. data on euro area holdings of securities issued by non-euro area residents (b.o.p./i.i.p. assets, i.e. not considering intra-euro area holdings) was very high for long-term debt securities (97%) and listed shares (90%) and somewhat lower for short-term debt securities (76%) and investment fund shares (72%). This high coverage of SHSS data makes it an appealing data source to construct complementary micro-based statistical indicators.

4. Evidence based on security-by-security data

In this section we analyse the 'active' portfolio rebalancing (i.e. in terms of net purchases/sales) of euro area investors since the launch of the PSPP by using additional statistics from the SHSS dataset. Hence, we are able to provide additional insights compared to those based on more aggregate statistics, such as the balance of payments presented in Figures 1 to 3. Furthermore, the dataset allows us to integrate euro area investors' financial transactions in securities issued globally (i.e. domestically, in the rest of the euro area and outside the euro area).

Figure 5: Euro area investors' net transactions of debt securities

(EUR bn)

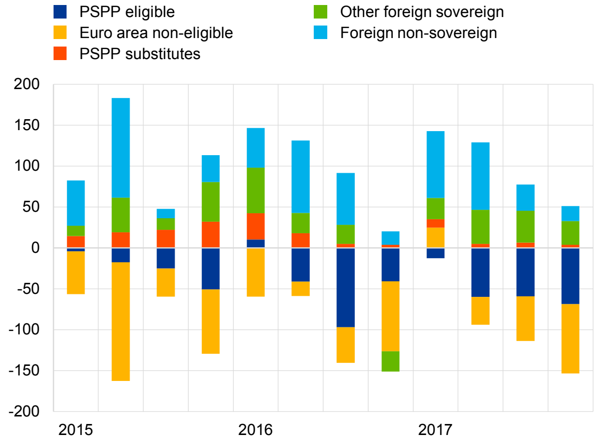
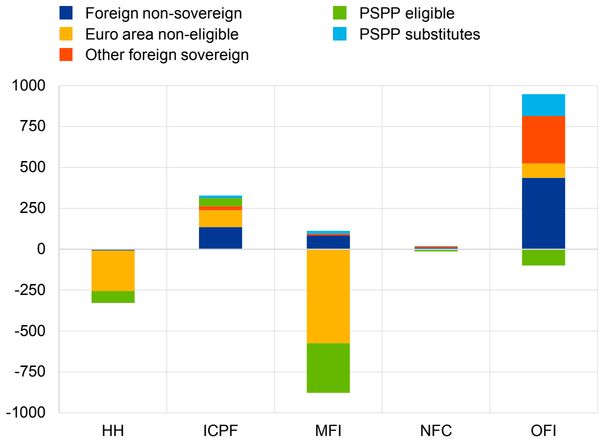


Figure 6: Euro area sectors' net transactions of debt securities

(EUR bn, cumulated 2015Q1 to 2017Q4)



Source: ECB.

Notes: A positive (negative) number indicates net purchases (sales) of securities by euro area investors. PSPP eligible assets are securities eligible to be bought by the Eurosystem under PSPP. PSPP substitutes are sovereign debt securities from advanced countries outside the euro area which would otherwise fullfil the eligibility criteria of the PSPP programme. The latest observation is for 2017Q4.

Starting with transactions in debt securities, Figure 5 shows that euro area investors were net sellers of securities eligible to be bought by the Eurosystem under the PSPP in the period 2015Q1 to 2017Q4.[7] The SHSS dataset enables us to identify transactions in these eligible securities at the security level and use those in aggregated form in descriptive analysis.

Net sales of PSPP eligible securities by euro area residents amounted to more than EUR 470 bn in the period 2015Q1 to 2017Q4. At the same time, even larger net sales of around EUR 670 bn were recorded for other debt securities issued in the euro area, of which the most important component consisted of those issued by euro area MFIs. These net sales can be attributed to spillovers from the PSPP programme to other euro area debt instruments as well as negative net issuance of bonds by the banking sector in light of deleveraging pressures. These net sales of euro area debt instruments were mirrored in sizeable net purchases of foreign debt securities by euro area residents. More than half of these net purchases consisted of foreign debt securities issued by the foreign private sector, thereby closely matching in size the net sales of non-eligible euro area debt securities. Moreover, we also observe significant net purchases (of around EUR 500 bn) of foreign sovereign debt securities, of which around 35% qualify as close substitutes for PSPP eligible assets.[8] Figure 6 shows which sectors drove these overall patterns: MFIs and households accounted for the largest net sales of euro area debt securities (both PSPP eligible and other debt securities), while ICPFs were net buyers of both types of euro area debt securities. OFIs – mainly consisting of mutual funds – bought the largest amounts of PSPP substitutes as well as foreign debt securities in general, followed by ICPFs and MFIs.[9]

In Figure 7 the analysis is broadened to include equity securities, i.e. investment fund shares and listed shares, in order to investigate the transmission of quantitative easing in the euro area from targeted securities towards other instruments. In contrast to the b.o.p. based analysis in Figure 2, also securities issued by euro area residents are considered, i.e. including securities issued in the country of residence of a euro area investor. The evidence shows that euro area investors rebalanced their portfolios towards euro area investment fund shares, debt securities issued outside the euro area, and to a lesser extent to (euro area and foreign) listed shares. The rebalancing towards investment fund shares was particularly pronounced for euro area households.

Figure 8 provides additional detail on euro area flows into investment fund shares. Based on additional security characteristics from the ESCB's CSDB, we differentiate investment funds at the ISIN level according to their main investment purpose/mandate. The largest net purchases by euro area residents of investment

7 Securities eligible to be bought under the PSPP are those (i) issued by euro area governments or (ii) by certain international/supranational institutions. In addition, they need fulfil specific requirements, e.g. a maturity between 2 and 30 years, ratings above credit quality step 3 in the Eurosystem's harmonised rating scale (i.e. at least a rating BBB- from Standard & Poor's or Fitch, BBBL from DBRS, or Baa3 from Moody's), a yield to maturity above the Eurosystem's deposit facility rate, which was equal to -20bp at the time of the announcements of the programme in January 2015.

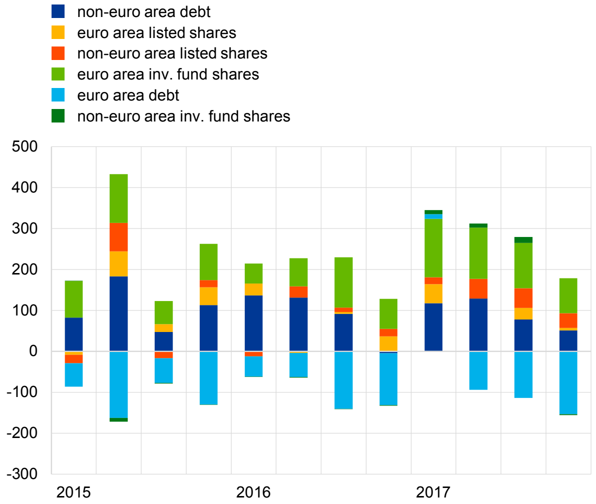
8 We define PSPP substitute as sovereign debt securities of foreign advanced countries which otherwise fulfil the requirements of the PSPP, e.g. a 10-year US treasury bond.

9 For a formal regression-based analysis of sectoral portfolio rebalancing in response to the PSPP, please see Bergant, Fidora and Schmitz (2018).

funds shares targeted 'mixed' investment funds, followed by those funds with explicit mandates to invest in bonds, equity and real estate. Combining the evidence contained in Figures 6 and 8 suggest that at the end of the investment chain, euro area investment funds channelled large funds towards the acquisition of non-euro area debt securities.

Figure 7: Euro area investors' net transactions of euro area and non-euro area securities (EUR bn)

(EUR bn)

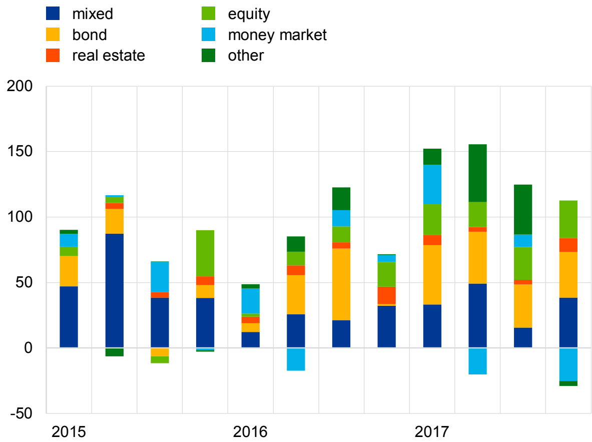


Source: ECB.

Notes: A positive (negative) number indicates net purchases (sales) of securities by euro area investors. Euro area securities include domestic securities. The latest observation is for 2017Q4.

Figure 8: Euro area investors' net transactions of investment fund shares split by main mandate

(EUR bn)



Source: ECB.

Data on the mandate of the respective investment funds are from an extract of the CSDB on 31/01/2018. Other includes unallocated. The latest observation is for 2017Q4.

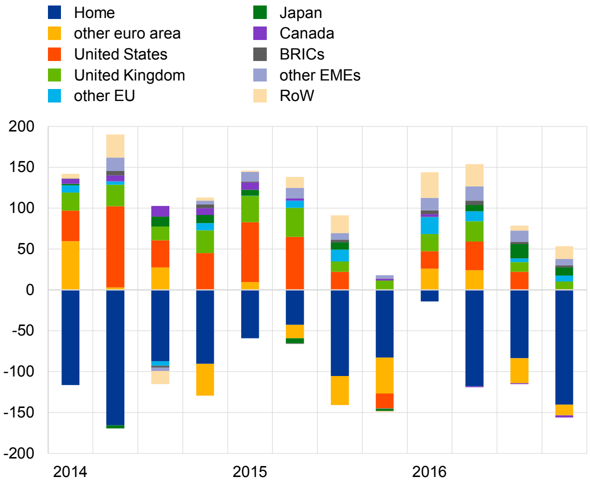
As regards the geographical decomposition of euro area residents' net purchases of debt securities we go beyond the b.o.p. evidence by also including transactions in debt securities issued in the investor's country of residence ("Home") and those issued in "other euro area countries" (Figure 9). The security-level data also allows for constructing geographical counterparts on an ad-hoc basis. In this instance, we construct an aggregate of "other emerging market economies (EMEs)" which we include alongside the BRICs aggregate.[10] Figure 9 shows that euro area residents' net sales of debt securities were largely concentrated on those issued in their home countries, which points to a decline in the home bias of debt securities. Apart from the patterns already observed in the b.o.p. analysis – most strikingly the large amount of net purchases of debt securities issued by the United States of around EUR 450 bn since 2015Q1 – the relatively large volume of net purchases of debt securities issued by other EMEs of around EUR 110 bn stands out.

The importance of the US as euro area residents' preferred issuers of debt securities since the launch of the PSPP warrants a closer analysis. Indeed, the two

[10] Our definition of other EMEs which is broadly consistent with the IMF's definition includes Argentina, Bangladesh, Chile, Columbia, Indonesia, Malaysia, Mexico, Pakistan, Peru, Philippines, Thailand, Turkey, South Africa, Uruguay and Venezuela.

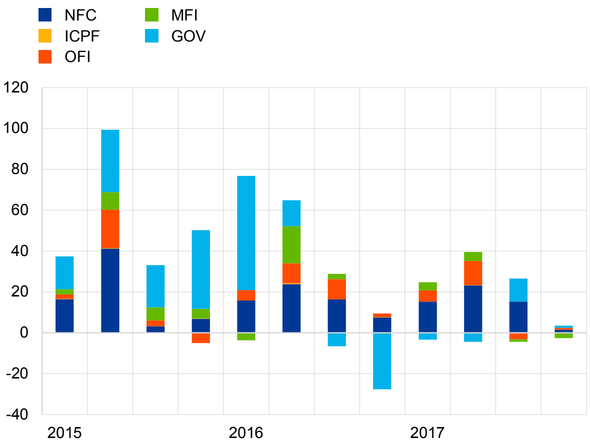
single issuing sectors receiving the largest net debt securities purchases by euro area residents' were US non-financial corporations and the US government sector. Figure 10 also reveals important time dynamics: from 2015 up to mid-2016 large euro area net purchases of debt securities issued by the US government were recorded, while these turned negative afterwards. Net purchases of debt securities issued by US NFCs on the other hand were recorded persistently in all quarters since 2015Q1.

Figure 9: Geographical breakdown of euro area investors' net transactions of debt securities (EUR bn)
(EUR bn)



Source: ECB.
Notes: A positive (negative) number indicates net purchases (sales) of securities by euro area investors. The latest observation is for 2017Q4.

Figure 10: Euro area investors' net transactions of debt securities issued by US residents, by issuing sector
(EUR bn)

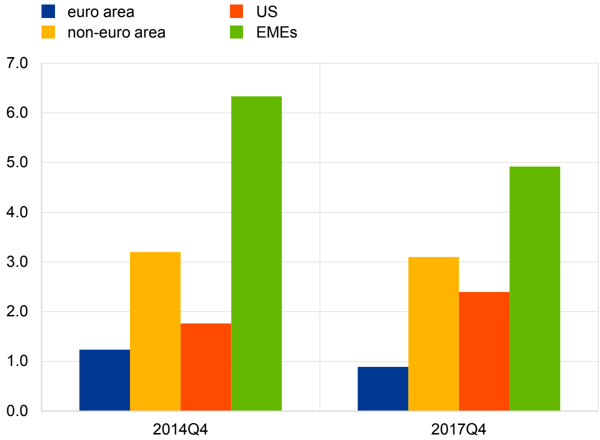


Source: ECB.
Notes: A positive (negative) number indicates net purchases (sales) of securities by euro area investors. The latest observation is for 2017Q4.

Large net purchases of US debt securities are in line with euro investors eyeing the closest substitutes to PSPP eligible securities and can also be explained by the substantial yield differentials between the euro area and the US in recent years. In fact, as our security-level dataset also contains information on the yield to maturity of debt securities, we are able to calculate the average yields euro area investors are obtaining on their debt security holdings, broken down by issuing counterparty. Figure 11 focuses on sovereign debt securities: since the launch of the PSPP, a key development has been the growing interest rate differential between euro area and non-euro area (in particular US) sovereign debt securities. Moreover, the yield on government debt securities issued by EMEs has remained substantially higher than the yield on euro area government debt.

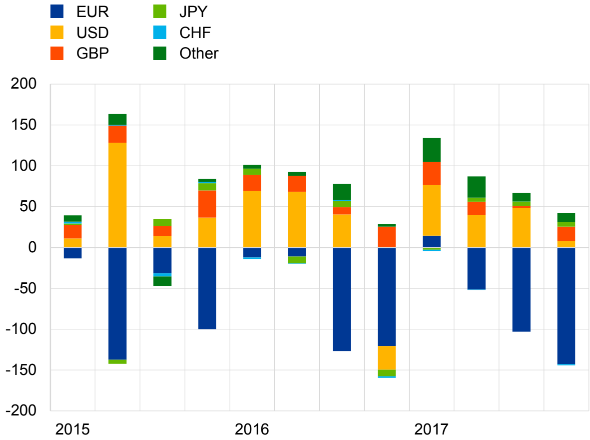
A further dimension of euro area residents' transaction in debt securities concerns the currency of denomination. Starting from the security-level, we find that the five most relevant currencies in euro area residents debt securities' portfolios are the euro, US dollar, British pound, Japanese Yen and the Swiss Franc. The geographical decomposition of euro area residents' net purchases of debt securities is mirrored in the currency of denomination of the underlying assets: Figure 12 shows large net purchases of debt securities denominated in US dollar and to a lesser extent in British pound, as well as net sales of euro-denominated debt securities.

Figure 11: Yield on euro area investors' government debt security holdings, by issuer (percentages)



Source: ECB.
Notes: Average yield to maturity on aggregate euro area investors' portfolio as contained in SHSS dataset. EMEs include the BRICs and "other EMEs" as outlined above.

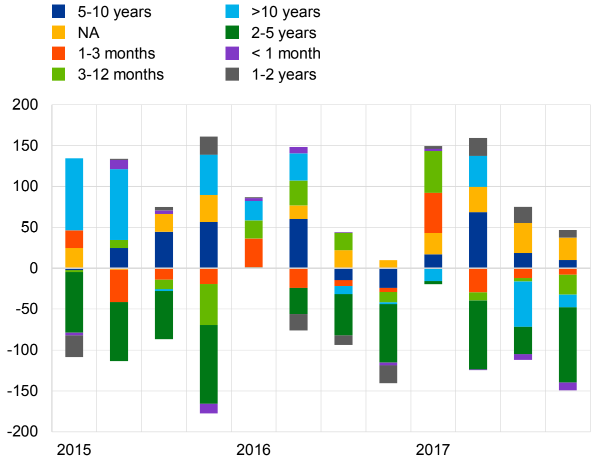
Figure 12: Currency breakdown of euro area investors' net transactions of debt securities (EUR bn) (EUR bn)



Source: ECB.
Notes: A positive (negative) number indicates net purchases (sales) of securities by euro area investors. The latest observation is for 2017Q4.

As our dataset contains very detailed information on the original and residual maturity of a security (in number of days), we are able to construct various maturity intervals and report net purchases of debt securities belonging to each of these intervals. This is particularly relevant for the PSPP period, because the euro area yield curve shifted downwards, which might have induced euro area investor to increase the average maturity of their debt security holdings in order to achieve a certain nominal yield. Figure 13 points to evidence in the direction of a shift towards longer term maturities as the vast majority of net sales over the PSPP period consisted of assets with an original maturity between 2 and 5 years. Net purchases of debt securities on the other hand largely fell within the maturity intervals of 5 to 10 years and more than 10 years. Further evidence at the sector level shows that the large net purchases of assets with a minimum original maturity of 10 years is driven by ICPFs and OFIs. In particular for the latter, the switch to longer-term maturities may be driven by "search for yield" considerations, while for ICPFs these net purchases are likely driven by the inherent need to match long-term liabilities with long-term assets. The large net sales of 2-5 year original maturity securities were mainly driven by MFIs and households.

Figure 13: Maturity breakdown of euro area investors' net transactions of debt securities
(EUR bn)



Source: ECB.
Notes: A positive (negative) number indicates net purchases (sales) of securities by euro area investors. Maturity refers to original maturity of debt securities at issuance. The latest observation is for 2017Q4.

5. Conclusions

In this paper, we use security-by-security data from the ESCB's SHSS to provide detailed account of portfolio rebalancing in response to the Eurosystem's asset purchase programme (APP). The granular nature of the dataset enables us to complement the information available from b.o.p. statistics.

Our analysis reveals for instance that euro area investors rebalanced away from euro area debt securities (including PSPP eligible securities) towards foreign debt securities (including the "closest substitutes" to securities targeted under the PSPP). While the aggregate patterns for the euro area are in line with "textbook portfolio rebalancing", we find sector heterogeneity as ICPFs were net buyers of PSPP eligible assets and other euro area debt securities since the launch of the PSPP.

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Irving Fisher Committee on
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BANK FOR INTERNATIONAL SETTLEMENTS

Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

International financial flows and the Eurosystem's asset purchase programme: evidence from b.o.p and security by security data [1]

Katharina Bergant and Martin Schmitz,

European Central Bank

[1] This presentation was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

EUROPEAN CENTRAL BANK

EUROSYSTEM

Katharina Bergant
Martin Schmitz

European Central Bank

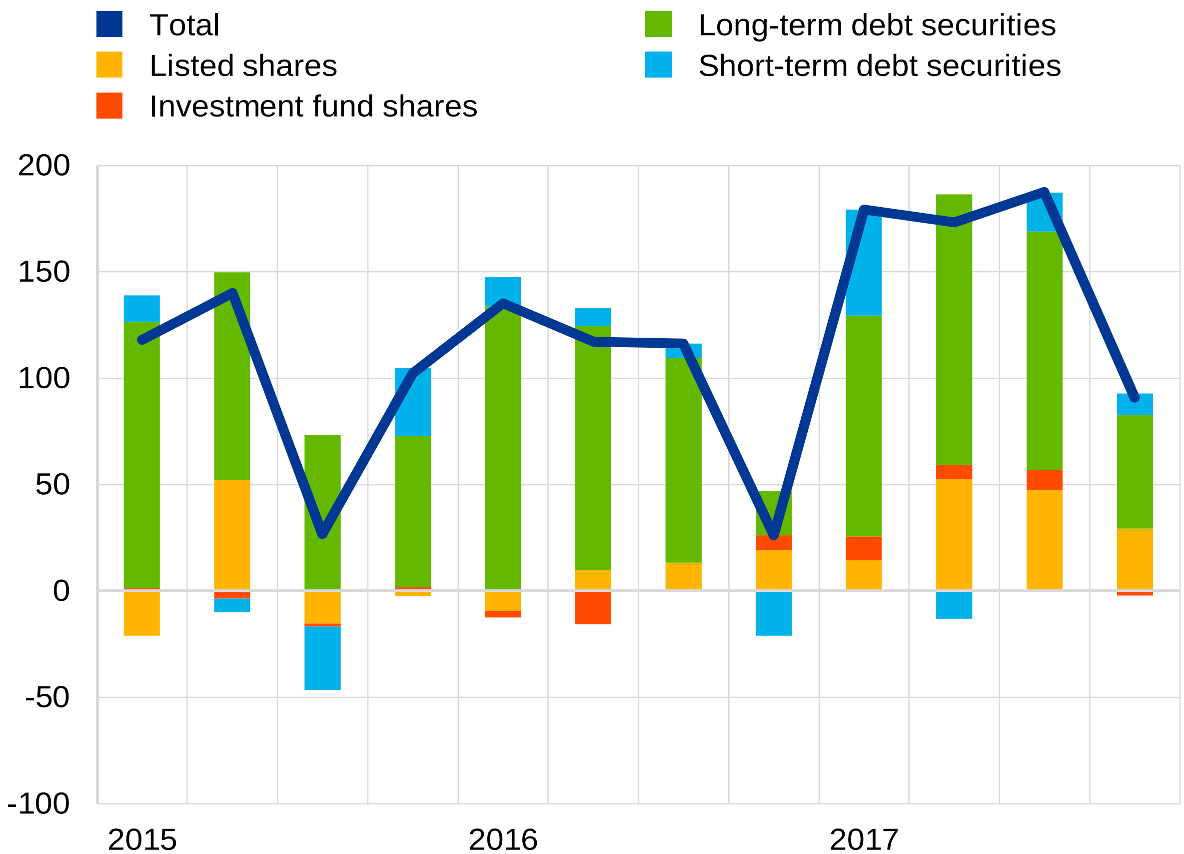
International financial flows and the Eurosystem's asset purchase programme: evidence from b.o.p and security-by-security data

Basel, 30 and 31 August 2018

B.o.p. evidence: euro area residents rebalanced towards foreign debt securities

Euro area portfolio investment asset flows

(EUR bn)



Source: ECB.
Notes: For assets, a positive (negative) number indicates net purchases (sales) of non-euro area securities by euro area investors. The latest observation is for 2017Q4

The APP and international financial flows – the need for granular data

- Incorporating micro data for policy analysis due to **complexity of international financial system and sector heterogeneity** (Lane 2015; Shin 2016)

- Limitations of **macroeconomic statistics**
  - Sectoral information on holders/buyers and issuers of securities
  - Integrated information on domestic and foreign securities
  - Data on country-level capital flows offer limited geographic breakdown

- **Security-by-security** data
  - Enable data users and statisticians to drill down to security-specific dimensions of financial positions and transactions
  - In this paper: ESCB's security holdings statistics by sector (SHSS)

Security holdings statistics by sector (SHSS)

- Sectoral **security-level portfolio holdings** and transactions of all 19 euro area countries

- **All securities** (domestic and foreign) held by euro area investors
  - Debt securities (short-and long-term) and equities (listed shares and investment fund shares)

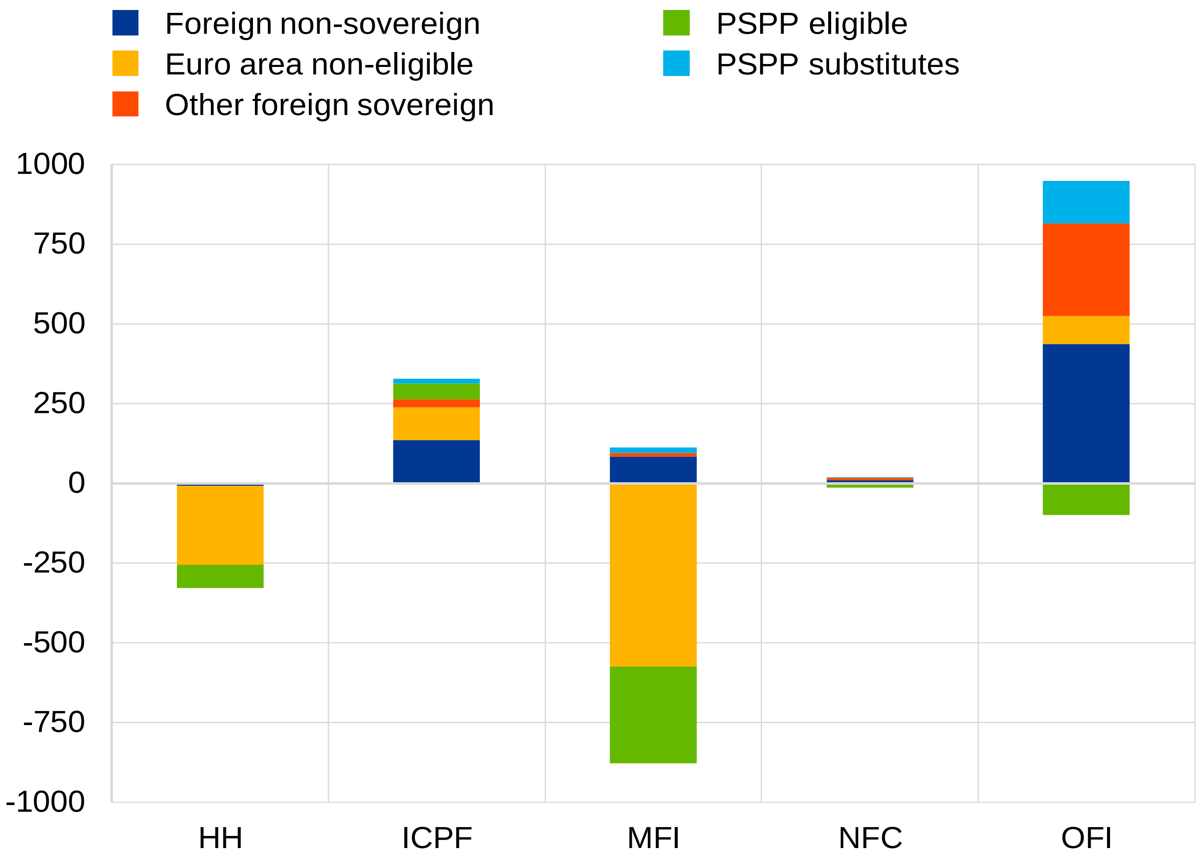
- ISIN allows for obtaining **individual asset characteristics** from the ESCB's Centralised Securities Database (CSDB)
  - issuer country and institutional sector, currency denomination, yield, maturity…

- **High consistency** with euro area b.o.p./i.i.p. statistics
  - makes SHSS appealing source to construct complementary micro-based statistical indicators

Euro area rebalancing away from PSPP eligible assets towards PSPP substitutes

Euro area sectors' net purchases of debt securities

(EUR bn; cumulated 2015Q1 to 2017Q4

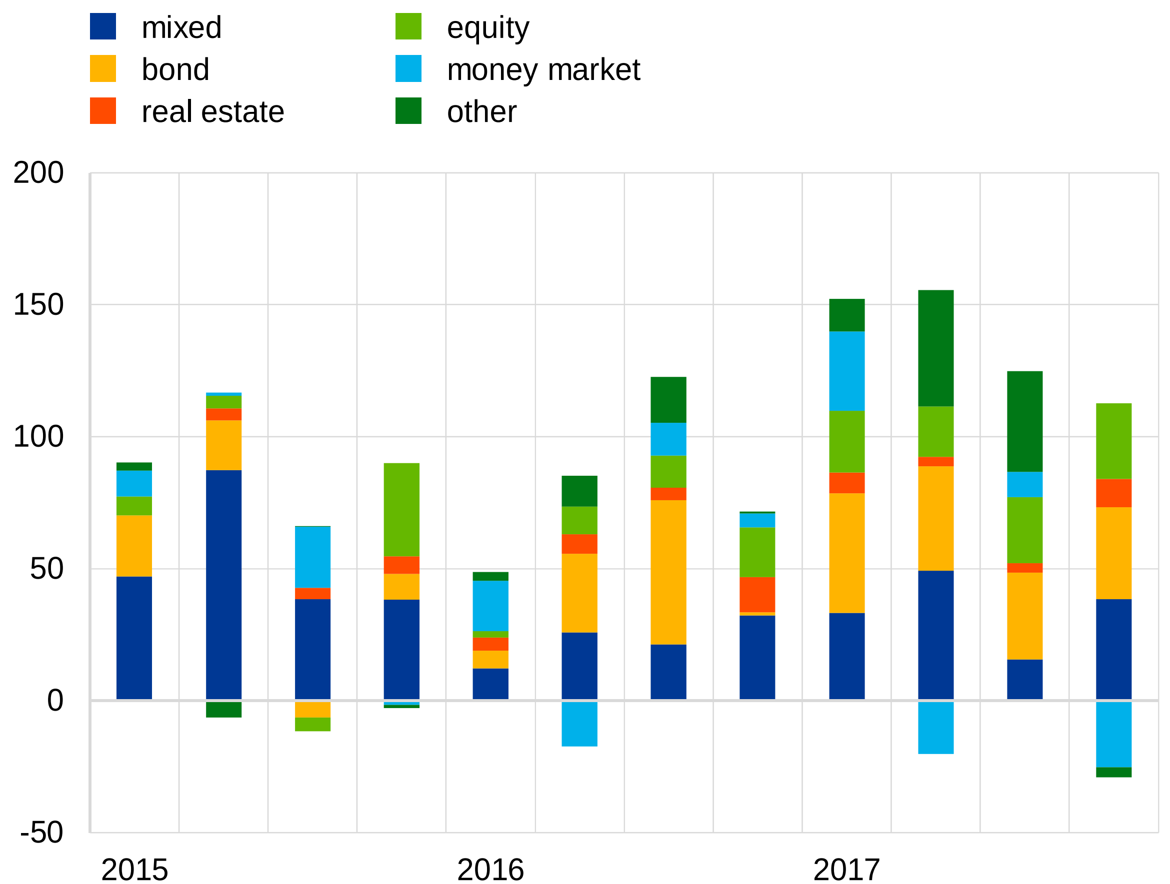


Source: ECB.
Notes: A positive (negative) number indicates net purchases (sales) of securities by euro area investors. PSPP eligible assets are securities eligible to be bought by the Eurosystem under PSPP. PSPP substitutes are sovereign debt securities from advanced countries outside the euro area which would otherwise fullfil the eligibility criteria of the PSPP programme. The latest observation is for 2017Q4.

Rebalancing into “mixed” and bond investment funds

Euro area investors’ net purchases of investment fund shares split by main mandate

(EUR bn)

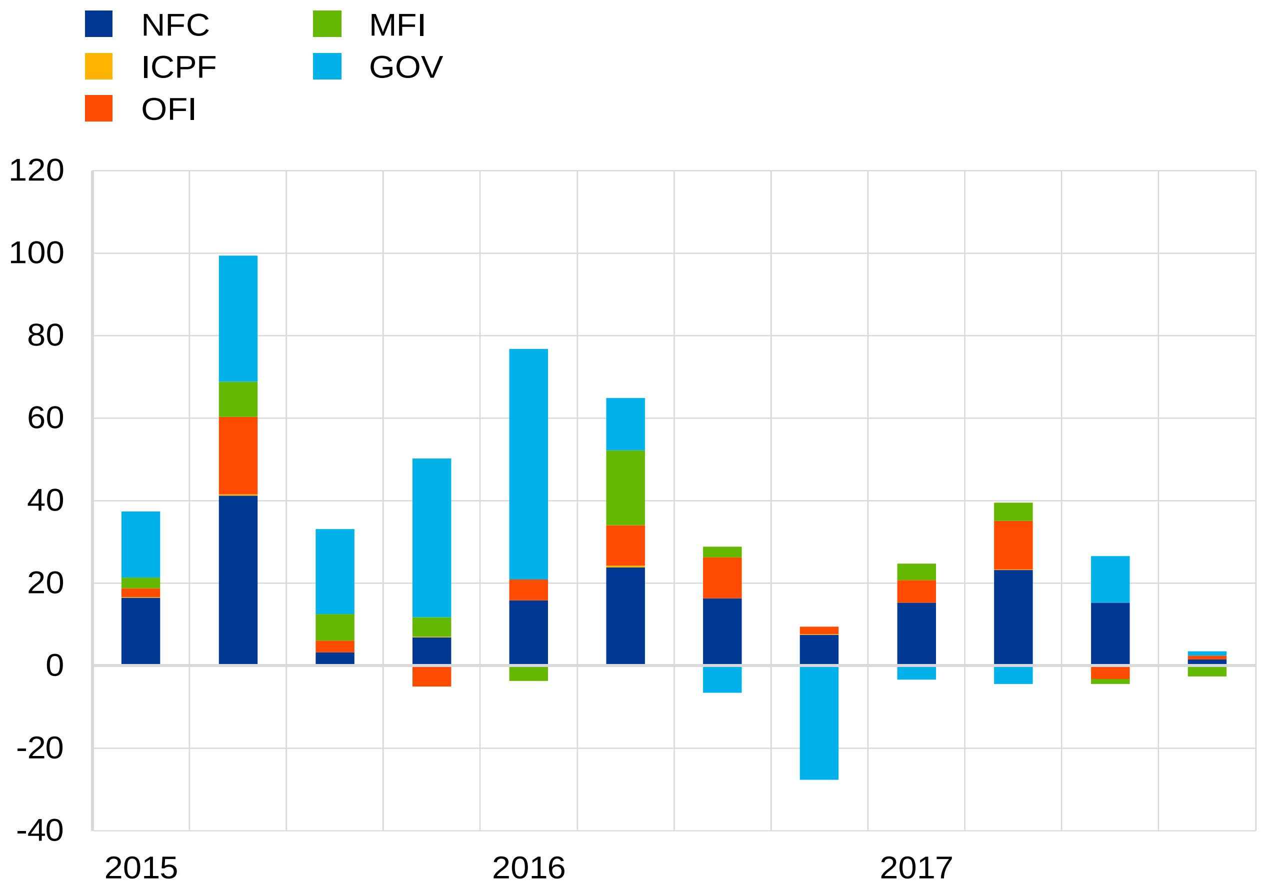


Source: ECB.

Notes: A positive (negative) number indicates net purchases (sales) of securities by euro area investors. Data on the mandate of the respective investment funds are from an extract of the CSDB on 31/01/2018. Other includes unallocated. The latest observation is for 2017Q4.

US has been the euro area's preferred issuers of debt securities since launch of PSPP

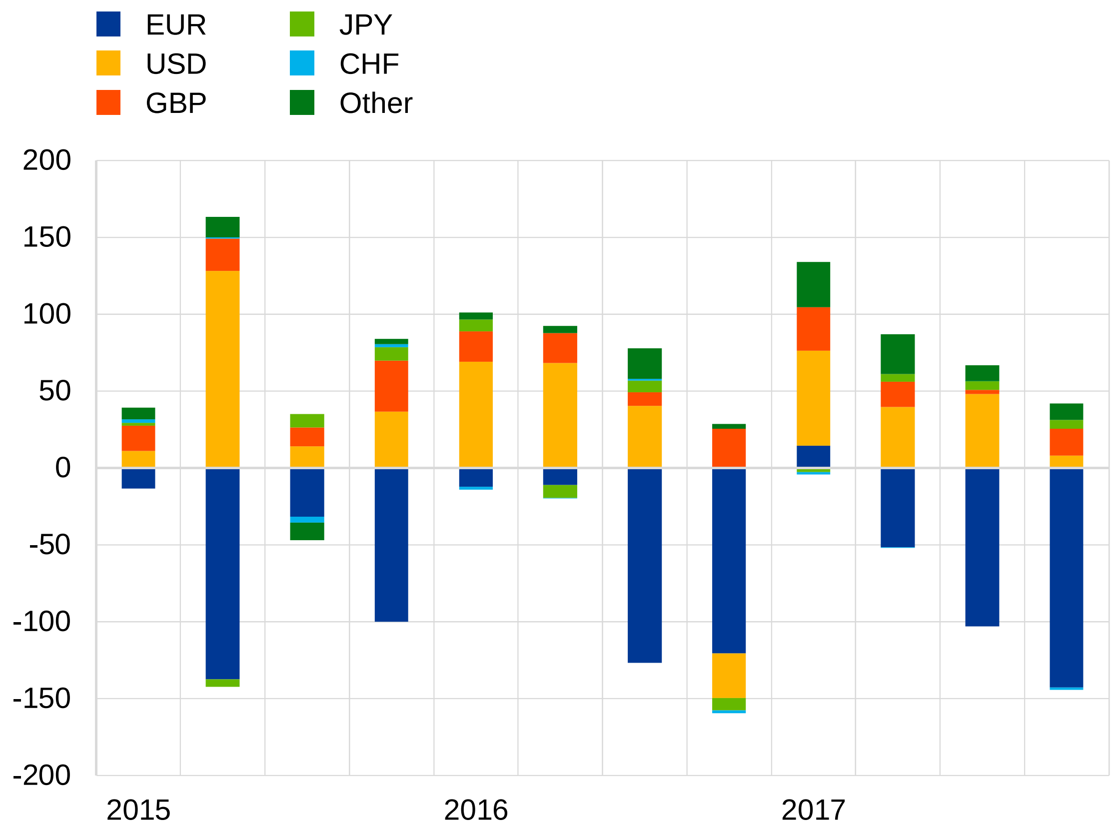
Euro area investors' net purchases of debt securities issued by US residents, by issuing sector *(EUR bn)*



Source: ECB.
A positive (negative) number indicates net purchases (sales) of securities by euro area investors. The latest observation is for 2017Q4.

Rebalancing into foreign-currency denominated debt (especially US dollar)

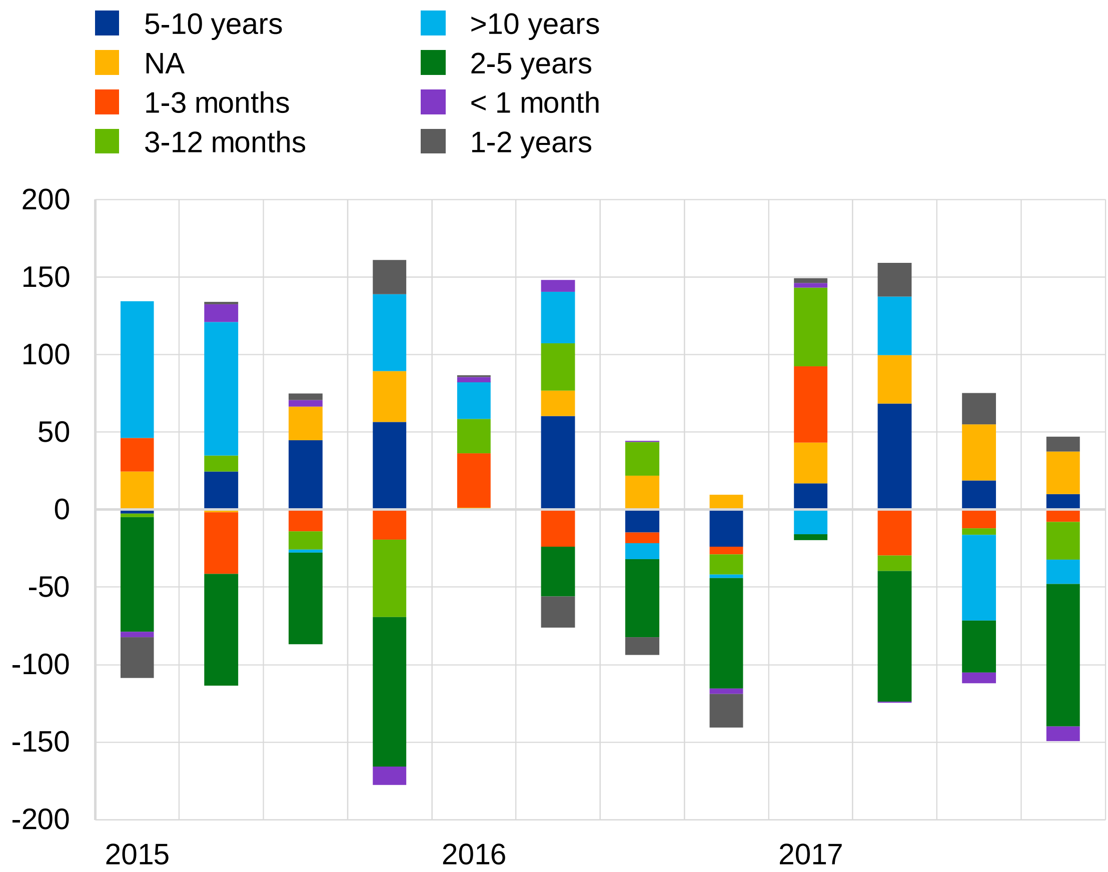
Currency breakdown of euro area investors' net purchases of debt securities *(EUR bn)*



Source: ECB.
A positive (negative) number indicates net purchases (sales) of securities by euro area investors. The latest observation is for 2017Q4.

Rebalancing into securities with original maturity exceeding five years

Maturity breakdown of euro area investors' net purchases of debt securities *(EUR bn)*



Source: ECB.
A positive (negative) number indicates net purchases (sales) of securities by euro area investors. Maturity refers to original maturity of debt securities at issuance. The latest observation is for 2017Q4.

Thank you for your attention!

Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

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Developing distributional household balance sheets[1]

Ilja Kristian Kavonius and Juha Honkkila,
European Central Bank

1 This paper was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

Developing distributional household balance sheets[1]

Ilja Kristian Kavonius, European Central Bank

Juha Honkkila, European Central Bank

Abstract

In view of the potential role that distributional data can play in explaining macroeconomic developments, the Statistics Committee (STC) established EG-LMM in December 2015. This is a part of a broader trend to develop timely distributional data. The aim of the EG has been to understand, quantify and explain the main differences between the Household Finance and Consumption Survey (HFCS) and the Financial Accounts (FA). This work aims investigating possibilities to develop distributional household balance sheet measures. This paper discusses this development work.

Keywords: micro macro link, balance sheet, wealth survey, financial accounts

JEL classification: E01, D01 and D31

[1] The views expressed in this paper are those of the authors and they do not necessarily reflect the views or policies of the European Central Bank or the European System of Central Banks.

Contents

1. Introduction

There is an increasing interest in having distributional measures on household wealth. Two underlying reasons can be seen for this development: increasing interest in household wellbeing and the increasing importance of wealth in particular of financial wealth.[2] The latter one is related to the liberalisation of financial markets as well the subprime mortgage crisis which started in 2008. The liberalisation of financial markets took already place in the majority of the European countries in the 1980s but this has also led to the continuous increase in investing in financial wealth. The subprime mortgage crisis also showed the importance having timely distributional measures showing the indebtedness and risks of different households. The underlying concerns are related to the counter-part risk, i.e. that the high-yield debt is a risk for the issuer of loan as well as the potential instabilities caused by large differences in the societies.

Several central bank presidents have emphasised the increasing importance of distributional issues. The ECB president Mario Draghi emphasised in his speech which was held in Washington in May 2015: *"First of all, it is important to make clear that there are also distributional effects from monetary policy inaction […] Secondly, there are always distributional consequences to monetary policy decisions[3]"*. A month later the U.S. Federal reserve governor Ben Bernanke said in the New York Times: *"Monetary policy is a blunt tool which certainly affects the distribution of income and wealth, although whether the net effect is to increase or reduce inequality is not clear.[4]"* In the IMF/FSB report to the G-20 Finance Ministers and Central Bank Governors was already in 2009 recommending distributional measures for financial and non-financial accounts.

Concerning the increasing interest in household wellbeing the release of the Stiglitz, Sen and Fitoussi Commission report in 2009 had an important role. This report did not really include anything new but the timing and political weight increased the importance of this report. This commission was mandated by the French president Nicolas Sarkozy and it included two Nobel Prize winners in economics. Additionally, the report was published in the middle of financial crisis and thus, the time was optimal for the data analysis which was also suggested by the report.

The main message in the measurement of quantitative welfare was to focus on households. The report emphasised the important of having comprehensive picture, i.e. to cover income, consumption and wealth and preferably to have an integrated view on those. These recommendations translated in the European Commission, OECD and other international organisations to different expert groups and practical recommendations and actions to move the focus of economic analysis on households and different aspects of household material wellbeing.

The Vienna Memorandum, which was adopted by the European Statistical System Committee (ESSC) in September 2016, confirmed much of the targets of Stiglitz et al. (2009) recommendations related to the measurement of household wellbeing.

[2] van de Ven 2017, S266-S86.

[3] IMF, Washington, DC, 14 May 2015.

[4] The New York Times, 1 June 2015.

The key message of the memorandum is to develop a joint framework measuring household income, consumption and wealth. At theoretical level European System of the Accounts 2010 (ESA2010) and System of the Accounts 2008 (SNA2008) provide a consistent framework but the consistency is reached rarely even at the macro level. In practice, the household net lending/borrowing which is calculated on the non-financial side of the accounts is different from the net lending/borrowing which calculated on the financial side of the accounts. On the survey side the integration is even more relevant as there are hardly any surveys which cover complete income, consumption and wealth items. The integration of surveys which have different underlying sample populations or even different statistical target years is difficult.

The second aspect of the data integration which is expressed by all of these above mentioned initiatives is the integration of household surveys and national accounts (NA) and in particular, distributional NA. At the European level this work has been divided into two: the OECD and European Commission are leading the Expert Group on Disparities in National Accounts which is focusing on developing distributional accounts for income, consumption and savings. The household distributional balance sheets are tackled by the European System of Central Banks (ESCB) Export Group on Linking Macro and Micro Data for the Household Sector (EG-LMM). The background of this labour distribution is the distribution in Europe, i.e. the European Commission (Eurostat) is typically responsible for the non-financial statistics as the European Central Bank (ECB) is typically responsible for the financial statistics and balance sheets. In this context, the ECB is also responsible for the quarterly Financial Accounts (FA) and coordinates the only European wide household wealth survey: the triannual Household Finance and Consumption Survey (HFCS).

The analysis has been done less in the context of balance sheets. The EG-LMM analysis is much based on the link which was established by Kavonius and Törmälehto (2010) and later completed by Kavonius and Honkkila (2013). This work created the first link between the FA and HFCS and also made the first comparisons for three countries. In some individual countries, comparisons and linking micro and macro balance sheets had at the time already been done. The work of EG-LMM started in 2015 and the project was kicked off with a separate meeting which also included presentations from France and the U.S. where they have analysed the linkage between macro and micro balance sheets.[5]

Statistics Committee (STC) of the European System of Central Banks (ESCB) agreed in the beginning of 2016 on the first mandate of the EG-LMM. The main elements of the mandate were to confirm the linkage between the FA and HFCS. The target was to understand, quantify and to explain the differences between these two statistics. This work was completed in 2017 and it was agreed that the group will continue by further closing the gaps between the two statistics, by developing further the FA breakdowns which could be estimated by using this link and additionally, consider methods how to estimate time series for these breakdowns. This group should deliver its final report by summer 2019.

[5] Dettling et. al. 2015. Durier et. al. 2012.

2. The linkage, different concepts and comparison

2.1. Generic differences between micro and macro data on household wealth

First, the project focused on analysing generic and other differences. The purpose of this linkage was first to identify the differences and then adjust those if possible. The following clear generic differences were identified: (1.) aim and set-up; (2.) definition of household; (3.) periodicity, timeliness and reference period; and (4.) valuation. The aim and set-up refers mainly to the fact that the FA is made to cover sectoral interlinkages and the balance sheet interlinkages between economic sectors as the HFCS is focused on the distribution between households. This appears in the collection of data. The FA data are often reported by counter-parts, i.e. often banks as the HFCS data are typically surveyed directly from the households. This can also lead to different interpretation of economic concepts.

Concerning the definition of household, the FA defines the households as a sector, while the HFCS as a group of households. The populations in two statistics differ slightly, i.e. persons living institutions are excluded from the survey population. Concerning the periodicity, timeliness and reference period, the FA are quarterly statistics which are available maximum four months after the reference period (last day of the quarter for balance sheet items). The HFCS is conducted every three years in most countries and there is typically a long lag between the data collection and data availability. The fieldwork periods are also typically varying from country to country, i.e. there is no one common fieldwork period for all countries. Finally, concerning the valuation, the FA follow in principle market valuation although this is not always really possible as there is no market price for all assets. Unlisted shares and other equity can be mentioned as an example of these types of assets. The valuation of the HFCS is based on self-assessment of households. This is supposed to be coherent with market valuation but particularly in the case of less liquid assets households may not be able to report market prices.

The purpose of this exercise is to minimise the differences, i.e. to adjust the data when it is possible. This means in the case of the definition of household as well as periodicity, timeliness and period. This was done by choosing the closest quarter of the FA to the HFCS reference period which varies from country to country. The population adjustment was done by adjusting the balance sheet items by the differences of the population in two statistics, i.e. it was assumed that the portfolio of households living in the institutions correspond with the average portfolio of the whole population.

Additionally, the HFCS and FA specific issues and potential errors related to these issues are analysed. However, these are typically issues which cannot be corrected in the short-term. In the case of the HFCS – and households surveys overall – these are typically related to reporting and sampling bias. Particularly, the sampling biases vary from country to country and different countries are dealing those with the different oversampling strategies, largely depending on the availability of external data sources applicable for oversampling. These different strategies typically effect on the comparability of the results between the countries. Additionally, the way of collecting data vary from country to country. The majority of countries are collecting the most of their data with traditional surveys via CAPI (Computer Assisted Personal Interviews), but the Netherlands is collecting their data through a web-survey and Finland is using a combination of telephone interviews, registers and register-based estimations. These different data collection practices effect also on the reporting biases. In the case of Finland reporting bias does not exist for most balance sheet variables as in the case of the Netherlands the reporting error is different from the "traditional survey countries". The underlying reason is that it is easier for respondents to underestimate/overestimate their answers if they reply in internet rather than replying to physical person.

Concerning the FA, these errors are related to the source statistics. The household sector data are typically based on the counter-part reporting, i.e. the reporting of banks and other financial institutions. There are typically weaknesses in the valuation of assets which do not necessarily have an obvious market price. Additionally, as the FA are a balanced system, which covers all the economic sectors, some sectors need to be adjusted. In the case of households, deposits and other accounts payable/receivable are typically items which are adjusted. This means to say that these are typically items which are considered to be less reliable than other parts of the accounts – and therefore, the inconsistencies are typically allocated to these less reliable items.

2.2. Asset-specific differences and the linkage

After identifying generic and source-specific differences, the EG-LMM assessed the comparability of financial wealth and its components. The concepts and definitions of items included in household wealth in the HFCS and FA are different. In the FA the definitions of instruments, sectors and concepts such as valuation are given by the European System of Accounts (ESA 2010) and are mandatory in the all EU countries. The HFCS data collection is based on a set of common definitions and descriptive features according to an output-oriented approach. The definition of household wealth in the FA is the entire balance sheet, while the HFCS is able to measure only items that can be reliably collected during an interview. Due to sensitivity issues, values of cash are usually not collected in household surveys. In addition, the collection of public pension wealth has proven to be difficult in both sources. Money owed by other households is included in the wealth concept of the HFCS, but not in the FA.

As a conclusion of this exercise a bringing table between the HFCS and FA was constructed.[6] The updated version is included in appendix 1. The main difference between these two versions was that the first was version was based on the European Systems of Accounts 1995 as the current version was updated to correspond to the European System of Accounts 2010. Additionally, comparing to the previous work, the linkages between different assets types has been assessed, i.e. whether the concepts are low, medium or high comparable. It is important to notice that this assessment is based only on the conceptual comparability and does not indicate anything concerning the actual differences.

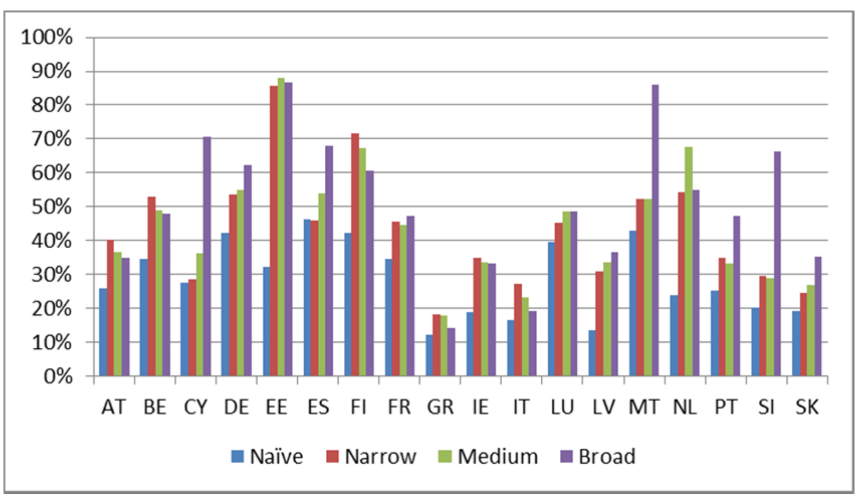
[6] The linkage has been presented before in: Kavonius and Törmälehto 2010. Kavonius and Honkkila 2013.

In contrast to the strategy applied by the OECD/Eurostat Expert group assessing macro-micro differences of income and consumption, the macro-micro comparison on wealth should not necessarily include the entire balance sheet, but only items that are assessed to be medium or high comparable. According to the bridging table, items with high comparability are deposits, quoted shares, mutual funds and bonds, as well as loans. Voluntary pensions and business wealth have medium comparability. Business-related wealth is a specific topic that has gained a lot of attention in the work combining micro and macro data. HFCS data on businesses not publicly traded are separated to self-employment businesses, i.e. ones in which a household member either is self-employed or has an active role in running the business, and businesses in which the household is a passive owner. Wealth in self-employment businesses is classified as non-financial assets in HFCS reporting, although it may include financial assets. Furthermore, the item is collected in net terms. The concept of business wealth as such does not appear in the FA.

The adopted working method was a similar than adopted by Dettling et. al. 2015., i.e. the comparisons were made by using different wealth concepts. The starting point is a naïve concept which shows simple comparison of the HFCS and FA financial wealth concepts without any adjustments. This concept disregards major differences in the definitions and methodologies between the two statistics and the coverage ratio cannot be expected to be 100%, since the wealth definition in the FA is broader than in the HFCS.

The second, narrow adjusted concept includes only items with high comparability, as shown in Appendix table 1. A third medium adjusted concept includes the narrow concept and voluntary pension wealth. The final, broad adjusted concept includes additionally a part of the HFCS concept business wealth, namely that of businesses having legal form other than sole proprietor or partnership[7].

Figure 1: Comparison of naïve, narrow, medium and broad wealth concept for 18 euro area countries



Source: ECB calculations.

[7] See more on business wealth in Annex 2.

Coverage ratios with the four financial wealth concepts are shown in figure 1 for the 18 euro area countries having participated in the second HFCS wave. In the assessment of coverage ratios it is important to recognise that coverage ratio of 100% does not necessarily indicate perfect comparability. If the adjusted wealth concept potentially includes HFCS assets that are not covered by the FA – beyond items that are considered of high comparability – a high coverage ratio may only imply that the low coverage of comparable items is artificially compensated by non-comparable items.

Comparisons for euro area countries have indicated that the FA may produce significantly higher levels of financial wealth than the HFCS. In the comparison presented in the table the adjustments for differences in reference periods and the household definition as described above are done. All figures are shown in per capita terms, using the source-specific population as a denominator. These accounts are adjusted implicitly for the differences in population between the two sources, assuming that the wealth of persons living in institutions is on average not different from the population covered by the survey.

The first conclusion from figure 1 is that limiting the analysis only to comparable items improves comparability, both from theoretical and practical point of view. The impact of adding items with medium comparability differs across countries. In most countries, the coverage ratio of private pension wealth is higher than the coverage ratio of assets included in the narrow concept. This is not unexpected, since private pension wealth is probably much less concentrated than e.g. quoted shares, bonds or mutual fund shares, and sampling bias can be assumed to be smaller. On the other hand, one may expect higher reporting bias for pension wealth, but this bias may be positive or negative.

In some countries adding business wealth to the analysis increases coverage ratios quite significantly. However, it is not obvious that this is a conceptual improvement of comparability. The huge impact of classifying business wealth as financial wealth with rather generic methodologies leads to suspect that this item may not be conceptually comparable between the HFCS and FA. More work needs to be done on business wealth at the national level to ensure the feasibility of the classification applied in this exercise.

The working approach of the group has been that first, the corrections, which are possible with the given data, are implemented by reclassifying or adjusting the figures. However, several of the comparability issues are such that they require comprehensive work either with the FA of HFCS. The EG-LMM indicated to the Working Group on Financial Accounts (WG-FA) and Household Finance and Consumption Network (HFCN) improvements which would increase the comparability of these two statistics. These are typically issues which cannot be solved directly and require work in the medium term. These topics are discussed in the following section.

2.3. Follow-up topics in the medium term

One of the most complicated conceptual comparability issues is related to the business wealth. Two issues related to this have been identified. First, the follow-up for the financial accountants concerning this item is particularly related to the estimation and valuation of unlisted shares and other equity. These assets should be valued at market prices, i.e. for instance at the value of similar kind of company which has a market value but in practice several countries value these at book value. This is a complicated issue and several countries will need to further develop their methodologies and sources to better value these assets.

The second is related to the different definitions and delineations of business wealth. In the field of NA much time concerning this has already been dedicated. The difficult issue is the borderline between the producer households, i.e. the entrepreneurs whose assets are classified as the assets of households, and quasi-corporations whose assets are recorded in the corporation sector. Correspondingly, the household holds hold either unlisted shares or other equity of the quasi-corporations. The ESA2010 as well as SNA2008 are somewhat wake in defining this borderline as the classification is depended on the independence of these corporations. Independence is reflected by issues like own book-keeping and whether these corporations (and their assets and economic activity) can be distinguished from households. In the most of cases sole proprietorships and partnerships are recorded in the household sector and the rest in the corporation sector although there is much variation in the country practices. In practice, the classification of these assets is depended on how well counterparts, i.e. for instance banks, are able to identify whether the counterpart is a household or corporation.

In the HFCS all these assets are classified in the business wealth and more detailed data collection of self-employment business wealth in surveys would improve the comparability of these assets. However, due to a heavy response burden, this is not feasible in the short or even medium term. During the second mandate of the EG-LMM several methodologies to improve the comparability of business-related assets have been developed (see Chapter 3).

The EG-LMM also concluded that rent deposits (i.e. money deposited by tenant households as a security for renting a flat) are not well covered by the HFCS. Such deposits are part of financial wealth in the FA, and can be significant in countries with low homeownership rates. The collection of this item is difficult in surveys. Furthermore, it is not clear to what extent rent deposits should be considered household wealth with the definition relevant for the analysis of survey data.

The final long-term follow-up item is the treatment of missing rich. In the case of the FA, this means how the wealth of rich people is captured. Rich people can own their property either directly or through different property arrangements like foundations. In theory, if these types of property arrangements are owned by one person, the balance sheet should be directly recorded on the balance sheet of household. If the property arrangement has several owners then on the balance sheet of households is recorded the equity of the property arrangement, i.e. typically other equity. In practice, however, countries are rarely following this convention and it is difficult to say how the property is recorded. In this type of cases, the property is typically included in the total wealth but it is difficult to say how it is recorded. Additionally, as indicated earlier, other equity is often under-valued.[8]

The large problem related to the wealth of rich is capturing the property which is abroad. Even directly owned assets which are located abroad can be difficult to capture but particularly, different property arrangements are hardly captured in the

[8] See: Final Report of the Task Force on Head Offices, Holding Companies and SPEs.

FA. Similarly, non-financial assets, i.e. for instance second residences or holiday houses which are located abroad should be treated as notional units. The equity of these notional units, i.e. the worth of these non-financial assets, should be recorded as equity of the households. As the b.o.p./i.i.p. is often either the main source for foreign assets data or it is consistent with the FA, the potential measurement problems should be solved together with the b.o.p./i.i.p. The WG-FA and WG-External Statistics (WG-ES) have discussed this topic and decided to organise a workshop to clarify it. It has been recognised that there are problems in capturing these assets but in reality, only in the medium- to long-term it is possible to develop data sources to capture these assets.

As mentioned in Chapter 2.1., the HFCS is missing information from the richest households in the population, often holding a significant share of total household wealth. The impact of the missing rich on micro-macro gap has been estimated by Vermeulen (2018). Chakraborty et. al. (2018) continued this work by linking the missing rich estimations with the framework by Kavonius and Honkkila (2013) and estimated how much these missing rich would explain the gap between the HFCS and FA. After this Chakraborty and Waltl (2018) develop this method further to identify in which asset types the underestimation is largest and how the distribution should be corrected. Overall, the outcome of this analysis is that this missing rich does explain only a small share of the gap between the FA and HFCS. The share of missing rich is larger in the countries where oversampling of rich households has not been implemented. This is illustrated in Table 1 which shows the impact of the rich households with different estimation thresholds. Using a lower threshold generally bears the risk to include observations in the estimation that may not be Pareto distributed. The main message of the table is anyhow clear: the effect in Austria and Germany is large, i.e. in the countries, where the oversampling is not done or it is based on geographical areas the impact is large, as in other countries, where the applied oversampling strategies are more effective, the impact is relatively small.

Table 1: the impact of estimated Pareto tail above with the threshold of EUR 500 000, EUR 1 million and EUR 2 million on the coverage ratio on the coverage ratio of broad concept (Figure 1)

	>2 mil threshold	>1 mil threshold	>500 000 threshold
Austria	+12%	+7%	+5%
Germany	+14%	+14%	+18%
Spain	+3%	+6%	+3%
Finland	+4%	+4%	+1%
France	+4%	+4%	+1%

Source: Chakraborty et. al. 2018.

For the further work of adjusting the gap between the FA and HFCS, this analysis is handicapped as the analyses have been conducted rather at the macro level, not allowing an assessment of this impact at the level of household groups, except for wealth deciles. Ideally, current methodologies to estimate the wealth of the missing rich in surveys should be further developed at the instrument level, as well as at the level household groups or even households. Access to administrative data sources on financial wealth with information on the entire population offers further possibilities for this topic. Finland, Estonia and Denmark (for the 2017 wave) are already using administrative sources in the compilation of HFCS results. While it is not realistic to assume numerous other national level data sources to become available in the short term, experiences from existing data to assess the impact of sampling bias on the coverage ratios should be further collected. This would require a change in the working approach, i.e. the different approaches should be solved at national level as the work is much defined by the availability data at the national level. Currently, the work is mostly done by the ECB for all the countries conducting the HFCS.

3. The second mandate and distributional indicators

In spring 2017 the STC decided that the work of the EG-LMM should continue with a second mandate. This mandate is divided into two work streams. The first work stream covers the following tasks: i) to further assess the impact of generic and instrument-specific differences on HFCS-FA coverage ratios and their varying impact across instruments and across countries; ii) to develop recommendations for improving the link between the HFCS and FA and for achieving better coverage ratios for future HFCS waves; iii) to assess the availability of administrative sources for improving the HFCS-FA linking. The second work stream covers the following issues: i) to define a set of distributional indicators for the household sector balance sheet, with focus on items with comparability “medium” and “high”; ii) to calculate experimental results for 2010 and 2014 (or the two periods closest to the HFCS fieldwork) for these indicators and assess the feasibility of deriving estimates at annual frequency; iii) to extend the comparison to non-financial assets; and finally, iv) to seek the views of potential ECB/ESCB users to identify user priorities.

During the second mandate, the work of the EG has organised in the following way: The EG has been divided into separate task teams and the task teams have taken care of separate issues. The HFCN and WG-FA are also working parallel on the issues which are discussed in the previous section. Moreover, the ECB has continued working on the administrative sources and time series estimation. As referred earlier, the ECB has only the possibility of taking stock of available administrative sources. The administrative sources as well as the possibility to access those vary much from country to country and therefore, the only realistic possibility is that the potential utilisation of these sources would be analysed at the country level.

The following task teams were established within the EG-LMM: distributional indicators and user requirements, business wealth, non-financial assets, methods for integrating macro and micro sources and pension wealth. Concerning the pensions it was concluded that the EG will focus on “private pensions” which are covered in tables of sector accounts. At this stage the work focusing on “social security pensions” was postponed later as with the current data availability is more limited.

Concerning the work of the task team on indicators, it has conducted a survey to seek the views of potential users to identify user priorities. The requirements are related to data requirements. i.e. which detail of data or indicators were requested and how timely. The survey was conducted by interviewing a number of users in the ECB, national central banks, European Commission and OECD. Overall, the user requirements are quite moderate, i.e. simple indicators covering assets and liabilities at annual frequency are expected to become available.

The task team on business wealth intends to improve the conceptual comparability between the HFCS concept ‘business wealth’ and the FA instruments ‘unlisted shares’ and ‘other equity’, and maximise the practical comparability of both the current available data as well as launch recommendations on how to improve the collection of data in the long term. The task team recognised three possibilities for improvement. First, to be implemented already in the short term, national level classifications to separate quasi-corporations and producer households in the FA should be applied to HFCS data on self-employment business wealth instead of the simple delineation between sole proprietors and partnerships vs. other legal forms. Second, in the longer term, the HFCS classification of legal form may be improved to enable a reliable distinction between incorporated and unincorporated businesses. Third and finally, a more detailed breakdown of balance sheets of producer households should be conducted, particularly separating between financial and non-financial assets. After the last proposal was brought forward to the HFCS, a more detailed data collection was not consider feasible due to already heavy response burden for self-employed households. A modelling-based approach using external information is seen as an alternative to be developed.

The non-financial task team focused on the ways of including non-financial assets in this comparison. The non-financial assets were not included in this exercise for three reasons. First, the non-financial assets are not a part of financial accounts and it was first decided to focus on the core assets of the financial accounts. Second, there are/were problems in availability of non-financial assets, namely land became obligatory only in the beginning of 2018 in the ESA Transmission Programme. As this is large share of the housing wealth, the comparison would have been incomplete. Third, there are number comparability issues in the transmitted data. The ESA Transmission Programme data include non-profit institutions serving households (NPISH). Additionally, the land data cover all land, not only land which is underlying dwellings. This implies that if the housing wealth is estimated by aggregating dwellings and land, the housing wealth would overestimated by land underlying other building as well as by agricultural and forestry land owned by the household and NPISH.

The task team decided to estimate housing wealth aggregate as well as possible. Through the questionnaire of the Working Group on General Economic Statistics (WG-GES) the task team collected data from several countries on land underlying dwellings. For these countries by adding up dwellings and the collected land data, the housing wealth is estimated. The rest of the reported assets are assumed to be "business wealth assets" of the sole proprietorships and partnerships (i.e. producer households). As indicated in the outcome of the "business wealth team", from the HFCS business wealth the corresponding business wealth are separated and this is assumed to be comparable with the rest of the FA non-financial assets.

The task team on developing methods for integrating macro and micro sources was assigned the task to align to the largest extent possible micro and macro estimates using of statistical methods available in the literature. During the stock taking exercise the task team has analysed re-weighting approaches (constructing a new set of weights to meet benchmark constraints on known population totals) and imputation methods to correct for the differences between micro and macro data. The task team will also assess various ways to account for the missing wealth of very rich households. The first conclusion of the task team has been that different models may need to be applied for different countries and indicators.

As referred earlier even though the time series estimations are not the highest priority in this work flow, there have been some attempts to test different methods to estimate time series for the distributional measures. In longer run time series aspect will be important, as vis-à-vis to the survey the value added of these data is time series and timelier data. Bankowska et al. (2017) as well as Kavonius and Honkkila (2016) estimate time series by using the approach of applying distribution of an earlier year. The results of applying this methodology are not satisfactory. Honkkila et al. (2018) tests auxiliary data sources, i.e. to use related property income flows in estimating underlying stocks, and a microsimulation method where the effect of recent macroeconomic changes are simulated on households at the micro level. These methods give better results than the previous exercise in which the old distributions are used. However, the optimal methods vary from country to country and the paper concludes that one individual method cannot be recommended for all countries.

In the context of the EG, the ECB has also developed also aggregation methods for the euro area aggregates. These calculations are based on naïve assumption but the whole philosophy of this work is that the sources and methods will improve later. As the reference years of the national surveys are different, interpolation methods between the two conducted waves have also already been tested.

4. Epilogue

The work linking micro and macro data has started and this EG will provide its final report in spring 2019. The report will include several recommendations and already on the basis of work several workflows have been started. As an example we can name the recording of wealth of rich individuals in the FA. Most likely also some distributional balance sheet or a part of distributional balance sheets which are based on naïve assumptions will be provided.

It would not be an intellectual challenge to find aspects and reasons to criticise this work. However, this work is unavoidable. Even though we would not ever have distributional household balance sheets, we need to be position of explaining these differences between the statistics for users as well as for the fellow-statisticians. This process has also already now raised problems in different statistics. From this point of view, the first results are not necessary the best one but the process of integrating and harmonising these statistics has started. This also means that in the future the results can be expected to be in future better than they are now.

Appendix 1: Overview of the main balance sheet items of NA/FA (ESA 2010) and of the HFCS

NA/FA (ESA 2010)	**HFCS**	**Conceptual comparability**
	FINANCIAL ASSETS (+)	
F21 Currency	N/A	N/A
F22+F29 Deposits	Deposits	High
F3 Debt Securities	Bonds and other debt securities	High
F4 Loans	Money owed to household	High
F5 Equity and investment fund shares	Shares, publicly traded	Medium to High
	Investment in non-self-employed business	
	Investment in self-employed business[9]	
	Mutual Funds	
F6 Insurance, pension and standardised guarantee schemes	Voluntary pension/whole life insurance schemes	Medium
	Occupational Pension Plans[10]	Low
F7 Financial derivatives and employee stock options	Other financial assets	Low
F8 Other accounts receivable		
N/A	Managed Accounts	Low
	LIABILITIES (-)	
F4 Loans	Mortgages and loans	High
	Outstanding debts on credit cards, credit lines and overdraft balances	
F8 Other accounts payable	N/A	N/A
	FINANCIAL NET WORTH	
	NON-FINANCIAL ASSETS (+)	
AN.111 Dwellings	Household main residence	
AN.112 Other buildings/structures	Other properties	
AN.113 Machinery and equipment	N/A	
AN.13 Valuables	Valuables	
N/A	Vehicles	
AN.211 Land	N/A (included in entries above)	
	NET WORTH	

[9] Classified as real wealth in the survey.

[10] Usually excluded in the survey definition of financial wealth in the HFCS, but collected in most countries.

Appendix 2: Business wealth

The HFCS collects two variables that are comparable with the FA concepts 'unlisted shares' and 'other equity'. The HFCS concept 'non-self-employment unlisted shares' is consistent with this FA definition, but only includes assets of enterprises in which no household member is either self-employed or has an active role in running the business. In addition, HFCS collects values of self-employment business, a part of which is also consistent with the above mentioned FA concepts. The value of self-employment business wealth in the HFCS can be described as the market value of businesses. The item is collected in net terms[11], i.e. assets and liabilities related to the business are not collected separately, which causes a conceptual discrepancy, the extent of which is difficult to evaluate.

The way unincorporated self-employment business assets of the HFCS are treated in the FA depends on whether the enterprise is classified as a producer household (to be classified within the household sector) or as a quasi-corporation (to be classified within the non-financial corporations sector). In the case of producer households, no separation is assumed to exist between the firm and its owner(s). Consequently, the financial assets and liabilities of firms classified as producer households are recorded as assets/liabilities of the household under the corresponding instrument class. On the contrary, quasi-corporations are treated as separate entities and their total net worth appears in the FA as an asset of the households sector recorded in one of the two items "unquoted equity" or "other equity".

For self-employment businesses the HFCS collects information on the legal form. Based on the legal form, all other legal forms except for sole proprietors and partnerships can be identified as incorporated enterprises or quasi-corporations, and the assets associated with these enterprises correspond to unlisted shares and other equity in the FA. Such businesses, as well as non-self-employment businesses, are aggregated to construct a concept of business wealth comparable to the unlisted shares and other equity in the FA.

On the other hand, sole proprietors and partnerships can be interpreted as producer households. The assets of such enterprises would not be included in the FA concept 'unlisted shares and other equity'. Since there is no information on the type of assets included in the balance sheets of sole proprietors and partnerships, the assets included in such businesses are in the current analysis classified as real assets, as in the reporting of the HFCS results, and excluded from the comparison of financial wealth in this paper. This is a careful approach which ensures that only assets that really correspond to the FA financial wealth are included.

[11] The wording in the blueprint questionnaire is: "What is the net value of (your /your household's) share of the business? That is, what could you sell it for, taking into account all (remaining) assets associated with the business and deducting the (remaining) liabilities?"

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Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

Ninth IFC Conference on “Are post-crisis statistical initiatives completed?”

Basel, 30-31 August 2018

Developing distributional household balance sheets[1]

Ilja Kristian Kavonius and Juha Honkkila,

European Central Bank

[1] This presentation was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

EUROPEAN CENTRAL BANK

EUROSYSTEM

Developing distributional balance sheets

Ilja Kristian Kavonius

European Central Bank

9th IFC Conference on

“Are post-crises statistical initiatives completed?”

Introduction

- Increasing interest in wellbeing and increasing importance of (financial) wealth
- Importance of distributional data on household income, consumption and **wealth**
  - Stiglitz, Sen and Fitoussi (2009)
  - Vienna Memorandum (2016)
  - Importance for monetary policy / central banking (Draghi, Bernanke)
- Practical work on distributional national accounts indicators
  - International level: OECD (income and consumption)
  - US, Canada, Australia (including wealth), France
- Expert Group on Linking Macro and Micro Statistics on Household Wealth (EG-LMM), 2016->
  - ECB initiative, several micro and macro experts from EU (NCB + NSI)
  - First mandate completed in April 2017 and the group continued its work (second mandate)

The linkage, different concepts and comparison

Most important generic and HFCS/FA-specific differences:

- Valuation
  - Self-assessment vs. ESA valuation concepts
  - Accuracy of self-assessment if prices change rapidly or are difficult to know?
  - Accuracy of ESA valuation if no observed market prices?
- Measurement
  - Unit and item non-response, underreporting in HFCS
  - Counterparty sector reporting, variety of data sources, estimates & balancing adjustments in FA
- Conceptual issues
  - Instrument-specific comparability
  - Delineation of the household sector
- Population definition and reference periods
  - Impact limited and can (to a large extent) be identified and/or adjusted for

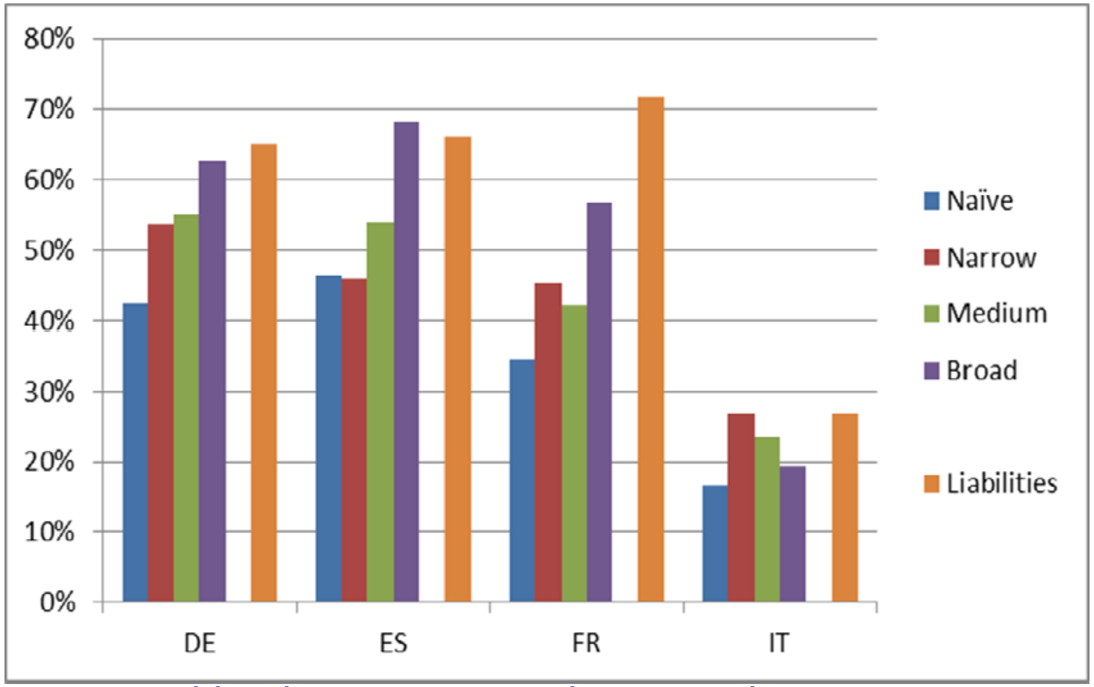
Conceptual comparability of financial instruments

NA/FA (ESA 2010)	HFCS	Conceptual comparability
FINANCIAL ASSETS (+)		
F21 Currency	N/A	N/A
F22+F29 Deposits	Deposits	High
F3 Debt Securities	Bonds and other debt securities	High
F4 Loans	Money owed to household	High
F5 Equity and investment fund shares	Shares, publicly traded	Medium to High
	Investment in non-self-employed business	
	Investment in self-employed business	
	Mutual Funds	
F6 Insurance, pension and standardised guarantee schemes	Voluntary pension/whole life insurance schemes	Medium
	Occupational Pension Plans	Low
F7 Financial derivatives and employee stock options	Other financial assets	Low
F8 Other accounts receivable		
N/A	Managed Accounts	N/A
LIABILITIES (-)		
F4 Loans	Mortgages and loans	High
	Outstanding debts on credit cards, credit lines and overdraft balances	
F8 Other accounts payable	N/A	N/A
FINANCIAL NET WORTH		

- Starting point for differences and linkages: Kavonius and Törmälehto 2010. Kavonius and Honkkila 2013.

The linkage, different concepts and comparison

- First: adjust for differences in the household definition and align reference periods
- Similar approach than adopted by Detlling et. al:
  - Naïve concept: financial wealth as it is in each source
  - Narrow concept: Deposits + Mutual Funds + Bonds + Quoted shares (good conceptual comparability)
  - Medium concept: Narrow + Voluntary pensions and whole life insurance
  - Broad concept: Medium + Comparable business wealth*



* Incorporated businesses + quasi-corporations

Follow-up topics in the medium term

- First to the distributional measures as well as possible with the given the data the increasing comparability is a longer process…
- Main conceptual issues identified:
  - Business wealth: (1.) valuation of unlisted shares/other equity and (2.) delineation and classification of different corporations (hh vs. nfc)
  - Treatment of the rent deposits (HFCS)
  - Missing rich in the FA: (1.) How are treated – different property arrangement; (2.) where are located – legal and not-legal tax planning; how well non-financial assets abroad are captured? ---> WG-ES/WG-FA workshop on this topic
  - Missing rich in the HFCS: Vermeulen (2018). Chakraborty et. al. (2018) and Chakraborty and Waltl (2018): in particularly countries with problems in oversampling – **the method applicable only on wealth distribution**
  - The impact of estimated Pareto tail above with different thresholds to the coverage of broad concept:

	>2 mil threshold	>1 mil threshold	>500 000 threshold
Austria	+12%	+7%	+5%
Germany	+14%	+14%	+18%
Spain	+3%	+6%	+3%
Finland	+4%	+4%	+1%
France	+4%	+4%	+1%

The second mandate and distributional indicators

- The ongoing work of the EG is divided into two work streams:
- The tasks of the first work stream are:
  - Assess generic and instrument-specific differences on HFCS-FA coverage ratios;
  - Recommendations for improving the link;
  - Assess the availability of administrative sources.
- The tasks of the second work stream are:
  - Define a set of distributional indicator, with focus on items “medium” and “high”;
  - Calculate experimental results for 2010 and 2014 and assess the feasibility of deriving estimates at annual frequency;
  - Extend the comparison to the non-financial assets;
  - Seek the views/priorities of potential ECB/ESCB users.
- Open issues identified in the final report (first mandate), 4 specific task teams

The second mandate and distributional indicators – task teams

- Distributional indicators and user requirements:
  - Useful indicators and a selection process to pick up most relevant indicators;
  - Stock-taking will be followed by user consultations.
- Business wealth:
  - Comparability issues to be solved - HFCS business wealth identify separately:
    (1.) items comparable with FA unlisted shares and other equity;
    (2.) producer household assets;
- Methods for integrating macro and micro sources:
  - Stock-taking exercises and reviewed existing experiments;
  - In particular decreasing the gap, response and sampling biases
- Non-financial assets:
  - Include non-financial wealth in the analysis
  - Compare housing wealth and business wealth separately;
- Pension wealth:
  - Currently included only the pensions included in the national accounts main tables

Future work and epilogue

- This work will be completed by spring 2019 and the report delivered to the STC
- This work is only start – how will be continued?
- Several issues to be tackled: improve linkage/comparability, time series aspect etc.
- This is only the first step but it is necessary – the credibility of statistics requires that we are able to explain the differences and improve the results!

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Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

Bank of Korea consumer credit panel: a new statistical initiative for financial stability[1]

Mira Kim,
Bank of Korea

[1] This paper was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

BOK Consumer Credit Panel:[1]

A New Statistical Initiative for Financial Stability

Mira Kim[2]

Abstract

Since the 2007-2008 financial crisis, the statistical value of personal credit information has been increasing and major countries have been compiling statistics that make use of personal credit information. The BOK also uses personal credit information to create new financial statistics to analyze systemic risk and solve the household debt problem. With this motivation, we created the BOK Consumer Credit Panel (BOK CCP), which includes detailed information on consumer debt and credit.

This panel can help to measure and analyze the levels of and changes in individual liabilities, derived from consumer credit reports, to track individuals' and households' access to debt and credit every quarter. The data collected from 2012Q1 comprises identifying information (age, sex, income, address, etc.), loans, credit cards, payments in arrears, and defaults for a random sample of one million persons (2.4% of the total population).

The BOK CCP includes individuals' financial information, which can be sensitive in terms of data security. Careful consideration should be given to privacy protection issues and appropriate data sharing. Information is managed by stages from collecting to reporting and sharing. In addition, efforts are made to reduce the misuse of data and to increase the reliability and accuracy of data.

This paper explains the motivation for setting up the BOK CCP, the sample design, the BOK CCP content, data confidentiality protection and database usage in the BOK for financial stability.

Keywords: microdata, household debt, panel data

JEL classification: C81

[1] The views expressed in this paper are those of the author and are not necessarily reflective of views at the Bank of Korea. Any errors or omissions are the responsibility of the author.

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Contents

1. Introduction

With microdata being needed to address data gaps after the 2007-2008 financial crisis, the statistical value of personal credit information has been increasing. The interest in microdata has increased in recent years, and due to its popularity, the availability of microdata also has gradually increased during that time. Microdata has been expected to play an important role in financial stability analysis, including analysis of the vulnerability of the household sector, which is the main cause of financial crises.

The current financial statistics are compiled as part of the conduct of monetary policy but are not sufficient quantitatively or qualitatively for the purpose of macro-prudential policies. This is the main reason that microdata has been spotlighted. It is increasingly recognized that statistically edited microdata derived from individual credit information held by credit registers can help generate new financial statistics (household credit by age, credit score or income) and also strengthen statistical bases that can be utilized for macro-prudential assessment and research.

In the United States, the FRBNY created a new quarterly panel dataset called the Consumer Credit Panel (CCP) in 2010 based on personal credit information to analyze household-level debt and credit. The CCP is used for research and its value is highly evaluated, although the United States has similar statistics such as the Survey of Consumer Finance and Flow of Funds.

Referring to the FRBNY CCP as an example, the Bank of Korea (BOK) established the Bank of Korea Consumer Credit Panel, (BOK CCP). We were tasked with a financial stability role by the revised Bank of Korea Act of 2011, and with this responsibility, we found it necessary to obtain individual credit data for conducting macro-prudential policies and addressing the household debt problem.

Besides traditional financial statistics and processed aggregated data, the use of micro-information can be also useful in terms of its diversity. The aggregated data derived from the balance sheets of financial institutions offers only limited information.

Moreover, the BOK CCP can help to measure and analyze the levels of and changes in individual liabilities to track individuals' and households' access to debt and credit every quarter. This makes it possible to acquire the same individual’s longitudinal information in the long term. The data collected from 2012Q1 comprises identifying information (age, sex, income, address, etc.), loans, credit cards, payments in arrears, and defaults for a random sample of one million persons (2.4% of the total population).

The BOK CCP includes individuals' financial information, which can be sensitive in terms of data security. Careful consideration should be given to privacy protection issues and appropriate data sharing. Information is managed by stages from collecting to reporting and sharing. In addition, efforts are made to reduce the misuse of data and to increase the reliability and accuracy of data.

This paper is organized as follows: Sections 2 and 3 describe the sample design and the BOK CCP content. Section 4 explains data confidentiality protection and database usage in the BOK. Finally, section 5 provides conclusion.

2. Sample design

2-1. Target population

The target population of the BOK CCP is all residents at least 18 years of age with credit histories. Most individuals start to build their credit histories when taking out loans, obtaining and using credit cards or retail cards, and so on.

The population excludes minors, some seniors without credit histories, those who do not perform credit activities in their own name. For those over 90 years of age, only those who maintain currently valid credit transactions are included in the target population, while those who have past credit histories but no currently valid transactions are excluded.

The target population also includes individuals with thin-files, who have had few loans or credit cards, while it excludes consumers with no-file and with inquiry-only files. Many individuals with inquiry only files have been registered by going though credit inquiry when taking out a loan or opening a cellular phone.

The table 2.1 below provides the information on individuals by credit activities. As of the end of 2014, there were 41 million individuals who have credit histories, which is the target population. It was approximately 6 million for those who did not have sufficient credit histories such as individuals with no-file or inquiry-only files.

Table 2.1: Individuals by Credit Acitivity[1]

Table 1

Individuals (50 million)		
Under 18 years of age	Over 18 years of age (47 million)	
	With credit history[2]	With insufficient credit history
(3 million)	(41 million)	(6 million)

Notes: ① As of end-2014

② It is the target population

Sources: NICE Information Service

An individual-level credit database obtained from the NICE Information Service, a credit bureau, is used for the sampling frame. Table 2.2 shows the similarity of the target population and the estimated population projected by Statistics Korea. As you can see in the table, the target population from the credit bureau is 99.5% of the estimated population of Statistics Korea at the end of 2014. The estimated population by age group differs somewhat between the credit bureau and Statistics Korea. It appears that the number of database registrants in the 20-69 age groups is slightly larger than the estimated populations for those age groups of Statistics Korea, mainly due to Koreans living overseas.

For the estimated population compiled by Statistics Korea, people residing overseas for 90 days or longer due to emigration are classified as non-residents. However, since the BOK CCP includes long-term credit histories, non-residents are not immediately excluded. This is the main reason for the difference between the target population and the estimated population.

Table 2.2: Comparison of age groups

between the target population and estimated population Table 2

Age group	Credit history holders[1] (A)	Estimated population[2] (B)	Ratio(A/B)
18-19	493 (1.2)	1,300 (3.2)	37.9
20-29	6,913 (16.8)	6,775 (16.4)	102.0
30-39	7,985 (19.4)	7,779 (18.9)	102.6
40-49	9,007 (21.9)	8,514 (20.6)	105.8
50-59	8,346 (20.3)	7,949 (19.3)	105.0
60-69	4,830 (11.8)	4,584 (11.1)	105.4
Over 70	3,495 (8.6)	4,359 (10.6)	80.2
Total	41,070 (100.0)	41,260 (100.0)	99.5

Notes: ① NICE Information Service (as of end-2014)

② Statistics Korea (as of July 1, 2014)

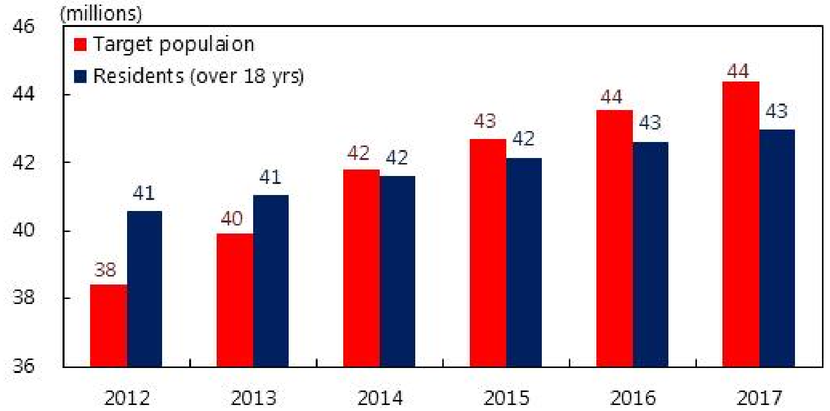
③ Figures in ( ) represents proportions

④ thousand, %

Figure 2.1 illustrates the increase of the target population from 38 million in 2012 to 44 million in 2017, showing a faster increase than the estimated population growth. To be specific, the target population, represented by red bar, has exceeded the estimated population represented by blue bar since 2014. Meanwhile, the target population, the red bar, had been lower in 2012 and 2013.

Figure 2.1:

Comparability between target population and estimated population[1] Figure 1



Notes: ① The estimates are based on the 2015 Census(1.11.2015) and reflect changes to the July 1, 2015 population

Sources: the BOK CCP, Statistics Korea

The target population has increased sharply and has exceeded the number of residents aged 18 or older since 2014. This is mainly due to Koreans residing overseas. Koreans residing overseas are excluded from the estimated population from Statistics Korea after 90 days, while they are still included in the BOK CCP approximately for five years.

2-2. Sampling procedure

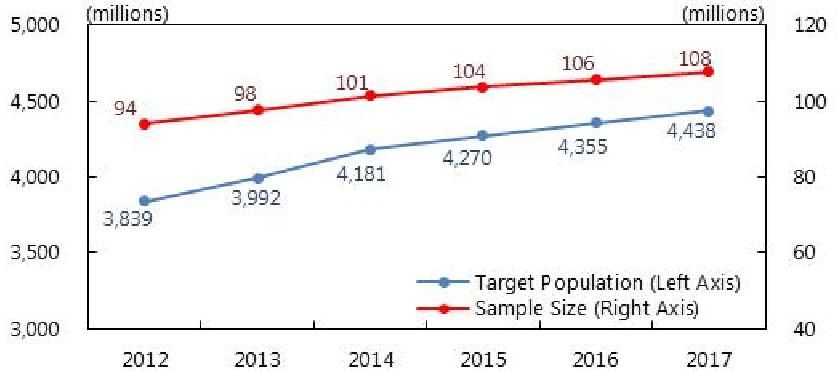
The sampling procedure is carried out using a method called "simple random sampling". The advantages of this sampling method are that it can guarantee that each individual is chosen entirely randomly with the same probability to extract and its simplicity can also make sampling easier. For these reasons, simple random sampling is suitable for big data management.

We generated the longitudinal data by selecting a specific number of random numbers created using a person's birth date from the individual information and extracting the sample; panel data can be obtained to track individuals' and households' access to debt and credit every quarter. In other words, we are able to track the same individuals in each quarter. On average, 99% of the sample remains unchanged from the previous quarter.

This sampling procedure creates a 2.4% random sample, which is representative of the target population. The sample size is automatically held constant by adjusting the number of individuals who enter and exit the target population. The sampling procedure maintains the representativeness and stability of the sample by automatically adjusting the flows in and out of the population. In the sample, the flows in and out of the total population are the same. Figure 2.3 gives that the sample can be seen to be increasing in proportion to growth in the target population.

Figure 2.3: Target population and sample size

Figure 2

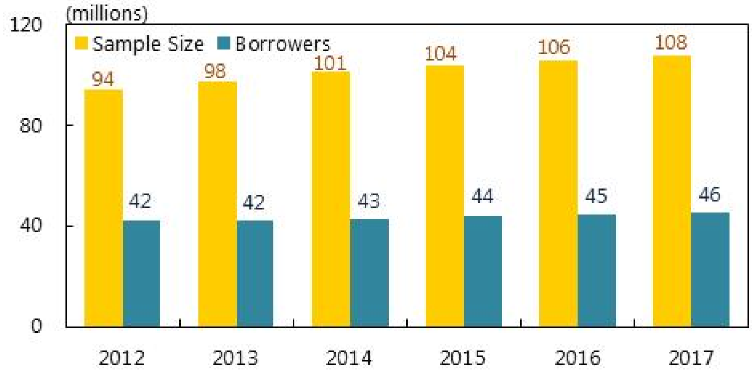


Sources: NICE Information Service, the BOK CCP

In addition, the target population and sample of the BOK CCP include those who have their own credit histories, but are not necessarily borrowers. Even if an individual does not presently have any loans, he can remain in the population with his credit history by having a history of past overdue payments or borrowing. At the end of 2017, the sample size is 108 million individuals, while borrowers with outstanding household loans are 46 million, which is 42.3%

Figure 2.4: Sample size and borrowers

Figure 3



Sources: the BOK CCP

2-3. Sampling results

The sampling procedure provided the sample which represents 2.4% of the individuals with credit histories. In order to verify the adequacy of the procedure, we examined the results by observing the same characteristics of the sample and the target population in terms of age, region and credit score.

The sample proportion (2.4%) appeared very similar to the target population in terms of key variables (age, region and credit score), confirming that the sampling procedure resulted in a representative random sample of individuals.

Table 2.3: Sample proportions by age, region and credit rating

Table 3

Age		Region		Credit Rating	
20~29	2.5	Seoul	2.4	1st decile	2.4
30~39	2.4	Busan	2.4	3rd decile	2.4
40~49	2.5	Daegu	2.4	5th decile	2.5
50~59	2.4	Incheon	2.4	7th decile	2.4
60~69	2.4	Gwangju	2.4	9th decile	2.4
Total	2.4	Total	2.4	Total	2.4

Notes: ① 1ST decile includes individuals with the highest credit score.

② %

Sources: NICE Information Service (as of end-2014)

As the BOK CCP is a panel database that samples 2.4 % of the target population with credit histories, it can be used to track the credit activities of individuals and to identify changes in distribution by characteristics of borrowers. However, since the sum of samples cannot be used as they are, a parameter estimation process is definitely necessary. The simple method for parameter estimation is to multiply the statistics by a constant (the reciprocal of the sample proportion, 1/0.024). Estimates of population aggregates can be acquired simply in this way.

We compared the estimates of population obtained by multiplication with the target population, and found that the differences were not significant.

Table 2.4:

Comparability between sample statistics multiplied and population Table 4

	Sample statistics (multiplied, A)	Population (B)	Ratio (A/B)
Total (trillion)	1,120.9	1,126.1	0.995
Borrowers(thousand)	17,655	17,629	1.001
(Seoul)	7,811	8,064	0.969
(Age; 40~49)	9,156	9,007	1.016
(Credit rating; 5^{th} decile)	7,110	6,996	1.016

Sources: NICE Information Service (as of end-2014)

3. The BOK CCP content

The data is collected from 2012Q1 every quarter. The BOK CCP is broadly composed of five categories: individual background information, loans, accounts, cards, and overdue payments and defaults. The key variables in these categories are described in detail below.

Table 3.1: Structure of the BOK CCP

Table 5

Categories	Key variables
Individual background information	Consumer identification number, age, birth, sex, region, credit score, income (estimate), etc.
Loans	· Household debt: financial institution, loan type, amount, total number of lenders that borrowers have taken out loans from, total number of accounts, origination, etc. · Commercial loans: industry, financial institution, loan type, purpose of loan, amount, maturity, etc.
Accounts	Financial institution, loan type, purpose of loan, payment method, first date of borrowing, amount, maturity, etc.
Cards	Credit limit, total amount, revolving balance, cash advance, etc.
Overdue payments and defaults	Amount registered in arrears, amount pending or in default, origination registered in arrears, etc.

Sources: the BOK CCP

Income (estimate)

The income information is generated using the evidence that individuals submitted to the financial institution when they applied for or took out a loan. If there is little evidence available, the credit bureau (NICE Information Service) estimates income. The estimate is based previous evidence of income, card records, occupation and real estate information.

Credit score

The credit score is a credit rating that evaluates an individual's credit risk by assessing repayment capacity and measuring the probability of default. A credit score of 0 occurs only for those who are not subjects of a credit rating (under 18 years or over 90 years of age) or for those whom it is difficult to evaluate due to insufficient credit information. However, the ratio of consumers with a credit score of 0 to the total sample is only 0.54% in 2018Q1.

Credit rating is independently determined by the credit rating agency (in the case of the BOK CCP, NICE information Service), which considers various information such as repayment history information (late payments, etc.), level of debt (loans and cards), and type of credit information (financial institution and product), etc.

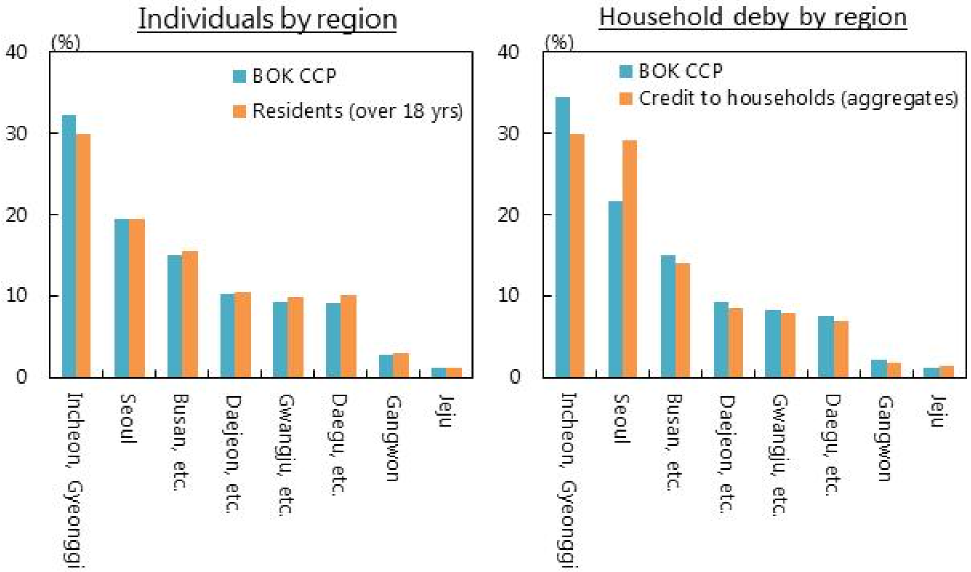
Residence/address

Residential information is the address listed on an individual’s credit report, and it offers detailed information on small administrative divisions, showing the first 3 digits of the postal code. Figure 3.1 describes the distributions of individuals and household debt by region. The first graph shows the similarity between individuals from the BOK CCP and residents (at least 18 years old).

The second graph illustrates the distribution of household debt by region, showing the difference between the statistics from the BOK CCP and the aggregated statistics; Credit to households. The difference between two statistics is larger in Incheon&Gyeonggi area and Seoul. This is because many individuals, dwelling in Incheon or Gyeonggi area, take part in economic activities in Seoul, the capital of Korea. The statistic on ‘Credit to Households’ provides regional information based on the location of financial institution branches. Therefore, if the address where an individual resides and the location of the branch at which the individual borrowed are not consistent, the total loan balance by region can be different. You also can confirm that, in Incheon&Gyeonggi, the household debt from the BOK CCP is larger than the aggregate, while it is even lower in Seoul.

Figure 3.1: Individuals and household debt by region[1]

Figure 6



Notes: ① as of 2018Q1

Sources: the BOK CCP, Statistics Korea, the Bank of Korea

Loan amount

We can acquire data on loan amount with 9 digits, but since the unit value is 100,000 won, the amount can go up to 100 trillion won, meaning that there is, in effect, no cap. Amounts of less than 100,000 won will be written as "0”. Thus, you cannot interpret “0” as actually zero.

In addition, an outlier can be observed because the sample size is large (about 1 million). If it is observed that an outlier is large enough to interfere with parameter estimation, the outliers can be excluded for accurate estimation. However, we also provide guideline on outliers for appropriate usage. Also, the data is available on request.

Meanwhile, a limited loan, such as an overdraft, can be counted on the basis of the limit and therefore differ from the actual loan balance.

Loan type

The BOK CCP provides detailed information on household debt by type, compared to the aggregated statistics provided by ‘Credit to Households’ and ‘Flow of Funds’. In the BOK CCP, loans are classified in more details (mortgage, credit card, student loan, auto loan, etc.), while statistic on ‘Credit to Households’ is classified into two loan types (mortgage and others). Figure 3.2 shows the total debt balance and its composition from the BOK CCP. A secured loan included a loan in which collateral is savings, securities, etc. But, a secured loan in which collateral is a property such as home belongs to Mortgage, which makes up the largest proportion of total household debt.

4. Data confidentiality protection and database usage in the BOK

4-1. Data confidentiality protection

As interest in personal information security has increased in recent years, we felt it necessary to approach the personal identifiable information sensitively. It was carefully reviewed whether the BOK CCP data could be interpreted as personal information subject to the Personal Information Protection Act. Since it can be considered as personal credit information, special security measures are needed.

De-identification method

The important issue in the data confidentiality protection is the possibility of person identification and personal information leakage. NICE information service assigned each consumer the unique number, a Consumer identification number, instead of an individual's social security number. These consumer identification numbers in the BOK CCP are unique to each individual, who can easily be identified by combining the consumer identification numbers with other information from the credit bureau. Also, individuals can be personally identified by combining the consumer identification numbers with external information.

Therefore, de-identification measures are required. In consideration of the data needed to analyze household debt, we adopt measures such as categorization or aggregation. The goal to prevent an individual's privacy problem can be achieved by obtaining unidentified raw data using total processing, data value deletion, and categorization.

Table 4.1:

De-identification measures

Table 6

Variables		Measures
Cards	The number of card issuers, the card issue date, debt-to-limit ratio	Not obtained
Overdue	The first and last date when an individual is registered in arrears	Not obtained
Default	The first and latest date of public record (bankruptcy, tax liens, etc.)	Categorization (month, not day)
Account	The date of account creating, expiration date	Categorization (month, not day)
Region		Categorization
Debt Amount		Aggregation (100,000 won)

Sources: the BOK CCP

The BOK CCP is a large data panel that tracks credit activities such as loans, late payments, and card use of approximately 1 million individuals every quarter. Thus, in addition to de-identification measures, additional measures are also required to prevent a leak of the raw data.

As a principle, we utilize a system that does not allow for the downloading of raw data, in order to prevent a re-identification of personal information in the database. Therefore, users who want to obtain the data set for analysis are able to process and manipulate it only within the given system. It is impossible for raw data regarded as personal information to be transferred to a user's personal computer. These measures are adopted for the purpose of data confidentiality. However, even though it is impossible for users to download raw data directly to their personal computers, we do allow analysis results to be taken out of the system and transferred to users' personal computers.

4-2. Database usage in the BOK

This longitudinal data can be used in the analysis of topics such as the distribution of household liabilities and the dynamic changes of vulnerable groups, which were difficult to analyze with existing statistics. In other words, the BOK CCP can complement existing aggregated statistics to give a different method of analysis. However, the BOK CCP contains a vast amount of microdata, and it is not possible to completely avoid a variety of problems such as missing data, errors and outliers in the process of credit information registration in financial institutions. Therefore, data cleansing is necessary for usage.

Data cleansing

Credit information is fundamentally based on the information registered individually and independently by financial institutions. Thus, the process of data cleansing is conducted in a manner that follows its source. Even after a basic verification process, there may occasionally be outliers in infrequently used datasets. In such a case, it will confirm with the credit bureau whether the data were registered incorrectly or whether they are just simple outliers. After the data is revised, a notice will be provided to users to prevent misleading analytics. Users have discretion to decide how to deal with these outliers in their analyses, and we just provide guidelines for user convenience.

Financial Stability Report

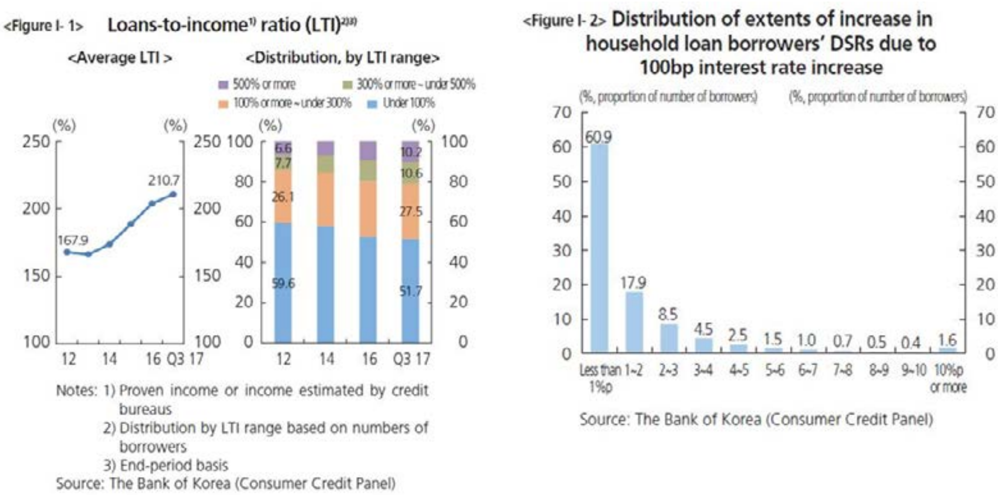
The individual-level information enables the examination of the current distribution of total debt balance and loan origination specifically by age, income, credit rating and region. The structure of household debt can also be determined. Moreover, it is possible to identify the characteristics of the vulnerable (age, region, income, debt structure, etc.) and analyze the dynamic changes of multiple-debt-holding borrowers.

The BOK CCP is, in fact, actively used in the BOK in various ways and the most significant example is a "Financial Stability Report". The Bank of Korea has published the report on a biannual basis as part of its conduct of macro-prudential policies. Since December 2015, the Consumer Credit Panel data has been used for analysis in the report.

Microdata in the BOK CCP is used in the case of household debt, analyzing and assessing the potential risks inherent in the Korean financial system. Figure 4.1 below is a part of the Financial Stability Report (Dec. 2017) analyzing household debt using the loans-to-income ratio and DSR.

Figure 4.1: Financial Stability Report (Dec. 2017)

Figure 7



Sources: the Bank of Korea; Financial Stability Report (Dec. 2017)

5. Conclusion

Unlike macroeconomic statistics, the BOK CCP contains individual-level information, thus allowing for flexible analysis tailored to the purpose of use. In addition, it has advantages over conventional survey panels in terms of coverage, sample size, timeliness, frequency, and reliability.

However, it also has some limitations, despite the fact that the data is very timely and extensive. First of all, the information is presented not at the household level but at the level of the individual. It is important to obtain information on households, because the basic economic unit is a household rather than an individual, and household data enables the analysis of matters such as the transfer of wealth between generations.

The BOK CCP also lacks information indicating the individual's demographic characteristics. Information such as occupation, education level, and marital status is limited. Despite the information on liabilities, it is difficult to perform a comprehensive study of financial activity that takes both assets and liabilities into account. This is due to the lack of information on assets, especially housing tenure, housing types, tangible assets and financial assets.

In spite of these limitations, the BOK CCP, which has been constructed across all types and financial institutions, will be available for various analyses and will also be used for further analysis, by merging with other panel data or adding other important variables in the future.

However, the database is a major asset of the Bank of Korea and is growing in value, as it reflects accumulated data management know-how and methods. It has been actively used for analyzing and addressing the household debt issue. The more time series are accumulated and the more analysis capabilities are improved, the greater the value of the data is expected to become.

References

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BOK (Dec. 2017): Financial Stability Report. Retrieved from https://www.bok.or.kr/eng/bbs/E0000737/list.do?menuNo=400042

Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

Bank of Korea consumer credit panel: a new statistical initiative for financial stability[1]

Mira Kim,
Bank of Korea

[1] This presentation was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

BOK Consumer Credit Panel

- A New Statistical Initiative for Financial Stability

MiRa, Kim

The Bank of Korea

Aug. 2018

Overview

- Introduction
- Sample design
- The BOK CCP content
- Database usage in the BOK
- Conclusion

Introduction

- With microdata being needed to address data gaps after the 2007-2008 financial crisis, the statistical value of personal credit information has been increasing.
- The current financial statistics (aggregated data) are compiled as part of the conduct of monetary policy, but are not sufficient quantitatively or qualitatively for the purpose of macro-prudential policies.
- Moreover, individual-level information has been expected to play an important role in financial stability analysis, including analysis of the vulnerability of the household sector, which is the main cause of financial crises.
- With this motivation, we established the BOK Consumer Credit Panel, which can help to measure and analyze the levels of and changes in individual liabilities to track individuals' and households' access to debt and credit.

Sample design

Target population

- The target population of the BOK CCP is all residents at least 18 years of age with credit histories.

Individuals by Credit Acitivity[1]

Individuals (50 million)		
Under 18 years of age (3 million)	Over 18 years of age (47 million)	
	With credit history[2] (41 million)	With insufficient credit history (6 million)

Notes: ① As of end-2014

② Target population

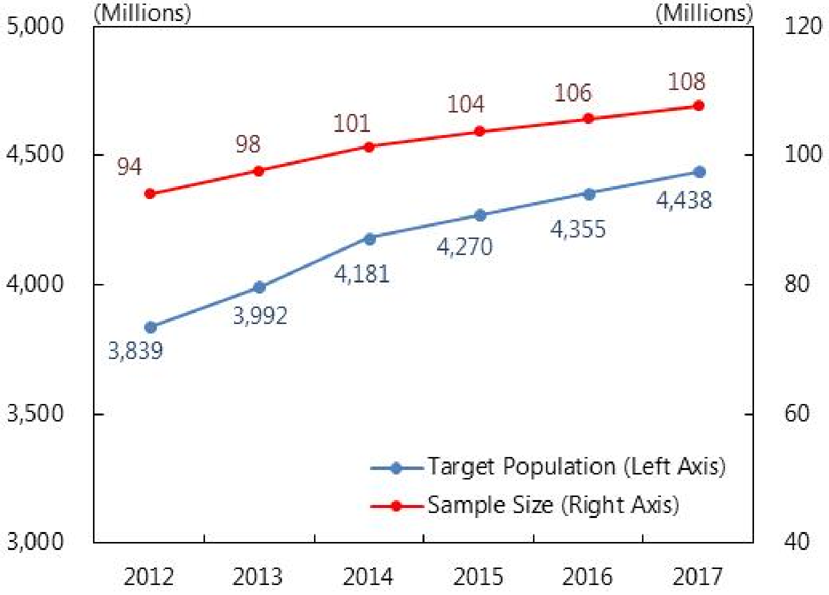
Sources: NICE Information Service

Sample design

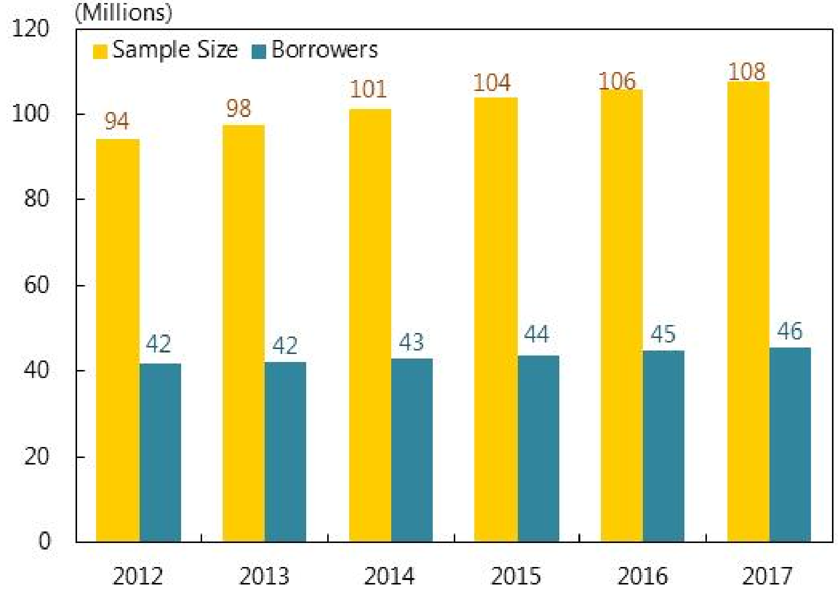
Sampling procedure

- Simple random sampling; by selecting a specific number of random numbers generated using a person's birth date from the individual information.

Target population and sample size



Sample size and borrowers



The BOK CCP content

Categories	Key variables
Individual background information	Consumer identification number, age, birth, sex, region, credit score, income (estimate), etc.
Loans	· Household debt: financial institution, loan type, amount, total number of lenders that borrowers have taken out loans from, total number of accounts, origination, etc. · Commercial loans: industry, financial institution, loan type, purpose of loan, amount, maturity, etc.
Accounts	Financial institution, loan type, purpose of loan, payment method, first date of borrowing, amount, maturity, etc.
Cards	Credit limit, total amount, revolving balance, cash advance, etc.
Overdue payments and defaults	Amount registered in arrears, amount pending or in default, origination registered in arrears, etc.

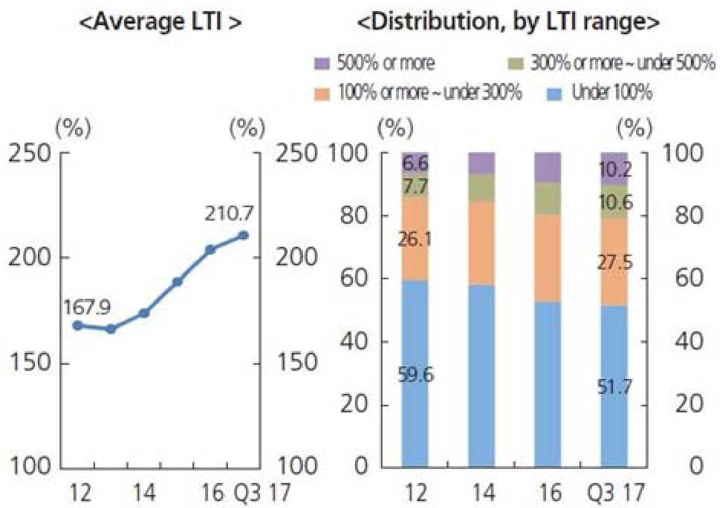
Sources: The BOK CCP

Data usage in the BOK

- The BOK CCP can complement existing aggregated statistics to give a different method of analysis.

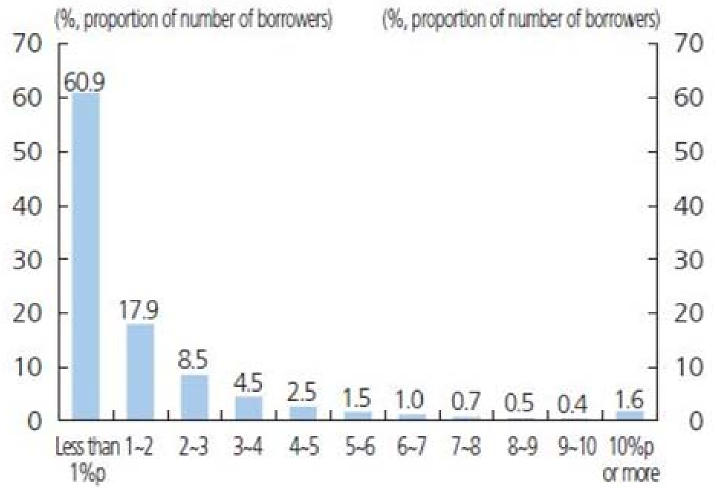
Financial Stability Report

<Figure I- 1> Loans-to-income[1] ratio (LTI)[2)3)]



Notes: 1) Proven income or income estimated by credit bureaus
2) Distribution by LTI range based on numbers of borrowers
3) End-period basis
Source: The Bank of Korea (Consumer Credit Panel)

<Figure I- 2> Distribution of extents of increase in household loan borrowers' DSRs due to 100bp interest rate increase



Source: The Bank of Korea (Consumer Credit Panel)

Conclusion

- Unlike macroeconomic statistics, the BOK CCP contains individual-level information, thus allowing for flexible analysis tailored to the purpose of use.
- However, it also has some limitations, despite the fact that the data is very timely and extensive. First of all, the information is presented not at the household level but at the level of the individual.
- The BOK CCP also lacks information indicating the individual's demographic characteristics such as occupation, education level, and marital status.
- In spite of these limitations, the BOK CCP, which has been constructed across all types and financial institutions, will be available for various analyses and will also be used for further analysis.
- The more time series are accumulated and the more analysis capabilities are improved, the greater the value of the data is expected to become.

Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

Disentangling the supply and demand factors of household credit in Malaysia: evidence from the credit register[1]

Jiaming Soh,

Central Bank of Malaysia

[1] This paper was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

Disentangling the supply and demand factors of household credit in Malaysia: evidence from the credit register

Soh Jiaming [1]

Abstract

This paper isolates the demand and supply factors of credit extension. We construct a new dataset that combines loan application information from the credit register with individuals' income and banks' balance sheet for the period 2014-2016. Using this dataset, we verify the importance of banks' balance sheet (supply factor) and individuals' income (demand factor) in determining housing and car loan approval empirically. We have two main findings. First, we find that banks' balance sheet matters. Banks with a higher funding ratio, higher capital ratio, and lower liquidity ratio are more likely to approve a housing and car loan. Among the supply factors, the funding ratio of the banks is the strongest determinant of household lending. Second, we find that the supply factors have a greater impact on household loan approval than the demand factor. Specifically, the effect of banks' funding ratio on loan approval is twice the size of income. Therefore, the declining funding ratio due to higher net external outflows may potentially explain the moderation in aggregate household loan approval growth in 2014-2016. The findings fill a research gap for the Malaysian economy and could serve to inform policies, especially in relation to the discussion on the role of banks' balance sheet in lending activities.

Keywords: Supply factor, demand factor, household loan approval, credit register, funding ratio

JEL classification: G21, E51

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Contents

1. Introduction

To what extent do individuals' and banks' balance sheet affect credit extension? A complete understanding of their respective roles requires the separation of the two. In this paper, we attempt to isolate the demand and supply factors of credit. A better understanding of the drivers of credit is essential to inform appropriate policy responses. For example, if slow credit growth is explained mainly by weak credit demand, economic policies aimed at expanding aggregate demand would be more appropriate. On the other hand, if credit growth is driven by weak banks' balance sheet, policies would need to focus on improving the financial health of banks to increase their willingness to lend[2].

However, to disentangle the two factors is an inherently difficult task. Most of the studies overcame this difficulty by relying on the rich micro-level dataset from the credit register (Khwaja and Mian (2008), Jimenez et al. (2017) and Schepens et al. (2018)). Therefore, this paper aims to provide new findings by using a novel micro-level dataset to trace how supply and demand factors affect household loan approval in Malaysia.

The main contribution of this paper is twofold. First, we create a novel borrower-bank pair dataset that links the loan application information to individuals' income and banks' balance sheet. Second, to our knowledge, this is among the first few papers that quantify and assess the relative role of supply and demand factors of credit for an emerging country in Asia[3].

For the first contribution, we match three primary official data sources to create the borrower-bank pair dataset. The data sources are 1) a credit register database that contains the universe of loan application information, 2) an income tax database that includes the borrowers' profile and income information and 3) a banking database that contains detailed information on banks' balance sheet. However, at this juncture information from the income-tax database is only available for the period 2014-2016. In addition, only individuals who filed the income tax return forms *and* applied for loans will be included in our dataset.

For the second contribution, using the borrower-bank dataset, we identify the respective roles of demand and supply factors in determining the probability of household loan approval. The demand factor is proxied using borrowers' income. The supply factors are proxied using banks' capital ratio, funding ratio, and liquidity ratio.

Utilising two different empirical methods (more details in Section 4), we regress the credit application status on a set of individual-time fixed effect and bank-varying supply-side controls. We have two main findings. First, banks' balance sheet matters. Banks with a higher funding ratio, higher capital ratio and lower liquidity ratio are more likely to lend. Among the supply factors, the funding ratio is the strongest determinant of household lending. Second, we find that the supply factors have a greater impact on household loan approval than the demand factor. Specifically, the effect of banks' funding ratio on loan approval is twice the size of income. This result highlights the importance of the funding ratio in determining household loan

[2] Everaert et al. (2015).

[3] Jimenez et al. (2017) studied Spain, Khwaja and Mian (2008) studied Pakistan and Schepens et al. (2018) studied Belgium.

approval. A declining funding ratio due to high net external outflows can potentially explain the moderation in aggregate household loan approval growth in 2014-2016.

Our study could therefore serve as a starting point for discussions on the impact of policies on banks' balance sheet and ultimately lending activities. In particular, our empirical findings on the importance of banks' funding ratio in credit extension highlight the importance of promoting diversification of the sources of funding for financial institutions, which can help reduce the sensitivity of lending activities to movements in deposit.

The paper will proceed as follow. Section 2 describes the literature review on the demand and supply factors of credit. Section 3 details the creation of a borrower-bank pair dataset. Section 4 elaborates the two identification strategies that we utilise to disentangle the demand and the supply factors. Section 5 presents the results. Section 6 discusses the policy implications and the limitations of results, and finally, Section 7 concludes.

2. Literature review

The importance of demand factors such as borrowers' profile and income in getting loan approvals is well accepted, but the role of banks' balance sheet on lending is less studied in Malaysia. Early efforts to disentangle the demand and supply factors of credit was done by Kashyap et al. (1993; 2000). They found that banks' balance sheet matters in monetary policy transmission and the impact of monetary policy on lending is stronger for banks with less liquid balance sheet.

In a more recent paper by Khwaja and Mian (2008), they investigated the impact of liquidity shocks on banks' balance sheet and lending. They found that for the same firm borrowing from two different banks, the loan extended by the bank that experienced a larger decline in liquidity dropped significantly. This provides further evidence on the importance of the supply factors of credit. The studies described above can be summarised as arrow A and arrow B in Chart 1.

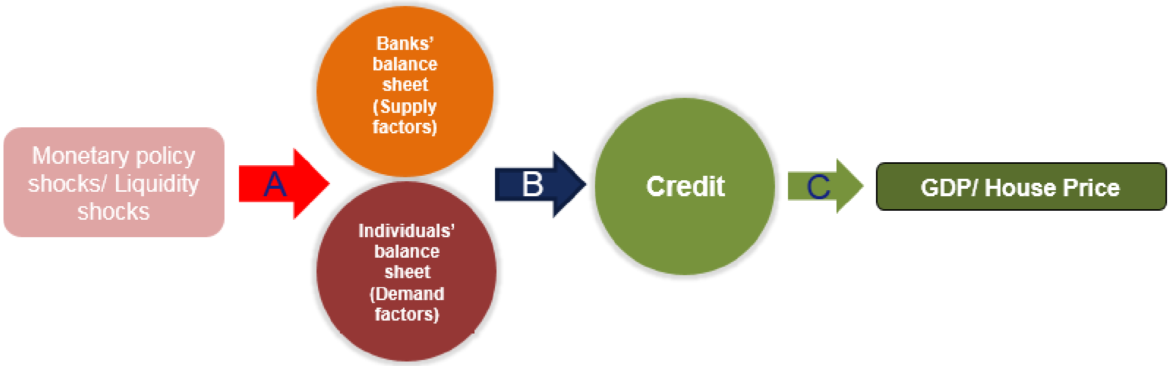
Understanding the roles of demand and supply factors of credit goes beyond unravelling the mechanics of credit creation. They do have different impacts on the real economy (arrow C in Chart 1). For example, Mian and Sufi (2017) describes a credit supply expansion as the increase in the quantity of credit or a decrease in the interest rate on credit for reasons unrelated to changes in income or productivity of the borrowers. They found that expansion in credit supply is an important source of business cycle fluctuations and is often associated with a larger growth in loans to households and a larger growth in house prices[4], with a subsequent deep recession when the credit supply shock reverts.

Therefore, the focus of this study is to first understand the drivers of credit (arrow B). We will leave the investigation of arrow A and C for future research.

[4] Favara and Imbs (2014) found similar result for house price.

Summary literature review

Chart 1



Source: Kashyap (1993); Kashyap and Stein (2000); Khwaja and Mian (2008); Favara (2014); Mian and Sufi (2017); Jimenez et al. (2017) ; Schepens et al. (2018)

3. The borrower-bank pair dataset

The availability of a rich micro-level dataset is crucial for our analysis. To create a borrower-bank pair dataset, we use three primary official data sources that are housed at the Central Bank of Malaysia. The three data sources include 1) the credit register database containing the universe of individual-level loan applications information, 2) an income tax database containing individual-level gross income information, and 3) a supervisory bank-level database containing banks' balance sheet information.

The credit register

The credit register is collected by the Central Bank of Malaysia to monitor the lending activities of banks. Information in the credit register includes lenders, status of loan application (accepted or rejected), the purpose of loan application, the application amount and the collateral value for housing loan. It has monthly information on the universe of all household loan application in Malaysia. For the purpose of our analysis, we remove joint borrowers. Each loan application is linked to only one borrower's characteristics. We restrict our borrowers to residents only. In this paper, we focus only on housing and car loan applications given that they constitute the majority of household loan[5]. Only new loan applications are considered. Applications for renewal of existing loans are not considered in our analysis.

The credit register has information on borrowers' characteristics such as age, location of residence and employment. Unfortunately, we do not have information on the risk profile of the borrowers (for example, credit score) in the dataset. Also, the income of the borrowers - which is an important demand indicator that we need for

[5] Housing and car loans comprise 66% of total household loan approval in the 2014-2016 period.

our analysis - is not available in the credit register. Therefore, we rely on the income tax database to fill this missing gap.

The income tax database

We use the income tax database to extract individual-level gross income. This information, however, is only available for those who submitted their income tax return forms in Malaysia. In addition, the income tax database has information on age, gender, location of residence, and marital status. For borrowers' characteristics that are not available from the credit register, we fill the missing information from the income tax database. This provides us with the most comprehensive list of characteristics and loan application information for the borrowers.

Unfortunately, due to the data constraint at this juncture, we only have the 2014-2016 data available in the income tax database. We also do not have information on individuals' wealth or assets.

The bank-level database

The final dataset we use is the monthly banks' balance sheet data collected by the Central Bank of Malaysia. We use banks' capital ratio, funding ratio, liquidity ratio, and size to proxy for the supply factors[6]. The following is the definition for the banks' balance sheet indicators that we use in this paper:

1) *Capital ratio* is defined to be the ratio of tier 1 capital[7] over risk-weighted assets[8]. It measures how much additional buffer a bank has to meet claims in the event of insolvency. We use this to proxy for the financial soundness of banks.
2) *Funding ratio* is defined to be the ratio of deposit[9] over total liabilities. We use this to proxy for funding availability of banks as deposit constitutes the main supply of loanable funds in Malaysia and may act as the driving force of bank lending.
3) *Liquidity ratio* is defined to be the ratio of liquid assets[10] over total assets. We use this indicator to represent the available stock of liquid assets to cover unexpected cash outflows and liquidity shocks (for example, unpredictable deposit withdrawal or unpaid credit). Since liquidity comes at a cost, a bank faces a trade-off between the safety of greater liquidity and the expense of obtaining it.
4) *Size* is defined as log total assets.

[6] We restrict our sample to commercial and Islamic banks only.

[7] Tier 1 capital consists of ordinary share capital, retained earnings and reserve fund.

[8] Assets include cash, deposit with the Central Bank and other banks, government debt, debt securities and loans extended to the private sector.

[9] We exclude deposit that are placed by banks.

[10] Liquid assets is defined as the sum of cash, deposit placed at other banks, financial assets and reverse repurchase.

Finally, using a unique identifier for banks and borrowers, we create a borrower-bank pair dataset that links loan application information to individuals' and banks' balance sheet. Note that there will be more loan applications than the number of borrowers since one borrower can apply to multiple banks. Our final sample consists of 530,000 borrowers and 47 banks, with approximately 1.5 million data points over 2014-2016. Chart 2 below summarises the process of creating the borrower-bank pair dataset for Malaysia.

The demand factors are proxied mainly by borrowers' income and other characteristics that could affect the demand for loans. This includes age, occupation, location of residence and marital status. We utilised all the available borrowers' characteristics in the dataset. Supply factors are proxied by banks' capital ratio, funding ratio and liquidity ratio as they indicate banks' capacity and willingness to lend. All relevant demand and supply indicators are standardised in the regression for ease of direct comparison.

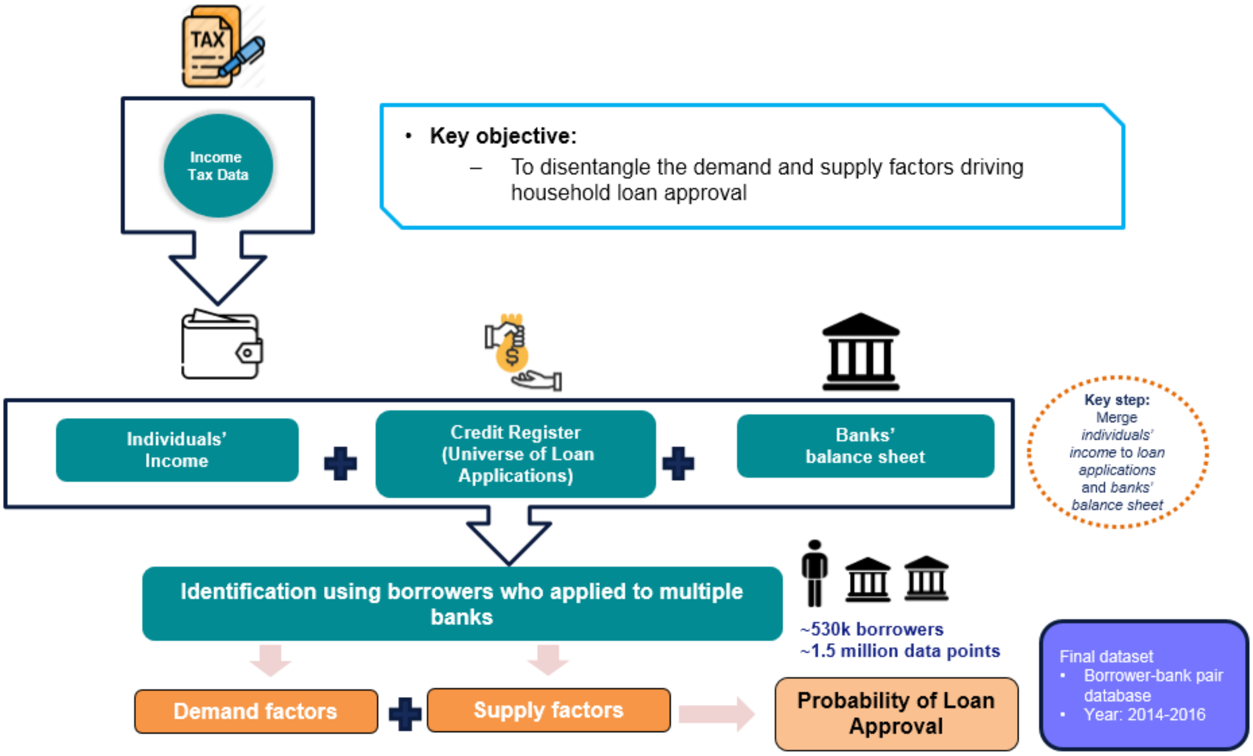
It is important to note that since we rely on information that are available from all three data sources, this study only covers individuals who filed the income tax return forms and applied for loans. In addition, many banks in Malaysia pre-filter the loan applications by income before registering the eligible applicants in the credit register. This could potentially induce a sample selection bias as we do not observe individuals from the lower income group, especially those who did not to submit any loan applications given their lower probability of obtaining an approval. In fact, individuals in our sample may consist of those with relatively high income in the population.

Table 1 in the Appendix presents the summary statistics for the borrowers' and banks' characteristics. For banks' characteristics, the average funding ratio in the sample is 75%, and the average capital and liquidity ratio is around 10%. Note that compared to other supply factors, the standard deviation for the funding ratio is relatively high, suggesting a significant disparity in the funding ratio across banks in Malaysia.

For borrowers' characteristics, the average monthly gross income is RM 8,600. This confirms our previous claim that individuals in our dataset are relatively well off in the population. The mean income in our dataset is roughly 3 times the average monthly salaries and wages in the population[11]. On average, the borrowers in our dataset applied to 4 banks and the majority of the loan applications are accepted (~80%).

[11] The average monthly salaries and wages in the population is around RM 2500 in 2016. We do not observe the average gross income for the population. Source: Salaries and Wages Survey Report 2016, Department of Statistics Malaysia.

Process of Creating a Borrower-Bank Pair dataset for Malaysia Chart 2



Source: Author's estimate.

4. Empirical Methodologies

This section outlines the econometric models that we use to overcome the classical identification problem of separating the demand and supply factors of lending. We rely mainly on two methods: the first from Khwaja and Mian (2008), and the second from Schepens et al. (2018). Chart 3 summarises the two methods (Equation 1 and Equation 2) described below.

4.1 Method 1

The first method originates from Khwaja and Mian (2008). We use the sample of borrowers who applied to multiple banks for identification. Intuitively, since the comparison is across banks for the *same* individual, any difference in the loan approvals is arguably due to heterogeneity in banks' balance sheet. Specifically, we regress individual-bank level credit application status on a set of individual-time fixed effect and bank-varying supply controls as shown in Equation 1:

$$Prob(Loan\ Approval)_{i,j,t} = \beta_i + \boldsymbol{\beta_1 S_{j,t=1}} + \boldsymbol{\beta_2 X_{i,j,t}} + \beta_3 Z_t + \varepsilon_{i,j,t} \quad (1)$$

where i refers to individual i who applied to multiple banks, j refers to bank j, and t refers to time.

We use a linear probability model for the estimation. The key dependent variable is a dummy to indicate the status of the loan application made by individual i to bank j at time t (1 if loan application is approved, 0 otherwise). In this study, we only focus on the quantity of loans as our dependent variable due to the lack of data for the price of loans (i.e. effective interest rate).

β_i refers to individual-fixed effect. Since the comparison is across banks for the same individual i, individual-specific demand factors such as income, age, occupation, location of residence and marital status will be absorbed by the individual fixed effect β_i.

The key independent variable is the vector $\boldsymbol{S_{j,t=1}}$. It consists of bank j 's funding ratio, capital ratio, liquidity ratio at time t=1. All these supply factors are estimated simultaneously in one regression[12]. We use the supply factors at the beginning of the year to proxy for banks' initial position. This is to reduce the potential reverse causality from loan to deposit. All standard errors are clustered at individual-time level.

Some controls are capture in the vector $\boldsymbol{X_{i,j,t}}$. It includes the amount applied by the borrower, the collateral value[13], and the banks' size and market share[14]. Z_t refers to the time fixed effect to capture macroeconomic shocks during the year. The loan applications must also be submitted in the same year for the same purpose.

However, there are two setbacks in using Equation 1. First, we can only estimate the fixed effect coefficient β_i in the sample of individuals who submitted their loan applications to multiple banks. This will omit individuals who applied to only one bank. Even though the majority of the loan applicants in our dataset (85%) applied to multiple banks, excluding a subset of individuals from the analysis may potentially induce a sample selection problem. Second, under Equation 1 the role of income will be absorbed by the individual-time fixed effect and we will not be able to compare the relative strength of demand and supply factors. Therefore, we rely on an alternative methodology used in Jimenez et al. (2017) and Schepens et al. (2018).

4.2 Method 2

Under this method, instead of using the individual-time fixed effect, we replace it with industry-location-age-marital-time fixed effect. Because we directly observe the borrowers' characteristics in the dataset, we do not have to rely on the individual fixed-effect. The benefits of this approach is two-fold. First, it allows us to include all borrowers in our analysis. Second, since the income effect is not absorbed, we can compare the size of the coefficient for the demand factor (proxied by income) and supply factors (proxied by banks' characteristics) to assess their relative strength. Specifically, we estimate the following:

[12] We also estimate each of the supply factor in separate regressions. The results are quantitatively similar.

[13] Collateral value is only available for housing loan.

[14] Market share refers to the share of loan applications in each bank during the year.

$$Prob(Loan\ Approval)_{i,j,t} = \beta_{ILAM,t} + \beta_0 D_{i,t} + \boldsymbol{\beta_1}\, \boldsymbol{S_{j,t=1}} + \boldsymbol{\beta_2 X_{i,j,t}} + \beta_3 Z_t + \varepsilon_{i,j,t} \quad (2)$$

where similar to Equation 1, i refers to individual i who applied to bank j at time t. We estimate Equation 2 using the linear probability model as well.

$\beta_{ILAM,t}$ refers to the *industry-location-age-marital-time* fixed effect. This is the key difference from Equation 1. Intuitively, borrowers will be placed into bins based on their occupation, location of residence, age and marital status. These are the available characteristics in the dataset that can determine loan demand. The underlying assumption is individuals in the same bin will have a similar level of credit demand based on these characteristics.

The coefficient of interest under this method is β_0. This captures the impact of the demand factor $D_{i,t}$ on the probability of loan approval. We proxied $D_{i,t}$ with borrower i's income from the income tax database.

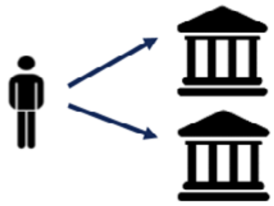
Similar to Equation 1, the dependent variable is a dummy variable representing the status of loan applications. $\boldsymbol{S_{j,t=1}}$ is the vector of supply factors for bank j at time 1 , $\boldsymbol{X_{i,j,t}}$ refers to the vector of controls and Z_t refers to the time fixed effect.

The coefficient of interest under this method is β_0 and β_1. With these two coefficients, we can compare the relative strength of demand and supply factors. If $\beta_0 > \beta_1$, demand factor is stronger than the supply factors in household loan approval. Standard errors are clustered at industry-location-age-marital-time level.

Empirical Methods: Isolating Supply and Demand Factors Chart 3

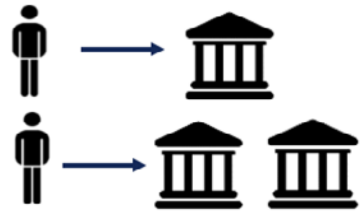
First strategy (Equation 1)

Only individuals who applied to multiple banks



Second strategy (Equation 2)

All individuals



- Using individual-year fixed effect
- Since the comparison is across banks for the *same* individual, only differences in banks' characteristics will affect the probability of loan approval
- Coefficient of interest is β_1 in Equation 1. This is the effect from the supply factors

- Using industry-location-age-marital-year fixed effect
- We can compare the relative strength of demand (proxied by individual's income) and supply factors for the same *group* of individuals
- Coefficient of interest is β_0 (demand factor) vs β_1 (supply factors) in Equation 2

Source: Author's illustration.

5. Results

5.1 Results from Method 1

Table 2 in Appendix shows the results using Equation 1. Column 1 shows the result for housing loan and column 2 for car loan.

The results show that banks' balance sheet matters. Banks with a higher funding ratio and capital ratio is more likely to approve a housing and car loan. A one standard deviation increase in the banks' funding ratio and capital ratio would increase the probability of approval for a housing loan by 0.06 and 0.04 respectively, which represents a 9% and 5% increase in the probability of approval from the mean[15] probability of approval. Similar results are observed for a car loan. However, the impact of liquidity ratio is different between a housing and car loan. It does not have a significant impact on the probability of housing loan approval but it does affect the car loan approval negatively. Banks with a higher liquidity ratio are more likely to reject the car loan application. A one standard deviation increase in banks' liquidity ratio leads to a decline in the probability of a car loan approval by 0.04, which is a 6% decrease from the mean.

Among the supply factors, the funding ratio of the banks is the strongest determinant of household lending. As illustrated in Table 2 the size of the coefficient for the funding ratio is at least twice the size for the capital ratio and liquidity ratio.

5.2 Results from Method 2

Table 3 in Appendix displays the results for Method 2. We replace individual-time fixed effect with industry-location-age-marital-time fixed effect. The advantage of this method is discussed at the earlier section.

Similar to the results from Equation 1, banks with a higher funding ratio and capital ratio are more likely to approve a housing loan and car loan. A one standard deviation increase in the banks' funding ratio and capital ratio increase the probability of housing loan approval by 0.05 and 0.03 respectively, which represents a 7% and 4% increase from the mean probability of approval. Similar results are observed for car loan approvals. In addition, banks with a higher liquidity ratio are less likely to approve a housing loan and car loan, especially the latter.

Under this method, we can compare the relative strength of demand and supply factors. From Table 3, we observe that a one standard deviation increase in the monthly income of the borrowers increases the probability of approval by 0.03, which represents a 5% increase in the probability of approval from the mean. This magnitude is smaller than the impact from funding ratio and comparable to that of capital ratio. This supports the case where $\beta_0 < \beta_1$ in which the supply factor is stronger than the demand factor in determining the housing and car loan approvals.

It is worth highlighting the potential selection issue in this sample that may explain the strength of the income factor. Given that borrowers in our sample paid income tax and applied for loans, they are likely to have a higher income level than

[15] The mean probability of approval for a housing loan is 0.7, and for a car loan is 0.8. This is estimated from the constant term in the regression as shown in Table 2.

the general population. This may create a downward bias to the income result. The role of income may be much stronger if we take into account the broader population, especially those who did not file the income tax return forms or those who did not have access to submit a loan application.

6. Discussion and Policy Implications

The micro-level results show that banks' funding ratio is the strongest determinant of household lending in Malaysia during the 2014-2016 period. This is consistent with the fact that deposit constitutes the main supply of loanable funds for banks in Malaysia and thus may act as the driving force of bank lending (see Chart 4). Banks with a lower funding ratio may thus be more risk-averse and restrictive in their lending activities.

The positive relationship between the capital ratio and lending activities is supported by the role of bank capital that acts as a buffer to insulate banks from the risk of insolvency (Rajan (1994); Jokipii and Milne (2008)). Banks with a higher level of capital can therefore accommodate a faster loan growth than banks with lower capital due to their higher capacity to absorb more losses in the event of a loan default (Kosak et al. (2014)).

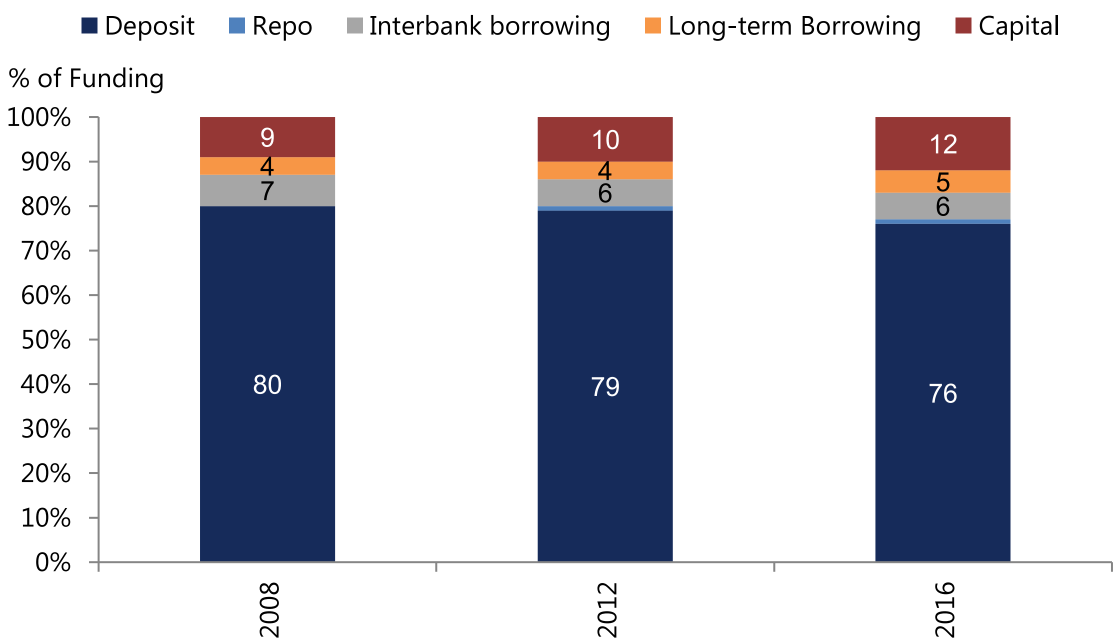
However, the negative relationship between the liquidity ratio and lending activities is an interesting finding. A higher liquidity ratio should enable banks to draw down their cash and securities to meet any unexpected cash outflows without adjusting their loan portfolio (Gambacorta (2005); Kashyap and Stein (2000)). However, for the case of Malaysia, banks that have more liquid assets extend fewer car loans. More investigation is required to understand this unique feature of Malaysian banks.

Our findings on the importance of the funding ratio may explain the moderation in aggregate household loan approval growth during the 2014-2016 period. Household loan approval growth in Malaysia, especially for housing and car loans, has been declining despite stable GDP growth (Chart 5). Our micro-level findings suggest that the moderation may be driven more by the supply factors instead of demand. As shown in Chart 6, the aggregate funding ratio in the banking system did decline quite substantially during this period due to high net external outflow[16].

[16] BNM Annual Report 2014, 2015, 2016

Malaysian Banking System: Composition of Funding Sources

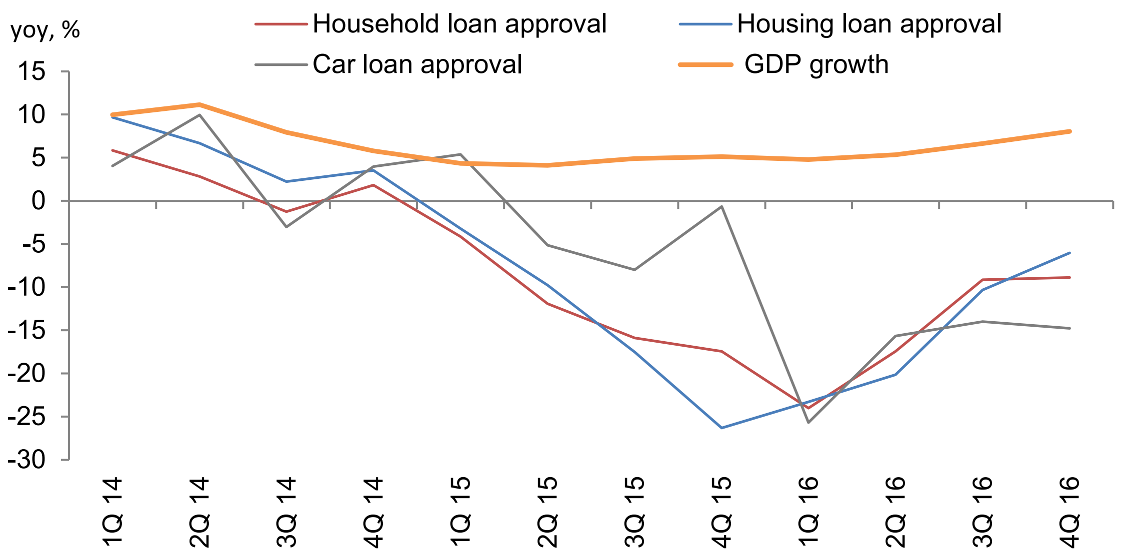
Chart 4



Source: "Evolving Dynamics of Banks' Funding and Liquidity Management" BNM Financial Stability and Payment Systems Report 2016

GDP Growth and Household Loan Approval Growth

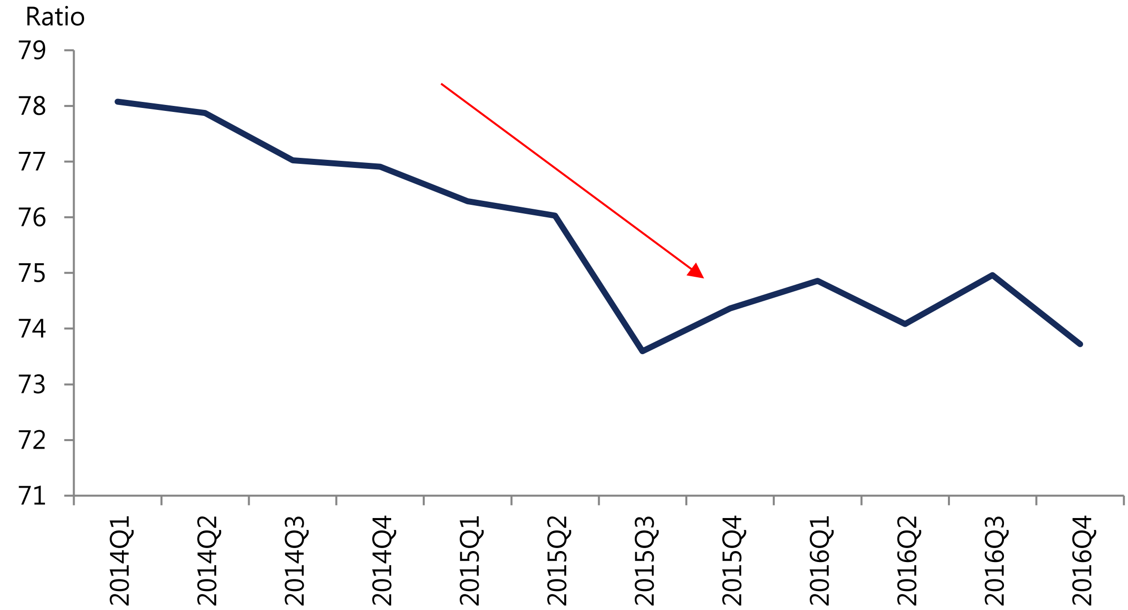
Chart 5



Source: Author's estimate.

Malaysian Banking System: Aggregate Deposit to Total Liabilities ratio

Chart 6



Source: Author's estimate.

Our study could therefore serve as a starting point to discuss the impact of policies on banks' balance sheet and ultimately lending activities. In particular, our empirical findings on the importance of banks' funding ratio in credit extension have several policy implications. First, the results highlight the importance of promoting developments in the financial system to encourage diversification in the sources of funding for financial institutions. For example, a deeper bond and equity market will reduce banks' heavy reliance on deposit as the primary source of funding, which will help decrease the sensitivity of lending activities to movements in deposit.

Second, the unequal distribution of deposit in the banking system may have a non-trivial impact on the lending activities of smaller banks. Unlike the large banks, small banks rely more on deposit as their primary source of funding. Due to the lower concentration of deposit among the small banks, this may potentially affect their willingness to lend given the lack of available funds.

However, there are several key limitations to our findings. First, as highlighted in the previous section, there are selection issues in our sample. Only individuals who filed the income tax and applied for loans are captured in our dataset. Also, many banks in Malaysia pre-filter the loan applications by income. Thus any prospective applicants who are below a certain income threshold may have already been rejected before they are registered in the credit register.

Second, unlike the supply indicators, we have limited demand indicators in the dataset. Only income and basic households' characteristics such as age, marital status, the location of residence and industry are available in the dataset. Other important factors such as the historical credit score and the debt-service ratio (DSR) of the applicants are not available. Of note, we also do not observe the price of the loan (i.e., the interest rate) offered to the applicants, which limit our analysis to only the quantity of loans.

Third, it is also important to note that the role of demand and supply factors may change depending on the economic environment. For example, using a dataset of loan applications covering Spain from 2002 to 2010, Jimenez et al. (2012) found that banks' balance-sheet only matters during crisis periods. Firms' balance-sheet, on the other hand, matters in both good and bad periods. Unfortunately, for Malaysia, the time period of 2014-2016 is too short to differentiate the channels during good and bad economic periods, which we leave for future research.

7. Conclusion

This paper aims to trace how supply and demand factors affect household loan approval. We create a borrower-bank pair dataset to do the isolation. We utilise two different methods to disentangle the demand and supply factors. There are two key findings from our results. First, we find that banks' balance sheet (the supply factors) matters. Second, we find that the supply factors affect household loan approval more than the demand factor. The declining funding ratio due to high net external outflows can potentially explain the moderation in the aggregate household loan approval growth between 2014 and 2016. Overall, the findings in our paper fill a research gap for the Malaysian economy by identifying the role of banks' balance sheet in household lending. Our empirical findings on the importance of the funding ratio could serve to inform the calibration of policies especially those in relation to lending activities.

8. Appendix

Table 1: Summary Statistics		
Variables	Mean	S.D.
Banks' Characteristics		
Funding ratio (%)	75	13.5
Capital ratio (%)	13.7	5.6
Liquidity ratio (%)	11.6	9.7
Size (Log total assets)	10.5	1.2
Borrowers' Characteristics		
Monthly income (RM)	9016.1	15030.1
Loan Application amount (RM, thousand)	246.9	340.6
Collateral value for housing loan only (RM, thousand)	2438	10500
Number of banks applied	4.2	2.8
Age	38.3	9.6
	% accepted	% rejected
Status of loan applications	83%	17%
	Male	Female
Sex	63%	37%
	Married	Single
Marital status	40%	60%

*Note: Table 1 shows the summary statistics for the borrower-bank pair dataset. There are 530000 borrowers and 47 banks. Only individuals who paid income tax and applied for loan will appear in the dataset. We also restrict our borrowers to residents only. Only new loan applications are considered.

Table 2: Effect of demand and supply factors on the status of loan applications (using the sample of individuals who applied to multiple banks (Equation 1))		
Dependent variable	Status of Loan Applications (1 if accepted, 0 otherwise)	
	[Column 1: Housing Loan]	[Column 2 : Car Loan]
Standardised Capital Ratio	0.037***	0.052***
	[0.006]	[0.004]
Standardised Funding Ratio	0.060***	0.072***
	[0.004]	[0.003]
Standardised Liquidity Ratio	-0.004	-0.049***
	[0.005]	[0.005]
Constant	0.662***	0.770***
	[0.017]	[0.012]
Loan's Characteristics Controls		
Loan Application Amount (Value)	Yes	Yes
Collateral Value	Yes	No
Bank's Characteristics Controls		
Size of Bank	Yes	Yes
Bank's Market Share	Yes	Yes
Time fixed effect	Yes	Yes
Loan Type	Housing	Car
Observations	247,069	354,598
Robust standard errors in brackets, *** p<0.01, ** p<0.05, * p<0.1		

*Note: Table 2 shows the results from Equation 1. The regression examines how the probability of loan approval is affected by the supply factors. This is estimated using the sample of borrowers who applied to multiple banks. Housing loan and car loan applications are estimated separately in Column 1 and Column 2. We use a linear probability model for estimation. The dependent variable is a dummy variable to indicate the status of loan applications (1 if approved, 0 if rejected). Individuals' characteristics are absorbed by the individual-time fixed effect. The key independent variables are banks' supply factors (capital ratio, funding ratio and liquidity ratio) at the beginning of the year. Controls include the loan application amount, the collateral value, the size and the market share of banks. All variables are standardised for ease of comparison. Only new loan applications are considered. Robust standard errors in parentheses.

Table 3: Effect of demand and supply factors on the status of loan applications (using all individuals (Equation 2))

Dependent variable	Status of Loan Applications (1 if accepted, 0 otherwise)	
	[Column 1: Housing Loan]	[Column 2: Car Loan]
Standardised Monthly Income	0.029***	0.025***
	[0.004]	[0.003]
Standardised Capital Ratio	0.025***	0.056***
	[0.001]	[0.001]
Standardised Funding Ratio	0.051***	0.064***
	[0.001]	[0.001]
Standardised Liquidity Ratio	-0.014***	-0.045***
	[0.001]	[0.001]
Constant	0.683***	0.847***
	[0.005]	[0.004]
Loan's Characteristics Controls		
Loan Application Amount (Value)	Yes	Yes
Collateral Value	Yes	No
Bank's Characteristics Controls		
Size of Bank	Yes	Yes
Bank's Market Share	Yes	Yes
Time fixed effect	Yes	Yes
Loan Type	Housing	Car
Observations	263,058	399,573

Robust standard errors in brackets, *** p<0.01, ** p<0.05, * p<0.1

*Note: Table 3 shows the results from Equation 2. The regression examines how the probability of loan approval is affected by both demand and supply factors. This is estimated using the sample of all borrowers. Housing loan and car loan applications are estimated separately in Column 1 and Column 2. We use a linear probability model for estimation. The dependent variable is a dummy variable to indicate the status of loan applications (1 if approved, 0 if rejected). Individuals' characteristics are absorbed by the industry-location-age-marital-time fixed effect. The key independent variables include banks' supply factors (capital ratio, funding ratio and liquidity ratio) at the beginning of the year and the demand factor proxied by individuals' monthly gross income. Controls include the loan application amount, the collateral value, the size and the market share of banks. All variables are standardised for ease of comparison. Only new loan applications are considered. Robust standard errors in parentheses.

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Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

Disentangling the supply and demand factors of household credit in Malaysia: evidence from the credit register[1]

Jiaming Soh,

Central Bank of Malaysia

[1] This presentation was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

Disentangling the Supply and Demand Factors of Household Credit in Malaysia: Evidence from the Credit Register

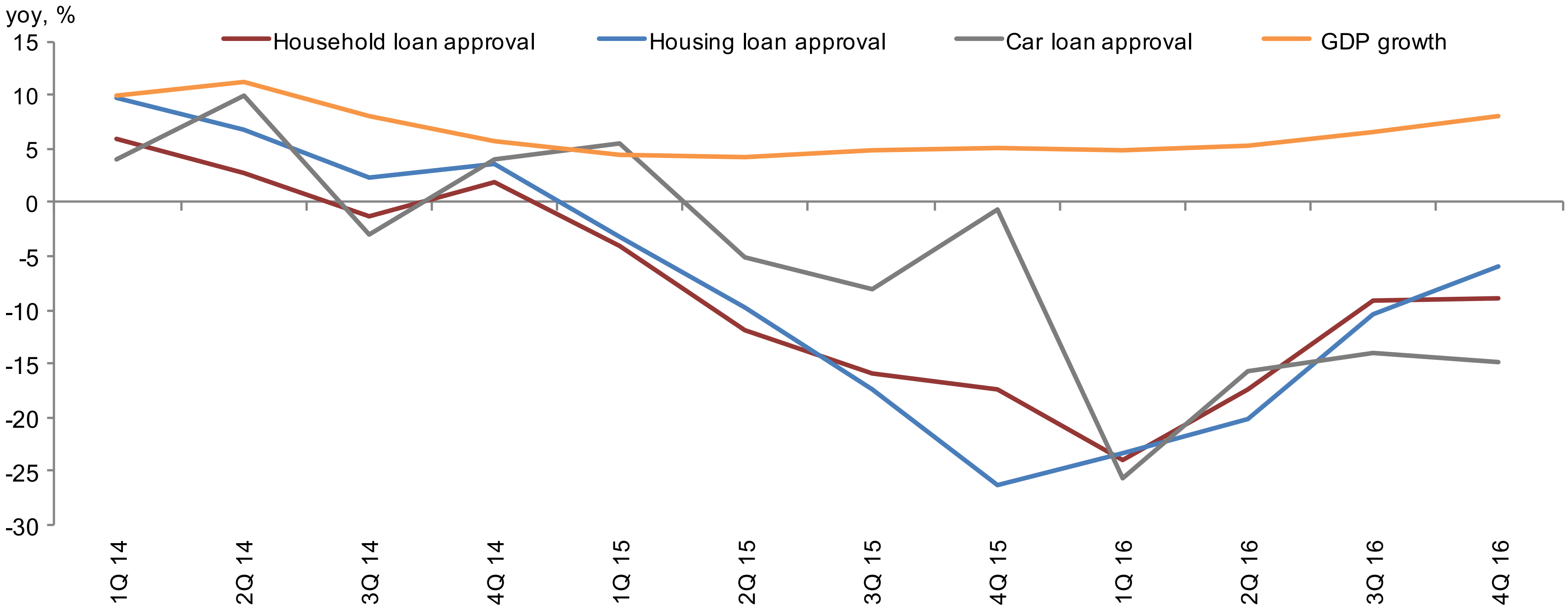
Author: Soh Jiaming

*Presented at the 9th biennial BIS-IFC Conference on "Are post-crisis statistical initiatives completed?“ BIS, Basel, 30-31 August 2018

Disentangling the demand and supply factors of credit is an inherently difficult task

- Moderation in loan approval could be attributed to either demand or supply factors. Separating the two factors is essential to inform appropriate policy responses
- However, to disentangle the two factors using macro data is an empirical challenge
- Using a novel micro-level dataset, this paper traces how supply and demand factors affect household loan approval in Malaysia during the 2014-2016 period

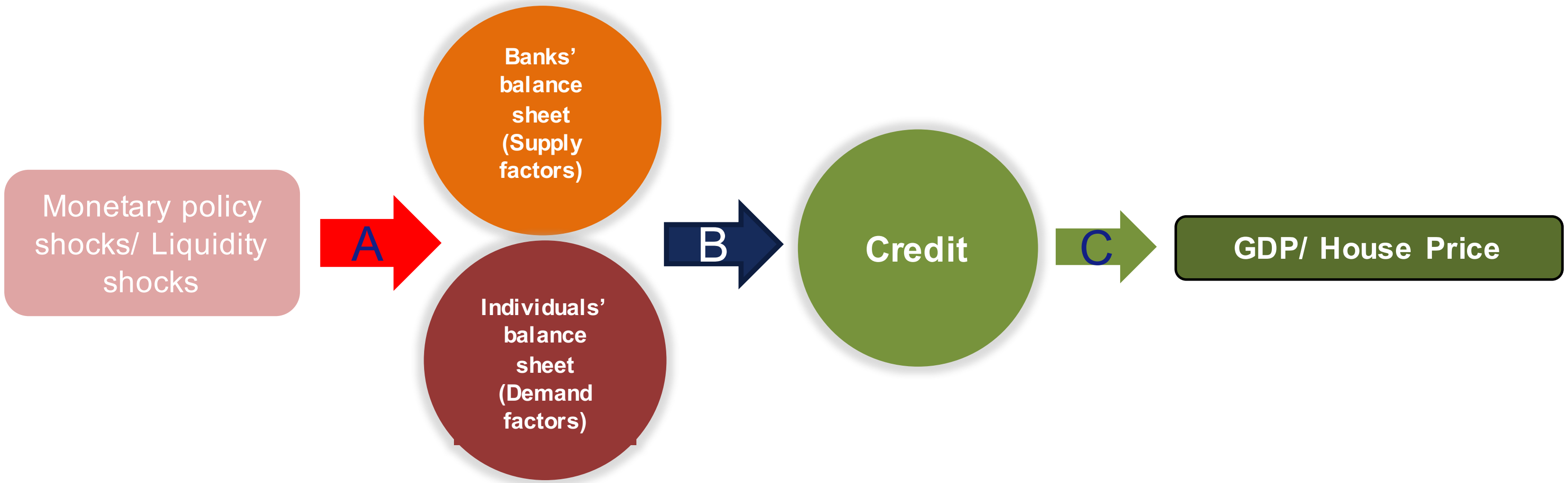
Household Loan Approval Growth vs GDP growth



Source: Author's estimate. Approximately 66% of total household loan approval are housing and car loans.

BANK NEGARA MALAYSIA
CENTRAL BANK OF MALAYSIA

Quantifying the role of banks' balance sheet is essential to link the financial sector to real activity



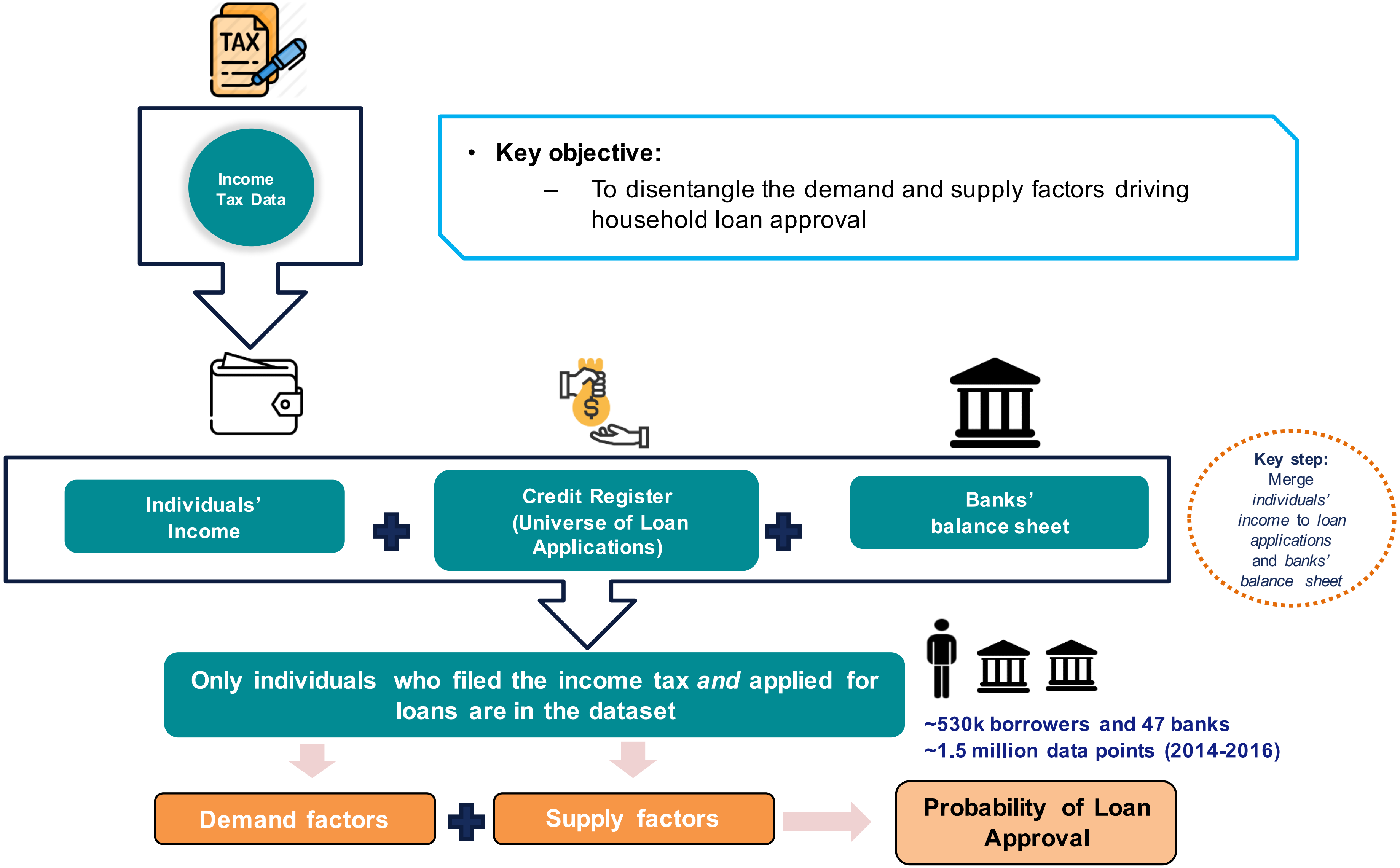
Two main contributions of this paper

1. Create a novel borrower-bank pair dataset that links the loan application information to individuals' income and banks' balance sheet

2. Among the first few papers to quantify and assess the relative role of supply and demand factors of credit for an emerging country in Asia

*Kashyap (1993); Kashyap and Stein (2000); Khwaja and Mian (2008)
**Jimenez et al (2017) ; Schepens et al (2018)
***Favara et al (2014); Mian and Sufi (2017)

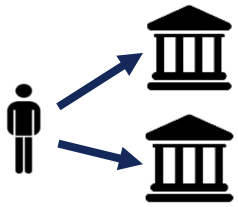
First contribution: create a database of matched borrower – bank pair to isolate the supply and demand factors



Source: Author's illustration.

Second contribution: use two identification strategies to isolate supply from demand

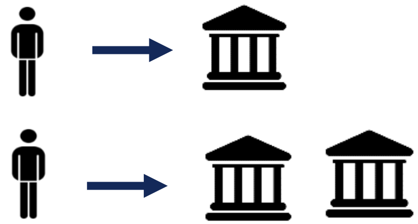
Equation 1: Use only individuals who applied to multiple banks (85% of borrowers)



$$Prob(Loan\ Approval)_{i,j,t} = \beta_i + \boldsymbol{\beta_1 S_{j,t=1}} + \boldsymbol{\beta_2 X_{i,j,t}} + \beta_3 Z_t + \varepsilon_{i,j,t}$$

- β_i refers to individual–time fixed effect that absorbs all individual-specific demand factors.
- $S_{j,t=1}$ refers to the vector of banks' supply factors at t=1.
- $X_{i,j,t}$ refers to the vector of controls.
- **Since the comparison is across banks for the *same* individual, only heterogeneity in banks' balance sheet will affect the probability of loan approval.**
- Coefficient of interest is β_1 . This is the effect of the supply factors.

Equation 2: Use all borrowers



$$Prob(Loan\ Approval)_{i,j,t} = \beta_{ILAM,t} + \beta_0 D_{i,t} + \boldsymbol{\beta_1 S_{j,t=1}} + \boldsymbol{\beta_2 X_{i,j,t}} + \beta_3 Z_t + \varepsilon_{i,j,t}$$

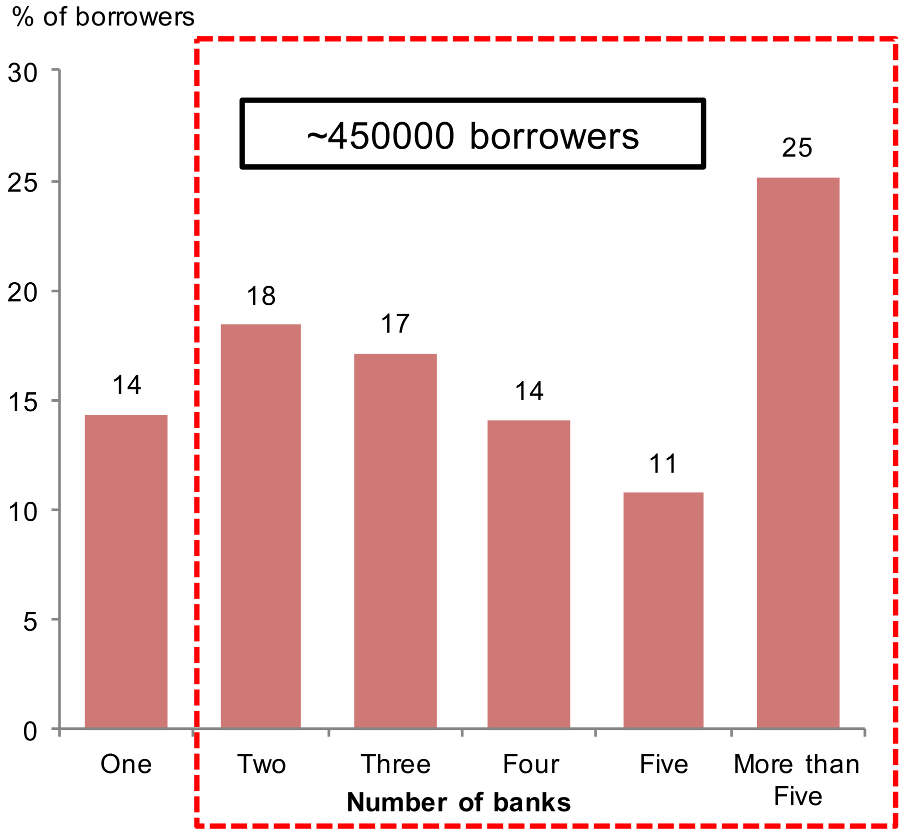
- $\beta_{ILAM,t}$ refers to the occupation-location-age-marital-time fixed effect.
- $D_{i,t}$ refers to the individual-specific demand factor at t.
- **Under this method, we can compare the relative strength of demand (β_0) and supply factors (β_1) for the same *group* of individuals.**
- Coefficient of interest is β_0 vs β_1.

Notes: Demand factor is proxied using borrowers' monthly gross income. Supply factors are proxied using banks' capital ratio, funding ratio and liquidity ratio. Capital ratio is the ratio of tier 1 capital over risk-weighted assets. Funding ratio is the ratio of deposit over total liabilities. Liquidity ratio is the ratio of liquid assets over total assets. Banks' size is the log of total assets. Only commercial and Islamic banks are included in the sample.

Summary statistics: compared to the general population, the income of the borrowers in our dataset is relatively higher

Most of the borrowers in the sample (~85%) applied to multiple banks…

Applications submitted by borrowers to multiple banks for housing and car loans



Source: Author's estimate. There are a total of 47 banks and 530000 borrowers in the sample.

…and these individuals are relatively well off in the population (~3 times higher than the wages in the population)

Table 1: Summary Statistics

Variables	Mean	S.D.
Banks' Characteristics		
Funding ratio (%)	75	13.5
Capital ratio (%)	13.7	5.6
Liquidity ratio (%)	11.6	9.7
Size	10.5	1.2
Borrowers' Characteristics		
Monthly income (RM)	9016.1	15030.1
Application amount (RM, thousand)	246.9	340.6
Collateral value for housing loan only (RM, thousand)	2438	10500
Number of banks applied	4.2	2.8
Age	38.3	9.6
	% accepted	% rejected
Status of loan applications	83%	17%
	Male	Female
Sex	63%	37%
	Married	Single
Marital status	40%	60%

*Note: Table 1 shows the summary statistics for the borrower-bank pair dataset. There are 530000 borrowers and 47 banks. Only individuals who paid income tax and applied for loan will appear in the dataset. We also restrict our borrowers to residents only. Only new loan applications are considered.

Results: Supply factors matter more than demand in household credit

First main finding: Banks' balance sheet matters for household lending in Malaysia

- Banks with a higher funding ratio, higher capital ratio, and lower liquidity ratio are more likely to approve a housing or car loan application
  - Funding ratio has the strongest effect

Table 2: Effect of demand and supply factors on the status of loan applications (using the sample of individuals who applied to multiple banks (Equation 1))

Dependent variable	Status of Loan Applications (1 if accepted, 0 otherwise)	
	[Column 1: Housing Loan]	[Column 2 : Car Loan]
Standardised Capital Ratio	0.037***	0.052***
	[0.006]	[0.004]
Standardised Funding Ratio	0.060***	0.072***
	[0.004]	[0.003]
Standardised Liquidity Ratio	-0.004	-0.049***
	[0.005]	[0.005]
Constant	0.662***	0.770***
	[0.017]	[0.012]
Loan Characteristics Controls		
Loan Application Amount (Value)	Yes	Yes
Collateral Value	Yes	No
Bank Characteristics Controls		
Size of Bank	Yes	Yes
Bank Market Share	Yes	Yes
Time fixed effect	Yes	Yes
Loan Type	Housing	Car
Observations	247,069	354,598

Robust standard errors in brackets, *** p<0.01, ** p<0.05, * p<0.1

Second main finding: Supply factors have greater effect on household loan approval than demand

- The effect from income is smaller than the impact of banks' funding ratio and capital ratio, especially the former (i.e. $\beta_0 < \beta_1$)

Table 3: Effect of demand and supply factors on the status of loan applications (using all individuals (Equation 2))

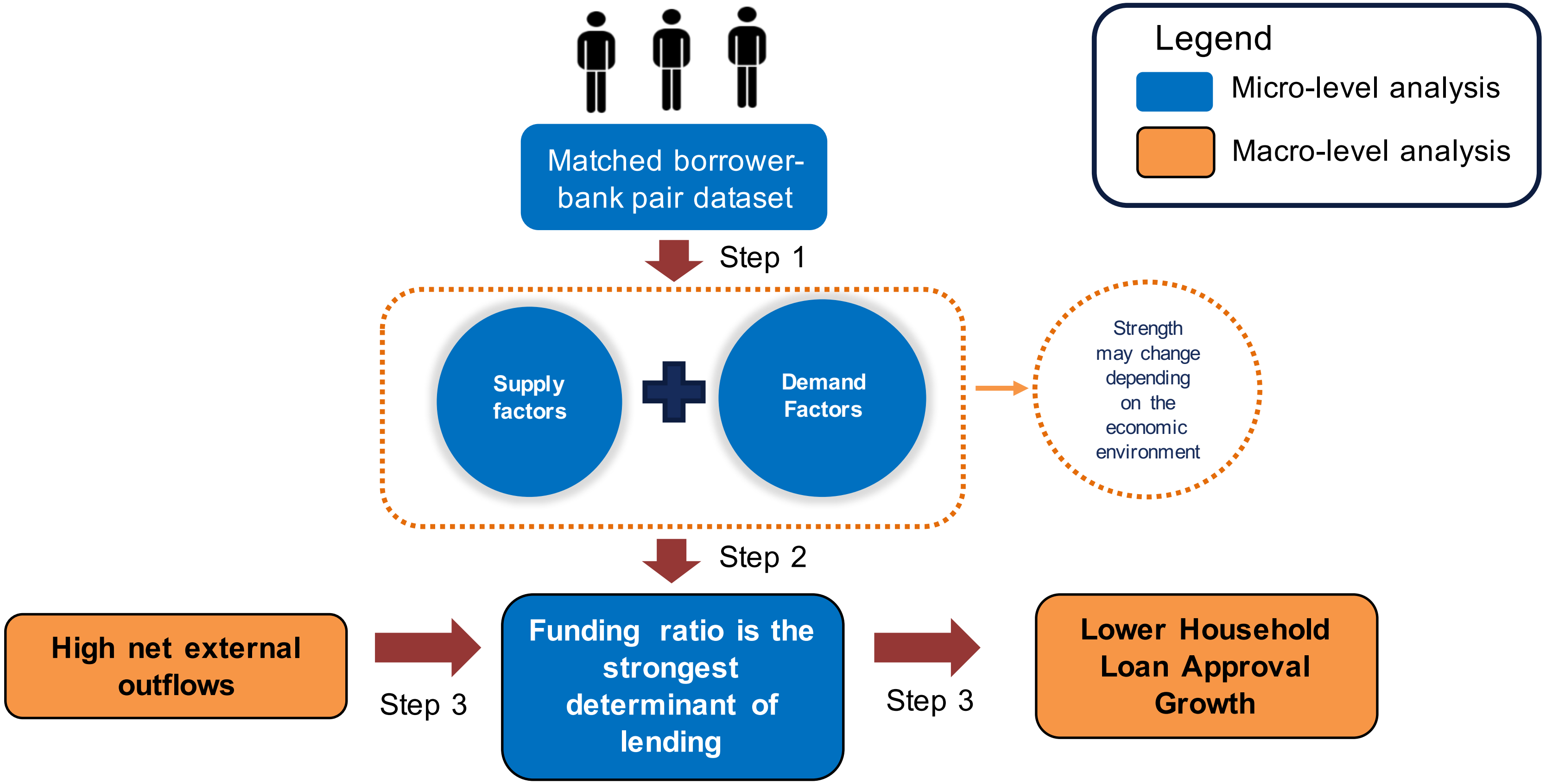
Dependent variable	Status of Loan Applications (1 if accepted, 0 otherwise)	
	[Column 1: Housing Loan]	[Column 2: Car Loan]
Standardised Monthly Income	0.029***	0.025***
	[0.004]	[0.003]
Standardised Capital Ratio	0.025***	0.056***
	[0.001]	[0.001]
Standardised Funding Ratio	0.051***	0.064***
	[0.001]	[0.001]
Standardised Liquidity Ratio	-0.014***	-0.045***
	[0.001]	[0.001]
Constant	0.683***	0.847***
	[0.005]	[0.004]
Loan Characteristics Controls		
Loan Application Amount (Value)	Yes	Yes
Collateral Value	Yes	No
Bank Characteristics Controls		
Size of Bank	Yes	Yes
Bank Market Share	Yes	Yes
Time fixed effect	Yes	Yes
Loan Type	Housing	Car
Observations	263,058	399,573

Robust standard errors in brackets, *** p<0.01, ** p<0.05, * p<0.1

Limitations of findings

- **Potential sample selection issue**
  - Only individuals who filed the income tax *and* applied for loans will be in the dataset. Many banks also pre-filter the loan applications by income before registering the applicants in the credit registry
    - The group of individuals in our dataset may consist of those with relatively high income in the population
- **Limited demand indicators in the dataset**
  - Supply indicators are richer than the demand indicators
  - In addition, we do not observe the price of a loan (i.e. effective interest rate) offered to the applicants, which limit our analysis to only the quantity of loans
  - Information not captured by the dataset includes the risk profile of the borrowers (for example credit score and debt-service ratio) in the dataset, individuals' wealth and individuals' assets. Only income, age, location, occupation sector and marital status are available
- **Short time series in the dataset**
  - The analysis is constrained to 3 years (2014-2016)
  - The role of demand and supply factors may change depending on the economic environment. Our time period is too short to investigate this hypothesis

Conclusion : We find that supply factors affect household loan approval more than demand. The declining funding ratio due to high net external outflows can potentially explain the moderation of household loan approval growth in 2014-2016



Source: Author's illustration.

BANK NEGARA MALAYSIA
CENTRAL BANK OF MALAYSIA

Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

Profitability, equity capitalization and net worth at risk: update of the former ECCBSO Financial Statement Working Group paper with Spanish, Italian and Turkish data[1]

Merve Artman,
Central Bank of the Republic of Turkey

[1] This paper was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

PROFITABILITY, EQUITY CAPITALIZATION AND NET WORTH AT RISK

Update of the former ECCBSO Financial Statement Working Group paper with Spanish, Italian and Turkish data

Author: Merve Artman,

Abstract

Since 2008-2009 financial crisis, there is still not enough information available for policy evaluation on how companies in different size classes were affected and which non-financial companies were able to participate in the catch-up process in the period. European Committee of Central Balance Sheet Data Offices Financial Statement Analysis Working Group (WG FSA) has produced some studies about the impact of the financial crisis on profitability and equity capitalization, and concentrate on the explanations for the observable differences between European countries. In this paper, we analyse post-crisis financial statements of non-financial companies through the concept of net worth at risk (NWaR) with subsequent two-year losses as conditional and the average of the last eight-year losses as unconditional. NWaR can be considered as very important because it is a kind of stress test to evaluate sector-size level performance when having heavy losses in the countries Spain, Turkey and Italy. The year before and after the financial crisis of 2008, the highest conditional NWaR has been recorded for the large manufacturing companies. As regards to the other sector-size combinations, conditional NWaR results were more severe between the years 2010-2013 due to the subsequent European Crisis implying that the companies should have greater equity cushions. Although conditional NWaR can reflect some country specific characteristics, the recovery has seen in almost all sectors in three countries. Difference between conditional and unconditional NWaR is a kind of way to assess the sensitivity of sector profitability to recessions. The differences between these two important measures have also become smaller after 2013.

Keywords: profitability, capital structure, financial crisis, SMEs, Net Worth at Risk

JEL classification: E32, G32, L25

Table of Contents

PROFITABILITY, EQUITY CAPITALIZATION AND NET WORTH AT RISK[1]

THE RESILIENCE OF THE NON-FINANCIAL CORPORATIONS IN A CRISIS ENVIRONMENT

Introduction

The 2008-09 economic crisis revealed that only little information is available from the macroeconomic national accounts data on the relative severity of the crisis in different parts of the non-financial sector. Besides, little is known how companies in different size classes were affected and which non-financial companies were able to participate in the catch-up process seen in the period after the crisis. In this respect, European Committee of Central Balance Sheet Data Offices Financial Statement Analysis Working Group (WG FSA) conducted a study in 2013 to analyse profitability and equity capitalization in six European countries for the manufacturing, construction and trade sector focusing on the economic crisis in the years 2008-2009 and one year later. For the countries Belgium, Germany, Spain, France, Italy and Portugal, the WG FSA compared these two key financial ratios through quantiles. Because the countries have extensive balance sheet data available for a long time horizon, the group could relate the impact of the recent economic crisis to a longer period. This study is the extension of the former study until the year 2015 with Spain, Italian and Turkish data. Likewise, the former one, this study aims to create a tool for the stress test to evaluate if companies in sector, size and country classification are enough capitalize to afford a period of crisis with possibility of having heavy losses.

DATA AND DEFINITION OF RATIOS

Data

The financial statements used in this study are restricted to corporations and cooperatives. Partnerships and sole proprietorships are excluded. This study covers the period from 1987 to 2015. Depending on the availability of the data source, the starting year is later for some sectors. Individual financial statements that are reported in the form of generally accepted accounting principles (GAAP) are used. For the sectoral coverage, manufacturing, trade and construction are selected due to their importance in contribution to a national economy. Sectors have been differentiated according to the NACE Rev.2 classification. Demolition and site preparation is excluded from the construction sector. For analysing the data according to size classes; micro, small, medium and large enterprises are defined by applying the

[1] Former studies of the FSA WG: Delbreil, Michel; Esteban, Ana; Foulcher, Sandra; Elgg, Dominik; Favale, Vincenzo; Körting, Timm and Varetto, Franco (2005): *Net Worth at Risk*; Brun, Matthieu; Chai, Flavia; Elgg, Dominik; Esteban, Ana; van Gastel, George; Körting, Timm; Momo, Rossella; Nigro, Valentina; Poiares, Rita; Servant, François; Solera, Irune; Vivet, David (2013): *Profitability, Equity Capitalization and Net Worth at Risk. How resilient are non-financial corporations in a crisis environment?*

thresholds for turnover. The corresponding thresholds for separating micro, small, medium and large corporations are £2 million, £10 million and £50 million.

Definition of Ratios

Profitability

In this study, profitability is measured as the ratio of "net income" in the income statement to the total assets in the balance sheet of non-financial corporations. For the total asset used in the denominator of the ratios, adjustments are made for equity. Subscribed capital uncalled (or unpaid), bond redemption premium, intangible fixed assets and investment grands are subtracted from total assets and discounted trade bills are added.

Equity Capitalization

Equity capitalization is the ratio of net worth to total assets. Net worth is simply the amount by which assets exceed liabilities. It is calculated by adding share issues, revaluation reserves, retained earnings, net profit or loss for the financial year and special tax based reserves. Subscribed capital uncalled (or unpaid) and intangible fixed assets are subtracted from the calculation. Net worth is divided by total assets for assessing equity capitalization as a percentage of total capital provision to a company.

Net Worth at Risk (NWaR)

NWaR is the share of cumulative losses (as a percentage of total assets) that companies may have to face with a certain level of confidence calculated over a given period of time. This ratio also serves as a benchmark of minimum capital required in a given sector-size class enabling companies to absorb losses that might potentially arise.

Two NWaR approaches are used: conditional and unconditional NWaR at three confidence levels: 95%, 90% and 80%. The first two levels of confidence represent rather worst-case scenarios and the last displays a rather moderate loss scenario. For practical issues, we use 90% confidence level for the comparison of figures at sector and size levels.

At 90% confidence level, conditional NWaR is calculated as follows: for each company cumulative two-year net income figures in terms of total assets are calculated[2]. From the resulting two-year net income distributions in each sector-size combination the 10th percentile is chosen; resulting in a time series of overlapping two year values. From the time series, the minimum level of the time span 1987-2015 is chosen for conditional NWaR 90%.

For the unconditional NWaR 90%, the mean of the last eight conditional NWaR 90% is used. The differentiation of conditional and unconditional NWaR is important to assess the impact of recessions on the income distribution.

[2] The sum of net income in period t and t+1 is divided by total assets in period t.

Percentage of the Companies with Net Worth below NWaR

The ratio "Percentage of the companies with Net Worth below conditional NWaR" is calculated as a time series, because conditional NWaR represents a worst-case scenario independent of time. However, the ratio "Percentage of the companies with Net Worth below unconditional NWaR" is only represented for the specific year. The ratio is important in that this displays how well a sector is endowed with equity to cope with the NWaR loss scenario.

COUNTRY EXPERIENCES BETWEEN THE YEARS 1987-2015[3]

Spain

Two-year cumulative losses for the whole time span reveal that the couple of years for the worst losses in all size classes of manufacturing companies is 1992/1993. This ratio is the highest for the micro companies with -48.1. Large companies has higher ratio than medium and small companies with -35.0. This result is similar for the actual losses for the financial crisis (2008/2009). The losses is the worst for the micro companies with -39.7. Large companies still have the higher ratio than small and medium companies do in 2008/2009 however closer values to these size classes than in 1992/1993 figures. After the financial crisis, couple of years with the worst losses for the micro companies is 2011/2012. Although the year with the highest risk values for different size classes of the manufacturing companies can change from 2009 to 2012, for all them, the recovery in profitability has started from 2013. Like the manufacturing sector, the couple of years for the worst losses in all size classes of trade sector are also 1992/1993.

Spain- Unconditional Net Worth at Risk and Cumulative two year losses at 10th percentile

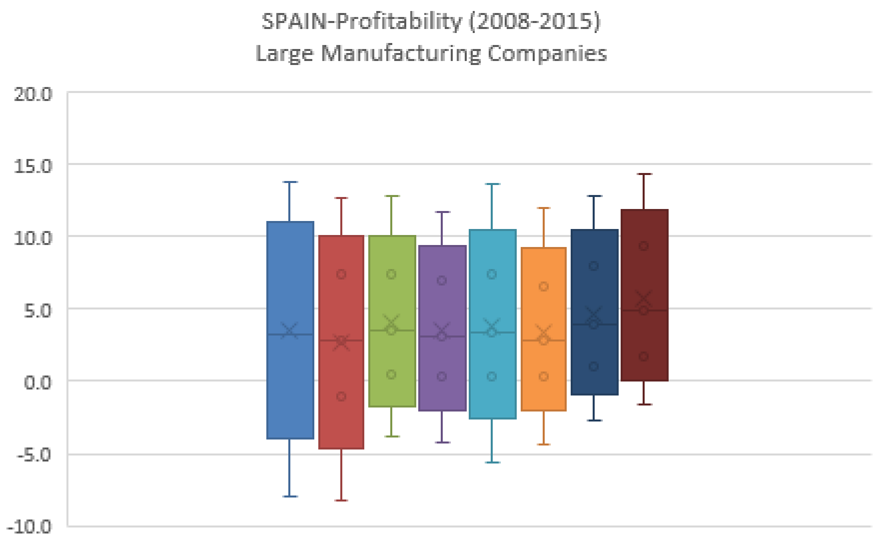
Manufacturing, Trade and Construction Companies (NACE Rev.2 C,G,F sectors)

Table 1

	07/08	08/09	09/10	10/11	11/12	12/13	13/14	14/15	Unconditional
C-micro	-26.9	-39.7	-43.3	-43.0	**-45.7**	-43.2	-33.7	-25.6	-37.6
G-micro	-34.7	-43.7	-44.1	-45.4	-50.2	**-51.1**	-47.3	-39.6	-44.5
F-micro	-33.6	-42.7	-45.2	-46.8	**-48.4**	-42.9	-34.2	-26.5	-40.0
C-small	-2.7	-7.2	-7.1	**-8.2**	-7.0	-6.3	-3.9	-0.8	-5.4
G-small	-1.1	-4.6	-5.0	-5.5	**-6.9**	-5.6	-3.4	-0.8	-4.1
F-small	-0.7	-3.3	-6.5	-11.9	**-12.2**	-9.5	-7.5	-2.7	-6.8
C-medium	-5.5	-11.7	**-12.0**	-8.9	-9.2	-8.2	-5.5	-2.7	-7.9
G-medium	-1.9	-6.2	-5.5	-5.5	**-7.4**	-5.5	-3.6	-1.6	-4.7
F-medium	0.0	-3.2	-10.8	-12.4	**-19.9**	-18.6	-12.4	-5.9	-10.4
C-large	-8.6	**-12.7**	-11.2	-7.0	-9.0	-9.9	-6.2	-3.4	-8.5
G-large	-4.2	-7.0	-9.2	-6.1	**-10.6**	-7.0	-4.6	-3.3	-6.5
F-large	-0.2	-6.6	-4.3	-10.1	-14.3	**-21.4**	-14.0	-10.6	-10.2

[3] Please note that in this study, there are data for previous years but the table is restricted to the last 8 years

The level of the worst-case loss and the loss in financial crisis time is much worse in micro trade companies compared to manufacturing micro. Although, on average profitability is higher in small, medium and large manufacturing companies than the same size of trade companies, the risk level of loss is higher due to the higher percentage of the companies with negative net profit or loss to total assets ratio. For the micro trade companies, the worst losses has seen in 2012/2013, the ratio -51.1 is worse than the 2008 crisis year ratio of -43.7. For other size classes of trade sector, the worst losses after crisis has seen one year before in 2011/2012 and the ratio is worse than the crisis year ratio similar to the micro companies. Likewise, the manufacturing sector, the recovery has started from 2013. For the construction sector, the couple of the years with worst losses is 2011/2012 after the financial crisis. The conditional NWaR of the micro construction companies is -48.4, very close to the micro manufacturing NWaR (-48.1) and lower than the micro trade NWaR (-54.1). The difference between the conditional and unconditional NWaR is the highest in large construction companies because the worst loss in 2012/2013 is differently higher than other years after the financial crisis. In 2012, the dispersion between lowest and highest percentile profitability is the highest since 1987. 2015 is the year of increasing in profitability of construction sector except for the large companies. In this year, the median profitability is the highest for small companies.



Unconditional net worth at risk, the mean of the years 2007/2008 to 2014/2015, is lower than the conditional NWaR for all size classes of manufacturing. In addition, the results are lower than the actual losses for the financial crisis. However, for the micro and small companies these results are very close. The differentiation of the conditional and unconditional NWaR is important to assess the impact of recessions on the income distribution. Therefore, it can be said that manufacturing companies have recovered better after the crisis as size increases. For the trade sector, the mean of the worse loss levels are lower in all sizes than manufacturing sector. Although, the average profitability is higher in manufacturing sector, the dispersion between the 90th and the 10th percentile of profitability ratio is also higher for all size classes.

The reduction of the percentage of the companies with capital below NWaR is a good indicator to show how well a sector is endowed with equity to cope with NWaR loss scenario. For micro manufacturing companies, this percentage is in a declining trend after 2008. In addition, percentage of the companies with equity over total assets higher than 50% has increased in the same period. The increase in the equity ratio can be caused either from the contraction of the total assets or an increase in equity. 2014 and 2015 are the good years for the large manufacturing companies in terms of profitability and net worth. Equity capitalization below zero is higher in micro trade companies than other size classes of trade sector. We can see more companies in the highest range (over 50% equity capitalization ratio) in small and medium sized trade companies. For the large construction companies, different from large companies in other sectors, the percentage of the companies with net worth to total assets ratio over 50% is very low. The percentage of the companies is concentrated between the ratios of 10% and 25% in this sector-size level. Therefore, the capability of large construction companies to cope with the NWaR loss scenario is worse than the other large companies in the manufacturing and trade sector. As a result, the percentage of companies that cannot cope with the loss scenario has decreased in these years. In 2015, the percentage of companies with capital below NWaR is the lowest in all the sectors and sizes.

Spain-Percentage of the Companies with capital below Unconditional NWAR

Manufacturing, Trade and Construction Companies (NACE Rev.2 C,G,F sectors)

Table 2

	2007	2008	2009	2010	2011	2012	2013	2014	2015
C-micro	**63.8**	61.9	60.6	60.1	58.7	56.5	56.3	55.2	52.8
G-micro	**74.0**	72.3	70.7	69.7	68.6	66.6	66.4	65.9	64.2
F-micro	**66.0**	65.6	64.2	62.7	61.1	58.7	57.6	56.3	54.8
C-small	**6.9**	5.7	5.8	5.5	5.8	5.1	4.8	4.8	3.9
G-small	**9.1**	8.1	8.1	7.7	7.7	8.0	7.3	6.7	5.6
F-small	**17.0**	12.9	11.9	11.8	12.3	9.9	6.7	6.9	4.5
C-medium	6.6	6.5	8.8	**9.5**	8.4	8.2	6.1	6.7	6.2
G-medium	6.6	6.8	6.7	7.5	7.7	**7.9**	7.4	7.7	7.2
F-medium	19.9	17.9	18.1	**24.7**	20.5	16.8	20.1	16.2	7.1
C-large	7.0	9.0	10.1	10.2	9.5	**10.4**	10.1	9.3	7.9
G-large	13.3	13.7	13.4	13.4	12.8	**14.9**	13.3	12.1	10.1
F-large	4.6	6.2	6.5	7.1	**12.6**	10.3	11.2	10.3	10.8

As a measure of spread in the lower distribution, the interpercentile range between the 80% and 95% conditional NWaR may be used. For the micro companies, the year with the highest range is 2011 and for the trade companies, the spread is wider in the low distribution. As the size increases, the highest dispersion went back to the financial crisis years. For the construction companies, 2013 is the year for the highest differences.

Italy

Two year cumulative losses for the whole time span show that the years with worst losses are in the crisis period of 1992/1993[4] for all firms' sectors of activities. In particular, for manufacturing companies the income losses during the financial crisis are very close to the conditional NWaR value. In fact, in the whole time horizon, the

[4] Please note that Italian data has a jump in the sample size for micro and small firms between 1992 and 1993

distribution of NWaR is quite stable, less cyclical than in Spain and Turkey. Micro firms had greater losses: the range of their NWaR is between -15 to -30; for the other size classes is between -1 to -12. After 2009/2010, the recovery started in the manufacturing sector for all size classes. In recent years, median profitability has overshot the pre-crisis level. As regards the companies active in the trade sector, they had the worst actual losses in the years 1992/1993 and 1993/1994. At each size level, conditional NWaR is very similar to manufacturing figures.

Italy - Unconditional Net Worth at Risk and Cumulative two year losses at 10th percentile

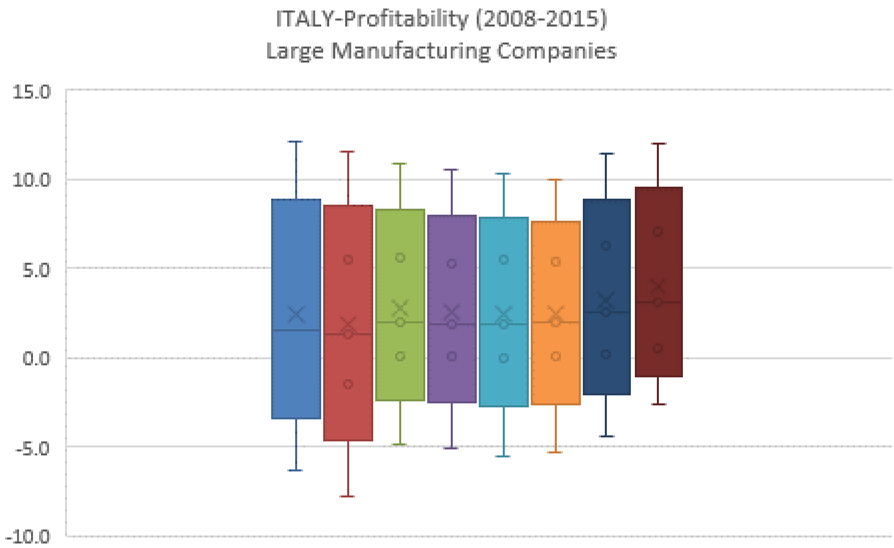
Manufacturing, Trade and Construction Companies (NACE Rev.2 C,G,F sectors)

Table 3

	07/08	08/09	09/10	10/11	11/12	12/13	13/14	14/15	Unconditional
C-micro	-20.4	-23.1	-24.0	-20.1	**-21.1**	-21.1	-19.1	-15.2	-20.5
G-micro	-24.1	-25.7	-24.7	-23.5	-25.5	**-26.6**	-24.1	-20.3	-24.3
F-micro	-9.4	-10.2	-10.2	-10.1	**-11.9**	-13.2	-13.2	-10.9	-11.1
C-small	-6.3	-8.5	-8.3	**-6.6**	-6.9	-6.5	-4.9	-3.1	-6.4
G-small	-5.1	-6.2	-5.6	-5.3	**-6.6**	-6.9	-5.4	-2.9	-5.5
F-small	-2.1	-2.5	-2.6	-3.0	**-4.2**	-5.2	-4.6	-2.6	-3.3
C-medium	-6.2	-8.0	**-8.4**	-6.0	-7.2	-6.5	-4.6	-3.1	-6.3
G-medium	-4.5	-5.6	-4.9	-4.9	**-5.8**	-6.2	-4.4	-2.0	-4.8
F-medium	-1.5	-2.2	-2.0	-2.8	**-5.8**	-5.1	-5.3	-2.7	-3.4
C-large	-7.9	**-10.5**	-10.6	-8.4	-9.3	-9.2	-8.1	-5.1	-8.6
G-large	-4.6	-5.5	-4.3	-3.6	**-4.9**	-6.5	-5.2	-3.3	-4.7
F-large	0.0	-0.8	-0.3	-3.6	-3.7	**-5.8**	-4.6	-0.4	-2.4

The worst years 9 are 2012/2013 for all size classes of trade companies after the actual losses of 2008/2009. As regards the construction sector, after the great financial crisis, the worst years were during the European Crisis (2012/2013) similarly to the trade sector. In 2015, the percentage of the companies in the highest profitability class (above 5%) increased for all size classes of the construction sector.

Unconditional NWaR is lower than the conditional NWaR for all size classes of manufacturing. The difference has increased as the size decreased. Therefore, like the Spanish companies, Italian manufacturing companies have recovered better after the crisis as size level increases.



After 2011, firms' capitalization improved: for all sector and size combinations, the percentage of companies with capital below NWaR is in a declining trend. Micro firms appear relatively undercapitalised, especially in the trade sector where there is the highest percentage of the companies with net worth below NWaR. Among the large firms, manufacturing companies are the least capitalized.

Also, the percentage of companies with equity capitalization over 50% has increased in the same period. The increase in the equity ratio can be caused either from the contraction of the total assets or an increase in equity. The upper percentile level of net worth to total asset ratio has increased after 2013. Also, the net profit ratio has increased in these years, this may imply the net worth increase due to the increase in the net profit.

Italy -Percentage of the Companies with capital below Unconditional NWaR 90%

Manufacturing, Trade and Construction Companies (NACE Rev.2 C,G,F sectors)

Table 4

	2007	2008	2009	2010	2011	2012	2013	2014	2015
C-micro	**63.9**	60.6	59.9	60.2	59.7	58.8	58.1	57.6	55.6
G-micro	**69.8**	67.6	66.6	65.9	65.6	64.5	63.9	63.2	61.5
F-micro	**53.7**	52.4	51.7	50.1	48.8	47.2	45.7	43.8	40.4
C-small	**29.7**	25.7	23.8	24.3	25.2	23.7	22.7	21.7	20.0
G-small	**35.1**	32.5	31.5	30.6	31.1	29.8	28.5	26.8	24.5
F-small	**30.5**	29.6	28.1	27.4	26.9	26.4	24.7	22.8	19.6
C-medium	**17.0**	13.8	12.5	13.5	13.5	13.5	11.9	11.0	9.3
G-medium	**25.7**	22.6	21.7	21.3	22.1	21.0	20.0	18.7	15.4
F-medium	**25.5**	24.3	22.9	23.6	24.0	24.5	25.1	23.1	22.8
C-large	**15.5**	13.6	12.9	13.7	13.2	14.0	13.0	11.8	9.9
G-large	**24.2**	22.5	21.1	19.6	20.1	18.6	17.2	15.5	14.5
F-large	18.6	13.2	20.0	19.7	26.5	**27.2**	23.7	20.7	19.5

The interpercentile range between the 80% and 95% conditional NWAR is the highest for the micro trade companies; the years just before and after the financial crisis showed the highest dispersion. For the other size classes, the years between 2010 and 2012 represented the highest results.

Turkey

Two year cumulative losses for the whole time span reveal that the couple of years with worst losses are the years of financial crisis in Turkey. The NWaR in these years are higher than the actual losses in the 2008/2009 financial crisis. The years with the lowest profitability levels have changed according to sector size combinations. For the micro manufacturing companies, these are 1994/1995; for small and medium sized; the years just before and after the financial crisis of 2001; for large companies; these years are exactly the financial crises of 2008. In the trade sector results, it can be said that 2001 crisis had the important effect on the profitability of the companies. The couple of the years with the worst losses have fluctuated around 2001. The results have been valid for the construction companies except for the medium and large companies with the worst result in 2014/2015: probably due to the geopolitical unrest in the countries that these companies working with and the exchange rate effect. Exchange rate effect also decreased the profitability of large manufacturing companies in these years due to the fact that the majority of the FX debt is belonged to the large corporates in Turkey.

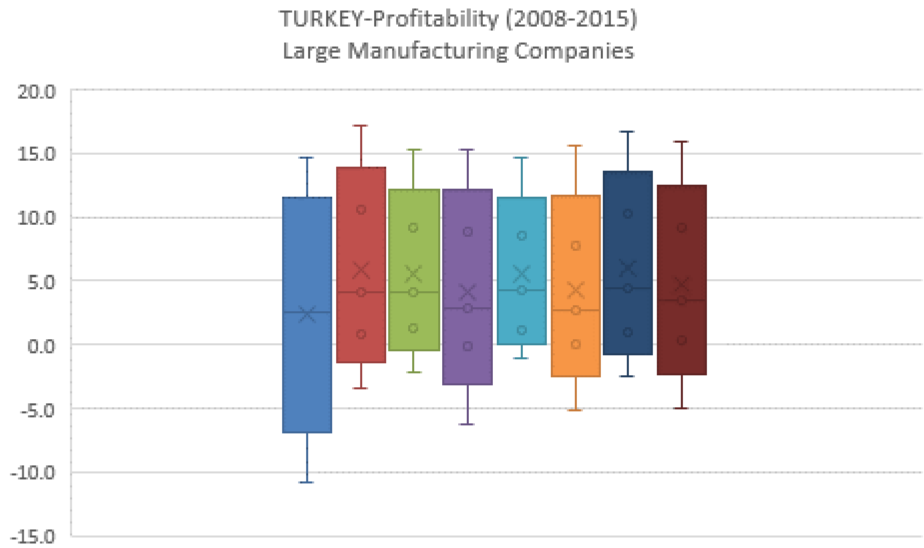
Turkey - Unconditional Net Worth at Risk and Cumulative two year losses at 10th percentile

Manufacturing, Trade and Construction Companies (NACE Rev.2 C,G,F sectors)

Table 3

	07/08	08/09	09/10	10/11	11/12	12/13	13/14	14/15	Unconditional
C-micro	-13.3	-17.8	-17.7	-27.6	**-30.0**	-24.6	-25.1	-27.8	-23.0
G-micro	-11.3	-16.9	-19.2	-21.6	-32.7	**-9.8**	-13.2	-22.3	-18.4
F-micro	-8.1	-10.6	-12.8	-21.7	**-19.9**	-14.3	-16.9	-14.0	-14.8
C-small	-9.9	-14.7	-12.1	**-19.3**	-16.1	-7.7	-12.0	-10.2	-12.7
G-small	-6.5	-9.1	-5.9	-15.0	**-15.4**	-5.3	-7.6	-7.8	-9.1
F-small	-3.2	-5.0	-4.8	-17.9	**-11.3**	-11.4	-9.4	-8.7	-9.0
C-medium	-10.5	-14.7	**-6.2**	-9.9	-8.6	-4.4	-5.6	-5.4	-8.2
G-medium	-9.1	-12.9	-4.8	-10.2	**-7.9**	-1.6	-3.8	-3.8	-6.7
F-medium	-1.5	-7.5	-6.2	-11.3	**-12.3**	-6.0	-7.1	-17.0	-8.6
C-large	-9.4	**-11.2**	-4.4	-6.8	-5.7	-6.0	-6.2	-6.9	-7.1
G-large	-3.2	-8.7	-4.7	-5.3	**-4.5**	-3.0	-3.0	-3.4	-4.5
F-large	-2.3	-5.1	-2.2	-4.6	-5.5	**1.2**	-2.9	-5.5	-3.4

After 2008 financial crisis, the years with the worst losses are 2010/11 or 2011/12. These are the years of the subsequent European Crisis after the Great financial crisis of 2008. Due to the international trade relations, it is not surprising that the companies in Turkey have also experienced lower profitability figures in these years. 2010/2012 are also the years of rapid credit growth. In these years, the dispersion between low and high percentile of profitability has increased.



Unconditional NWaR results have been more moderate than the conditional NWAR because after 2001 crisis, there are so many precautions have been taken in Turkey for debt management and the stability of the banking sector. Therefore, the losses after 2001 did not generally match the high level of losses recorded in early years. The unconditional NWaR is the lowest for the large construction companies; the profitability of the construction has increased and contributed most to the GDP of the country.

Percentage of the companies with capital below unconditional NWaR reveals that after 2012, for all sizes and sector combinations the percentages have increased, the capability to cope with the loss have decreased. After 2001, net worth to total assets ratio has decreased for the large trade companies. This is either because of the percentage of bank credit increase in the total assets and the decrease in equity; or just decrease in equity due to the decrease in the profitability at that class. The percentage of the companies in the low-level class, the ratio of the class level of profitability between 0% and 1%, has increased in these years. In terms of the large companies' profitability, the average of the high-upper percentile of the profitability is the highest in large construction companies among the others.

Likewise, the other countries, the interpercentile range between the 80% and 95% conditional NWaR is the highest for the micro trade companies around the year 2011. The years just before and after the financial crisis showed the highest dispersion as the size classes increases. Like in the Spain, 2013 showed the highest spread in the lower distribution.

Turkey -Percentage of the Companies with capital Below Unconditional NWAR

Manufacturing, Trade and Construction Companies (NACE Rev.2 C,G,F sectors)

Table 6

	2007	2008	2009	2010	2011	2012	2013	2014	2015
C-micro	15.6	19.7	19.1	21.4	31.7	28.9	34.7	39.2	**38.8**
G-micro	18.1	19.1	26.3	24.3	33.7	33.9	41.5	53.1	**49.0**
F-micro	26.4	32.0	29.0	37.0	43.4	42.0	52.4	**59.3**	57.3
C-small	5.6	9.4	8.0	9.7	19.0	12.1	16.9	**23.5**	22.8
G-small	6.0	10.6	11.9	10.0	20.6	16.6	22.1	**25.3**	24.0
F-small	21.6	24.5	24.5	21.7	38.1	28.2	30.7	36.7	**39.1**
C-medium	1.8	6.2	3.5	3.9	7.2	4.4	6.2	7.5	**10.5**
G-medium	4.3	10.5	6.2	6.2	12.2	8.5	11.0	**13.0**	11.9
F-medium	18.8	26.5	22.5	19.0	29.5	20.3	27.2	33.3	**36.2**
C-large	0.2	**5.9**	1.0	1.3	5.6	2.4	4.4	2.5	4.6
G-large	3.3	**8.1**	5.8	4.6	**8.1**	4.3	4.6	6.1	4.5
F-large	0.0	0.0	5.3	2.2	8.2	8.6	5.0	**13.5**	7.1

CONCLUSION

Micro level analysis for non-financial corporations at sector and size level and their cross-country comparisons is crucial to understand the performance of the real sector and develop macroeconomic policies accordingly. Financial Statement Analysis Working Group that is a sub-group of European Committee of Central Balance Sheet Data Offices performs common microeconomic research on specific topics of the economic and financial situation of the non-financial entities in an international setting. The group introduced the concept of “Net Worth at Risk” as a kind of stress test evaluate if companies in sector, size and country classification are enough capitalize to afford a period of crisis with possibility of having heavy losses. This study is an update of the previous study from 1987 to 2015 for the countries Spain, Italy and Turkey.

Net Worth at Risk is an important concept to evaluate if companies in sector, size and country classification are enough capitalize to afford a period of crisis with possibility of having heavy losses. Conditional NWaR is the share of cumulative (as a percentage of total assets) that companies may have to face with %95,%90 and %80 confidence level calculated for consecutive two years. The mean of the last eight overlapping years is unconditional NWaR influenced by the business cycle of the countries. Before 2008, the highest conditional NWaR belonged to the years 1992/1993 in Spain and Italy. NWaR values showed that Spain had stronger deterioration in losses because of high inflation and interest rates in these years. In Turkey, the highest conditional NWaR has experienced in the years of financial crisis of 1994 and 2001. Following lower profitability figures before 2008, manufacturing generally has the highest conditional NWAR for all levels of confidence and independently of size. This could be explained by a higher performance of costs in times of crisis due to the rigidity of labour costs and the capital intensity in this sector.

It is also noticeable that the last crisis did not generally match the high level of losses recorded in earlier 1990s or 2000s.

From 2008 to 2015, NWaR results have been more severe between the years 2010-2012 due to the subsequent European Crisis after the Great Financial Crisis of 2008. These are also the years of the credit enlarging, the figures show us the dispersion between the profitability of the lower and upper quartile has increased for micro, small and medium companies in these years. This implies that the companies particularly in the lower percentile should have a greater equity cushion to handle a possible recession. In Turkey, it is noticeable that manufacturing and trade companies of same size has experienced the worst NWaR in the same years after 2008. Medium and large construction companies have lower profitability figures in the years 2014/2015 due to the some geopolitics unrest in the regions working and the exchange rate effect. However, in general for all three countries, the recovery has seen after 2013 in the profitability figures. The percentage of the companies with capital below NWaR has decreased after this year. Although conditional NWaR can reflect some country specific characteristics, the recovery have seen in almost all sectors in three countries. Difference between conditional and unconditional NWaR is a kind of way to assess the sensitivity of sector profitability to recessions and these differences have become smaller after 2013.

Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

Profitability, equity capitalization and net worth at risk: update of the former ECCBSO Financial Statement Working Group paper with Spanish, Italian and Turkish data[1]

Merve Artman,

Central Bank of the Republic of Turkey

[1] This presentation was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

Profitability, Equity Capitalization and Net Worth at Risk

ECCBSO Financial Statement Analysis Working Group

30 August 2018 | 9th biennial IFC conference

AGENDA

- Motivation and Importance

- Profitability, Equity Capitalization, Net Worth at Risk

MOTIVATION AND IMPORTANCE

Motivation and Importance

Financial Statement Analysis Working Group (WG FSA)

- Working Group of The European Committee of Central Balance-Sheet Data Offices (ECCBSO)
- Scope is common microeconomic research on specific topics of the economic and financial situation of non-financial entities in an international setting.
- Any field of financial statement analysis like profitability, equity endowment, liability structure or asset composition.
- Structural, cross-sectional and time-series analyses are mainly applied.
- Investigate whether accounting or institutional characteristics can explain differences in the results.

Motivation and Importance

NET WORTH AT RISK (NWaR)

- The concept first introduced by FSA WG in 2005

- NWaR can be considered as very important because it is a kind of stress test to evaluate sector-size level performance when having heavy losses

- Serves as a benchmark of minimum capital required in a given sector-size class enabling companies to absorb losses that might potentially arise

- For each company cumulative two-year net income figures in terms of total assets are calculated

- From the resulting two-year net income distributions in each sector-size combination, the 10th percentile is chosen, resulting in a time series of overlapping two-year values negative values result normally, these time series are consequently labeled Two-year Losses 90%.

Conditional and Unconditional NWaR

- Conditional NWaR is calculated as follows: for each company cumulative two-year net income figures in terms of total assets are calculated . From the resulting two-year net income distributions in each sector-size combination the 10th percentile is chosen; resulting in a time series of overlapping two year values. From the time series, the minimum level of the time span 1987-2015 is chosen for conditional NWaR 90%.

- For the unconditional NWaR 90%, the mean of the last eight conditional NWaR 90% is used. The differentiation of conditional and unconditional NWaR is important to assess the impact of recessions on the income distribution.

- Percentage of the companies with Net Worth below conditional NWaR” is important in that this displays how well a sector is endowed with equity to cope with the NWaR loss scenario.

Profitability, Equity Capitalization and Net Worth at Risk

Unconditional Net Worth at Risk and Cumulative two year losses at 10th percentile

Spain- Unconditional Net Worth at Risk and Cumulative two year losses at 10th percentile

Manufacturing, Trade and Construction Companies (NACE Rev.2 C,G,F sectors)

Table 1

	07/08	08/09	09/10	10/11	11/12	12/13	13/14	14/15	Unconditional
C-micro	-26.9	-39.7	-43.3	-43.0	**-45.7**	-43.2	-33.7	-25.6	-37.6
G-micro	-34.7	-43.7	-44.1	-45.4	-50.2	**-51.1**	-47.3	-39.6	-44.5
F-micro	-33.6	-42.7	-45.2	-46.8	**-48.4**	-42.9	-34.2	-26.5	-40.0
C-small	-2.7	-7.2	-7.1	**-8.2**	-7.0	-6.3	-3.9	-0.8	-5.4
G-small	-1.1	-4.6	-5.0	-5.5	**-6.9**	-5.6	-3.4	-0.8	-4.1
F-small	-0.7	-3.3	-6.5	-11.9	**-12.2**	-9.5	-7.5	-2.7	-6.8
C-medium	-5.5	-11.7	**-12.0**	-8.9	-9.2	-8.2	-5.5	-2.7	-7.9
G-medium	-1.9	-6.2	-5.5	-5.5	**-7.4**	-5.5	-3.6	-1.6	-4.7
F-medium	0.0	-3.2	-10.8	-12.4	**-19.9**	-18.6	-12.4	-5.9	-10.4
C-large	-8.6	**-12.7**	-11.2	-7.0	-9.0	-9.9	-6.2	-3.4	-8.5
G-large	-4.2	-7.0	-9.2	-6.1	**-10.6**	-7.0	-4.6	-3.3	-6.5
F-large	-0.2	-6.6	-4.3	-10.1	-14.3	**-21.4**	-14.0	-10.6	-10.2

Unconditional Net Worth at Risk and Cumulative two year losses at 10th percentile

Italy - Unconditional Net Worth at Risk and Cumulative two year losses at 10th percentile

Manufacturing, Trade and Construction Companies (NACE Rev.2 C,G,F sectors)

Table 3

	07/08	08/09	09/10	10/11	11/12	12/13	13/14	14/15	Unconditional
C-micro	-20.4	-23.1	-24.0	-20.1	**-21.1**	-21.1	-19.1	-15.2	-20.5
G-micro	-24.1	-25.7	-24.7	-23.5	-25.5	**-26.6**	-24.1	-20.3	-24.3
F-micro	-9.4	-10.2	-10.2	-10.1	**-11.9**	-13.2	-13.2	-10.9	-11.1
C-small	-6.3	-8.5	-8.3	**-6.6**	-6.9	-6.5	-4.9	-3.1	-6.4
G-small	-5.1	-6.2	-5.6	-5.3	**-6.6**	-6.9	-5.4	-2.9	-5.5
F-small	-2.1	-2.5	-2.6	-3.0	**-4.2**	-5.2	-4.6	-2.6	-3.3
C-medium	-6.2	-8.0	**-8.4**	-6.0	-7.2	-6.5	-4.6	-3.1	-6.3
G-medium	-4.5	-5.6	-4.9	-4.9	**-5.8**	-6.2	-4.4	-2.0	-4.8
F-medium	-1.5	-2.2	-2.0	-2.8	**-5.8**	-5.1	-5.3	-2.7	-3.4
C-large	-7.9	**-10.5**	-10.6	-8.4	-9.3	-9.2	-8.1	-5.1	-8.6
G-large	-4.6	-5.5	-4.3	-3.6	**-4.9**	-6.5	-5.2	-3.3	-4.7
F-large	0.0	-0.8	-0.3	-3.6	-3.7	**-5.8**	-4.6	-0.4	-2.4

Unconditional Net Worth at Risk and Cumulative two year losses at 10th percentile

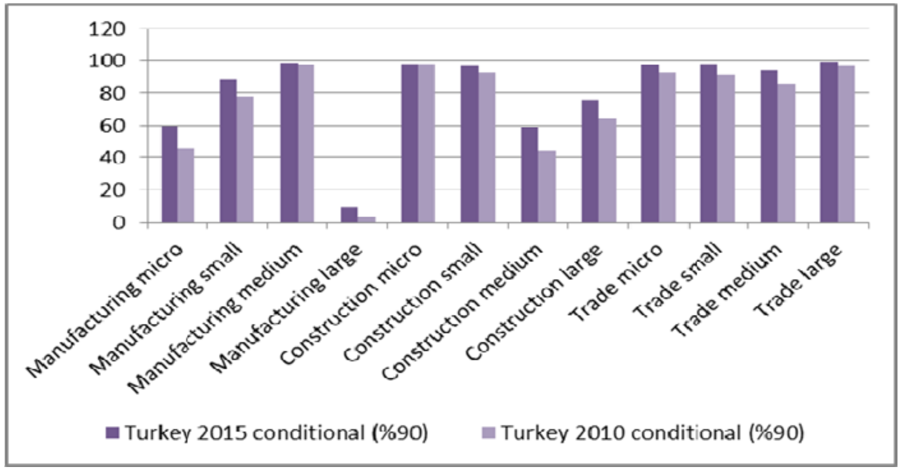
Turkey - Unconditional Net Worth at Risk and Cumulative two year losses at 10th percentile

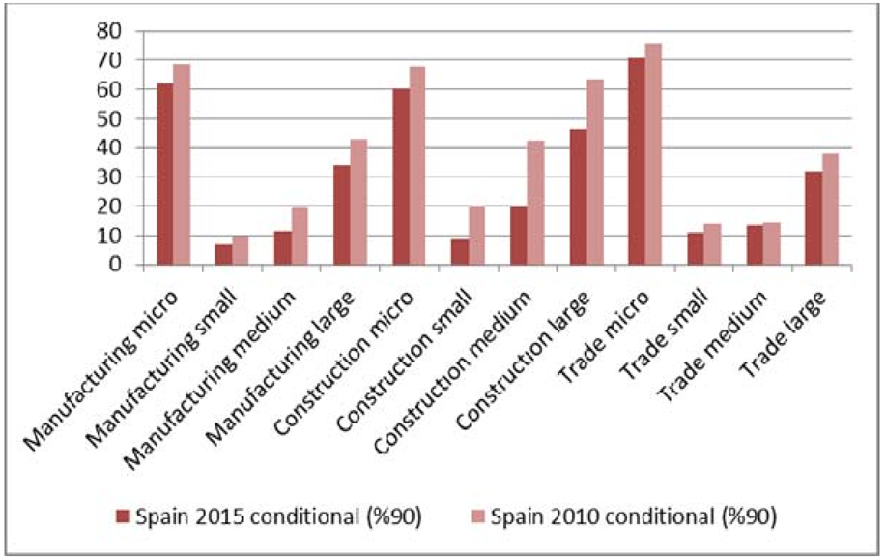
Manufacturing, Trade and Construction Companies (NACE Rev.2 C,G,F sectors)

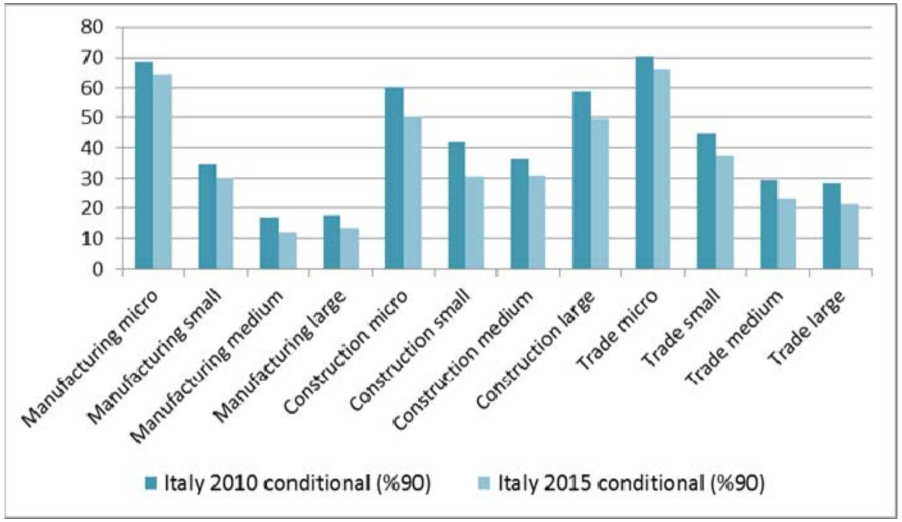
Table 3

	07/08	08/09	09/10	10/11	11/12	12/13	13/14	14/15	Unconditional
C-micro	-13.3	-17.8	-17.7	-27.6	**-30.0**	-24.6	-25.1	-27.8	-23.0
G-micro	-11.3	-16.9	-19.2	-21.6	-32.7	**-9.8**	-13.2	-22.3	-18.4
F-micro	-8.1	-10.6	-12.8	-21.7	**-19.9**	-14.3	-16.9	-14.0	-14.8
C-small	-9.9	-14.7	-12.1	**-19.3**	-16.1	-7.7	-12.0	-10.2	-12.7
G-small	-6.5	-9.1	-5.9	-15.0	**-15.4**	-5.3	-7.6	-7.8	-9.1
F-small	-3.2	-5.0	-4.8	-17.9	**-11.3**	-11.4	-9.4	-8.7	-9.0
C-medium	-10.5	-14.7	**-6.2**	-9.9	-8.6	-4.4	-5.6	-5.4	-8.2
G-medium	-9.1	-12.9	-4.8	-10.2	**-7.9**	-1.6	-3.8	-3.8	-6.7
F-medium	-1.5	-7.5	-6.2	-11.3	**-12.3**	-6.0	-7.1	-17.0	-8.6
C-large	-9.4	**-11.2**	-4.4	-6.8	-5.7	-6.0	-6.2	-6.9	-7.1
G-large	-3.2	-8.7	-4.7	-5.3	**-4.5**	-3.0	-3.0	-3.4	-4.5
F-large	-2.3	-5.1	-2.2	-4.6	-5.5	**1.2**	-2.9	-5.5	-3.4

PERCENTAGE OF COMPANIES WITH EQUITY BELOW UNCONDITIONAL NWaR COMPARISION FOR YEARS 2010 AND 2015

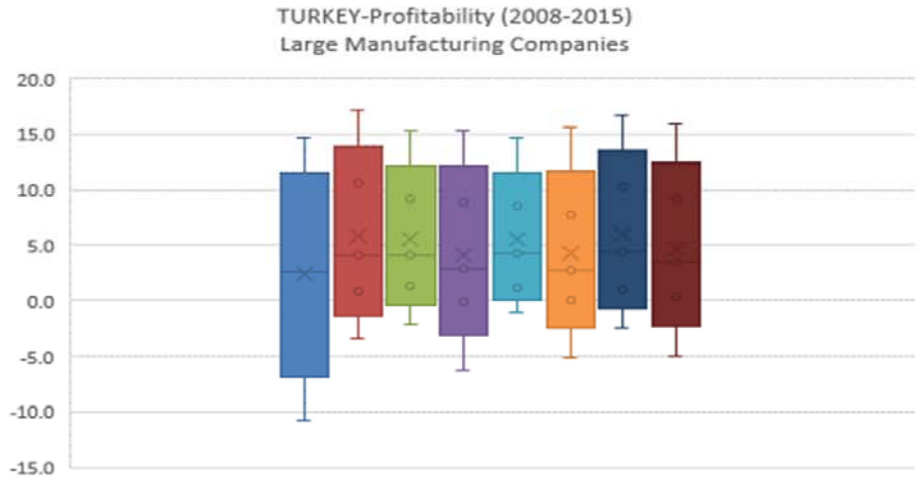


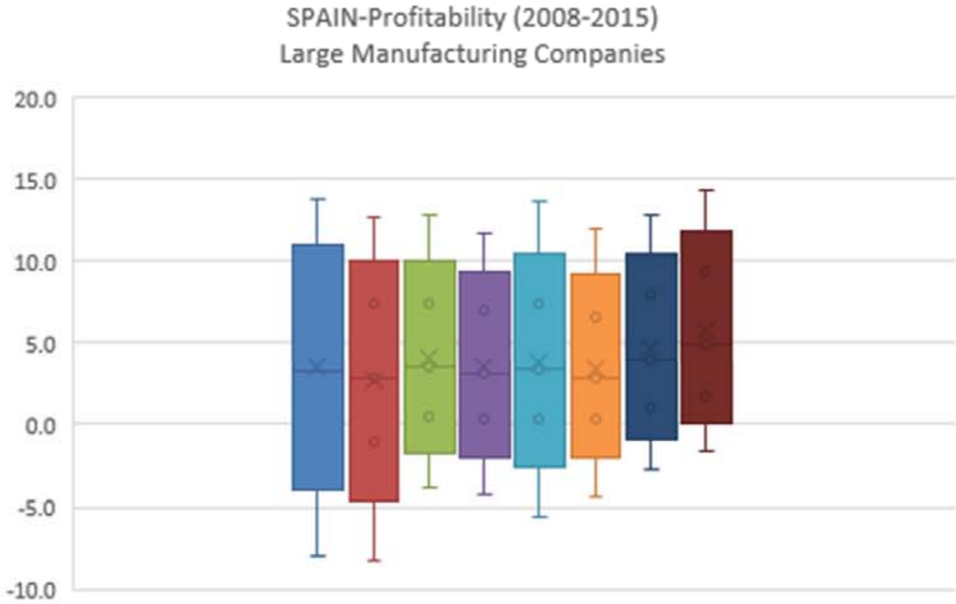


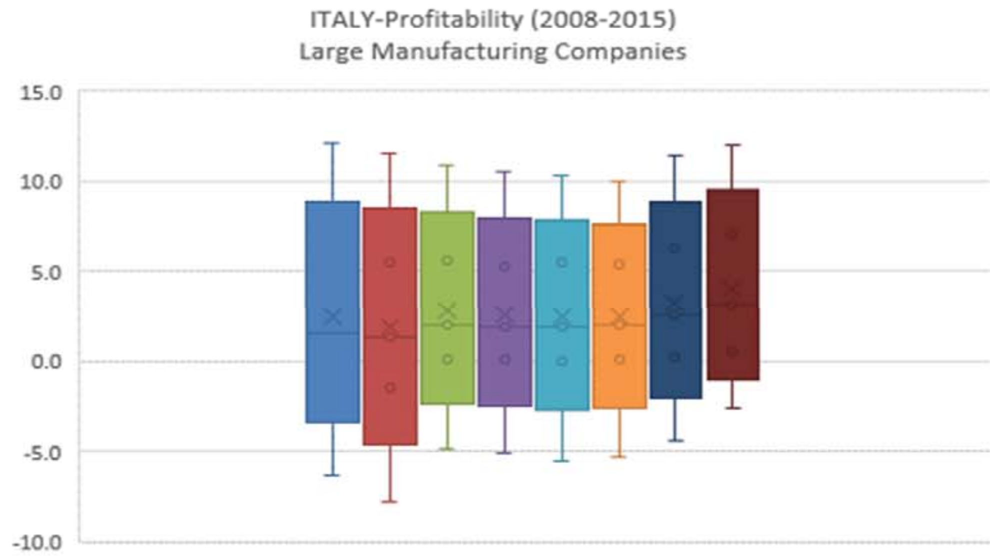


PROFITABILTY-LARGE MANUFACTURING COMPANIES

Net Profit or Loss/Total Assets (2008-2015)



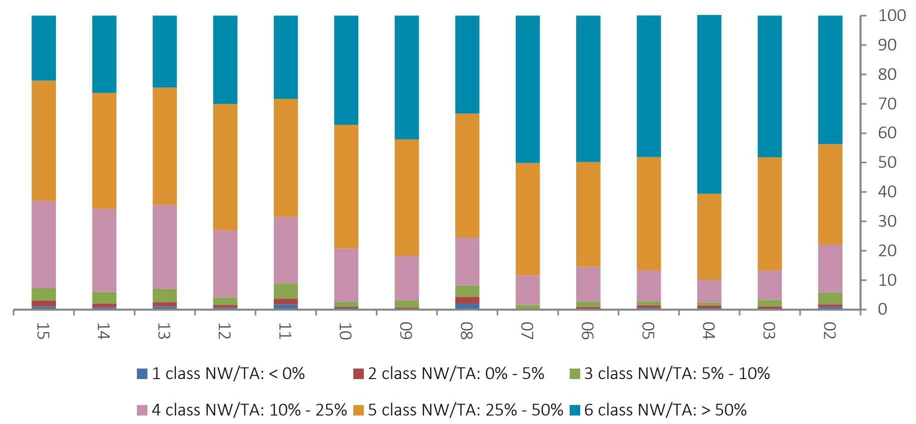




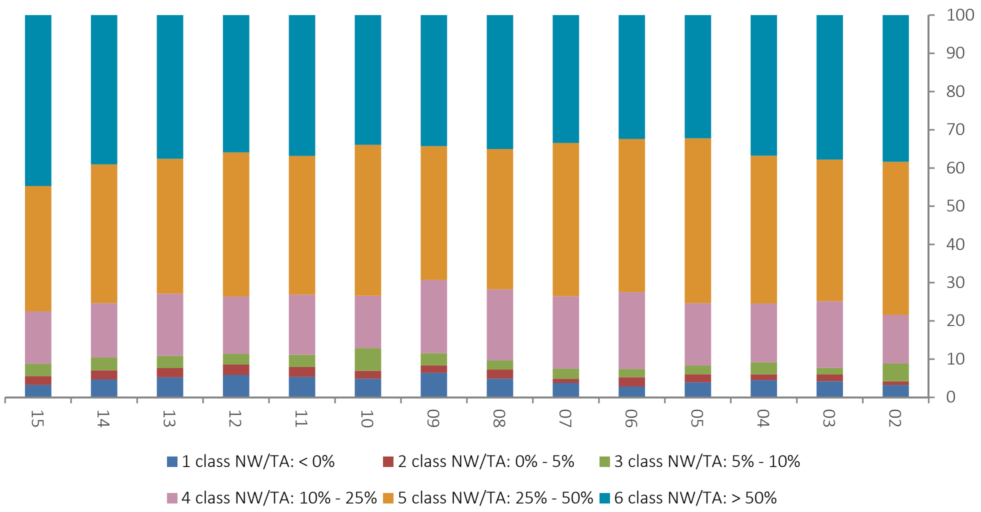
EQUITY CAPITALIZATION-LARGE MANUFACTURING COMPANIES

Net Worth/Total Assets (2002-2015)

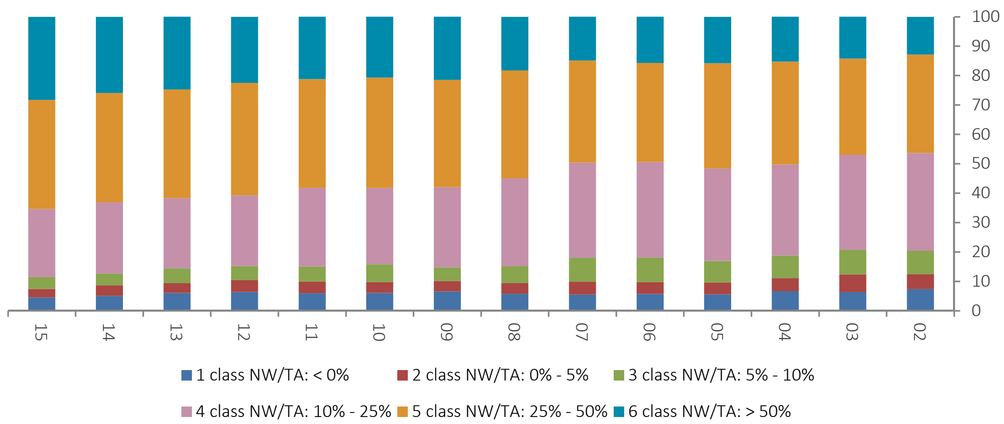
TURKEY



SPAIN



ITALY



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BANK FOR INTERNATIONAL SETTLEMENTS

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Sharing of data reported by complex multinational enterprises: a cooperative approach between Deutsche Bundesbank and Bank of France[1]

Tatiana Mosquera Yon, Bank of France
and Jens Walter, Deutsche Bundesbank

[1] This paper was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

Sharing of data reported by complex multinational enterprises: a cooperative approach between Deutsche Bundesbank and Banque de France

Tatiana Mosquera Yon (Banque de France) and Jens Walter (Deutsche Bundesbank)

Abstract

The financial crisis raised concerns about the worldwide interconnectedness of financial institutions and their ability to finance the economy. In the real economy, multinational enterprises generate more and more economic and financial flows due to their international organisation. In order to better understand and explain the contribution of multinational enterprises in their Balance of Payments (BoP), France and Germany undertook a common work on large and complex multinational enterprises operating in the two countries. Based on two work streams: an inter-institutional and an external one (in collaboration with the multinational enterprises), implying exchange of confidential information between institutions, this analysis improved the knowledge on the multinational enterprises involved. It underlined the increasing importance of intra-group real and financial flows that, thanks to this work, will be more coherently recorded in the BoP of the two countries and can be better explained in the future.

Keywords: Multinational enterprises, balance of payments, complex global production arrangements, international fragmentation of production process

JEL classification: F23, F60, M00

Contents

1. Motivation for a bilateral analysis by Deutsche Bundesbank and Banque de France

Links between multinational enterprises and globalisation

Multinational enterprises (MNEs) are the key drivers to the globalisation process in the last decades. International flows are increasing in amount and frequency as MNEs grow. They enhance the interconnectedness of the countries where they operate but also the competition among countries willing to attract them as investors to stimulate economic growth and employment.

The removal of restrictions on the movement of capital, the lowering of trade barriers by the World Trade Organisation GATT and GATS[1] agreements, sinking transport costs and the improvement of information technologies have allowed companies to relocate their production activities to even more remote places around the globe. This all has led to a steady growth in the number of MNEs which in turn intensify the globalisation process. New markets are created, new production chains being established leading to the birth of new leaders. A well-known example is the global production of the I-phone or the development of the digital market which led to the emergence of new actors such as Apple, Amazon, or Google. Their economic development relies on the possibilities offered by globalisation allowing them to grow faster by reaching more customers and to offer more products.

The understanding of the global thinking of MNEs - which are mainly driven by tax minimisation and profit maximisation at a global level - is of utmost importance for politicians today. An adequate statistical measurement of MNEs induced international flows of capital, goods, services and intellectual property is a prerequisite to assess the consequences of national economic and financial policies for employment, income and wealth. Thus, the comprehensiveness of all statistics affected by MNE decisions like the Balance of Payments (BoP), National Accounts (NA) and Business Statistics (BS) are necessary to establish efficient economic, trade or fiscal policies.

Relevant statistics are also important to produce more sophisticated indicators on globalisation, global value chain and international fragmentation of the production process. To give the best information, these indicators need to be produced with high quality data that can only be compiled if the contribution of MNEs is clearly identified.

Location of economic ownership in MNE-Groups

In the International Monetary Fund (IMF)'s sixth edition of balance of payment manual (BPM6), the time of recording of transactions is based on the change of ownership. "*The change of economic ownership is central in determining the time of recording on an accrual basis for transactions in goods, non-produced non-financial assets, and financial assets*"[2].

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[1] GATT: General Agreement on Tariffs and Trade. GATS: General Agreement on Trade in Services.

[2] Paragraph 3.41 of BPM6, p.55.

In the case of MNEs, the BPM6 specifies that "*goods may move between a parent and its branch abroad. In that case, possibilities exist that either the goods have changed economic ownership or they may have been sent for processing. The correct statistical treatment is to identify which location assumes the risks and rewards of ownership most strongly (e.g., from factors such as whether the goods are included in the accounts, and which location is responsible for subsequent sale of the goods)*"[3]. For BoP compilers, it is a real challenge to identify which entity assumes risks and rewards in an MNE-Group. It requires having a precise and complete knowledge of how the MNE is organized and operates.

Although the BPM6 gives in several paragraphs (e.g. paragraph 5.3) some guidance for compilers to identify the economic owner inside a group, the explanation of the concept of economic ownership versus legal ownership to their MNEs' correspondents is however not a simple and often time consuming task.

Once this definition is explained, it becomes important to analyse the organisation of MNEs to identify which entity assumes the risk and rewards. There may be several entities or just one, depending on how the MNEs is organised. In the MNEs involved in the analysis, the identification of the economic owner of the produced goods and services was a challenge. Their very complex organisation and the multiple flows between the entities of the group did not allow an unambiguous identification of the economic owner, despite the characteristics given by the BPM6.

When the economic owner is identified inside the group, it can have impact on BoP compilation since goods may be delivered from Germany, which is recorded in Foreign Trade Statistics (FTS), but sold by the economic owner located in France. Under such circumstances, the export must be reported in France outside the FTS source and to FTS in Germany, using a code which indicates that the goods are not owned by the exporter.

Once these flows are clearly explained by the MNEs, it becomes relevant to share the information with colleagues from the counterpart countries to make sure that the flows are treated in the same way and reported symmetrically in FTS and BoP.

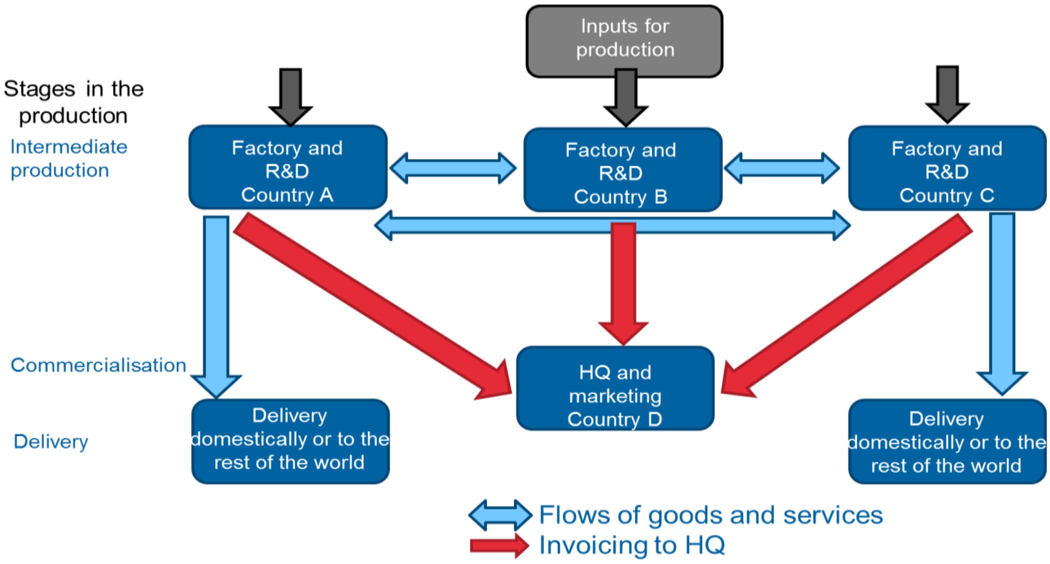
[3] Paragraph 3.46 of BPM6, p 56.

Overview of the MNEs involved in the work stream

The structure of the MNEs involved in the analysis can be schematized as shown below (see illustration 1).

Illustration 1

Organisation of the analysed MNEs



The affiliates are operating in different countries inside or outside the European Union. At least, one affiliate is established in France and in Germany. The affiliates exchange goods (semi-finished products) and services (use of intellectual property) and invoice each other at transfer prices (that can be agreed in an Advanced Price Agreement with the tax authorities of the countries). Thus, flows can occur between different countries or domestically.

It was recognized by the compilers that the (factoryless) headquarters don't usually manage the whole supply chain. Instead, the affiliates are responsible for certain stages of the chain, usually the production of a semi-finished good or the assembling of the final good. The affiliates invoice their headquarters to cover their operating costs at transfer prices. At the end of the production process, the final goods are owned by the headquarters which is in charge of marketing and customer services.

For the MNE-Group members the correct reporting of these complex arrangements for customs, FTS and BoP is challenging, depending on economic ownership and the movement of the goods. For example, if the headquarters buys semi-finished products from a foreign affiliate and send them for final assembly to another affiliate abroad (without selling them to its affiliate), the headquarter has no obligation to report this to customs/FTS (no movement of goods in its country) but to BoP (as an import, due to the change of ownership) and a subsequent import of manufacturing services (final assembling abroad). If the assembling takes place in the country where the headquarters reside, only a report for customs/FTS is necessary because the movement of the goods coincides with the change of economic ownership.

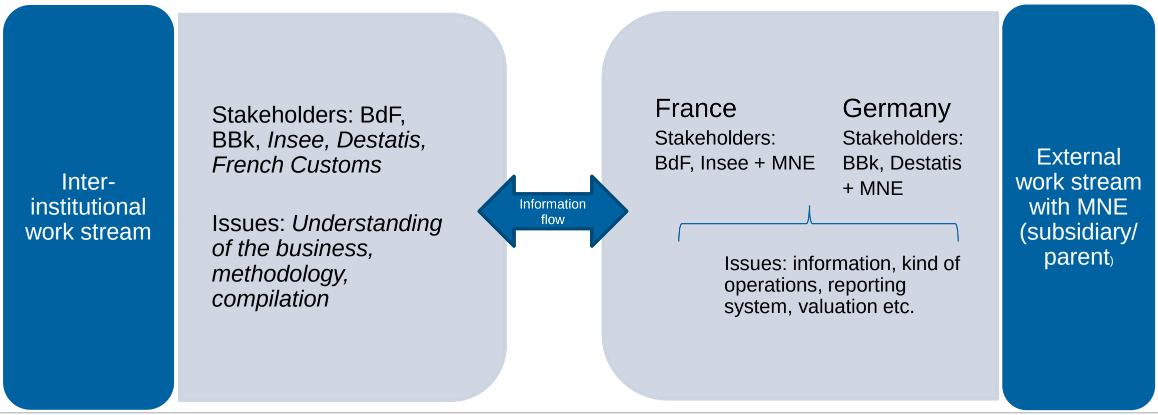
2. Cooperation between Banque de France and Deutsche Bundesbank

The Banque de France and Deutsche Bundesbank have been cooperating for decades on various fields of balance of payments. From conceptual or methodological issues to resorption of asymmetries, both institutions have been working together to improve their common knowledge by sharing their understanding and experiences. This cooperation is managed at various levels: senior managers or technical experts meet regularly to enhance their collaboration.

The organisation of the cooperation on MNEs mainly relies on two parallel work streams dealing with common topics but analysed under different perspectives. The outcomes of the two work streams are merged at the end of the process in order to have a comprehensive view of MNEs activities and their recording in the relevant statistics, notwithstanding the fact that interactions between the two work streams can happen.

Illustration 2

Organisation of the work streams



The inter-institutional work stream

The first work stream called "the inter-institutional work stream" deals with conceptual, methodological and compilation topics. It is constituted of experts from different statistical institutions such as the National Statistical Institutes (NSI), National Central Banks (NCB) and the Ministerial Statistical Department of the French customs and indirect taxation authority. Experts from the NSI come from three statistical areas: NA, FTS and Enterprise Statistics.

This inter-institutional work stream meets at two levels: a national level and at an international one. The national level meetings are designed to exchange views on the organisation of the MNEs, to share information on the current reporting, to identify problems and specific reporting practices as well as to clarify the statistical treatment acknowledging the conceptual background. At the beginning of the process, it appeared that each institution had its own comprehension of the MNEs, based on the data it collected. The data reported are usually analysed focusing on the needs of the specific institution/respective statistic and not aimed to design a coherent picture of the MNEs. However, this stovepipe approach sometimes leads to a partial comprehension of the MNEs organisation.

For example, one of the MNEs used the VAT number of one of its subsidiary to report exports of goods from France to Germany to the custom authorities. In the following year, this MNE decided to report its exports under its headquarters' VAT number, with a lower value of the exported goods (as required by the conclusions of an internal audit). For NA, this change was analysed as a major drop of exports of this subsidiary that was not completely balanced inside the group. For BoP compilers, total exports of the group had lowered. Thanks to the cross-checking of data with the custom authorities in one of the "inter-institutional work stream", the information of the change of value and reporting agent was shared, giving sense to the reported data.

The international level of the inter-institutional work stream is aimed at detecting differences in the treatment of cross border flows, to understand the reasons of current asymmetries, clarifying conceptual and methodological issues to get a common view and selecting questions to be addressed to the other work stream. In this work stream, experts can share their understanding of the MNEs organisation developed within the national inter-institutional work stream.

The common understanding of the organisation is a key element of the international inter-institutional work stream to solve asymmetries. Every difference in the assessment of the production process can lead to different customs/FTS codes (e.g. nature of transaction, partner country) reported by the affiliates of an MNE in the countries involved.

Therefore, in order to get a correct reporting, statisticians and reporters must be aware not only of the conceptual differences i.e. physical flows (customs oriented) and the concept of change of economic ownership (BoP oriented) but also have to take into account the whole production chain even if it takes place beyond the borders of their own statistical territory. Throughout the meetings, it was challenging for all the participants to put together the pieces of the puzzle from the external work streams into a picture on which a final decision could be taken, about how these transactions must be recorded in the statistics to provide a consistent dataset.

The external work stream with MNEs

The external work stream with MNEs can only be successful if the MNEs fully agree to cooperate. To reach this level of cooperation, it is really important to communicate and explain what the problems are, how the MNEs will be involved to help solving the problems and what is to be done when solutions are found.

As an in-depth analysis of the MNEs implies to talk about individual data, the principle of confidentiality must be guaranteed in order to allow the MNEs accounting, excise and custom teams to cooperate fully. Regarding confidentiality, it is also important to receive an allowance of the MNEs to share confidential data with the experts of the other statistical institutions of both countries. To reach these two goals it is of utmost importance to create an atmosphere of trust between all stakeholders. Therefore, all steps followed by the other work stream must be clearly presented to the MNEs team, which implies frequent and regular meetings explaining the achieved steps and the coming ones. These meetings took place on a face to face basis, mainly at the beginning and the end of the process. In between, due to practical considerations, these meetings were mostly conference calls.

Once the confidentiality is guaranteed, the conceptual and methodological issues can be debated. The first step is a stocktaking where the MNE team precisely explain how the group operates inside the countries and at the international level. This information is the key element to identify all relevant cross border flows and to characterise them. After the international flows are filtered out, the data reported by the MNEs are scrutinized to evaluate if they reflect the MNEs activities properly.

In some cases, it appeared that the reporting was not relevant, especially when it covers intra-group flows. When the organisation of the MNE is highly centralised, a significant part of the production process is guided by the headquarters, which sometimes also centralise purchases of key components of the final product. In such a case, the headquarters have the economic ownership of the purchased and final goods. Several options of reporting are open to the MNE. The most frequent is the following: Taking the example above i.e. a component is purchased by headquarters located in a country A and is delivered to a factory in a country C from a country B. The factory in country C reports an import from country B, to materialize the inflow of goods to the customs authority of country C. The headquarters in the country A report a financial flow to the country B to the BoP compilers of the country A to materialize the payment of the invoice from country B.

Regarding that reporting, the BoP compilers must be aware that the economic owner of the component is the MNE's headquarters but there is no reporting in the goods item of the country A's BOP. In country C, a final import of goods is reported that the BoP compiler (due to a wrong coding in its FTS) may take into account in the goods item even though there is no change of ownership between the countries C and B. As MNEs generate important flows of this type, this case was analysed by the two work streams to define a homogeneous reporting scheme for headquarters and the factories.

After taking all information about such transactions into account, it was decided that the import of the component in country C should be reported as an import for processing which enables compilers to identify these goods movements and to withdraw them from the BoP of country C because there is no change of ownership. In country A, the headquarters has to report an import for BoP to take into account the change of ownership from country B. If -at the end of the production process - the final product is exported to a third country directly from C, this has to be reported in C as an export after processing (and not as a final sale as it is often done) so that it could be again withdrawn from the BoP of country C. Further, this export has to be reported as a final sale of goods in country A to take into account the change of ownership (again, outside the customs/FTS reporting scheme). To complete the reporting, the factory in country C would also report processing fees charged to headquarters in country A as an export of manufacturing services on physical inputs owned by others; the headquarters in A has to report the corresponding service import.

These in-depth analyses lead finally to coordinated reporting instructions. They must be explained comprehensively to the members of the MNEs to better understand the needs and the interplay of the relevant statistics. The MNEs' accounting, customs and excise teams usually support this work because it is an efficient way for them to get a clearer view of what has to be reported by each subsidiary in the countries where they operate.

The fact that the external work-stream is fed by the inter-institutional work stream gave the experts in the local team much more legitimacy in the discussion with the local MNEs members regarding reporting advices because they can rely on the fact that the explanations given by the local experts are communicated in an identical way to their sister or mother company in the other country.

Once the conclusions were settled by the "inter-institutional" work stream, a final meeting was organised to explain what the new reporting should be, to decide when it could be implemented and to discuss technical aspects (IT development, backward revisions). One MNE, willing to report efficiently, ask French BoP to second experts to work on the changes and help them to identify the accounting elements to include in their reporting. Support all along the process is another key element to make the external work stream successful.

Conclusions

The increasing relevance of MNE-Groups in a globalised world and the influences of their economic decisions on national economies must be reflected in macroeconomic statistics like the BoP and national accounts in an adequate way. The current concepts of these statistics, focusing on the national territory, are questioned in various ways by users today. The basic question is: do these concepts are still able to reflect economic activities inside the economy and its international relations adequately?

The experience made with the cooperative approach between the Deutsche Bundesbank and the Banque de France turned out that a cross statistical approach combined with a cross-country approach could foster the understanding of MNE activities and enable compilers to measure their activities adequately and consistently without leaving the grounds of the existing concepts.

The insights into a group's operations, in its international production arrangements and internal pricing help to improve the statistical reporting of the MNE-Group members in a common and coherent way in all statistics. Even more, the work in the external work stream improved the understanding about statistical needs and interdependencies between various statistics of the responsible units in the group and it has fostered the internal communication between the group members in different countries.

The work in "two work streams" has eased the communication between the experts (rapid conclusions on conceptual issues and methods) on the one hand and talks with national group members (simple communication without language barriers, openness to admit mistakes) on the other hand.

In addition, what should not be underestimated for the future work between all stakeholders is the confidence in each other combined with the will to improve the meaningfulness and therewith the overall quality of the statistics. However, even with an optimal cooperation between all stakeholders the process is very time consuming. From our experience at least two years are needed from the initial start to a fully "harmonized" reporting in all countries.

But it is all worth to produce statistics which reflect faithfully the volume of trade of MNEs' complex global production arrangements.

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Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

Sharing of data reported by complex multinational enterprises: a cooperative approach between Deutsche Bundesbank and Bank of France[1]

Tatiana Mosquera Yon, Bank of France
and Jens Walter, Deutsche Bundesbank

[1] This presentation was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

Sharing data reported by complex multinational enterprises: a cooperative approach between Deutsche Bundesbank and Banque de France

Tatiana Mosquera Yon – Banque de France
Jens Walter – Deutsche Bundesbank

Introduction

- Not at least since the „Irish Case“ it has become clear that economic decisions of MNE in a globalized world could have sizeable effects on Business Statistics (BS), National Accounts (NA), Foreign Trade Statistics (FTS) and the Balance of Payments (BOP)

- The main characteristic of an MNE is the internationality of its operations, organized across borders to maximize the efficiency of production and to minimize their tax burden

- To measure their operations adequately and symmetrically in statistics like the BOP, a close cooperation of statisticians in all countries affected by MNE transactions are of utmost importance

- To better capture and understand intra-group flows between France and Germany the Banque de France (BdF) and the Deutsche Bundesbank (BBk) strengthened their cooperation in the last years by focusing on MNEs, which are of high relevance to their respective BOP

The approach

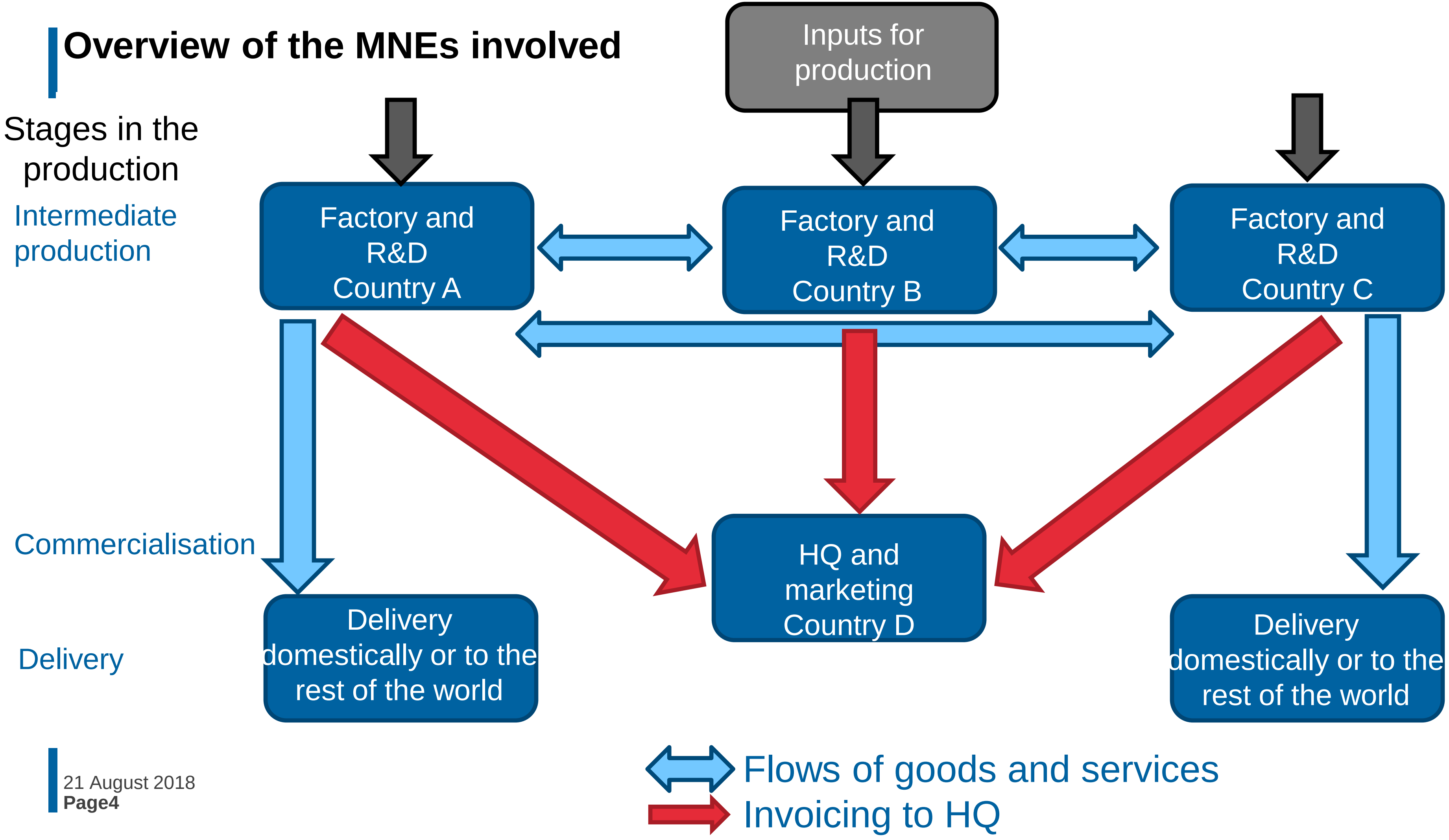
- Since decades, the BdF and the BBk have worked closely together in various fields of the BOP (conceptual/methodological issues, bilateral asymmetries and organizational questions)

- Regular meetings of the senior management and on the expert level reflect this constructive collaboration between both institutions

- Intra group flows (and stocks) of MNEs play always an important role in these meetings due to the close interconnection of both economies

- The cooperation established in the field of MNEs mainly rely on two parallel workstreams

Overview of the MNEs involved



The work streams

Inter-institutional work stream

Stakeholders: BdF, BBk, *Insee, Destatis, French Customs*

Issues: *Understanding of the business, methodology, compilation*

Information flow

France

Stakeholders: BdF, Insee + MNE

Germany

Stakeholders: BBk, Destatis + MNE

Issues: information, kind of operations, reporting system, valuation etc.

External work stream with MNE (subsidiary/ parent)

Work stream I in detail

Inter-Institutional Work stream

- Exchange views on the respective comprehension of the MNE, what are the operational tasks in the countries?
- Exchange information about the current reporting practice and problems
- Conceptual treatment of operations in the respective country
- Detecting differences in the treatment of cross border flows → reason for asymmetries
- Clarifying the issues to get a common view
- Open questions to be addressed in workstream II
- Discussion of outcomes of workstream II
- Final agreement on the future statistical treatment and data collection in the relevant statistics (BOP, FTS, NA)

Works tream II in detail
France (1/2)

External work stream with MNE (subsidiary/parent)

- Doubts about the consistency between the reporting of the MNEs and its activity
- Meeting with the MNEs to understand its global production arrangement
- Meetings with experts of related statistics
- Regular meeting with the MNEs to understand its reporting and the data reported to other statistical institutions (also allowing us to exchange confidential information between institutions)
- In-depth analysis between statistical institutions of our understanding (national accounts, foreign trade statistics and profiling division) in dedicated workshops

Work stream II in detail
France (2/2)

External work stream with MNE (subsidiary/parent)

- Meeting with workstream I to check our respective understanding and clarify doubts leading to a common vision but also new questions
- Explanation of our new questions to the MNEs and definition of answers
- Final meeting with workstream I to reach a common definition of the MNEs' activities and how they should be reported
- Meeting with the MNEs to explain our understanding of their global production arrangement and the new reporting requirements and definition of the main stages of the implementation of the new reporting
- Secondment of Banque de France's experts to the MNEs to adapt the reporting

Work stream II in detail
Germany (1/2)

External work stream with MNE (subsidiary/parent)

- Detection of anomalies in reported data of the MNE
- First discussion with experts of related statistics (FTS, NA)
- Contact with the national MNE (explaining the issue)
- Meeting with the MNE and all institutional stakeholders
- Agreement with MNE to exchange confidential information between institutions (very important!)
- Clarification of the production chain inside the group
- Organization of the MNE reporting system

Work stream II in detail
Germany (2/2)

External work stream with MNE (subsidiary/parent)

- Explanation of statistical treatment of the intra group flows (processing, final export/import, merchanting, valuation, institutional units)
- Documentation of new insights for workstream I
- Addressing questions from workstream I
- Final meeting with MNE and institutional stakeholders to agree on future reporting and corrections for backward revisions (BOP, FTS)
- Discussion of technical aspects i.a. time to change computer systems to fulfill the „new“ requirements by the MNE
- Agreement on the date to start with revised reporting

Conclusions (1/2)

- Exchange of views between all statistical stakeholders and MNE (parent, subsidiary) on national and international level fosters the understanding of MNE activities

- Insights into the group's operations, its international production arrangements and internal pricing help to improve the statistical reporting in a common and coherent way in all statistics

- A coordinated approach of statistical institutions across countries regarding reporting requirements of an MNE is of utmost importance also for the group entities

- It improves the understanding about statistical needs and interdependencies between various statistics of the responsible units in the group. Furthermore, it fosters the internal communication between the group members in different countries.

Conclusions (2/2)

- The work in „two work streams“ has eased the communication between the experts (rapid conclusions on conceptual issues and methods) on the one hand and talks with national group members (simple communication without language barriers, openness to admit mistakes) on the other hand.

- However, even with an optimal cooperation between all stakeholders the process is very time consuming. From our experience at least two years are needed from the initial start to a full „harmonized“ reporting in all countries.

- But it is all worth to produce statistics which reflect faithfully the volume of trade of MNEs’ complex global production arrangements.

Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

INEXDA – The granular data network[1]

Stefan Bender, Deutsche Bundesbank,
and members of the INEXDA network

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[1] This paper was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

INEXDA – the Granular Data Network[1]

Prepared by members of the INEXDA network[2]

The financial crisis of 2007-08 has highlighted the need for using granular data on financial institutions and markets to detect risks and imbalances in the financial sector. Data producers such as central banks and national statistical institutes are witnessing a growing need to improve granular-data access and sharing. When making granular data available, data producers face significant legal and technical challenges related to, among others, safeguarding statistical confidentiality. This paper introduces the INEXDA international network, which provides a platform for data producers to exchange practical experiences on the accessibility of granular data, metadata as well as techniques for statistical analysis and data protection.

Keywords: Microdata, International Network, Data Access

1 The views expressed here are those of the contributors and do not necessarily reflect those of the Banco de España, Banca d'Italia , Banco de Portugal, Banque de France, Bank of England, Deutsche Bundesbank, or European Central Bank.

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Contents

1. The motivation for INEXDA

In 2009, the finance ministers and central bank governors of the G20 endorsed the first phase of the Data Gaps Initiative (DGI-1) to promote actions to close data gaps that had come to light in the wake of the global financial crisis that emerged in 2008. During the process of DGI-1, data users and data compilers increasingly expressed the need for improving data sharing, particularly of granular[3] data, in order to foster the understanding of global developments, for example with regard to risks and imbalances. Consequently, the second phase of this initiative (DGI-2) contains a new recommendation (II.20) promoting the exchange of (granular) data as well as metadata.[4]

To help meet data users' and data compilers' demand for (granular) data sharing within the legal framework of the individual jurisdictions and to facilitate the implementation of Recommendation II.20 of DGI-2, a group of central banks established the **I**nternational **N**etwork for **E**xchanging E**x**perience on Statistical Handling of Granular **Da**ta (INEXDA). In accordance with the objectives of INEXDA outlined below, participation is open to other central banks, national statistical institutes, and international organisations. Other examples of exchanging experiences in the context of data sharing include the Conference of European Statisticians Task Force on the Exchange of Economic Data, which focuses particularly on the activities of multinational enterprises (MNEs), as well as the work on data sharing by the Bank for International Settlements (BIS) Irving Fisher Committee (IFC).

INEXDA was explicitly mentioned in the report of the Inter-Agency Group on Economic and Financial Statistics: "Update on the Data Gaps Initiative and the Outcome of the Workshop on Data Sharing", March 2017. The paper was welcomed by the G20 Finance Ministers and Central Bank Governors in March 2017 and by the G20 leaders: "We welcome the recommendations of the Inter Agency Group on Economic and Financial Statistics (IAG) for sharing and accessibility of granular data." (p. 5, Communiqué of the G-20 FMCBG Meeting (2017)).

2. A brief history of INEXDA

On 6 January 2017, the Banca d'Italia, Banco de Portugal, Bank of England, Banque de France and Deutsche Bundesbank (see also figure 1) founded INEXDA during a meeting at the Banco de Portugal. In this meeting, the BIS – which participated as a guest – offered to support the work of INEXDA by providing access to the eBIS[5] platform. All INEXDA information is therefore stored and shared via the eBIS system.

3 In this paper, granular data are defined as less aggregated data than traditional statistics (eg finer breakdowns of aggregates in traditional statistics) or microdata. Microdata are data at the level of individual reporters or at a low level of aggregation that may lead to the identification of individual reporting units.

4 More information on DGI-1 and DGI-2 can be found at http://www.imf.org/external/np/g20/pdf/2015/6thprogressrep.pdf.

5 https://www.ebis.org/auth/login.

The second INEXDA meeting took place at the Bank of England on 7 July 2017, where the Banco de España and European Central Bank (ECB) joined INEXDA as first-time guests. During this meeting, particular emphasis was placed on developing a metadata schema for the INEXDA network. In this regard, a presentation by the GESIS Leibniz Institute for the Social Sciences on "The da|ra Data Referencing System and its potential for the INEXDA Project" was considered very useful by INEXDA members (see Bender, Hausstein and Hirsch (2018) for a more detailed description of the INEXDA metadata schema).

At the third INEXDA meeting on 11 January 2018 at the Banque de France, the INEXDA network welcomed the Banco de España and ECB as new INEXDA members, increasing the number of INEXDA members from five to seven. Furthermore, the Banco Central de Chile, Banco de México, Oesterreichische Nationalbank, Central Bank of the Republic of Turkey and – for the first time, a national statistical institute – Office for National Statistics UK attended the meeting as guests. One notable outcome of the meeting was the consideration of establishing working groups on different topics within the framework of INEXDA (see section 4).

The fourth INEXDA meeting was held on 27 August 2018 at the BIS in Basel, where Banco Central de Chile and Central Bank of the Republic of Turkey participated as new members. Alongside the guests in attendance at the third meeting, the Bank of Russia, Federal Statistical Office of Germany, Eurostat, and the Swiss National Bank were attending the meeting as first-time guests.

3. INEXDA's objectives

INEXDA was established with the overall aim of facilitating the international use of granular data for analytical, research and policy purposes within the limits set by the applicable confidentiality regimes.[6] This overall aim can be further broken down into the following two, more specific objectives.

First, INEXDA will provide a basis for exchanging experiences on the statistical handling of granular data that are accessible to external users. Examples of "statistical handling" include the processes, methods, and tools for data and metadata access, techniques for the statistical analysis of granular data, procedures for data confidentiality and data security, and procedures for output control. Second, INEXDA will provide a framework for investigating possibilities to harmonise access procedures and metadata structures, to develop comparable structures for existing data, and to further foster the efficiency of statistical work with granular data.

The higher level of data disaggregation in the case of granular data is also associated with an increased need for data protection. European and national legal provisions regulate both the user group and the access channels to microdata and oblige data providers and data recipients to maintain data confidentiality at all times. Therefore, the overriding principle of the work of INEXDA is compliant with

6 INEXDA's objectives are outlined in the Memorandum of Understanding (MoU), which must be signed by each member and is available on the websites of each member institution.

the respective statutory secrecy and data protection requirements, and thus maintaining the confidentiality of the information submitted by the reporting agent.

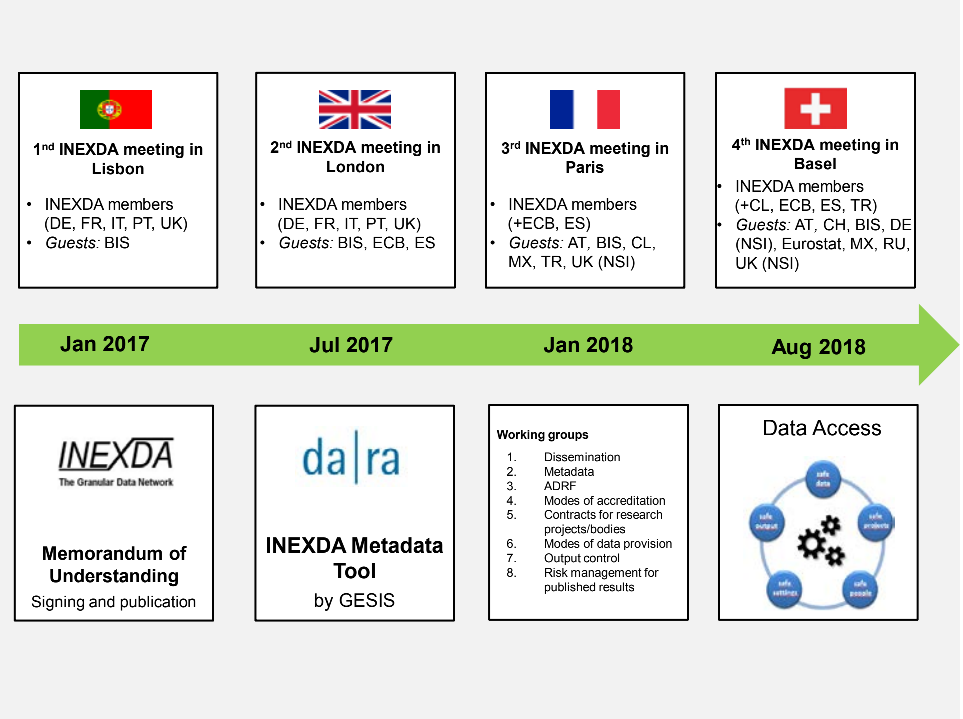

Figure 1: Overview of participants and important outcomes of the first four INEXDA meetings.

4. The current INEXDA work programme

For the current work programme, INEXDA members have decided to find a balance between keeping the momentum and not being overly ambitious. Therefore, INEXDA has identified eight potential topics for the work programme:

1. Dissemination (of granular data)
2. Metadata (see section 4.1 for a brief overview)
3. Tools for supporting the work of INEXDA members (ADRF, see section 4.2 for a brief overview)
4. Modes of accreditation (see section 4.3 for a brief overview of items 4, 5, and 6)
5. Contracts for research projects/bodies
6. Modes of data provision
7. Output control
8. Risk management for published results

INEXDA aims to have an agile structure, so the topics of the working programme should produce tangible results after six months as a minimum. Besides these activities and the contribution of INEXDA to the 9th biennial IFC Conference, INEXDA will also make contributions to the 2018 Conference of European Statistics

Stakeholders (CESS) in Bamberg, and the 62nd ISI World Statistical Congress in Kuala Lumpur in 2019.

4.1 Comprehensive inventory of data in member institutions

From the start, the INEXDA network has collaborated to harmonise metadata structures by conducting extensive stock-taking of available data sets in member institutions. The goals are:

1. to provide an overview of available and potentially comparable granular data sets from participating institutions;
2. to enable data users to discover and use appropriate data sets for their own research and analyses, which the participating institutions agree to share;
3. and to prepare a framework to facilitate a possible harmonisation of data sets in the (near) future.

Because the descriptions of the data should be comparable, an agreement on a metadata schema for the granular data was established between all members. To this end, the INEXDA metadata schema closely follows the da|ra metadata schema (version 4.0), which was jointly developed by the GESIS – Leibniz Institute for the Social Sciences and the ZBW – Leibniz Information Centre for Economics. The INEXDA metadata schema is designed to provide metadata for microdata at the data set level.

Adapting an existing metadata schema to fit the purpose of INEXDA provides a level of standardisation for microdata produced in different countries, institutions, and with different aims. Furthermore, the interoperability of the INEXDA metadata schema with the da|ra metadata schema allows for seamless transition between the INEXDA and da|ra databases, which makes it easier to obtain digital object identifier (DOI) for datasets in the future.

All INEXDA members agreed on a metadata schema, which, first, describes the data sets in a comprehensive way for the purposes mentioned above. Second, the schema is easy to use for potential users and data producers. It should be noted, that the metadata schema revolves around a "standardised data set", which is a snapshot of data produced in an institution (eg credit register) taken at a certain point in time (e. g. 1999-2017). To this end, INEXDA devised 21 items for its metadata schema (see table 1).

Furthermore, INEXDA has created a platform (see figure 2) for collecting and exchanging the metadata information produced during the inventory. This platform is available to all INEXDA member institutions. The platform is being developed jointly with GESIS.

Because of its sensitive nature, microdata are always subject to protection of confidentiality of individual observations. Metadata about microdata also have to adhere to the same high standards when it comes to protecting confidentiality. INEXDA's metadata system is designed to address these issues.

1	Resource Type
2	Resource Identifier
3	Name of Dataset
4	Creator
5	DOI Proposal
6	URL
7	Language of Resource
8	Publication Date
9	Availability
10	Sampled Universe
11	Sampling
12	Temporal Coverage
13	Time Dimension
14	Collection Mode
15	Unit Descriptions
16	Descriptions
17	Geographical Coverage
18	Keywords
19	Alternative Identifiers
20	Relations
21	Publications

Table 1: The INEXDA metadata scheme

4.2 Evaluating tools to support INEXDA's harmonisation process

While the highest priority is given to completing the inventory of available data described in 4.1, the investigation of harmonisation possibilities at other levels of the data lifecycle (eg access procedures and registration processes) remains an important task in the current INEXDA work programme. Standardised software applications could be a way forward, as these would not only facilitate communication between the INEXDA partners but also help to maintain common standards.

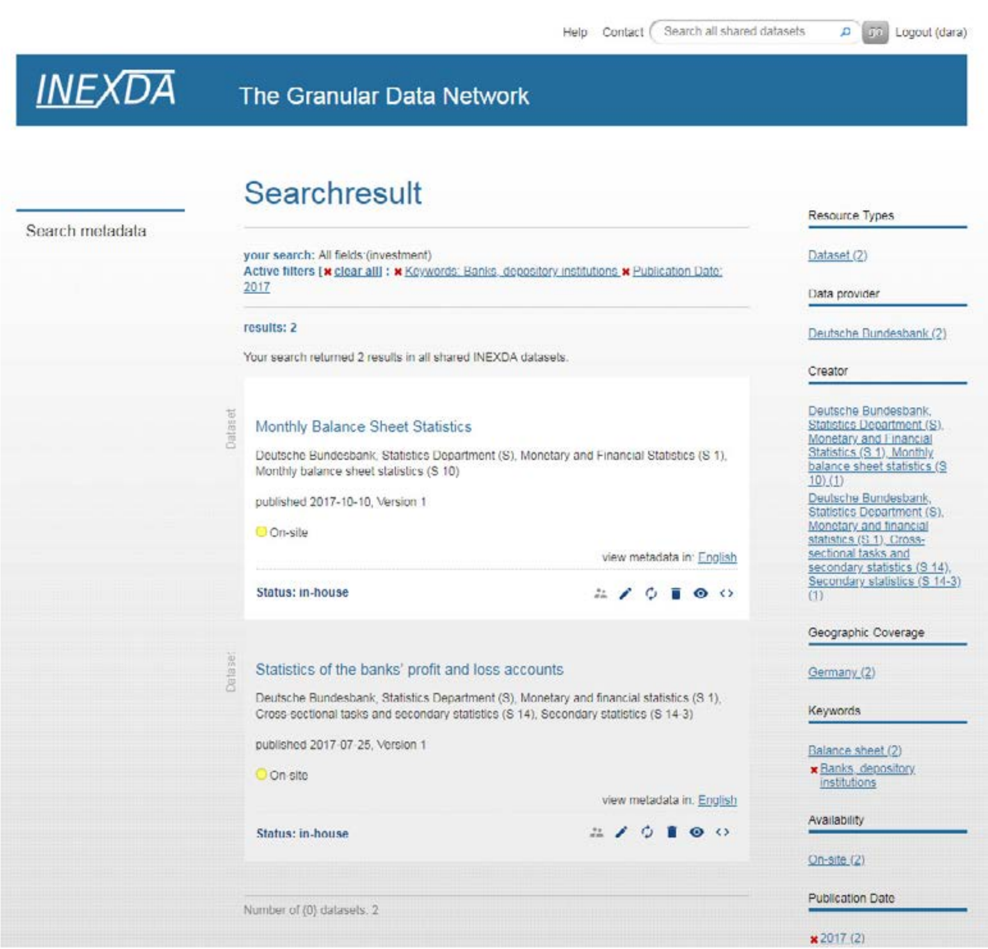

Figure 2: Hypothetical example of the INEXDA Metadata Platform

The New York University (NYU) has established, under the assignment of the Bureau of the Census, the Administrative Data Research Facility (ADRF), which provides a set of analytical tools, data storage and discovery services, and general computing resources based on cloud solutions for a diverse set of users, including government analysts and researchers. As the ADRF framework is considered to be potentially very useful for the harmonisation process, INEXDA will consider cooperation with NYU.

4.3 Taking stock of the access procedures and registration processes for researchers

One overarching goal of INEXDA is to provide a basis for exchanging experiences on the accessibility of data, procedures for data confidentiality, and security of data. Since access to microdata is in the scope of official statistics, INEXDA will benefit from national and international experiences to shape the outcome of this work stream. In the context of INEXDA, and following up on a survey of the Working Group of Statistical information Management (WGSIM) of the European System of Central Banks (ESCB) on national central banks' (NCBs) approaches to granting external researchers access to confidential data for research purposes, Emily Witt and Jannick Blaschke (ECB) conducted interviews with several central banks (Oesterreichische Nationalbank, Deutsche Bundesbank, Banco de España, Banque de France, Banca d'Italia, De Nederlandsche Bank, Banco de Portugal, Central Bank of the Republic of Turkey, Bank of England, European Central Bank) and Eurostat. The result is an overview[7] of selected NCBs' and Eurostat's approaches to providing access to non-published granular data for research purposes that complements other work in this area.[8]

Besides international experiences, national experiences are helpful in identifying the best practices with regard to access to microdata. For example, the Deutsche Bundesbank recently provided an overview of the microdata access procedures used, where three different user groups of microdata have been identified (internal analysts, internal researchers, and external researchers). The paper (Schönberg (2018)) described different access modes for each user group in detail. A unit called Internal Service for Micro Data Analysis handles internal analysts' data access requests following a multilevel approach (modelled after the European System of Central Banks (ESCB) standard approach).

At the end of August 2018, INEXDA will likely start a working group focusing on best practices on how data users could be allowed to access granular data once they have completed the accreditation process and have signed all relevant contracts. The task of this working group is to take stock of existing models of data provision used by INEXDA members. Possible topics may include:

- data access via secure access facility and/or remote access (eg technical design and specifications of limitations);
- anonymisation of methodologies and tools;
- provision of services to external researchers (eg provision of standard or ad hoc data sets, linkage of various data sets, upload of external data sets, access to licensed data sets);
- provision of analytical tools and allowing/facilitating code sharing.

4.4 INEXDA web page

A web page for the network will be launched by the end of 2018. The website is intended to be independent of the signing parties' websites and, to this aim, the following domains were reserved: www.inexda.org; www.inexda.com.

[7] The participating interviewees agreed to share the results with INEXDA members and guests.

[8] For example, the "Guidelines for the assessment of research entities, research proposals and access facilities" (Luxembourg, November 2016) from the European Commission, Eurostat, Directorate B: Methodology; Corporate statistical and IT services, Unit B-1: Methodology and corporate architecture, or the results from the FP7 project "Data without Boundaries" (DwB, see https://www.facebook.com/dwbproject).

5. INEXDA working arrangements

The members of INEXDA have implemented the following working arrangements.

- All decisions are made on a consensual basis.
- The work within INEXDA will be performed at the operational levels of the member institutions.
- INEXDA members convene at least once per year. Guests may be admitted to meetings. A pre-meeting will be organised prior to each INEXDA meeting for the purpose of inviting INEXDA guests to discuss the progress INEXDA has made so far.
- The chair of INEXDA is elected for a two-year term on a consensual basis. Responsibilities of the chair include co-organising the meetings in close collaboration with the local organiser, coordinating activities, and drafting a report at the end of the chairmanship, which has to be agreed on a consensual basis.
- The eBIS facility operated by the BIS provides the centralised location for exchanging documents and fostering collaborative activities among INEXDA members.

6. The INEXDA application process

The following procedure has been established for admitting new members. It is mandatory for institutions that want to join INEXDA to have a representative attending at least one INEXDA meeting in person before submitting a formal application. The application letter should be signed by the head of the statistical department of the respective institution (or, in the case of national statistical institutes or international organisations, by the head of the responsible department) and sent to the chair of INEXDA. Any application to join INEXDA from a new institution and the signing of the MoU must be agreed by all members. Furthermore, the applicant institution is invited to attend an INEXDA meeting to give a presentation on the current state of its granular data sharing and its motivation for becoming a member of INEXDA.

7. Conclusion

The International Network for Exchanging Experience on Statistical Handling of Granular Data (INEXDA) was founded to facilitate active dialogue on practical experiences – in particular on the accessibility of granular data, metadata, and techniques for statistical analysis and data protection. Until recently, the network was predominantly focused on establishing a metadata schema and conducting a comprehensive inventory of data in member institutions. In the next phase of the work programme, access procedures and registration processes for researchers will come to the forefront of INEXDA's activities.

The overall aim is to facilitate the international use of granular data for analytical, research, and comparative purposes without jeopardising and always subject to the respective applicable confidentiality regimes.

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Appendix: List of INEXDA members and INEXDA guests[9]

INEXDA members are institutions that have signed the MoU.

INEXDA members:

- Banca d'Italia
- Banco Central de Chile
- Banco de España
- Banco de Portugal
- Bank of England
- Banque de France
- Central Bank of the Republic of Turkey
- Deutsche Bundesbank
- European Central Bank

INEXDA guests are institutions that have participated or have confirmed participation in at least one INEXDA meeting but have yet to sign the MoU.

INEXDA guests:

- Banco de México
- Bank for International Settlements[10]
- Bank of Russia
- Federal Statistical Office of Germany
- Eurostat
- Oesterreichische Nationalbank
- Office for National Statistics UK
- Swiss National Bank

9 as of 12 October 2018

10 The Bank for International Settlements supports the INEXDA initiative without being a full member.

Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

INEXDA – The granular data network[1]

Stefan Bender, Deutsche Bundesbank,

and members of the INEXDA network

[1] This presentation was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

INEXDA

The Granular Data Network

1

International Network for Exchanging Experience on Statistical Handling of Granular Data (INEXDA)

Stefan Bender

(Deutsche Bundesbank)

July 2018

Motivation

- **Aggregate datasets** are important for **monitoring macroeconomic developments** and **macroeconomic policy**.

- **Granular data** is necessary to understand **global developments** and in particular **differences across countries**.

- Combining datasets and looking beyond aggregate statistics into heterogeneous developments require the **transformation** of **“data“** into **“knowledge“**.

- **Local constraints** make it difficult, or often impossible, to link micro datasets from different jurisdictions, even for research and financial stability analysis.

- **Better accessibility** and **sharing of granular data** would open up **new possibilities** for analysis by providing new **insights into the effect of policies**.

What can **we do** from the **statistical side** to support this process?

INEXDA
The Granular Data Network

INEXDA: The Granular Data Network

- On 6th January 2017,

BANCA D'ITALIA | BANQUE DE FRANCE EUROSYSTÈME | BANK OF ENGLAND | BANCO DE PORTUGAL EUROSISTEMA | DEUTSCHE BUNDESBANK EUROSYSTEM

- have launched the **I**nternational **N**etwork of **E**xchanging E**x**periences on Statistical Handling of Granular **Da**ta (INEXDA), an international cooperative project to declare their willingness to further strengthen their cooperation.
- Since its foundation, the following institutions have joined INEXDA as a member:

BANCO DE ESPAÑA Eurosistema | EUROPEAN CENTRAL BANK EUROSYSTEM

INEXDA
The Granular Data Network

General Mission

- General mission is to promote data sharing and data access.
- Promoting the G20 Data Gaps Initiative II, in particular recommendation 20, addressing the accessibility of granular data. INEXDA is mentioned in a G20 paper.
- Acknowledging and supporting the work on data sharing of the Irving Fisher Committee on Central Bank Statistics.
- INEXDA is governed by an MoU, that every member has to sign.
- Sharing of granular data between INEXDA members **not** part of this MoU.

INEXDA
The Granular Data Network

INEXDA is gaining momentum…

1st INEXDA meeting in Lisbon

- INEXDA members (DE, FR, IT, PT, UK)
- *Guests:* BIS

2nd INEXDA meeting in London

- INEXDA members
- *Guests:* BIS, ECB, ES

3rd INEXDA meeting in Paris

- INEXDA members (+ ES, ECB)
- *Observer:* BIS
- *Guests:* AT, CL, MX, TR, UK (NSI)

Jan 2017 **Jul 2017** **Jan 2018**

INEXDA
The Granular Data Network

Memorandum of Understanding

Signing and publication

INEXDA website

Prototype by Banque de France

da|ra

INEXDA Metadata Tool

Beta version by GESIS

Working groups

1. Dissemination
2. **Metadata**
3. **ADRF**
4. Modes of accreditation
5. Contracts for research projects/bodies
6. Modes of data provision
7. Output control
8. Risk management for published results

INEXDA
The Granular Data Network

Session 3.A – Managing granular financial data

1. **"Introduction to INEXDA's Metadata Schema"**
   Christian Hirsch, Deutsche Bundesbank

2. **"Sharing information by preserving individual privacy"**
   Giuseppe Bruno, Bank of Italy

3. **"Data Sharing Under Confidentiality: The CRBT Case"**
   Timur Hülagü, Central Bank of the Republic of Turkey

4. **"Sharing and Using Financial Micro-Data"**
   Alejandro Gaytán, Bank of Mexico

5. **"Sharing of data reported by complex multinational enterprises: a cooperative approach between Deutsche Bundesbank and Banque de France"**
   Tatiana Mosquera Yon, Bank of France and Jens Walter, Deutsche Bundesbank

INEXDA
The Granular Data Network

Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

An introduction to INEXDA's metadata schema[1]

Stefan Bender, Brigitte Hausstein and Christian Hirsch,
Deutsche Bundesbank

[1] This paper was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

An introduction to INEXDA's metadata schema[1]

Stefan Bender,[2] Brigitte Hausstein,[3] and Christian Hirsch[4]

This paper introduces the metadata schema used by the international network INEXDA to describe granular datasets from different countries. The schema, agreed on by all members, facilitates a comprehensive inventory of existing granular datasets conducted in the member institutions. This inventory, in turn, will foster harmonisation activities between INEXDA members, broaden metadata sharing and potentially future data sharing between institutions represented in the network, and pave the way for metadata on publicly available granular datasets to be shared with external researchers. The INEXDA metadata schema was developed to be easily adaptable for non-INEXDA institutions.

Keywords: Metadata, Microdata, International Network

1. Introduction

Metadata is essential for documenting data, citing it and finding it in catalogues. Metadata can be defined simply as information about data, ie a description of data. It is "…structured or semi-structured information which enables the creation, management, and use of records [i.e. data] through time and within and across domains in which they are created. Recordkeeping metadata can be used to identify, authenticate, and contextualize records; and the people, processes and systems that create, manage and maintain and use them" (Wallace, 2001, p.255). Metadata provides a means for visibility and presentation of data as well as discovery. It supports the re-use, management, exchange and long-term preservation of data. "Data without metadata is just stuff. Nobody needs more stuff today" (Recker, 2014).

The use of a metadata schema goes through various standardisation phases, from which more or less binding metadata standards develop. If such a standard is specified, documented and legally recognised, it is referred to as a standard. In addition, there are de facto or quasi standards based on discipline-specific practical experience and recognised rules of a community. Meanwhile, there is a large array of metadata standards focusing on a particular subject domain, content type, function or application, such as:

- Data Documentation Initiative (DDI)

[1] The views expressed here are those of the authors and do not necessarily reflect those of the Deutsche Bundesbank, GESIS, or the INEXDA Network.

[2] Head of Research Data and Service Centre, Deutsche Bundesbank.

[3] GESIS Leibniz Institute for the Social Sciences.

[4] Research Data and Service Centre, Deutsche Bundesbank.

- Dublin Core Metadata Initiative (DCMI)
- DataCite Metadata Schema
- da|ra Metadata Schema
- Metadata Encoding and Transmission Standard (METS)
- Preservation Metadata Maintenance Activity (PREMIS)
- Statistical Data and Metadata Exchange (SDMX)

The significance of a metadata standard lies in the uniform language, which makes it possible to record information about data in an understandable and structured manner. In the case of domain-specific standards, metadata often constitutes very granular – semantically rich – statements about an object. In order to describe data uniformly and unambiguously, standardised terminologies (eg controlled vocabulary such as thesaurus or keywords) are used for certain metadata elements to describe particular metadata with uniform information. This should be distinguished from semi-structured or unstructured metadata, which describe important contextual information on the creation of the data.

Since its foundation in January 2017, the members of the International Network for Exchanging Experiences on Statistical Handling of Granular Data (INEXDA) have, amongst other things, collaborated to harmonise metadata structures and complete an extensive stock-take of available datasets in member institutions. This stock-taking exercise has three aims.

- First, it is designed to give member institutions an overview of the available and possible comparable granular datasets.
- Second, it makes it easier for data users to discover and use datasets appropriate for research and analysis by using harmonised metadata.
- Third, it provides a framework to facilitate a possible harmonisation of datasets in the (near) future.

Because the description of the data should be comparable, all members agreed on a metadata schema for the granular data. This paper presents the metadata schema underlying the stock-taking exercise by INEXDA members. We also explain practical considerations when implementing a metadata schema for microdata, which can easily be adopted by other institutions. Naturally, the INEXDA metadata schema was designed with certain goals in mind. Therefore, some choices may not translate to other situations. For example, the INEXDA schema allows for information about the relation of different datasets to each other, which is essential for the possible harmonising of datasets.

2. The INEXDA metadata schema

2.1 Scope

The INEXDA metadata schema is designed to provide metadata for microdata on the dataset level. Since microdata are data at the level of individual reporters, the data may allow re-identification of individual reporting units. Because of its sensitive nature, microdata is therefore always subject to protection of confidentiality for individual observations. Metadata about microdata also has to adhere to the same high standards when it comes to protecting confidentiality.

The INEXDA metadata schema is based on the da|ra metadata schema (Version 4.0) which was jointly developed by GESIS – Leibniz Institute for the Social Sciences and ZBW – Leibniz Information Centre for Economics (Koch 2017). da|ra operates a registration service for social science and economic data which allocates a Digital Object Identifiers (DOI) to different types of datasets, allowing a unique identification of resources (https://www.da-ra.de). da|ra maintains a cooperation with DataCite (https://www.DataCite.org).

Adapting an existing metadata schema to fit the purpose of INEXDA provides a level of standardisation for microdata coming from different countries, institutions, and collection purposes. In addition, the interoperability with the da|ra schema allows for a seamless transition between the INEXDA and da|ra databases, which makes it easier to obtain a DOI identifiers in the future. However, ensuring interoperability may also result in restrictions on altering metadata items (see section 2.2).

2.2 Metadata items

All INEXDA members agreed on a metadata schema, which, on the one hand, describes the datasets in a sufficient way for the purposes mentioned above while, on the other hand, being easy to handle for potential users or data producers. Therefore, the INEXDA network came up with 21 items (see Table 1), which we describe below in more detail. For each metadata item, we also provide an example drawn from Bundesbank datasets to illustrate its use. Please note that you will find the example after the description of the item. These examples are written in italics.

1	Resource Type
2	Resource Identifier
3	Name of Dataset
4	Creator
5	DOI Proposal
6	URL
7	Language of Resource
8	Publication Date
9	Availability
10	Sampled Universe
11	Sampling
12	Temporal Coverage
13	Time Dimension
14	Collection Mode
15	Unit Descriptions
16	Descriptions
17	Geographical Coverage
18	Keywords
19	Alternative Identifiers
20	Relations
21	Publications

Table 1: INEXDA metadata schema: items

Resource Type

A description of the underlying resource for which metadata is compiled. In case of INEXDA, the resource type is always a dataset. This item is included in the INEXDA metadata schema to facilitate interoperability with the da|ra schema.

Resource Identifier

The "Resource Identifier" is a unique value to disambiguate between resources. A version number can be provided as a reference that changes have been made between versions.

Name of Dataset

This item displays the name of the dataset.
Example: Securities Holdings Statistics – Base (name of one Bundesbank dataset)

Creator

The item "Creator" refers to the name(s) of the institution, and/or division, and/or department responsible for developing, collecting and/or managing the dataset. Names of individual persons should not be provided.
Example: Deutsche Bundesbank, Statistics Department

DOI Proposal

The schema allows suggesting a DOI name for the dataset. A Digital Object Identifier (DOI) is a permanent, persistent identifier used for citing and linking electronic resources (texts, research data or other content).
Example: 10.12757/Bbk.SHSBase.05121603 (for one version of the Securities Holding Statistics)

URL

URL is the address of a webpage which displays information about the dataset, if available. Alternatively, the landing page of the research data centre or the institution could be used if no specific webpage exists for the dataset.
Example:
https://www.bundesbank.de/Redaktion/EN/Standardartikel/Bundesbank/Research_Centre/research_data_micro_data_securities_holdings_statistics.html?nsc=true&https=1

Language of Resource

This item refers not the language in which the metadata elements are expressed but instead refers to the language in which the dataset is available. Default is English. List a language other than English only if dataset is not available in English.
Example: English

Publication Date

The date on which the dataset was released internally or made publicly available needs to be entered here in ISO 8601 format. If a DOI has been assigned, the convention in the INEXDA network is to use the date of DOI registration.

Example: 2016-08-01

Availability

Providing information on procedures under which data are being made available to data users may help to better understand which datasets they might be able to access and how to access those datasets. Availability procedures are best described by controlled vocabulary, i.e. by a pre-defined list detailing possible procedures which avoids confusion of data users due to the same content being described by different language.

This item lists the procedures under which data is being made available to researchers. Entries allowed are restricted to the following predefined list:

- Download – researchers can directly download data from the website;
- Delivery – researchers can receive the data set or access data from any location via remote access or send codes to the data owner and receive controlled output;
- On-site – researchers have to come to the premises of the data owner to see or work with the data;
- Not available – researchers cannot access / use the data by any means;
- Unknown – other type of availability, please specify in free text.

Example: On-site[5]

Sampled Universe

The item "sampled universe" provides information on elementary units about which inferences are to be drawn and to which analytic results refer when analysing the dataset.
Example: The SHS-Base is a full census (no reporting thresholds apply), i. e. all financial institutions domiciled in Germany report any securities they are holding for domestic and foreign customers. In addition, domestic banks provide information about their own holdings, irrespective of where the securities are held. The financial institutions who are obliged to report comprise domestic banks (monetary financial institutions excluding money market funds), domestic investment companies and "other" domestic financial companies.

The data collection involves holdings of debt securities, shares and investment fund shares or units 3, irrespective where the securities were issued, in what currency they are denominated or if they are listed or not. Only securities which are in circulation and which can be assigned to an investor are included in the Securities Holdings Statistics.

A basic set of information is required to be reported on a security-by-security level. This includes the International Securities Identification Number (ISIN), the nominal amount or number of units held, and the sectoral classification and residency of the holder. For securities quoted as a percentage (eg bonds and debt securities), the

[5] Most Bundesbank data are available for non-commercial research via the Research Data and Service Center (https://www.bundesbank.de/Navigation/EN/Bundesbank/Research/RDSC/rdsc.html).

nominal value is stated in the relevant nominal currency and for securities quoted as a number of units (eg equities, mutual fund shares) the number of units held is reported. As the significance of securities repurchase and securities lending transactions has increased strongly in recent years, securities holdings which are passed on or acquired as part of such contracts are to be flagged separately. This information is mandatory for the own holdings of domestic banks only. Since reference month January 2014 the monetary financial institutions have to report the book values of their own securities holdings. Securities that are attributed to the trading portfolio must be labelled.

Sampling

This item describes the type of the sample and sample design used to select the observations to represent the population. As an INEXDA convention, the value of the item will be set to "Total Population" if dataset contains no sampling, i.e. dataset is the population.
Example: Total Population

Temporal Coverage

The item "Temporal Coverage" refers to the sample period of the dataset, which is the time period during which the data was collected or observations were made. The time period should be expressed in ISO 8601 format. As an INEXDA convention, information on month and quarter may be omitted if frequency of the dataset is annual.
Example: 2005-12 to 2016-03

Time Dimension

Describe the time dimension of the data collection. In the INEXDA schema, the following three time dimensions are allowed,

- "Panel" datasets contains information collected from the same (or almost the same) set of entities over time.
- "Time Series" data is collected repeatedly over time to study changes in observations. The "Time Series" category is appropriate for almost all macro datasets, e.g. data on GDP or unemployment rates.
- "Cross-section" dataset are data about a population collected only once.

These items are further broken down by the frequency (e.g. monthly, quarterly) with which data about entities is collected in the dataset.

Furthermore, the following INEXDA conventions apply to this metadata item.

- In case time intervals between consecutive data collections are not equally-spaced (e.g. datasets collected from event-driven reporting), the highest available frequency in the dataset is selected, that allows for a meaningful analysis of the data.

- In case the frequency of data collection changes over time (e.g. because of structural breaks following a change in regulation governing the collection of the dataset) the most recent frequency available in the dataset should be used.

Example: Panel: monthly

Collection mode

This item provides information on the method used to collect the data.
Example: Reporting agents file their reports electronically to Deutsche Bundesbank.

Unit descriptions

Microdata are data on the level of the individual observation. Microdata regularly contain numbers or strings attached to individual observations with the aim to make identification easier. These identifiers may exist on the company level (e.g. country tax number, LEI) or security level (e.g. ISIN). For analysis and research purposes it is often necessary to combine microdata from different sources or policy domains using these identifiers.

The item "Unit Descriptions" provides information about available identifier(s) in the dataset. More than one identifier is allowed, separated by a comma. Identifiers from external data vendors are allowed.
Example: Bank ID, ISIN

Descriptions

The purpose of the metadata item "Descriptions" in the INEXDA schema is twofold.

1. It provides a short description of the dataset.
2. It is used to share information about the scope of structural breaks in the dataset, where structural breaks are defined as major events and revisions that have impacted the dataset.

Designing a metadata schema for microdata needs to employ a procedure documenting significant changes made to a dataset over time stemming from a change in underlying reporting requirement rules. These structural breaks, if they occur, affect metadata items in that the appropriate documentation becomes time dependent. For example, the reporting frequency of a dataset changes in 2012 from quarterly to monthly. In the INEXDA metadata schema the item "Temporal Coverage" will now depend on the time period: before 2012 the appropriate value is quarterly, after the structural break in 2012 the value is monthly.

Besides changes to the time frequency with which data is collected, other examples of structural breaks include:

- Changes to the set of collected variables.
- Changes in the population or sampling.

Example:

The SHS-Base is the core module of the Deutsche Bundesbank's Securities Holdings Statistics (WpInvest). The motive behind creating the SHS-Base is to be able to answer the question: "Who holds what from whom and how much?". Financial institutions domiciled in Germany report securities which they hold for domestic or foreign customers ("custodian-approach"). In addition, domestic banks provide information about their own holdings, irrespective of where the securities are held. Reporting agents are domestic banks (monetary financial institutions excluding money market funds), domestic investment companies and "other" domestic investment companies. The SHS-Base is collected by means of a full census, i.e. every reporting agent has to send a report (if no securities are held in safe custody, a nil report is filed). The *reporting agents provide information on securities holdings broken down by the holder's economic sector and country of origin on a security-by-security basis. The reporting scheme comprises the holdings of debt securities, shares and investment fund shares or units. Holders are classified according to the ESA sectoral classification scheme and the amounts held in safe custody are transmitted to the Deutsche Bundesbank. Securities data are indispensable for monetary analysis as any shifts in financing between the banking system and the securities markets may affect the transmission of monetary policy. In addition, data are essential to monitor the development of amounts held and the distribution among different (groups of) investors. Financial stability analysis makes use of the data to measure the risks associated with different types of instruments and exposures to individual counterparties. Information on the composition and quality of the portfolios of holders is used to better understand investor behavior.*

• From 200512 to 201212: end-of-quarter collection

• From 201301 to 201603: end-of-month collection

Geographical Coverage

The item "Geographical Coverage" provides information on the region where the data was gathered or on which the data is focused.
Example: DE (for Germany)

Keywords

Please enter the keywords describing the general content of the dataset. You may choose up to 10 keywords. Entries allowed are restricted to a predefined list.
Example: Banks, Securities, Financial markets, Debt securities, Equity and investment fund shares or units, Financial derivatives

Alternative identifier

This metadata item is used to indicate that the information about the dataset provided here belongs to the metadata collection of INEXDA.
Example: INEXDA

Relations

The item "Relations" will be used in the future to describe relations between datasets and databases in the INEXDA metadata database. Examples of relations will include:

- Different versions of a dataset.
- Relation between dataset and database (in a given country)
- Relation between datasets containing similar units (in different countries)
- Dataset feeds into an ECB dataset

Publications

Allowing descriptions of publications be associated with related datasets provides additional information which is complementary to existing metadata. Publications include information on how a dataset is being used (e.g. variable transformation), what a dataset is being used for (e.g. topics or methodology), and who has used the

dataset. All this information is useful to help data user better understand and discover datasets relevant for their research.
Therefore, the INEXDA metadata schema contains an item that provides information on scientific publications relating to the registered dataset. Publications listed here may also include descriptions of datasets (e.g. technical reports, data reports, or user guides) which are publicly available.

Example: Bade, M., Flory, J. and T. Schönberg (2016). SHS-Base, Data Report 2016-02 - Metadata Version 1-1. Deutsche Bundesbank Data and Service Centre.

3. Conclusion

The relevance of metadata also becomes clear in connection with the re-use and corresponding citation of the data. Bibliometrical methods, which should make the performance of data production measurable similar to the impact factors in text publications, are based on metadata. In addition to the bibliographic and content information, these metadata should also include a persistent identifier (so called PID) that enables the identification and localization of the used data uniquely and permanently. There are now a number of services that offer the allocation of PIDs in the form of Digital Object Identifiers (DOI) for research data. The German Leibniz Institutes GESIS and ZBW are offering a special service for the assignment of DOI names for social and economic data.

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Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

An introduction to INEXDA's metadata schema[1]

Stefan Bender, Brigitte Hausstein and Christian Hirsch,

Deutsche Bundesbank

[1] This presentation was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

INEXDA

The Granular Data Network

Introduction to INEXDA's Metadata Schema

Christian Hirsch
(Deutsche Bundesbank)
July 2018

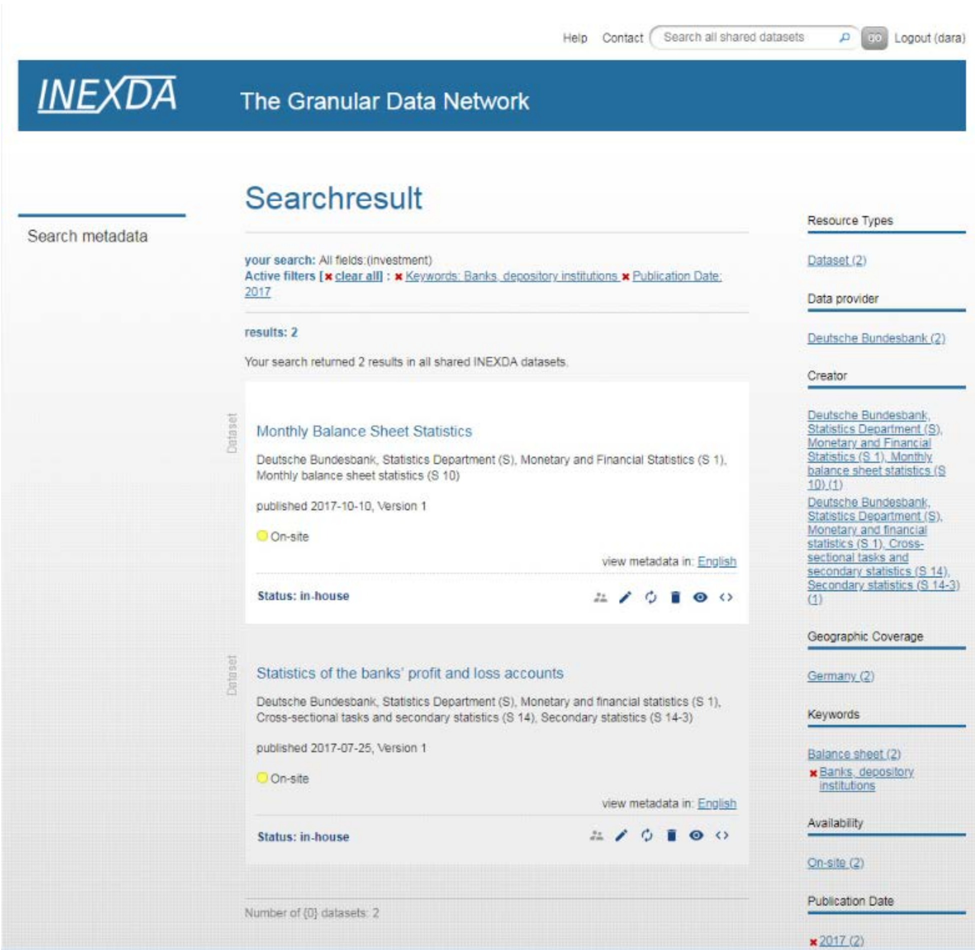
Motivation

- Metadata is data about data, i.e. a description of data

- Examples of existing metadata schema
  - Statistical Data and Metadata Exchange (SDMX)
  - Data Documentation Initiative (DDI)
  - da|ra Metadata Schema

- Important is the purpose
  1. Overview of available and possible comparable granular datasets
  2. Help data users discover and use datasets appropriate for research and analysis by using harmonised metadata.
  3. Provide framework to facilitate a possible harmonisation of datasets in the (near) future.

INEXDA Metadata Database



- The database serves
  1. as an information tool for INEXDA members, researchers and analysts
  2. as the basis for the harmonisation activities of INEXDA (e.g. item relation)

- Current contributions to the database come from
  - Deutsche Bundesbank 30 (12)
  - European Central Bank (6)
  - Banca d'Italia 26 (6)
  - Banco de España 21 (2)
  - Banco de Portugal 16 (2)

INEXDA
The Granular Data Network

Part 1: Basic Information

1	Resource Type
2	Resource Identifier
3	Name of Dataset
4	Creator
5	DOI Proposal
6	URL
7	Language of Resource
8	Publication Date
9	Availability
10	Sampled Universe
11	Sampling
12	Temporal Coverage
13	Time Dimension
14	Collection Mode
15	Unit Descriptions
16	Descriptions
17	Geographical Coverage
18	Keywords
19	Alternative Identifiers
20	Relations
21	Publications

- *Creator* is a mandatory item in da|ra. May be used to provide more granular information on the data compiler
- *URL* refers to the webpage which displays information about the dataset
- *Availability (controlled)* describes the procedure under which the data can be accessed (eg download or on-site)
- *DOI Proposal* provides the suggested DOI name of the dataset. A Digital Object Identifier (DOI) is a permanent, persistent identifier used for citing and tracking datasets

INEXDA
The Granular Data Network

Part 2: Methods

1	Resource Type
2	Resource Identifier
3	Name of Dataset
4	Creator
5	DOI Proposal
6	URL
7	Language of Resource
8	Publication Date
9	Availability
10	Sampled Universe
11	Sampling
12	Temporal Coverage
13	Time Dimension
14	Collection Mode
15	Unit Descriptions
16	Descriptions
17	Geographical Coverage
18	Keywords
19	Alternative Identifiers
20	Relations
21	Publications

- *Sampling* displays the type of sample design used to select the observations to present the population
- *Time Dimension* provides information on
  - frequency of observations.
  - whether dataset structure is panel, time-series or cross-sectional
- Structural breaks are defined as major events and revisions that have impacted the dataset
- Examples of structural breaks include:
  - changes to the time frequency with which data is collected
  - changes to the set of collected variables
  - changes in the population or sampling

INEXDA
The Granular Data Network

Part 3: Descriptions

1	Resource Type
2	Resource Identifier
3	Name of Dataset
4	Creator
5	DOI Proposal
6	URL
7	Language of Resource
8	Publication Date
9	Availability
10	Sampled Universe
11	Sampling
12	Temporal Coverage
13	Time Dimension
14	Collection Mode
15	Unit Descriptions
16	Descriptions
17	Geographical Coverage
18	Keywords
19	Alternative Identifiers
20	Relations
21	Publications

- *Unit Description* provides information on the entities that are being observed in the dataset
-
- Datasets may contain more than one unit of observation. For example, in a credit register information on the following units are collected:
  - Banks
  - Companies
  - Governments
  - Loans
- *Descriptions* also contains detailed information on structural breaks in the dataset

INEXDA
The Granular Data Network

Part 4: Relations and Publications

1	Resource Type
2	Resource Identifier
3	Name of Dataset
4	Creator
5	DOI Proposal
6	URL
7	Language of Resource
8	Publication Date
9	Availability
10	Sampled Universe
11	Sampling
12	Temporal Coverage
13	Time Dimension
14	Collection Mode
15	Unit Descriptions
16	Descriptions
17	Geographical Coverage
18	Keywords
19	Alternative Identifiers
20	Relations
21	Publications

- Describes relations between datasets and databases in the INEXDA metadata database...
  - ... in a given country
  - ... across countries

- Examples of use cases in INEXDA context
  1. Relation between datasets containing similar units (in different countries).
  2. Dataset feeds into a ECB dataset.

- *Publications* provides information on scientific publications related to the dataset.

INEXDA
The Granular Data Network

Conclusion

- INEXDA’s metadata schema is based on the GESIS DOI registration service da|ra (GESIS is cooperating with DataCite)
  https://www.da-ra.de/en/home

- Purpose is to foster harmonisation between INEXDA members and broaden metadata sharing within INEXDA and possibly outside

- Name of metadata items closely follows da|ra conventions to enable seamless DOI registration, if desired later in the project

- Using DOI for datasets may help
  - … facilitate datasets citations
  - … foster reproducibility of results

INEXDA
The Granular Data Network

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BANK FOR INTERNATIONAL SETTLEMENTS

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Privacy preserving set intersection[1]

Giuseppe Bruno and Diana Nicoletti,
Bank of Italy,

Monica Scannapieco and Diego Zardetto,
Italian National Statistical Office

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Privacy Preserving Set Intersection [1]

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Abstract

Modern societies are increasingly dependent on, and sometimes afraid of, huge amounts of information. There are numerous scenarios where sensitive data must — even if reluctantly or suspiciously — be shared between entities (or institutions) without mutual trust.
National privacy protection laws, however, forbid the processing of non-anonymized records between institutions and even within the same institution, thus making it difficult to carry out statistical studies. The goal of this paper is to explore viable techniques to carry out data linkage among institutions while preserving a desirable level of anonymity. Taking advantage of cryptographic techniques introduced since the 90s, we provide some examples of linkage of anonymized files, in an attempt to overcome the current privacy constraints.

Keywords: Data linkage, hash functions, encryption, record re-identification.

[1] The views expressed in the paper are the authors' only and do not imply those of their institutions

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1. Introduction

Modern societies are increasingly dependent on, and sometimes afraid of, massive amounts and availability of digital information. There are numerous scenarios where sensitive data must — even if reluctantly or suspiciously — be shared between entities (or institutions) without mutual trust. Administrative records including socio-economic and financial information, both for households and firms, have huge potential for statistical studies. In Italy, the Fiscal Code is a widely used identifier for individuals and firms, and this would theoretically provide wide margin for data matching, provided that the legislation on such matters was respected.
The law, however, forbids the processing of non-anonymized records within and between institutions, thus making it difficult to carry out statistical studies.
We would like to benefit from computer science, specifically cryptographic techniques introduced since the 90s, to provide safe linkage of anonymized files, in order to overcome the current constraints of such procedures.
In this paper, we propose some modifications on a protocol, based on hashing and cryptographic functions, to strongly distinguish among identifying and not-identifying data and carrying out the objective of performing privacy preserving analytics.
The examined scenarios offer a strict supervision over who is in possession of which information. This allows us to prevent unauthorized linkage of data and to protect individuals anonymity.
Here our goal is to explore viable techniques to carry out data linkage among institutions while preserving a desirable level of anonymity. We present some examples of empirical applications with the use of synthetic data.
Our view is that the main obstacle to setting up such a system is not technical, but rather organizational in that it is based on the concept of a third party as trusted Authority.
Although prior work has yielded a number of effective and elegant Private Set Intersection (PSI) techniques, the quest for efficiency is still underway. Here we propose some PSI variations of a well-known algorithm and security improvements that scale well up to a billion records.
The results achieved so far seem very promising therefore we deem of paramount importance the extension of our work along the following two lines:

1) a deeper experimentation with real data, different tools and protocols,
2) the cooperation of the Data Protection Authorities to play a specific role in the protocols;

The rest of the paper is organized in the following way: in the next paragraph we explain the need for Private Data Sharing Protocols and, later, we describe four reference scenarios that can possibly take place when a private information sharing need occurs (section 3). Then, section 4 provides a broad illustration of the two practical exercises that were implemented as empirical applications. Finally, section 5 draws the main conclusion of this paper.

2. Why Private Data Sharing Protocols

Privacy by Design is an approach to information system engineering that takes privacy into account throughout the whole engineering process. From a legislative perspective, the concept of Privacy by Design has been formally introduced in the EU Regulation 2016/679, where Article 25 is about "Data protection by design and by default".
The Italian National Institute of Statistics (Istat) and the Bank of Italy started a research collaboration with the following two goals:

1) Trying to figure out what concretely "privacy by design" can mean in a multi-organizational information sharing context.
2) Setting up some experiments to validate the feasibility, the performance and the open issues on adopted methods.

With the increasing presence of anytime-anywhere data, there are many realistic scenarios where sharing data among two parties could be beneficial for both of them. Even with the assumption of honest behavior from the two parties, there is always the need to devise robust protocols providing high security standards along with a limited computational power.

3. Scenarios for private data sharing

We envision four scenarios that can support the "generic" information sharing need, namely:

i) private set intersection (PSI);
ii) private set intersection with enrichment (PSI-E);
iii) private set intersection with analytics (PSI-A);
iv) private data mining.

3.1 Private Set Intersection (PSI)

Here two further specific scenarios can be identified, namely Exact and Approximate PSI.

Exact PSI Definition: Let P1 and P2 be parties owning (large) private databases D1 and D2. The parties wish to apply an exact join to D1 and D2 without revealing any unnecessary information about their individual databases. That is, ideally, the only information learned by P1 about D2 and by P1 about D1 is D1 $\cap$ D2.

Approximate PSI Definition: Let P1 and P2 be parties owning (large) private databases D1 and D2. The parties wish to apply an approximate join to D1 and D2 without revealing any unnecessary information about their individual databases. That is, ideally, the only information learned by P1 about D2 and by P2 about D1 is D1 $\cap$ D2.
An example of an exact PSI algorithm can be found in [1], while an example of an approximate PSI algorithm can be found in [2].
Differently from exact joins, approximate joins are an indirect, somewhat complicated process, as they require the computation of distance functions among records, the values of which have to be kept private[2].

3.2 Private Set Intersection with Enrichment (PSI-E)

PSI-E Definition Let P1 and P2 be parties owning (large) private databases D1 and D2. The parties wish to apply an exact or approximate join to D1 and D2 without revealing any unnecessary information about their individual databases. After that, they wish to enrich joined records with variables by both parties. At the end

[2] As an example, computing a distance dist(d1,d2), where d1 and d2 are two data items owned respectively by sources P1 and P2, requires both values to be available at the same time to one party. However, under privacy constraints, such simple condition cannot be met in that P1 cannot see d2 and P2 cannot see d1. Even if a third neutral party is introduced, it cannot compute neither the distance between the plain values of d1 and d2, nor the distance between encrypted values, because encryption functions do not generally preserve similarity distances. In order to overcome such a problem ad-hoc protocols need to be proposed that may require complex data processing.

of the process P1 will learn additional P2 variables on D1∩ D2 and P2 will learn additional P1 variables on the same intersection (see Figure 1).

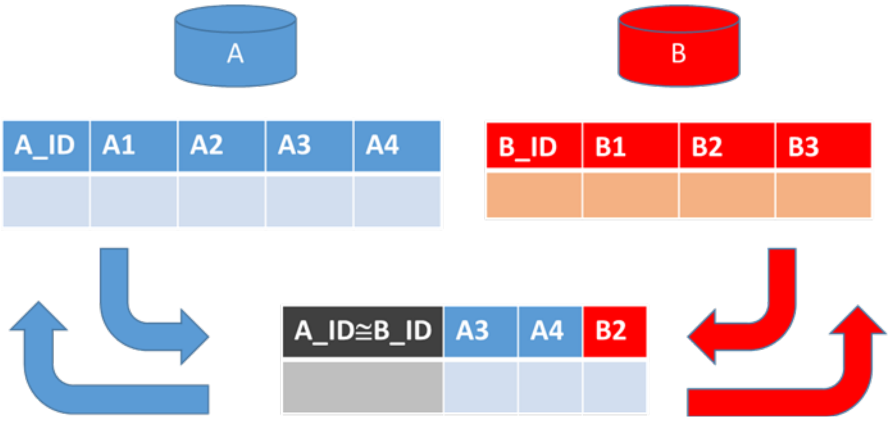

FIGURE 1: PRIVATE SET INTERSECTION WITH ENRICHMENT SCENARIO

3.3 Private Set Intersection with Analytics (PSI-A)

PSI-A Definition. The parties wish to perform a statistical analysis on the intersection of their databases in a private fashion. To identify the records belonging to the intersection, they agree to apply an Exact PSI. At the end of the process, the only information learned by the parties (beyond the keys of the records belonging to the intersection) is the result of the statistical analysis.

3.4 Private Data Mining

Private data mining. "Let P1 and P2 be parties owning (large) private databases D1 and D2. The parties wish to apply an analytics function to the joint database D1∪D2 without revealing any unnecessary information about their individual databases. At the end of the process, the only information learned by P1 about D2 is that which can be learned from the output of the analytics function, and vice versa " [3].

4. Case Study n. 1

4.1 General considerations

For this empirical application we have considered the interaction between two institutions that strictly adhere to the proposed protocol. This kind of behavior, in the literature, is usually defined as Honest but Curious (HbC). Within this framework, the institutions will not try to make queries purposefully designed to gain other attributes on particular individuals, for example by sending just one or multiple identical keys to receive the attributes owned by the server partner. A possible way to reduce the chance of re-identification would be the check that the number of different key-values is greater than a given threshold.

4.2 Description of the use case

This case study deals with an application of PSI-E described in chapter 0. We consider two organizations having two basic health information datasets. The record structure of the first dataset is the following:

1) Individual name; this field is a key in the whole table.
2) Weight, a positive continuous variable
3) Smoker, a binary variable (1=smoker, 0=not-smoker)

The second dataset has the following structure:

1) Individual name; this field is a key in the whole table.
2) Height, a positive continuous variable,
3) Blood_pressure, a positive continuous variable.

The owners of the two datasets wish to join them for statistical purposes without making the names available to the other party. In this empirical application we assume each party as honest but curious. This categorization imply that the institutions will not try to cheat the other party not abiding the protocol rules. This assumption is tantamount to say that institutions will not exchange dataset whose attributes are distributed in such a way to allow straight record re-identification. The interaction between the two institutions yields a joined dataset which retains the common elements without any reference to the individual's name. The following picture describes the employed testing framework.

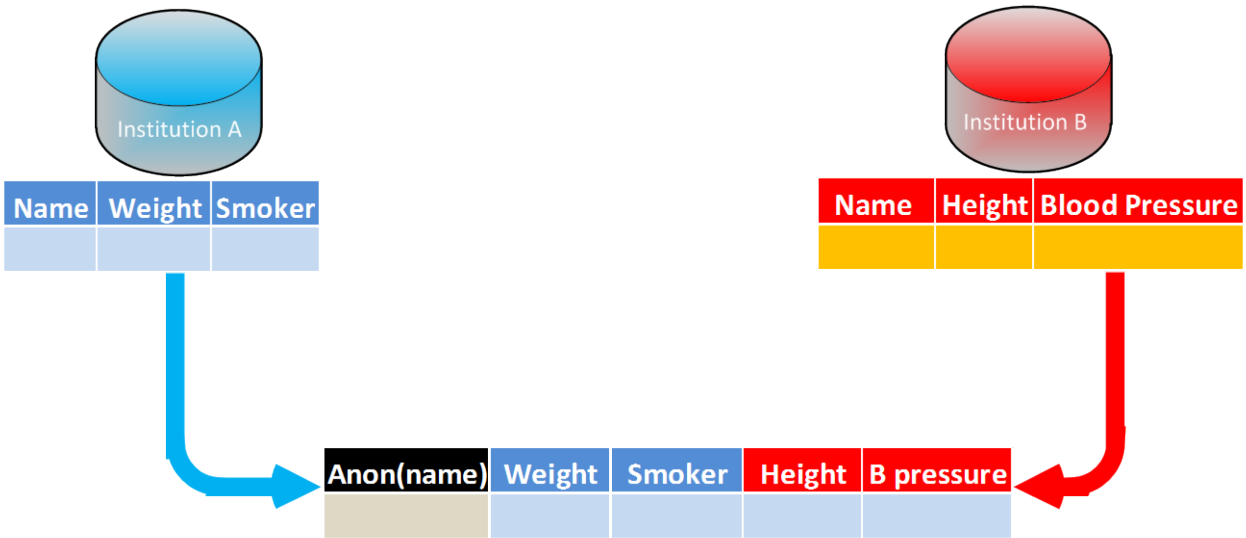

FIGURE 2: CASE 1 EXAMPLE

As can be seen from Figure 2 the shared dataset includes the variables provided by the two institutions but the identification key has been anonymized by a sequence of hashing and encryption steps which prevents re-identification from either parties.

4.3 Description of the Protocol

The protocol employed for the implementation of this case study is based on De Cristofaro-Tsudik (2010) (DCT). The Private Set Intersection (PSI) is a cryptographic protocol entailing two players, in our setup two institutions, which are called client and server.
In this empirical application we have considered a mutual version of the protocol where the roles of client and servers are exchangeable between the two institutions. Within this framework the outcome is available to both the players.

We have employed a modified version of the "Blind RSA-based PSI protocol" proposed in DCT. The original protocol has been improved along the following lines:

1) A proxy server has been put in front of the web server providing the data (for IT security purpose);
2) A code parallelization has been carried out for performance improving;
3) The communication between the client and the proxy server is encrypted through a digital certificate;

The protocol implementation has been carried out in Python starting from a version by Constantinos Patsakis available at: *https://github.com/kpatsakis/PSI_De_Christofaro* .
The protocol is based on the RSA[3] encryption algorithms and the SHA256[4] (256 bit Secure Hash Algorithm). RSA security is rooted on the key-length while resilience of hashing function comes from the length of the output digest. In our experiments we have checked the protocol performances by varying RSA key-length and the output digest length.

5. Case Study n. 2

5.1 Description of the use case

This case study has been developed with reference to the PSI-A scenario introduced in Section 2.3. The two involved parties own databases D1 and D2 respectively. D1 and D2 have a common key, which can be exploited to perform an Exact PSI. The parties wish to enrich their information assets by learning the results of a statistical analysis[5] applied to the *intersection* of their databases. This goal must be reached in compliance with *all* the following requirements:

- only the strictly necessary data are transmitted;
- only encrypted data are transmitted;
- secure data transmission protocols are used;
- the intersection of private databases is obtained by an Exact PSI;
- the parties learn *only* the results of the required statistical analysis (beyond the keys of the records belonging to the intersection);

To be more specific, let us suppose that D1 database has variables 'tax code' (common key), 'number of children' and 'age class', while the D2 database has variables 'tax code' (common key), 'income class', 'mortgage payment class' and the binary variable 'solvent/insolvent borrower'. The objective for both parties is to privately query the intersection of their databases and retrieve counts with respect to a given set of grouping variables. For instance, the first institution could be interested in learning how many insolvent borrowers have more than 2 children, e.g. in the context of actuarial risk modelling. The second institution, in turn, might want to know how many elderly

[3] RSA stands for Rivest, Shamir and Adleman, the three researchers who proposed the algorithm in 1978.

[4] See for example http://csrc.nist.gov/publications/fips/fips180-2/fips180-2withchangenotice.pdf

[5] In this preliminary phase, we have considered a very simple statistical analysis, namely the computation of absolute frequency distributions. Therefore, the parties will be able to learn only counts of units classified by a set of categorical variables.

people (aged 65 or more) belong to the lowest income class, e.g. in the context of poverty analysis. Note that in both these examples, each party takes advantage of variables which it does *not* own, but which are *privately provided* by the other party.

5.2 Description of the use case

To implement the use case described above, we assume to be in an honest-but-curious (HbC) context, so that all the involved parties will respect all the rules defined in the protocol.
The protocol requires, in addition to the parties who want to privately share their data, a third party named *Linker*. The role of the Linker is to:

- receive and store encrypted data from both parties;
- receive queries from the parties, process the encrypted data and return to the parties the results of the queries they submitted.

Considering its role, the Linker should be a *super partes* organization trusted by all the Institutions participating to the protocol. In this experimental phase we might assume this role is alternatively played by one of the institutions. From a theoretic perspective its role could be played by a national or super national Date Protection Authority.
The experimental protocol implemented requires the following four phases (the purpose of each phase is sketched in parentheses):

1) *Preliminary phase* (agreement between the parties on base protocol parameters)
2) *Exact PSI* (private intersection of common database keys)
3) *Loading* (transmission of encrypted data to the Linker)
4) *Query* (submission of queries to the Linker and transmission of results)

In the *Preliminary phase*, the parties agree on: (a) the name of the common database variable to be used for the Exact PSI, (b) the names of the database variables they want to share, (c) the symmetric cryptographic key that both parties will use to encrypt their private data (note that this symmetric key is transmitted through the RSA protocol).
In the *Exact PSI* phase, the PSI protocol of De Cristofaro [1] is applied, with the two parties playing alternately the client and the server roles. At the end of the phase, both parties have learned the keys of the records belonging to the intersection of their private databases.
In the *Loading* phase, the parties upload to the Linker the encrypted version of the data they want to share. More precisely, for each record of the intersection determined in the Exact PSI phase (and only for them), the parties provide the encrypted values of their private variables.
In the *query* phase, first, the parties asynchronously submit a query to the Linker; then, the Linker computes the query results by processing the encrypted data; finally, the Linker transmits the query results to the sender of the query.
The whole process is depicted in Figure 3.

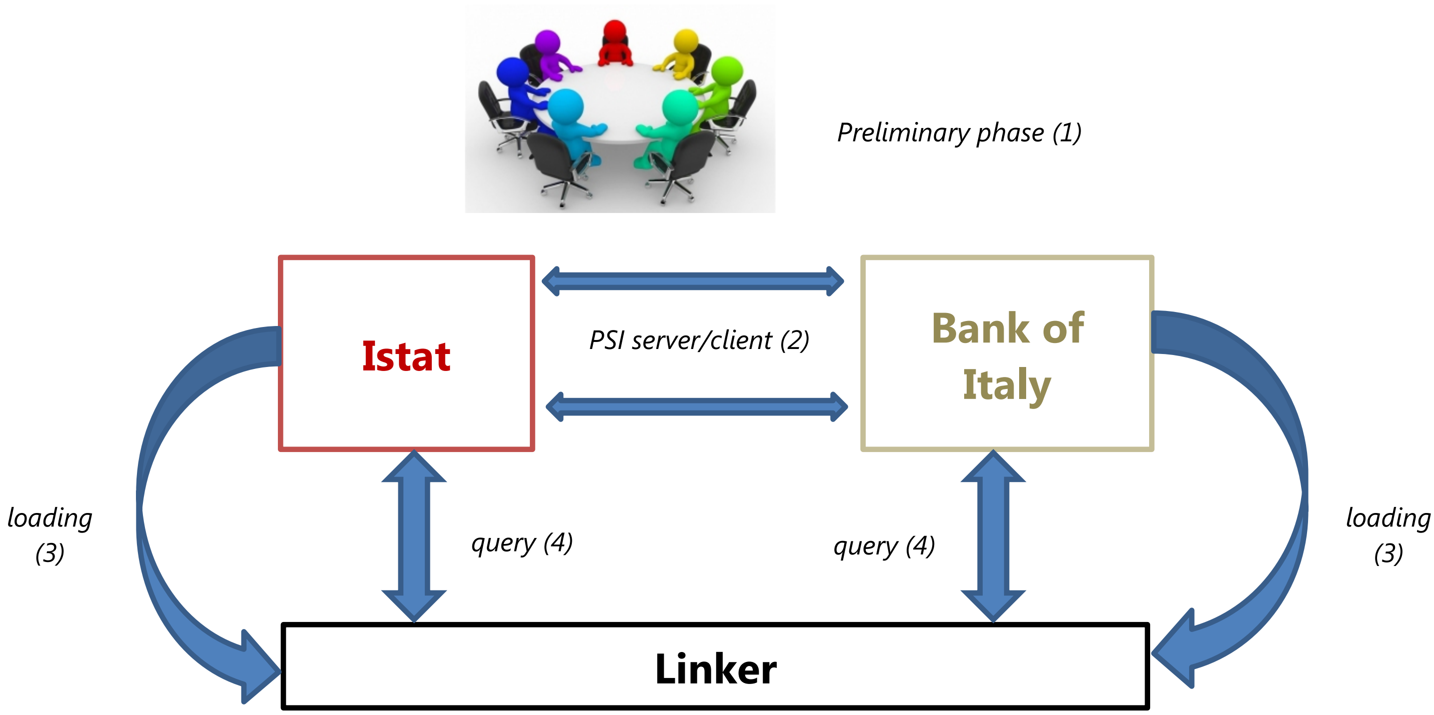

FIGURE 3: EXCHANGE OF INFORMATION BETWEEN THE PARTIES ACCORDING TO THE PROTOCOL

6. Concluding Remarks

In this paper we have considered some techniques to carry out data linkage among data bases belonging to institutions while preserving a desirable level of anonymity. We have shown some examples of empirical applications with the use of synthetic data.

The main findings of these experiments are the following:

1) Assuming an HbC environment (i.e. a trustful behavior), it is possible to address the data sharing goal between institutions in a *private* framework: each party will know either counts with respect to a given set of grouping variables or the actual values of the attributes of records belonging to the other party, with the privacy constraints enforced on identifier fields.
2) In situations with rarefied distribution of record attributes it could be required the employment of Statistical Disclosure control techniques to assess the risk of reidentification either on the Linker or in the client/server side.

3) The extensions of statistical analyses in the PSI-A framework could be explored with homomorphic cryptography[6] that has recently received a considerable attention in the literature (see e.g. [5]).

On the basis of the empirical applications carried out so far, we think that the field of private information sharing has potential for further investigation and adoption in concrete data sharing scenarios among institutions.
As discussed in the introduction, both technical and organizational actions are suggested to make the result of this work able to be concretely implemented within national and international institutions.

[6] Homomorphic Encryption is a special kind of encryption scheme that allows any third party to operate on the encrypted data without decrypting it in advance.

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Appendix

The employed cryptographic functions

1. RSA encryption

The RSA is an algorithm for encryption and digital signature introduced by Rivest, Shamir and Adleman at the MIT in 1977. It provides an asymmetric encryption based on two (public and private) keys distributed between the sender and the receiver.

The RSA algorithm can be split into the following the phases:

1) Key generation;
2) Message encryption;
3) Message decryption.

The key generation consists in:

1) choosing two huge prime numbers (~300 decimal digits) and computing their product $n = p \cdot q$;
2) Compute the value $\lambda(n) = lcm(\lambda(p) \cdot \lambda(q) = (p-1) \cdot (q-1)$ which is the maximum number of values a coprime with n;
3) Choose an integer e satisfying the conditions $1 < e < \lambda(n)$ and that e and $\lambda(n)$ are coprime;
4) Determine d in such a way that $d \cdot e \equiv 1 \, mod \, \lambda(n)$; i.e., d is the modular multiplicative inverse of e (modulo $\lambda(n)$)

The public key consists of the modulus n and the encryption exponent e; the private key consists of the decryption exponent d and $\lambda(n)$).

At this point the encryption and decryption steps are given by the following modular exponentiation:

encryption: $c \equiv (m)^e \, mod(n)$

decryption: $m \equiv (m^e)^d \equiv m^{e \cdot d} \equiv m^1 \, mod(n)$

2. Hash functions

Cryptographic hash functions are an essential building block

for privacy and security applications.

Cryptographic hash functions map input strings of arbitrary length to short,

fixed length output strings. They were introduced in cryptology in the 1976 seminal paper of Diffie and Hellman on public-key cryptography [7]. Hash functions can be used in a broad range of applications: to compute a short unique identifier of a string (e.g. for a digital signature), as one-way function to hide a string (e.g. for password protection and for privacy purposes).

In the empirical application here described we have employed the hash functions belonging to the SHA-2 (Secure Hash Algorithm) family. This family of algorithms has been designed by the U.S. National Security Agency (NSA).

A good hash function H should satisfy the following requirements:

1) *One-wayness*: for an arbitrary n-bit length string w it is hard to find a value of x such that $H(x) = w$;
2) *Second preimage resistant*: for an arbitrary n-bit length string x it is hard to find a value $y \neq x$ so that $H(x) = H(y)$;
3) *Collision resistance*: it is hard to find two values x and y satisfying $y \neq x$ so that $H(x) = H(y)$;

It is straightforward to see that collision resistance implies second-preimage resistance. In practice, collision resistance is the strongest property of all three, hardest to satisfy and easiest to breach, and breaking it is the goal of most attacks on hash functions.

In our implementation we have taken the hash functions present the Python library HASHLIB.

Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

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Privacy preserving set intersection[1]

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Privacy Preserving Set Intersection.

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Irving Fisher Committee Conference. BIS, Basel, August 30th 2018

Outline

1. Motivation
2. Some cryptographic preliminary
3. The Private Intersection protocol
4. Concluding Remarks

Why do we want to link datasets
merging datasets

- Administrative records on firms and individuals have a huge potential for statistical studies.
- The law forbids the merging and processing of non-anonymized data, thus making it difficult to carry out studies requiring several sources of data.
- It would be helpful to take advantage of hashing and cryptographic techniques to carry out safe linkage between different datasets.

Why do we want to link datasets
merging datasets

- Administrative records on firms and individuals have a huge potential for statistical studies.
- The law forbids the merging and processing of non-anonymized data, thus making it difficult to carry out studies requiring several sources of data.
- It would be helpful to take advantage of hashing and cryptographic techniques to carry out safe linkage between different datasets.

Why do we want to link datasets
merging datasets

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leveraging larger datasets

Possible social benefits from sharing otherwise private databases:

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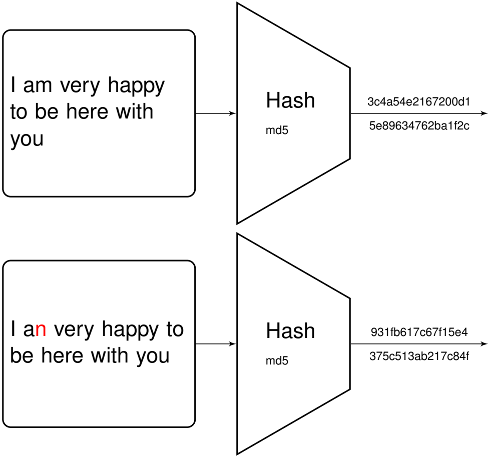
Asymmetric encryption and digital signature

RSA asymmetric encryption guarantees a bilateral secure communication.

- RSA (for Rivest, Shamir & Adleman) was introduced in 1977 MIT;
- known as public-key scheme;
- based on modular exponentiation on an integer field;
- security is linked to the complexity of factoring huge numbers (300 digits);

What is a hash function?



Residual disclosure risk

Main assumption: Honest but curious behaviour. A unit is defined at risk when it can easily be singled out from other records. We distinguish three cases:

- quasi-identifiers are of *categorical* kind;
- quasi-identifiers are of *continuos* kind;
- quasi-identifiers are of mixed kind.

Our protocol doesn't protect against malicious behavior aiming at individual re-identification. Generalization and suppression techniques could be helpful.

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Private Set Intersection flavours

Private Set Intersection: a cryptographic protocol involving two parties/institutions endowed with a private set. The two parties, a client and a server, want to jointly compute the intersection of their private input sets in a way that at the end the client learns the intersection and the server learns nothing.

- *Plain Private Set Intersection* (PSI)
- *Authorized Private Set Intersection* (APSI)

The difference between these two protocols is that in APSI each element in the client set must be authorized for sharing by some recognized and mutually trusted authority.

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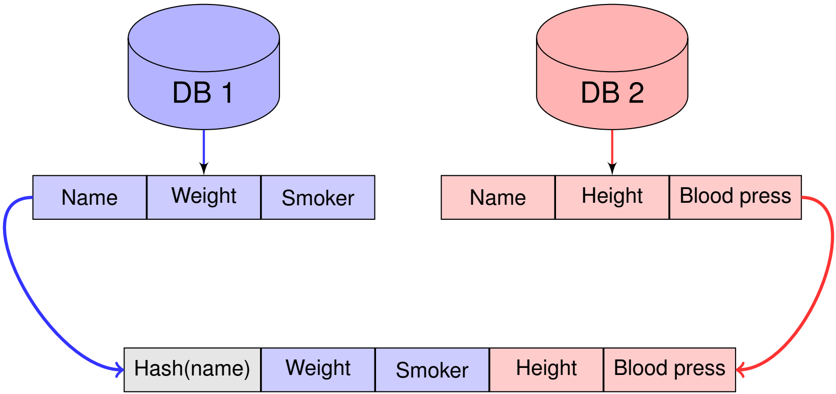
The Private set intersection scheme



The protocol: offline section

Initial data:

- RSA public and private keys;
- Client's input: $\mathcal{C} = \{hc_1, \ldots, hc_v\}$ where $hc_i = hash(c_i)$;
- Server's input: $\mathcal{S} = \{hs_1, \ldots, hs_w\}$ where $hs_i = hash(s_i)$;

The protocol is broken down into two phases:

$\boxed{\text{OFF-LINE:}}$

1. Server: $\forall j : K_{s:j} = \left(hash(s_j)\right)^d \mod n; \quad t_j = H'(K_{s:j})$
2. Client: $\forall i : R_{c:i} \sim \mathcal{U}[0, Z_n^*]; \quad y_i = hash(c_i) \cdot (R_{c:i})^e \mod n$

The protocol: online section

ON-LINE:

1. Client: $\xrightarrow{y_1, y_2, \ldots, y_v}$ Server;
2. Server: $\forall i : y_i' = (hash(y_i))^d \mod n$
3. Server: $\xrightarrow{\{y_1', \ldots, y_v'\} \quad \{t_1, \ldots, t_w\}}$ Client;
4. Client: $\forall i : K_{c:i} = y_i' / R_{c:i}$ and $t_i' = H'(K_{c:i})$
   Result: $\{t_1', \ldots t_v'\} \cap \{t_1, \ldots, t_w\}$

Protocol characteristics

Our protocol satisfy the following conditions:

- **Correctness:** at the end of *Interaction*, Client outputs the exact intersection;
- **Server privacy:** The client learns no information about the server elements not belonging to the intersection ;
- **Client privacy:** The Server learns no information about the client elements except the upper bound on the client's set size ;
- **Client unlinkability:** a malicious server cannot tell if any two instances of *Interaction* are related, (executed on the same inputs);

Concluding Remarks

- suggested how to take advantage of cryptographic functions for sharing private data;
- shown how to implement a Private Set Intersection protocol giving a Client only the anonymized common records;
- provided a data sharing environment without a trusted third party;
- improving the security with some form of authentication;
- outlining possible avenues for computing scalability up to 10^9;

For Further Reading

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Privacy Preserving Schema and Data Matching.
Sigmod Conference, 2007.

Thank you very much for your attention.

Vielen Dank für ihre Aufmerksamkeit.

Merci beaucoup pour votre attention.

Questions?

Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

Data sharing under confidentiality[1]

Erdem Başer and Timur Hülagü,
Central Bank of the Republic of Turkey,

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İrem Keskinkurt-Paksoy and A. Sevtap Selçuk-Kestel,
Middle East Technical University

[1] This paper was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

Data Sharing Under Confidentiality

Ersan Akyıldız[1], Erdem Başer, Adnan Bilgen, Murat Cenk, Timur Hülagü, İrem Keskinkurt-Paksoy and A. Sevtap Selcuk-Kestel

Abstract

Central Bank of the Republic of Turkey presents an approach to address the data sharing dilemma of maximizing the benefit for academic research while ensuring compliance with applicable data confidentiality legislations. The work in this paper compares the performance of different perturbation methods. Empirical estimates are presented over a wide range of statistical methods. The results in the paper are expected to be used to inform the design of access procedures to confidential microdata in central banks.

Keywords: Data perturbation, accuracy, privacy, financial dataset

Contents

[1] Akyıldız, Bilgen, Cenk, Keskinkurt-Paksoy and Selcuk-Kestel are affiliated with Middle East Technical University while Başer and Hülagü are affiliated with the Central Bank of the Republic of Turkey. All views expressed in this paper are ours and do not necessarily represent those of the Central Bank of the Republic of Turkey or Middle East Technical University.

Introduction

A statistical database is a collection of data which contains sensitive information of individuals (patient, student, company, etc.) which are commonly used in research, planning and decision making. Increasing amounts of such databases are provided by agents like census bureaus, universities, hospitals and business organizations. They contain confidential information such as income, credit ratings, type of disease, or test scores of individuals. Collected data is used extensively by researchers and decision-makers in different fields.

However, most collected datasets contain private or sensitive information. The curators sometimes apply some simple anonymization techniques, but the adversary can destroy the privacy and re-identify the dataset. In the early years some researchers de-anonymize a medical data set by linking with another public vote list dataset [1]. The linked information is defined as the background information [2]. The adversary with background information will be able to identify the individuals records with high probability.

The main purpose of this study is to make financial datasets available to researchers while ensuring the confidentiality of the data. We divide our works into three parts. In the first part, we study the techniques to obtain sanitized data and test the accuracy for selected statistical functions on masked data. In the second part, we study the existing attacks and apply them to the masked dataset. In this step, we also handle the weakness of the most widely used random number generator. In the last part, we develop a user-friendly software, to generate a secure masked dataset from the original data.

Method and Accuracy Tests

In the literature, there are a couple of existing approaches on masking techniques [3,4]. We have observed that the following additive masking techniques solves our accuracy problem: We first generate our noise from a normal distribution. In doing this, the random numbers are derived from the original data using its mean and the standard deviation. Figure 1 shows the masking strategies that we used in our system:

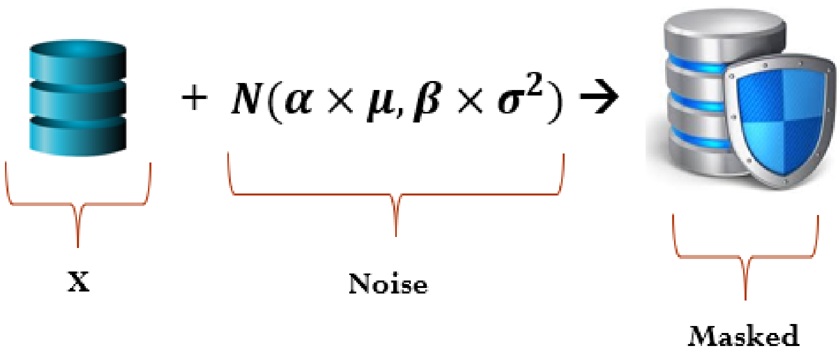


Figure 1. Masking original data set by random perturbation

Here, X denotes the original data set. We generate noise from a normal distribution and mask the original data additively which is aimed to be shared with researchers. There are two dimensions of the problem of applying this methodology: accuracy and privacy of the masked data have to be at desired levels. For the first, we observe that the accuracy is satisfied for original and log-transformed masked data over the following statistical analyses such as descriptive statistics (mean, standard deviation, skewness, and kurtosis), simple and multiple linear regression analysis, simple and multiple logistic regression analysis on masked datasets.

Some experimental results for accuracy are done and illustrated in tables 1-5. Each table presents the accuracy obtained in implementing the additive normal perturbation to some artificial data sets. The proportion of observed (O) data series and masked (M) data series is expected to remain within a certain accuracy which is taken to be 5% in our case. Table 1 and Table 2 indicate the results of descriptive statistics at which the mean, standard deviation, skewness and kurtosis of original data and log-transformed data remain within the target accuracy limit, respectively. Simple and multiple linear regression applied to original and masked data sets (Table 3 and Table 4) come up with the same accuracy results which verifies that the masked data yield a certain accuracy in linear modeling.

Descriptive statistic results of original series — Table 1

Variable	B59	B42	G62
Mean(O/M)	0.9777	0.9754	0.9756
Standard Deviation(O/M)	1	0.9995	1
Skewness(O/M)	1	1.001	1.002
Kurtosis(O/M)	1.001	1.001	1.006

Table 2: Descriptive statistics results for log-transformed data			
Variable	B30	B50	G600
Mean(O/M)	0.9756	0.9756	0.9756
Standard Deviation(O/M)	0.9997	0.9995	0.9998
Skewness(O/M)	1.001	1.003	1.002
Kurtosis(O/M)	1.002	1.008	1.004

Given the ratios presented in Table 1 and 2 (original / masked), it was observed that the values ranged from 0.95 to 1.05. This means that the statistics of the log transformed variables remain within the specified accuracy limits.

Table 3: Simple linear regression applied to original data

Dependent Variable	Independent Variable			
G69	B40			
Original				
Coefficients:				
	Estimate	Std.Error	t-value	p-value
(Intercept)	1471556.82	124927.49	11.8	<0.0001
B40	0.8733	0.0156	55.9	<0.0001
Multiple R-Squared: 0.2820	Adjusted R-Squared: 0.2820			
F-statistic: 0.0031	p-value: <0.0001			
Masked				
Coefficients:				
	Estimate	Std.Error	t-value	p-value
(Intercept)	1509476.22	125047.53	12.1	<0.0001
MB40	0.8731	0.0156	55.9	<0.0001
Multiple R-Squared: 0.2820	Adjusted R-Squared: 0.2820			
F-statistic: 0.0031	p-value: <0.0001			

Table 4: Multiple Linear Regression applied to original data

Dependent Variable	Independent Variable			
G69	G600, G601, B300, B40, G66, B590			
Original				
Coefficients:				
	Estimate	Std.Error	t-value	p-value
(Intercept)	40987.73	135028.06	0.30	0.7615
G600	0.02230	0.00343	6.50	<0.0001
G601	0.02839	0.00748	3.80	0.0002
B300	-0.06936	0.00808	-8.58	<0.0001
B40	-0.06358	0.00228	-27.85	<0.0001
G66	0.63973	0.01628	39.30	<0.0001
B590	1.12325	0.02196	51.15	<0.0001
Multiple R-Squared: 0.5230	Adjusted R-Squared: 0.5230			
F-statistic: 0.0015	p-value: <0.0001			

Masked				
Coefficients:				
	Estimate	Std.Error	t-value	p-value
(Intercept)	41896.84	136612.71	0.31	0.75909
MG600	0.02225	0.00343	6.49	<0.0001
MG601	0.02839	0.00748	3.80	0.0002
MB300	-0.06858	0.00808	-8.49	<0.0001
MB40	-0.06347	0.00228	-27.85	<0.0001
MG66	0.64025	0.01627	39.35	<0.0001
MB590	1.12128	0.02197	51.04	<0.0001
Multiple R-Squared: 0.5230	Adjusted R-Squared: 0.5230			
F-statistic: 0.0015	p-value: <0.0001			

In addition to linear regression, binary response variable case is considered and given a presumed threshold value the simple and multiple logistic regression analyses are repeated with the same approach. Tables 5 and 6 show that the estimates and the tests statistics are close and the masked data can be used in logistic regression modeling.

Table 5: Simple Logistic Regression applied to original data

Dependent Variable	Independent Variable		Threshold = 200000	
B590	G600			
Original				
Coefficients:				
	Estimate	Std.Error	t-value	p-value
(Intercept)	0.3622	0.0070	51.8	<0.0001
G600	0.4753e-8	0.0171e-8	27.8	<0.0001
Multiple R-Squared: 0.0885	Adjusted R-Squared: 0.0884			
F-statistic: 772	p-value: <0.0001			
Masked				
Coefficients:				
	Estimate	Std.Error	t-value	p-value
(Intercept)	0.3591	0.0070	50.9	<0.0001
MG600	0.4753e-8	0.0171e-8	27.8	<0.0001
Multiple R-Squared: 0.0885	Adjusted R-Squared: 0.0884			
F-statistic: 772	p-value: <0.0001			

Table 6: Multiple Logistic Regression applied to original data

Dependent Variable	Independent Variable		Threshold = 200000	
B590	G600, G601, G67			
Original				
Coefficients:				
	Estimate	Std.Error	t-value	p-value
(Intercept)	0.3389	0.0071	47.91	<0.0001
G600	0.4674e-8	0.0170e-8	27.49	<0.0001
G601	0.5681e-8	0.0385e-8	14.77	<0.0001
G67	0.0196e-8	0.1179e-8	0.17	0.8700
Multiple R-Squared: 0.1130	Adjusted R-Squared: 0.1130			
F-statistic: 337	p-value: <0.0001			
Masked				
Coefficients:				
	Estimate	Std.Error	t-value	p-value
(Intercept)	0.3354	0.0071	46.90	<0.0001
MG600	0.4672e-8	0.0170e-8	27.48	<0.0001
MG601	0.5666e-8	0.0385e-8	14.74	<0.0001
MG67	0.0212e-8	0.1179e-8	0.18	0.8700
Multiple R-Squared: 0.1130	Adjusted R-Squared: 0.1120			
F-statistic: 337	p-value: <0.0001			

Most of the econometric and financial data require logarithmic transformations. For such case, we test if the proposed approach gives the same accuracy. The log transformed original series is masked and the same statistical analyses are performed. As it is presented in Table 2 the descriptive statistics are found to remain within the accuracy level. To apply the linear regression models, we assume the regression model is as follows:

$$\log\big(Dependent\ Variable\big) = \alpha_0 + \alpha_1 \log(Independent\ Variable_1) + \cdots + \alpha_k \log(Independent\ Variable_k) + \varepsilon$$

The simple linear regression (Table 7) and multiple linear regression (Table 8) analyses show that after masking the log-transformed original data, the regression models stay in the accuracy bounds compared to the results obtained using original-log-transformed data sets.

Table 7: Simple Linear Regression on log-transformed data

Dependent Variable	Independent Variable			
G590L	G64L			
Original				
Coefficients:				
	Estimate	Std.Error	t-value	p-value
(Intercept)	9.4150	0.1748	53.87	<0.0001
G600	-0.0190	0.0143	-1.33	0.1800
Multiple R-Squared: 0.0002	Adjusted R-Squared: 9.78e-5			
F-statistic: 1.78	p-value: 0.1830			
Masked				
Coefficients:				
	Estimate	Std.Error	t-value	p-value
(Intercept)	9.6540	0.1784	54.10	<0.0001
MG600	-0.0191	0.0143	-1.34	0.1800
Multiple R-Squared: 0.0002	Adjusted R-Squared: 9.97e5			
F-statistic: 1.79	p-value: 0.1810			
We found that the results applied to the original log transformed and masked data are close within 5% limits and are compatible in statistical tests.				

Table 8: Multiple Linear Regression applied to log-transformed

Dependent Variable	Independent Variable			
B590L	G64L, B32L, B400L			
Original				
Coefficients:				
	Estimate	Std.Error	t-value	p-value
(Intercept)	5.5555	0.3996	13.90	<0.0001
G64L	-0.0207	0.0141	-1.47	0.1400
B32L	0.3401	0.0250	13.60	<0.0001
B400L	-0.0874	0.0098	-8.95	<0.0001
Multiple R-Squared: 0.0295	Adjusted R-Squared: 0.0292			
F-statistic: 80.6	p-value: <0.0001			
Masked				
Coefficients:				
	Estimate	Std.Error	t-value	p-value
(Intercept)	5.6829	0.4093	13.88	<0.0001
G64L	-0.0207	0.0141	-1.47	0.1400
B32L	0.3408	0.0250	13.63	<0.0001
B400L	-0.0871	0.0098	-8.91	<0.0001
Multiple R-Squared: 0.0296	Adjusted R-Squared: 0.0292			
F-statistic: 80.7	p-value: <0.0001			
We found that the results are within the 5% limits of the original log transformed and masked cases and that they are also compatible with the statistical tests.				

Privacy Tests

For privacy, we study some of existing attacks in the literature which are applicable to our datasets [5]. These are spectral filtering, singular value decomposition and principal component analysis. For each method, we apply the attack to our masked data sets and obtain so-called estimated data sets. Then, we measure the distance between the estimated to original values shown as d(O,E) and the distance between masked to original shown as d(O,M). A comparison indicator, m, is defined as

$$\mathrm{m} = \left[\frac{d(O,E)}{d(O,M)}\right]$$

where

$$d(A,B) = \sum_{i=1}^{n} |a_i - b_i|$$

If **m** is in (0,1), after attacking we come close to original data. If **m** is 1 we find masked data itself. The methods used to check the privacy are explained in detail. Each method is applied firstly a hypothetical data set which are generated using triangular and sinusoidal functions based on the study done in [5] for justification of the methods to be functional in detecting the attacks. Afterwards, these methods are applied to the financial data set to show how much privacy is preserved in case of such attacks.

Spectral Filtering

This technique, developed by Kargupta et al. [6], utilizes the fact that the eigenvalues of a random matrix are distributed in a fairly predictable manner. The steps in applying spectral filtering are as follows:

i. We calculate the covariance matrix of masked data.

ii. We calculate the eigenvalues and the corresponding eigenvectors.

iii. We calculate the boundaries for eigenvalues by using the following equations:

$$\boldsymbol{\lambda_{min}} = \boldsymbol{\sigma^2(1 - \frac{1}{\sqrt{\theta}})^2} \;, \qquad \boldsymbol{\lambda_{max}} = \boldsymbol{\sigma^2(1 + \frac{1}{\sqrt{\theta}})^2} \text{ where } \boldsymbol{\theta} = \frac{\boldsymbol{m}(\textbf{row numbers})}{\boldsymbol{n}(\textbf{column numbers})}$$

The attack is done by using the corresponding eigenvectors of eigenvalues greater than $\boldsymbol{\lambda_{max}}$. For estimating the masked observation

$$\boldsymbol{E} = \boldsymbol{M} \times \boldsymbol{A_O} \times \boldsymbol{A_O}^{\boldsymbol{T}}$$

where E stands for is the estimation, M is the released masked data set, and A_O is the matrix with calculated eigenvectors as columns. Afterwards, we compare the closeness to the exact dataset by using

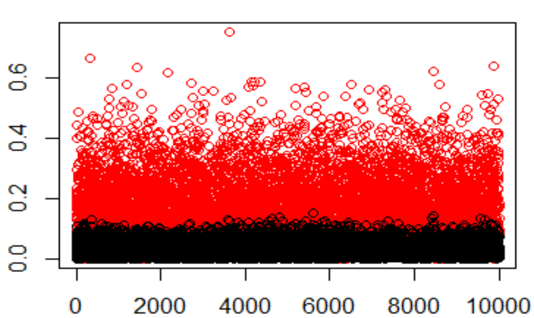
$$\mathrm{m} = \left[\frac{\mathrm{d(O,E)}}{\mathrm{d(O,M)}}\right]$$

To verification of the method we generate sinusoidal and triangular data and mask these according to the proposed model. We attack the masked data sets by using spectral filtering approach whose results are presented in Table 9 and Figure 2. In these graphs, red circles are the absolute difference between original and masked data points. The black circles are the difference between the original and estimated data points. We see that after attacking we come close to original data sets.

Table 9: Spectral filtering method tested on sinusoidal and triangular data sets

	Sinusoidal	Triangular
λ_{min}	0,01121	0,007627
λ_{max}	0,06104	0,04152
m x n	250x40	250x40
$d(O,M)$	1410	1163
$d(O,E)$	319,6	205,2
m	0,227	0,176

Sinusoidal | Triangular



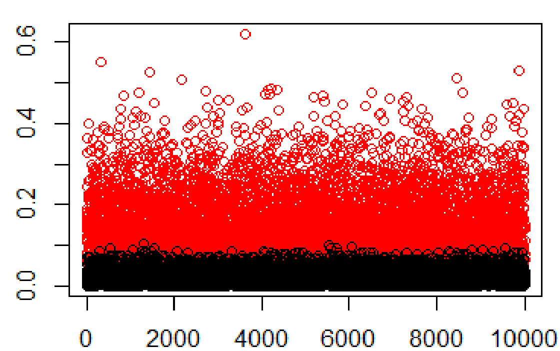


Figure 2: Spectral filtering method tested on sinusoidal and triangular data sets

Application of this attack method to masked financial data set yields the results presented in Table 10 and Figure 3. We see that, after attacking with spectral filtering to our masked financial dataset, we obtain the masked data itself. In other words, there is no disclosure of our financial data by applying this attack.

Table 10: Spectral filtering method tested on financial data set

	G69
$\boldsymbol{\lambda}_{\mathbf{min}}$	45870034800
$\boldsymbol{\lambda}_{\mathbf{max}}$	194658444176
m x n	250x30
$\mathbf{d}(\mathbf{O},\mathbf{M})$	1964402616
$\mathbf{d}(\mathbf{O},\mathbf{E})$	1964402616
m	1

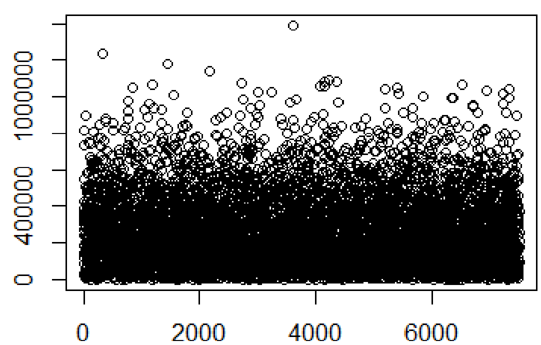


Figure 3: Spectral filtering method tested on sinusoidal and triangular data sets

Singular Value Decomposition(SVD)

Guo et al. [6] proposed a singular value decomposition-based data reconstruction approach and proved the equivalence of this approach to spectral filtering. SVD is applied as following:

a. We apply SVD to masked data matrix
b. $\mathrm{M} = \tilde{\mathrm{L}}\tilde{\mathrm{D}}\tilde{\mathrm{R}}^{\mathrm{T}}$
c. and we find the singular values, $\widetilde{\sigma_1} \geq \widetilde{\sigma_2} \geq \widetilde{\sigma_3} \geq \cdots$
d. We apply SVD to noise matrix and find the largest singular value, σ_V .

e. We find k,

f. $k = \min\{\, i : \{(\tilde{\sigma}_i < \sqrt{2}\sigma_v) - 1\}\}$

g. We attack by using the following equation,

h. $E = \hat{O}_k = \sum_{i=1}^{k} \tilde{\sigma}_i \times \tilde{l}_i \times \tilde{r}_i^T$

i. Then we compare the closeness to the exact dataset

$$\mathrm{m} = \left[\frac{\mathrm{d(O,E)}}{\mathrm{d(O,M)}}\right]$$

Similar to the first method, we first generate sinusoidal and triangular data and maske them. We attack the masked data sets by using SVD. The results of this attack method is shown in Table 11 and Figure 4. We see that the red circles in the graph are the absolute difference between original and masked data points. The black circles are the difference between the original and estimated data points. We see that after attacking we come close to original data sets.

Table 11: Singular value decomposition method tested on sinusoidal and triangular data sets

	Sinusoidal	Triangular
m x n	250x40	250x40
$\boldsymbol{d(O,M)}$	1410	1163
$\boldsymbol{d(O,E)}$	319,5	205,4
m	0,227	0,177

Sinusoidal	Triangular

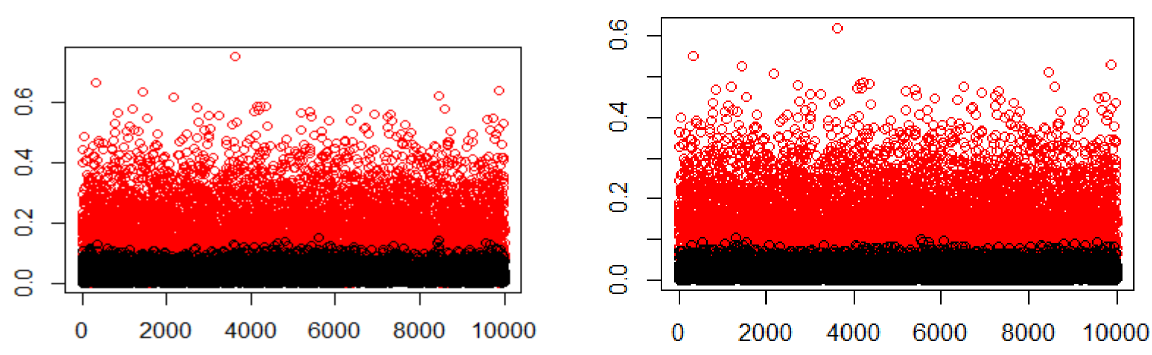


Figure 4: Singular value decomposition method tested on sinusoidal and triangular data sets

Then, we apply SVD to our masked financial dataset and see that attacking with SVD approach to our masked financial data set, we obtain masked data itself. There is no disclosure on our financial data

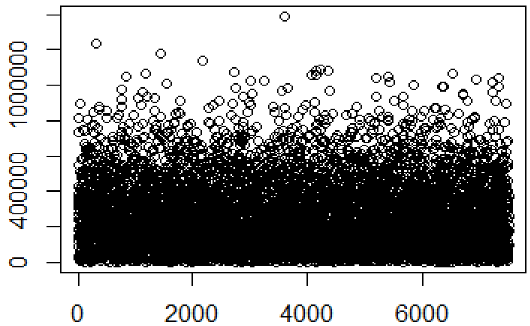


Figure 5: Singular value decomposition method tested on sinusoidal and triangular data sets

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Principle Component Analysis (PCA)

Huang et al. [7] proposed a filtering technique based on PCA. A major difference with spectral filtering, is that PCA filtering does not use matrix perturbation theory and spectral analysis to estimate dominant PCs of original data. PCA can be applied as following:

a. We compute the mean of each column of masked matrix, then subtract it from calculated column.

b. We calculate the covariance matrix of modified masked matrix. We produce:

c. $\sum \hat{X} = \sum \hat{Y} - \sigma^2 I$ an estimate of $\sum X$

d. We calculate the eigenvalues of $\sum \hat{X}$ and count the number of dominant eigenvalues and denote it as k.

e. From the k dominant eigenvalues, we calculate the corresponding eigenvectors.

f. $\hat{V}_x = [\hat{v}_x^1 \dots \hat{v}_x^k]$

g. We attack by using the following equation

h. $\hat{X} \approx Y \hat{V}_X \hat{V}_X^T$

i. Then we compare the closeness to the exact dataset

$$m = \left[\frac{d(O,E)}{d(O,M)}\right]$$

Implementation of PCA on experimental functions are presented in Table 12 and Figure 6. We observe similar result as in other two methods. The red circles are the absolute difference between original and masked data points. The black circles are the difference between the original and estimated data points. We see that after attacking we come close to original data sets

Table 12: Principal component analysis method tested on sinusoidal and triangular data sets

	Sinusoidal	Triangular
m x n	250x40	250x40
$d(O,M)$	1408	1173
$d(O,E)$	312,2	263,2
m	0,228	0,1224

Sinusoidal | Triangular

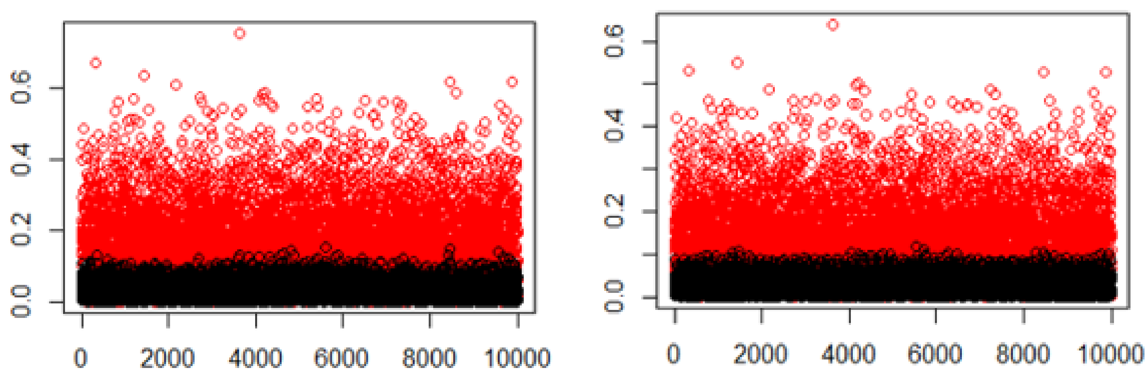

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Figure 6: Principal component analysis method tested on sinusoidal and triangular data sets

Application of PCA on financial data set yields no disclosure of original data as presented in Table 13.

Table 13: Principal component analysis method tested on sinusoidal and triangular data sets

	G69
m x n	250x30
m	1

The Inclusion of Random Number Generation in Privacy

In R-software system that we plan to use in the implementation, there are totally 2^{30} different seed values. If we use a seed value to generate all random numbers producing the noises, an attacker can recover the original data by constructing 2^{30} tables. In order to construct a table from a possible seed, the attacker generates the noises from this seed and then they are subtracted from the masked data. The tables from all other possible seeds are built similarly. Note that one of these tables is the original data. If there are n values of data, then the total size of the tables is $n2^{30}$. This amount of data can be efficiently stored in practice for the values of n used in practical applications. Therefore, while generating a masked data, a different seed value must be used for each value in the data in order to avoid such an attack. Moreover, if a masked data that was generated before is requested, the system must generate the same masked data, i.e., the same noises should be employed for generating the masked data. Otherwise, the system would be vulnerable against collusions. Under these requirements, we propose the following method described in Table 14 for noise generation. In this method, k is a key that must be kept secret by the authority generating noise. We use a function f to generate the seeds. The seed values are dependent on the original value of the data so that whenever the system gets a request of generating a masked data produced before, the same masked data will be generated. In the proposed system, we chose a nonlinear function $f(x) = \mu x^3+\sigma$ where μ and σ are the mean and the standard deviation of the original data, respectively.

Table 14: Privacy algorithm using proposed random number generation

Original data	Seed	Noise	Masked data
x_1	$s_1 = f(k + x_1) \bmod 2^{30}$	$\mathcal{E}_1 = RNG(s_1)$	$x'_1 = x_1 + \mathcal{E}_1$
x_2	$s_2 = f(x_2 + x'_1) \bmod 2^{30}$	$\mathcal{E}_2 = RNG(s_2)$	$x'_2 = x_2 + \mathcal{E}_2$
$\vdots$	$\vdots$	$\vdots$	$\vdots$
x_n	$s_n = f(x_n + x'_{n-1}) \bmod 2^{30}$	$\mathcal{E}_n = RNG(s_n)$	$x'_n = x_n + \mathcal{E}_n$

It should be remarked that μ and σ are also uncertain for the attacker. If it is easy to estimate those values for an attacker, then several more keys can be used in order to increase the security. In this case, we use $s_i = f(k_i + x_i) \bmod 2^{30}$ for $i=1,2,\ldots,t$ and $s_i = f(x_i + x'_{n-1}) \bmod 2^{30}$ for $i=t+1,\ldots n$ where t is a security parameter. In practice, selecting a master key of size about 1200-bit, splitting it in 40 equal parts having each 30-bit (that is t = 40) and assigning each 30-bit to a subkey k_i will be more than enough to provide approximately a security level of 100-bit.

Conclusion and Future Works

We achieve measurable accuracy on masked data. We observed that our system is secure for the attacks we studied. As a result, for the statistical functions we mentioned, we satisfy the privacy-accuracy balance.

As future work, we study two new attacks and the accuracy of some new statistical functions on our masked data set. Finally, we will produce a user-friendly software product to produce confidential data.

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Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

Data sharing under confidentiality[1]

Erdem Başer and Timur Hülagü,
Central Bank of the Republic of Turkey,

Ersan Akyıldız, Adnan Bilgen, Murat Cenk,
İrem Keskinkurt-Paksoy and A. Sevtap Selçuk-Kestel,
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[1] This presentation was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

TÜRKİYE CUMHURİYET MERKEZ BANKASI

Data Sharing Under Confidentiality: CBRT Case

Timur Hülagü, Ph. D.

AUGUST 30, 2018 | BASEL

Disclaimer

This is a joint project between CBRT and METU. All views expressed here are those of authors and do not necessarily reflect those of the two institutions.

Motivation

- **Main Goal**: Address the growing need of accessing micro data for academic research

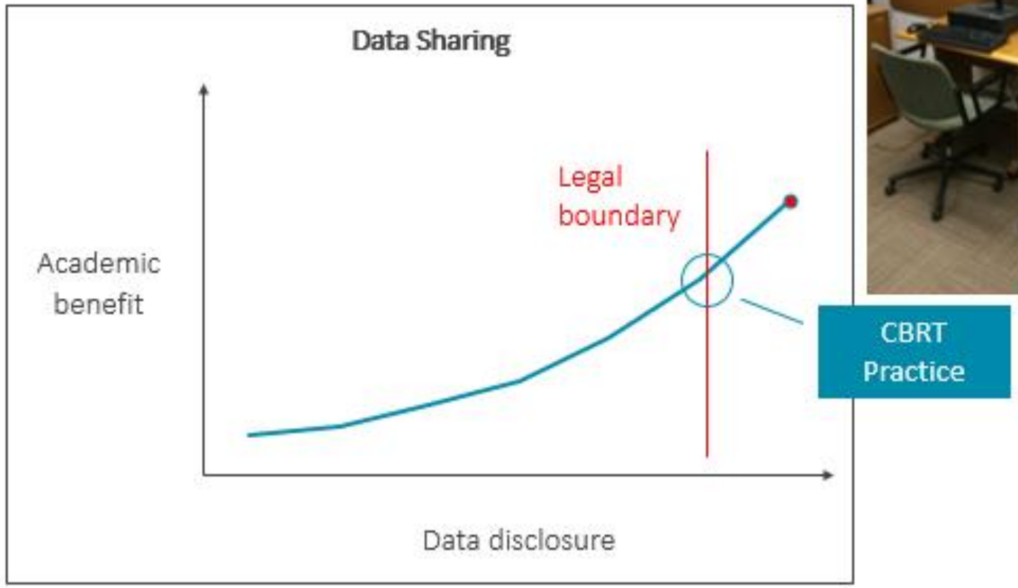
- **G-20 Data Gaps Initiative 2, Recommendation II.20:** Promotion of Data Sharing by G-20 Economies

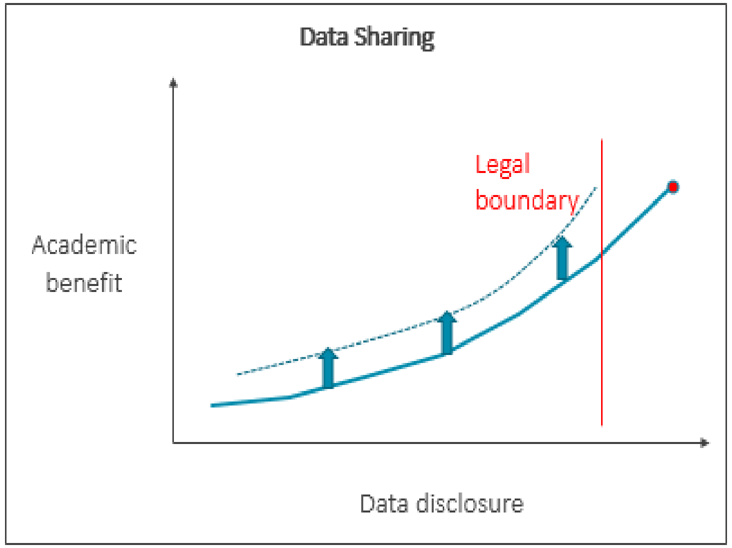
Share information and ideas on ways to apply confidential rules/arrangements in a manner that would allow sharing of more granular data

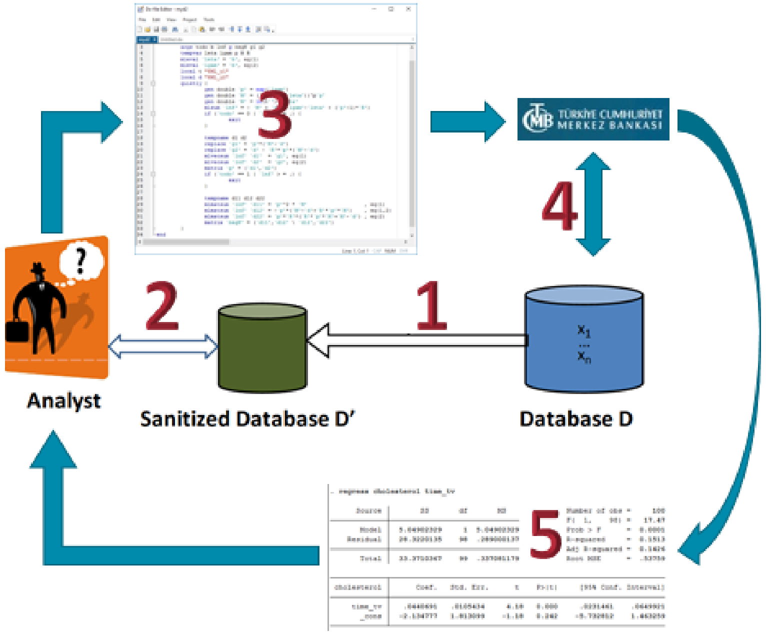
- **Eurostat Peer review report on the compliance with the Code of Practice and the coordination role of the National Statistical Institute in Turkey**

Recommendation 22: TurkStat should introduce remote access facilities for researchers, who are permitted to use its anonymized microdata for research purposes (European Statistics Code of Practice, indicator 15.4)

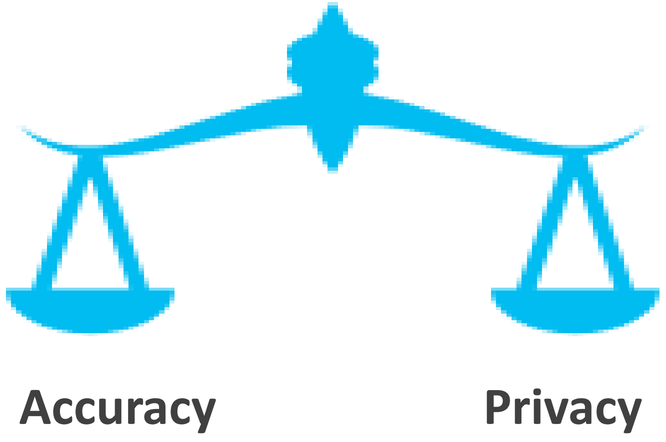
Data Sharing Trade-off







Main Aspects



Accuracy

- Descriptive Analysis ☑
- Univariate Regression Analysis ☑
- Multivariate Regression Analysis ☑
- Logistic Regression ☑
- Logarithmic Regression ☑

Accuracy

Descriptive analysis

Variable	B30	B50	B15	G600
Seed	123000	234000	345000	456000
Mean (O/M)	0.9756	0.9756	0.9756	0.9756
Standart Deviation (O/M)	0.9997	0.9995	0.9999	0.9998
Skewness (O/M)	1.001	1.003	1.002	1.002
Kurtosis (O/M)	1.002	1.008	1.004	1.004

Multiple Linear Regression Analysis

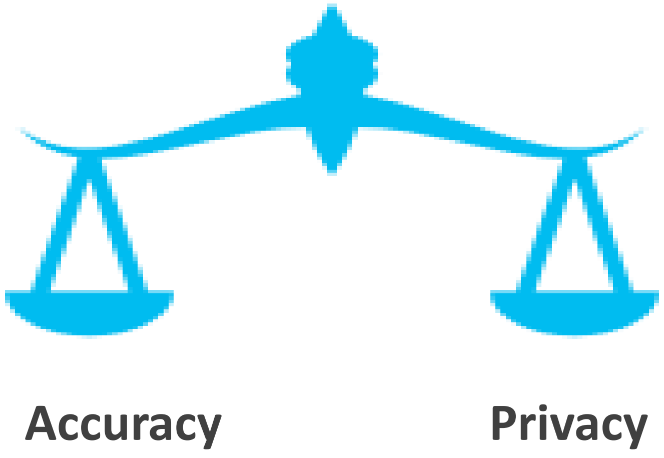
Original

```
Coefficients:
            Estimate Std. Error t value              Pr(>|t|)
(Intercept)  8.08888    0.11373   71.13 < 0.0000000000000002 ***
B2L          0.04716    0.00616    7.66    0.000000000000022 ***
B10L         0.21006    0.00486   43.22 < 0.0000000000000002 ***
B32L         0.32332    0.00583   55.44 < 0.0000000000000002 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.856 on 7342 degrees of freedom
Multiple R-squared:  0.511,     Adjusted R-squared:  0.511
F-statistic: 2.56e+03 on 3 and 7342 DF,  p-value: <0.0000000000000002
```

Masked

```
Coefficients:
            Estimate Std. Error t value              Pr(>|t|)
(Intercept)  8.28657    0.11670   71.01 < 0.0000000000000002 ***
B2L_M        0.04777    0.00617    7.75    0.000000000000011 ***
B10L_M       0.20994    0.00486   43.16 < 0.0000000000000002 ***
B32L_M       0.32314    0.00584   55.36 < 0.0000000000000002 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.857 on 7342 degrees of freedom
Multiple R-squared:  0.51,      Adjusted R-squared:  0.51
F-statistic: 2.55e+03 on 3 and 7342 DF,  p-value: <0.0000000000000002
```

Main Aspects



Privacy

- Deeper Focus on Privacy and Security

i. Spectral Filtering

ii. Singular Value Decomposition

iii. Principal Component Analysis

Attacks

$$\mathrm{m} = \left[\frac{d(O,E)}{d(O,M)}\right] \quad \text{where} \quad d(A,B) = \sum_{i=1}^{n} |a_i - b_i|$$

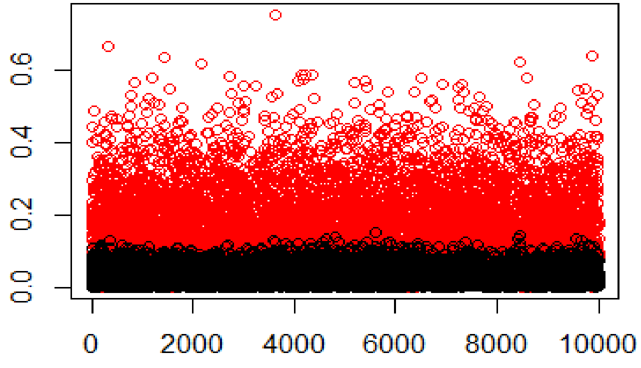
Privacy

Spectral Filtering

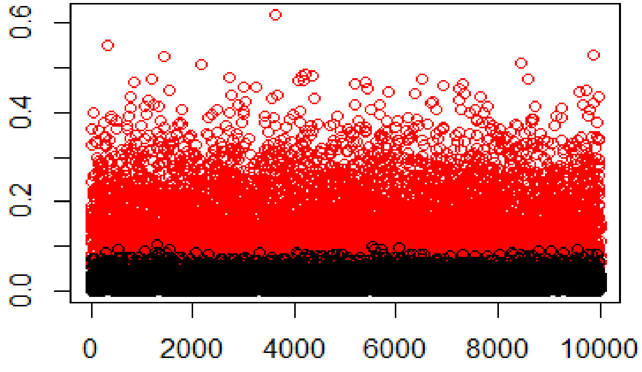
	Sinusoidal	Triangular
λ_{min}	$0,01121$	$0,007627$
λ_{max}	$0,06104$	$0,04152$
m x n	250x40	250x40
k	2	1
$d(O,M)$	1410	1163
$d(O,E)$	$319,6$	$205,2$
m	$0,227$	$0,176$

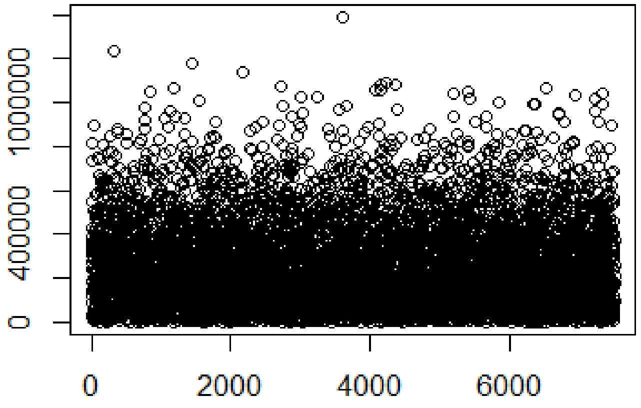
	G69
λ_{min}	45870034800
λ_{max}	194658444176
m x n	250x30
k	30
$d(O,M)$	1964402616
$d(O,E)$	1964402616
m	1

Sinusoidal



Triangular





No disclosure

TÜRKİYE CUMHURİYET MERKEZ BANKASI

Privacy

Random Number Generation In Our System

We can use 2^{30} different seed for generating random numbers. So that, brute force attacks may be a threat. To solve this problem we offer the following algorithm.

Original Data	Seed	Noise	Masked Data
x_1	$s_1 = f(\mathrm{IV} + x_1) mod\ 2^{30}$	$\varepsilon_1 = \mathrm{RNG}(s_1)$	$x'_1 = x_1 + \varepsilon_1$
x_2	$s_2 = f(x_2 + x'_1) mod\ 2^{30}$	$\varepsilon_2 = \mathrm{RNG}(s_2)$	$x'_2 = x_2 + \varepsilon_2$
$\vdots$	$\vdots$	$\vdots$	$\vdots$
x_n	$s_n = f(x_n + x'_{n-1}) mod\ 2^{30}$	$\varepsilon_n = \mathrm{RNG}(s_n)$	$x'_n = x_n + \varepsilon_n$

We choose nonlinear f(x), such that : $f(x) = \mu x^3 + \sigma$

Review

What is done

- We achieve, measurable accuracy on masked data.
- We observed that our system is secure for the attacks we mentioned.

Future Works

- We will study two new attacks called map estimation and distribution analysis.
- In the masked data set, we will check the accuracy of other statistical functions.
- Finally, we will produce a user friendly software product developed by using Java and R.

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Sharing and using financial micro-data[1]

Alejandro Gaytan González, Manuel Sánchez Valadez
and Mario Reyna Cerecero,
Bank of Mexico

[1] This paper was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

Sharing and Using Financial Microdata

Alejandro Gaytan González, Manuel Sánchez Valadez and Mario Reyna Cerecero[1]

Abstract

Banco de Mexico has been collecting financial microdata of all market operations by banks and brokerage houses for over 15 years. This data collection was possible because of a broad data sharing agreement between Mexican financial authorities after the 1995 financial crisis. More recently, new needs for monitoring financial institutions and markets, and the lessons of the 2008 global financial crisis, have made necessary improving data collection, data sharing and dissemination of microdata. Over the last years: i) Banco de Mexico has taken the task of a "Trade Repository Like" for derivative operations with new collection templates and new improvements on the quality of data and services; ii) a new data sharing framework with other financial authorities has been implemented, and new MoUs have been signed; iii) the revision and expansion of metadata is an undergoing process for improving the use of these microdata bases; and, iv) designed and developed a new dissemination portal for microdata.

Keywords: microdata, data sharing, derivatives.

JEL classification: C81, C82, G19, G29

Content

[1] Banco de Mexico. The views and conclusions presented in this paper are exclusively the responsibility of the authors and do not necessarily reflect those of Banco de Mexico. We would thanks to Andrés Escobedo for his valuable comments

1. Introduction

Banco de Mexico has been collecting financial microdata of all market operations by banks and brokerage houses for over 15 years. The Mexican financial crisis in the mid 1990's, unveiled several data gaps and potential improvements in the collection of financial information. As a response, Banco de Mexico started collecting financial microdata for its flexibility in providing solutions to different information needs of users in Banco de Mexico and other financial authorities. This decision transformed the financial information model from a traditional model to generate central bank statistics to a model heavily based on timely daily granular microdata, mainly with all market operations by all banks and brokerage houses (Gaytan and Sanchez, 2017).

Banco de Mexico concentrated the collection of microdata of financial market operations, regulatory regimes and consumer credit, while the Bank and Securities Supervisor collected microdata on mortgages, commercial credit portfolio, in addition to a set of other regulatory reports. This specialization was the result of an agreement to reduce the regulatory burden of information reporting and to share financial information between financial authorities. In 2000, different financial authorities signed this data sharing agreement: Banco de Mexico, the Ministry of Finance (SHCP), the Bank and Securities Supervisor (CNBV), the Financial Service protection Agency (CONDUSEF), the Deposit Insurance Agency (IPAB), and some years later, the Pension Funds Supervisory (CONSAR). Recently, the 2008 financial crisis and the international initiatives to improve financial stability, has implied several improvements in the acquisition, management and sharing of financial information, including the G-20 data gaps initiatives, the implications of Basel III, the initiative to mitigate risks in the Over the Counter (OTC) derivative market, shadow banking, among other.

Financial information at the level of market operations microdata allows attending different users and information needs, such as open risk positions of an individual institution or the network of exposures in different markets and in the whole financial system. The increased complexity of the interlinkages, instruments and institutions, require increasing capacity to identify potential risks, even though the costs of a detailed model of microdata is high, specially "in times of financial turmoil, the advantages of having the precise information surpasses any maintenance costs associated with such a model, nonetheless, there are also great benefits in steady times" (Gaytan, 2014). The costs of such an information model are high both, for the authority that collects it and for the reporting institutions. Thus, to maximize the social value of this model, it is important to broaden its use by improving the data sharing schemes among authorities and find ways to provide wider access to academic researchers, market analysts and the public.

The paper proceeds as follows: section 2 presents a description of current data sharing schemes at Banco de Mexico. In section 3 describes enhancements on the scope of information of financial system managed by Banco de Mexico, focusing on information of derivative operations. Meanwhile, section 4 describes recent undertakings to expand data sharing with other Mexican financial authorities and the improvement of tools for data dissemination for diverse audiences. Finally, section 5 mentions some challenges ahead regarding data sharing.

2. Current Schemes for Data Sharing at Banco de Mexico

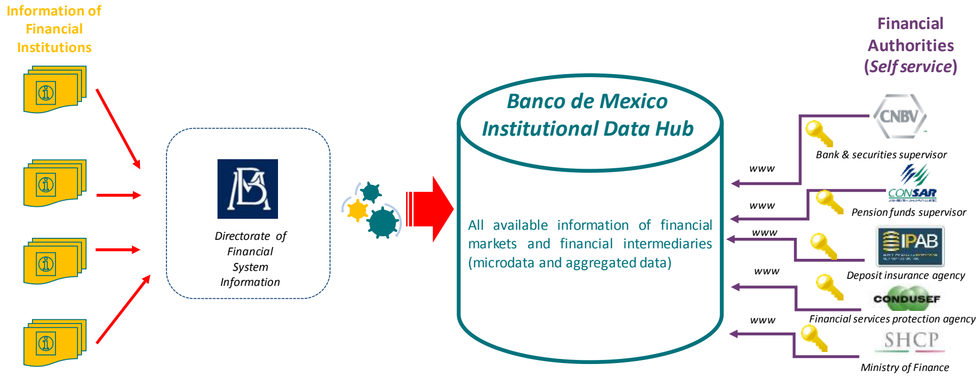
The 2000 agreement signed by financial authorities to coordinate actions to compile, store, share and disseminate the information received from financial intermediates, set the foundations of a more efficient system of financial reporting to authorities (Gaytan and Sánchez, 2017).

Currently, Banco de Mexico uses three main schemes for sharing data with other financial authorities and information users (Figure 1). First, a Central Data Hub which provides secure direct access both to granular and aggregated microdata of financial institutions reporting to Banco de Mexico. This hub provides querying tools to databases, reporting services and business intelligence tools. Second, a controlled service scheme to share very large volumes of a predetermined set of microdata delivered according to a calendar agreed with the user. Finally, public platforms to access time series and interactive graphics.

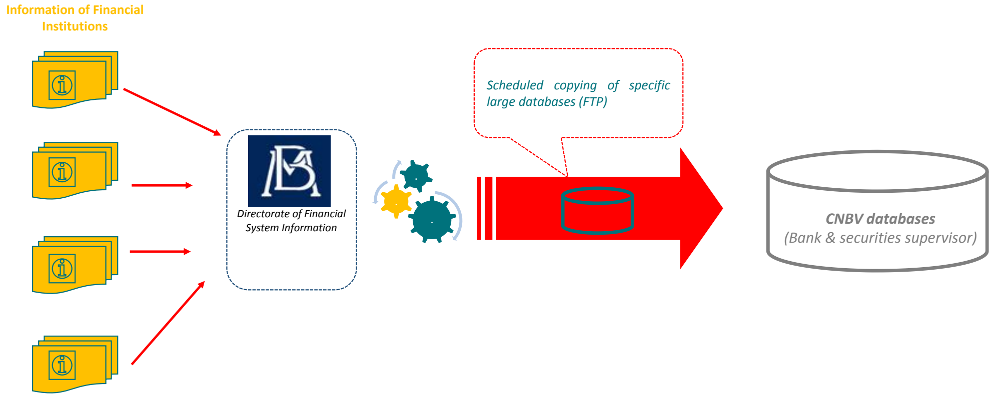
The data sharing schemes with financial authorities were significantly improved starting in 2014, when a financial reform included the basis of a new, mandatory framework of data sharing among domestic financial authorities for specific purposes: preserve financial stability, avoiding disruptions in the functioning of the financial system and/or the payments system. In addition, Banco de Mexico was given the faculty to share information with foreign financial authorities after the signing of Memorandums of Understanding (MoU) that establish the conditions of the information exchange and include the reciprocity principle. These changes made possible improvements in the analysis, supervision and regulation functions of financial authorities (Gaytan and Sánchez, 2017).

Figure 1. Data Sharing Schemes

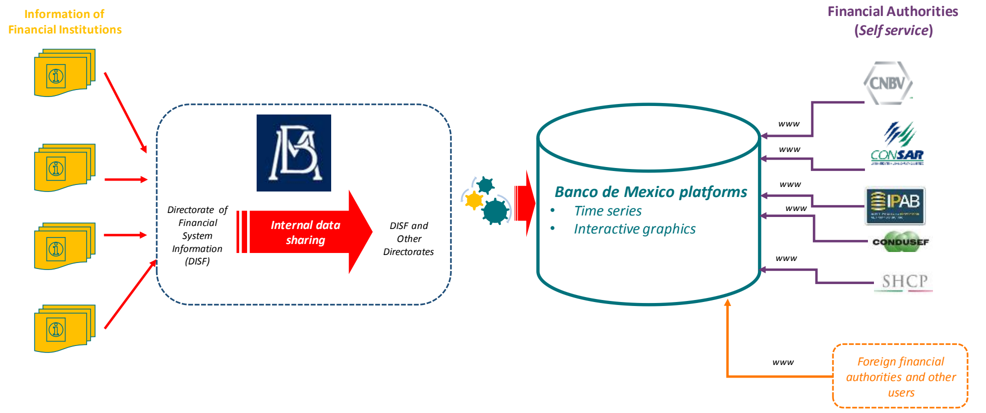
a) Central Data Hub (direct access)



b) Controlled Service



c) Self Service



Source: Gaytan and Sanchez (2017).

3. Recent Improvements in the Model of Financial Information

Over the last years, Banco de Mexico has been working on improving the scope of its financial system information model. With respect to the credit market, Mexican financial authorities have information loan by loan of banks and other regulated credit institutions (Sofomes E.R.), Banco de Mexico collects data on consumer credit portfolio (credit cards and other consumer loans) and the CNBV collects mortgage and the commercial loan portfolio. In recent years there have been important improvements. Banco de Mexico started requesting information Credit Bureaus´ databases on loans to firms and households, which has improved the integration of the information and has increased the availability of data on loans provided by unregulated financial institutions. In addition, the bank supervisory improved the collection of commercial portfolio with an improvement in the consistency and detail of information. On the other hand, Banco de Mexico has improved the collection of consumer credit by:

i) Improving individual credit risk information;

ii) Requesting information on the consumer credit clients, that will help to improve both financial stability and financial inclusion analysis; and,

iii) Including the initial Total Annual Cost (CAT),[2] which is the most appropriate cost of loans for comparison of credit products across institutions.

The global financial crisis also had important implications for the development of new precautionary regulation for financial institutions. Basel III established new standards for capital adequacy to incorporate several capital adjustments for financial stability, and new standards on liquidity the Liquidity Coverage Ratio (LCR) and the Net Stable Funding Ratio (NSFR) were implemented. In Mexico capital adequacy regulation, is a CNBV responsibility and liquidity is a join regulation of Banco de Mexico and the CNBV. However, Banco de Mexico collects and verifies the information of both regulatory regimes as it uses the microdata model to replicate a large proportion of these ratios using the microdata of operations. Currently the LCR is a daily requirement with a 10 days lag revision. These improvements have enhanced financial stability analysis and surveillance of financial institutions.

Banco de Mexico, has also implemented new information requirements to improve the surveillance of the payment system. In 2015 Banco de Mexico improve the template, timeliness and quality of the report of all credit and debit card transactions, increasing the fields of the information to include data on the location of each transaction and the activity of the business, among other. [3] The timeliness of the reporting is one day. More recently, this information was extended with a new requirement to include not only information on the transaction, but also, information that includes all the confirmation messages related to each transaction. In 2017 Banco de Mexico implemented a new requirement about all cross-border transactions made by financial intermediaries via correspondent banking.

Another important improvement has been the information model on derivatives. Banco de Mexico has been collecting information transaction by transaction on derivatives operations performed by banks and brokerage houses since 1999, and it was a natural step to operate with the functions of a "Trade Repository (T.R.) like" infrastructure for the international initiative of IOSCO-CPMI to reduce the risk in the OTC derivative market.

To better perform the functions of a T.R. like, in 2015 there was an important update of the reports to include new developments in markets and instruments, information to respond to new demands by users and information related to the regulatory changes, particularly the standardization of OTC operations and the central counterparty. In this respect it was designed to fulfil a set of data elements consistent with the reviewed by international institutions (IOSCO) and regional regulators (ESMA), which includes a better identification of underlying assets, products (ISDA taxonomy), netting agreements, among other.

Another improvement is to centralize in a single template, a catalogue of entities, the characteristics of counterparties of all operations, including derivatives, of the banks and brokerage houses in financial markets. These characteristics include the tax identifier as well as the Legal Entity Identifier (LEI), economic activity, residency, and relevant relations with the party, among other.[4] This new requirement allows a better

[2] The CAT is the domestic name of the Annual Percentage Rate (APR), which includes the annualized interest rate plus all fees attached to the loan.

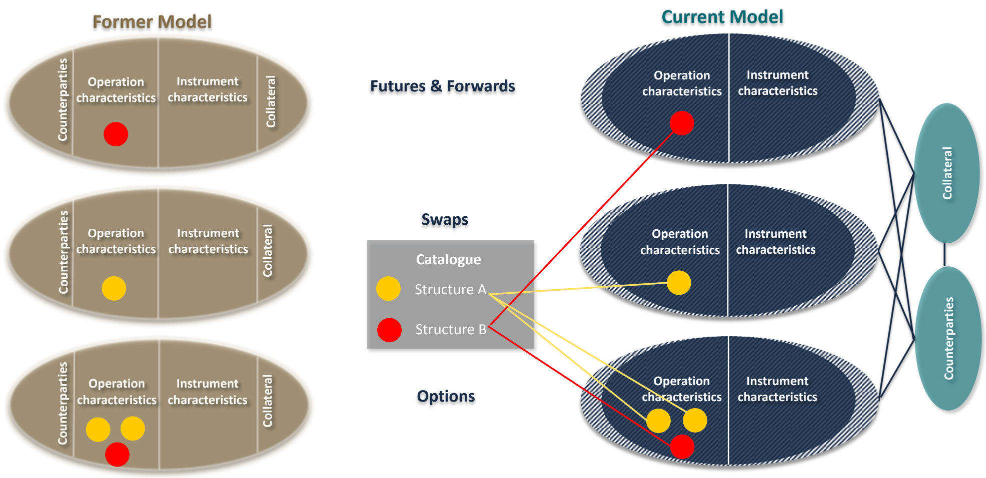
[3] To identify the kind of activity of merchant is used the Merchant Category Code (MCC).

[4] The economic activity identification is according to North American Industrial Classification System (NAICS).

identification of the different entities trading in the domestic financial markets and of foreign exposures. In addition, and linked to the counterparty information, the data on collateral of derivative operations was separated from the individual transaction as collateral is generally related to a set of operations with the same counterparty (Figure 2).

Before 2015, the template had some limitations to account precisely of the "strategies" with derivatives operations, and these limitations sometimes hindered the complete identification of what transactions were part of the strategy, to close this data gap, it was created a precise way to link transactions that form part of a "structure" or "strategy".

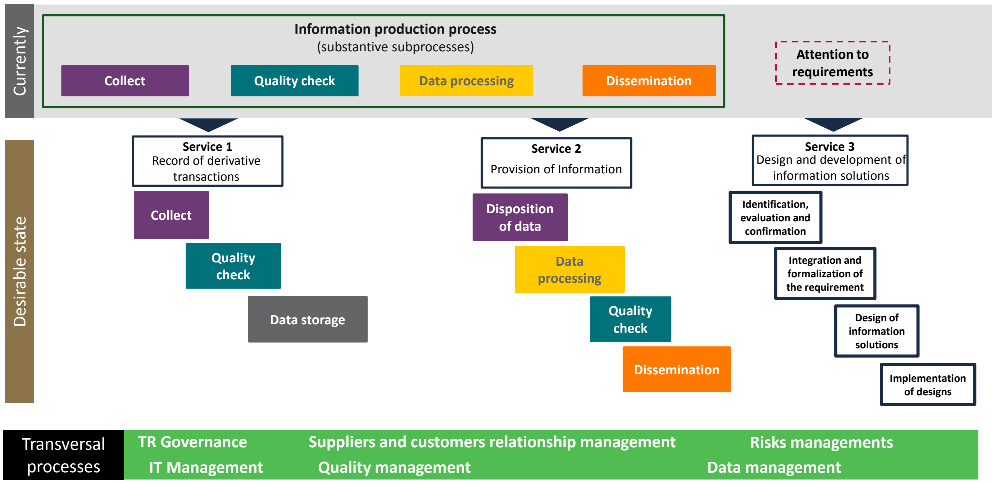
Figure 2. Changes in Derivatives Information Requirements



Source: Banco de Mexico.

Nevertheless, to operate as a T.R. like for derivatives it is not sufficient to improve the data model, it is also necessary to adjust the operation of processes of data and adjust the services provided to perform the functions of a Trade Repository in a central bank. IOSCO-CPMI define a series of best practices established in a set of Principles for Financial Market Infrastructures defined in the report "Principles for financial market infrastructures" (BIS & IOSCO, 2012). To implement the necessary changes, it was defined a new operational model for the functioning of the T.R. like. Figure 3 presents the change in the operational model, based on a services approach. The idea is to pass from a model centred on the service of the provision of information to another with three main services: Registration of derivative transactions, the provision of information and the design and development of information solutions. The registration of operations is a necessary service that Banco de Mexico will have to provide so that the financial institutions could comply with their obligation of reporting to a T.R.

Figure 3. Redesign of Operative Model of Trade Repository



Source: Banco de Mexico.

One of the main functions of the initiative of Trade Repositories is to increase the transparency of the OTC derivatives market, which implies the establishment of mechanisms of data dissemination and data sharing. A T.R. should provide information to market participants, other domestic and foreign financial authorities and provide publications of the operation of the derivative market. Currently, the scope of data dissemination is done using the schemes for data sharing at Banco de Mexico that were presented (Figure 1). The data hub and the direct access scheme to microdata are and can be used to attend data requirements of financial authorities and there is a broad set of statistics and graphs of the operation of the market published using the time series platform and the interactive graphic platform. Nonetheless, a broader definition and implementation of improvements of the data dissemination processes and tools is still work in progress.

4. Recent Improvements on Sharing and Dissemination of Microdata and some Potential Uses

As mentioned above, the financial reform strengthen the data-sharing scheme. In recent years as a complement to the 2000 general agreement, two MoUs have been signed between Banco de Mexico and the Financial Services Protection Agency (CONDUSEF) in 2015, and with the Pension Funds Supervisory Agency (CONSAR) in 2017. In addition, Banco de Mexico is currently working on MoUs with other domestic financial authorities.

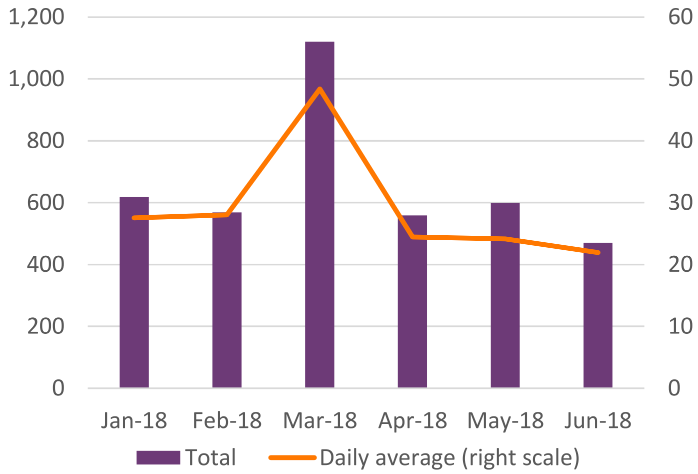
Banco de Mexico shares information with CONDUSEF about banks' financial products (deposit products and credit products) and their characteristics and services, fees and interest rates, transactions in retail payment systems (checks, ATM transactions, TPS transactions, electronic transfers, etc.) and e-commerce payments.

CONSAR and Banco de Mexico share information on derivatives and securities transactions performed by banks with the Pension Funds (SIEFORES), daily information of investment portfolio of these funds and data on savings, and the demographic characteristics of workers.

Data dissemination by publication is another important way of increasing the value of the information collected. Banco de Mexico has been expanding publication of financial data, particularly on derivatives.

In 2016, Banco de Mexico published a broad set of statistics on derivatives (turnover and outstanding operations, and the forward exchange rate). In the same year, it was launched an interactive portal for financial information (PIIF). In this platform, it was included a graphic overview of the derivative market in Mexico using some of the most relevant published derivative statistics. More recently, graphic information was published on outstanding government securities sectored by holder (securities issued by the Federal Government, the deposit insurance agency (IPAB), and Banco de Mexico). Figure 4 presents the access statistics to the PIIF, even though the current number of visits remain low, we expect an increase when data of other topics is incorporated.

Figure 4. Visits to PIIF

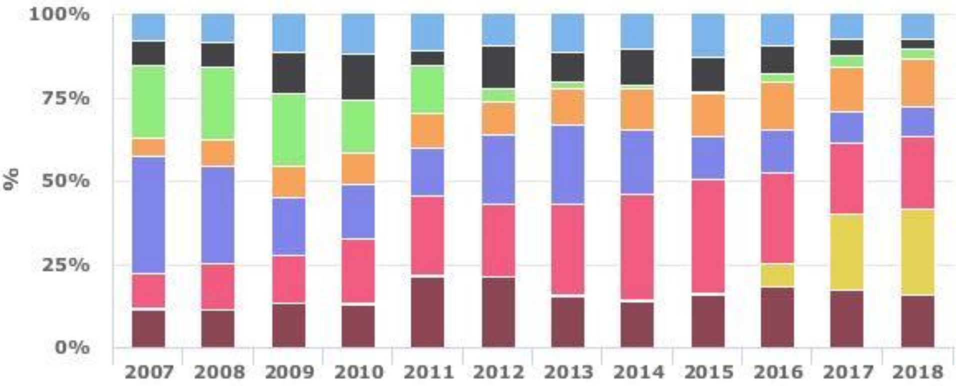


Source: Banco de Mexico.

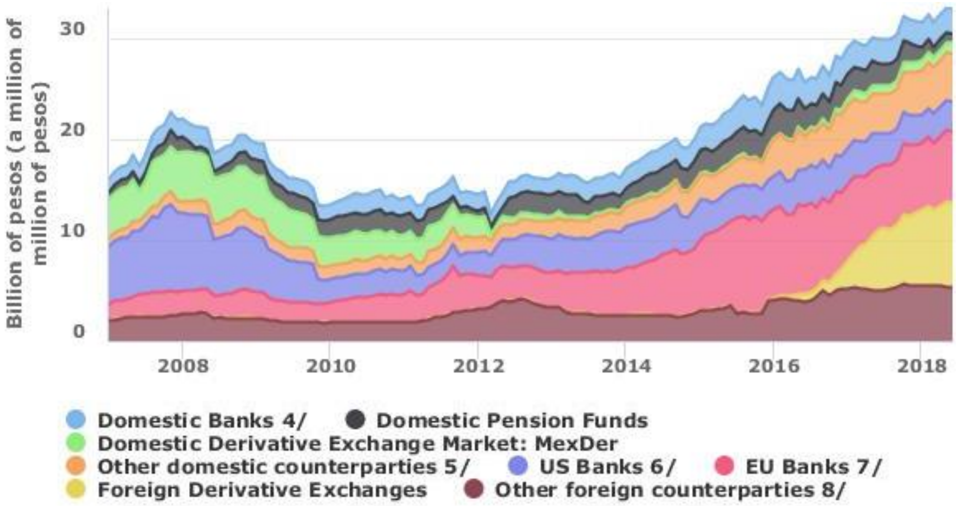
Although currently the PIIF has only being used to disseminate graphic information, this portal will be used to disseminate micro-data on loans and market operations. Figure 5 and Figure 6 are examples of derivate operations information included in the PIIF. Figure 5 shows outstanding derivatives by type of counterparty and, Figure 6 shows turnover and average exchange rates on forwards on US dollar vs Mexican peso.

Figure 5. Outstanding Derivatives by Type of Counterparty

a) Structure 1/ 3/

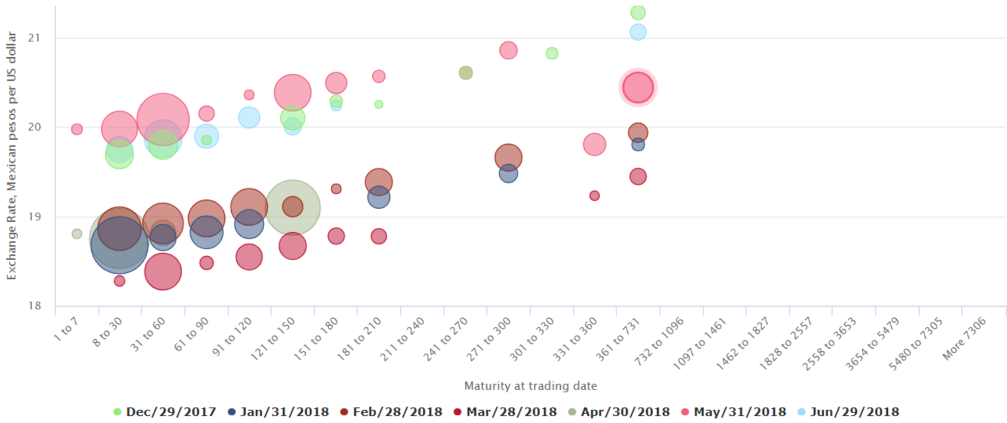


b) Outstanding 2/ 3/



1/ Figures at end of year. Figures at the end of June in 2018.
2/ Figures at end of month.
3/ Figures on Options and Warrants are preliminary from September 2015, due to significant revisions in course.
4/ Figures are only on domestic commercial banks transactions.
5/ Domestic development banks, brokerage houses, other financial entities, and non-financial entities other than private enterprises.
6/ Figures are only on commercial banks located in the United States.
7/ Figures are only on commercial banks located in the European Union
8/ Figures are only on commercial banks located in Latin America and others foreign financial entities and non-financial entities.
Source: Banco de Mexico.

Figure 6. Turnover and Average Exchange Rates on Forwards on US Dollar vs Mexican Peso related to FX Swaps



Source: Banco de Mexico.

Recently all financial information at Banco de Mexico went through a process of revision of its metadata to determine a set of characteristics that will help the identification of its characteristics and, thus, its use. These metadata are included in a new financial data inventory. The metadata includes information about the collection (frequency, timeliness, granularity, etc.), metadata about its content, the sources of information to help traceability, the reporting institutions, sensitivity information among other. It is worth mentioning, that the revision and expansion of metadata is an undergoing process for improving the use of the microdata bases managed by Banco de Mexico.

5. Concluding Remarks

In our view, one of the main objectives of enhancements in the model of information at Central Banks is to maximize the potential social value of data. According to the experience of Banco de Mexico, in order to maximize the social value of information it is necessary to improve: i) efficiency in the generation of information, ii) accuracy of information and iii) dissemination of information.

In the case of Banco de Mexico, the process of generation of derivative operations information is under revision and enhancement, which has implied adopting international best practices, improving information security and increasing the focus on solving user's needs. From this experience, these improvements will be adopted into the rest of the information process at Banco de Mexico.

As was mentioned above, having microdata allows improve the accuracy of information. In effect, having microdata allows the Banco de Mexico to check consistency between different information requirements, which in turns helps improve information quality. In particular, one potential enhancement is to join diverse data bases allowing an easy identification of parties and counterparties in different markets, which could be helpful to identify risk exposures.

Another key aspect is data sharing practices. Banco de Mexico has improve data sharing agreements and platforms. In this respect, the PIIF, a relatively new platform of data dissemination, has allowed to share new statistics under different formats.

These improvements notwithstanding, Banco de Mexico is still working on data dissemination, specifically in microdata dissemination. In this respect, a data room is an option to expand microdata dissemination to diverse audiences.

It is worth mentioning that our final objective of all improvements in the model of financial information and data sharing practices is to increase the amount and quality of information in order to do better analysis and to take better decisions, which as result will maximize the potential social value of information.

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Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

Sharing and using financial micro-data[1]

Alejandro Gaytan González, Manuel Sánchez Valadez
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Bank of Mexico

[1] This presentation was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

Sharing and Using Financial Microdata

9th IFC Biennial Conference

Basel August 30-31th, 2018

BANCO DE MÉXICO

The views and conclusions shown in this presentation are exclusively the responsibility of the authors and do not necessarily reflect those of Banco de Mexico.

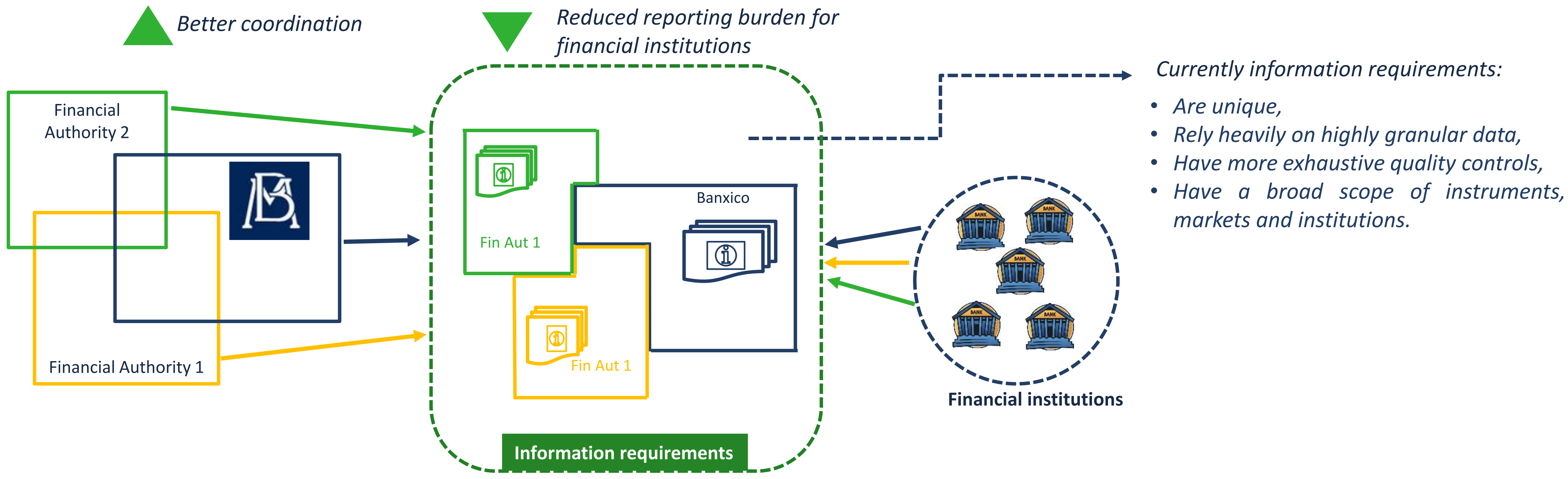
Introduction

- The Mexican financial crisis in the middle of 1990's, unveil data gaps and inefficiencies in the generation and collection of information. To tackle these deficiencies, Banco de Mexico started to collect microdata, which by its flexibility were used to solving information needs of both financial authorities and internal users. In our view, improvements to the model of information should have as objective the maximization of the social value of data.
- Having microdata of financial transactions offers several advantages for financial stability analysis, including the determination of open risk positions of an agent or the network of exposures in the financial system.
- Nonetheless, the costs of such an information model are high to both the authority that collects it and to the reporting institutions. Therefore, to justify these costs it is important that the data collected be used to the maximum of its capacity, and for that an efficient data sharing scheme is needed.
- In 2000, several financial authorities, including Banco de Mexico, signed an agreement to coordinate actions to compile, store, share and disseminate the information received from financial intermediates, setting the basis to improve efficiency on information requirements to financial institutions.

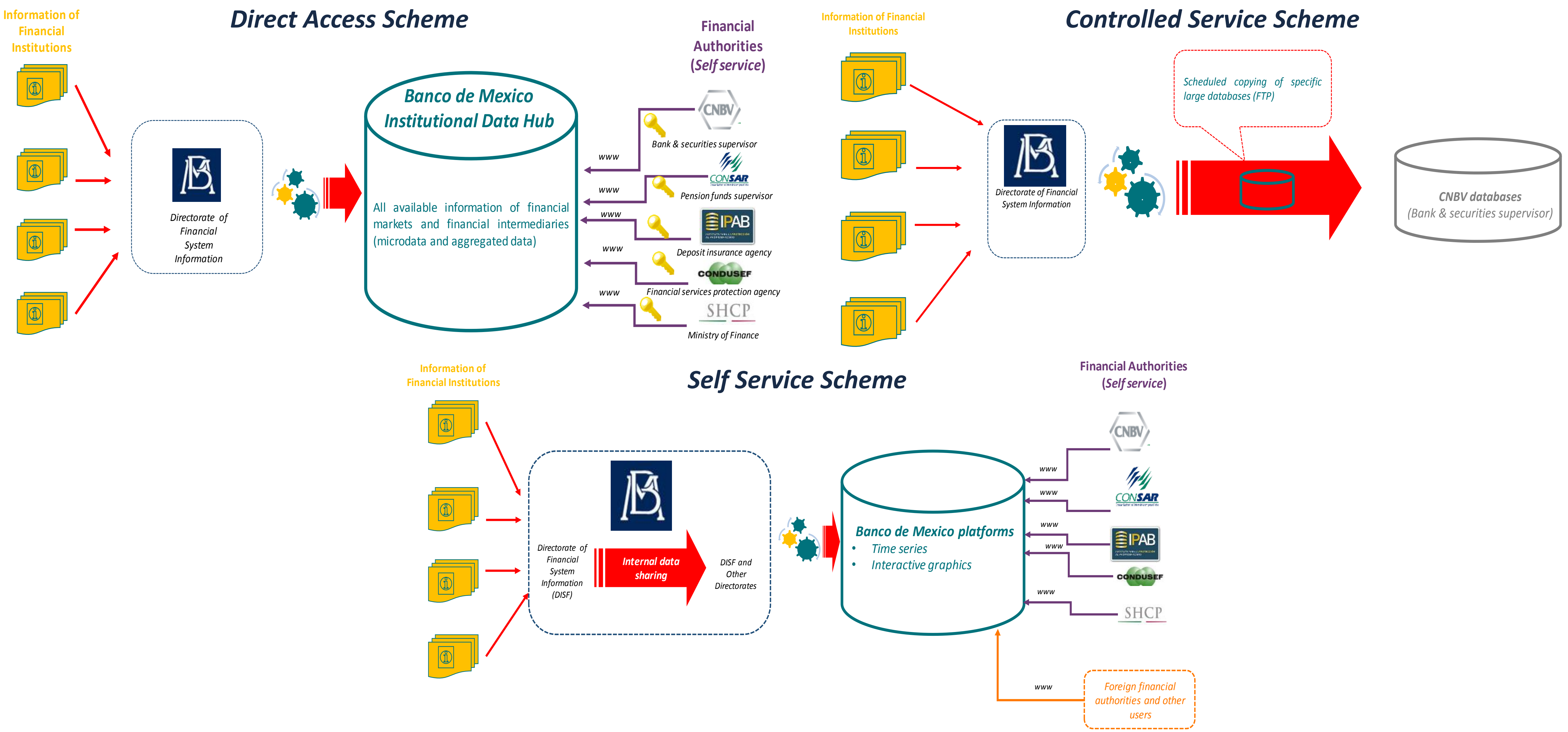
Current situation

- The cooperation framework build since 2000 has allowed Mexican financial authorities to improve significantly data sharing practices between them, completing the information used in their respective activities.

Information exchange among Mexican financial authorities current situation



Schemes for sharing Information at Banco de Mexico

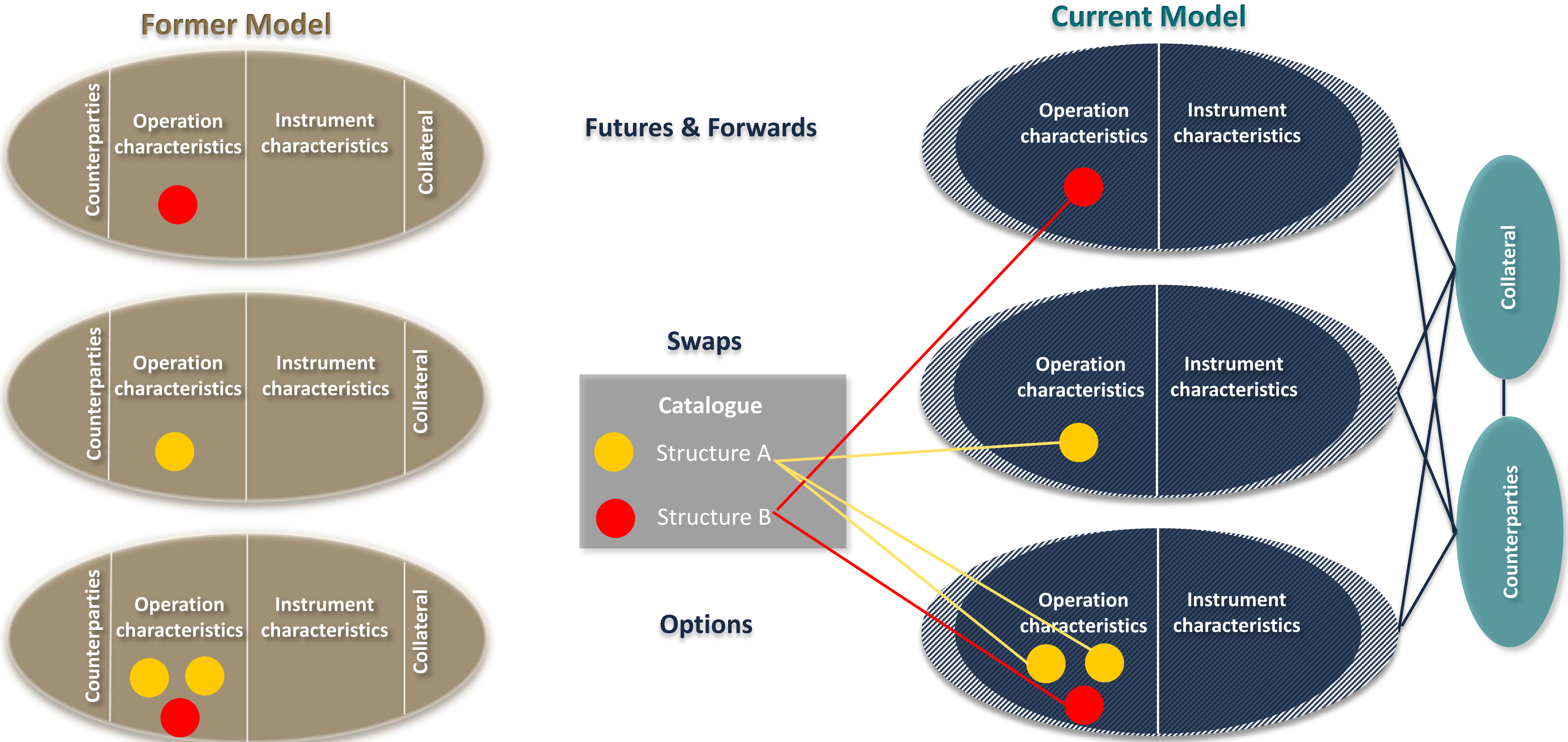


Recent Improvements on Model of Financial Information

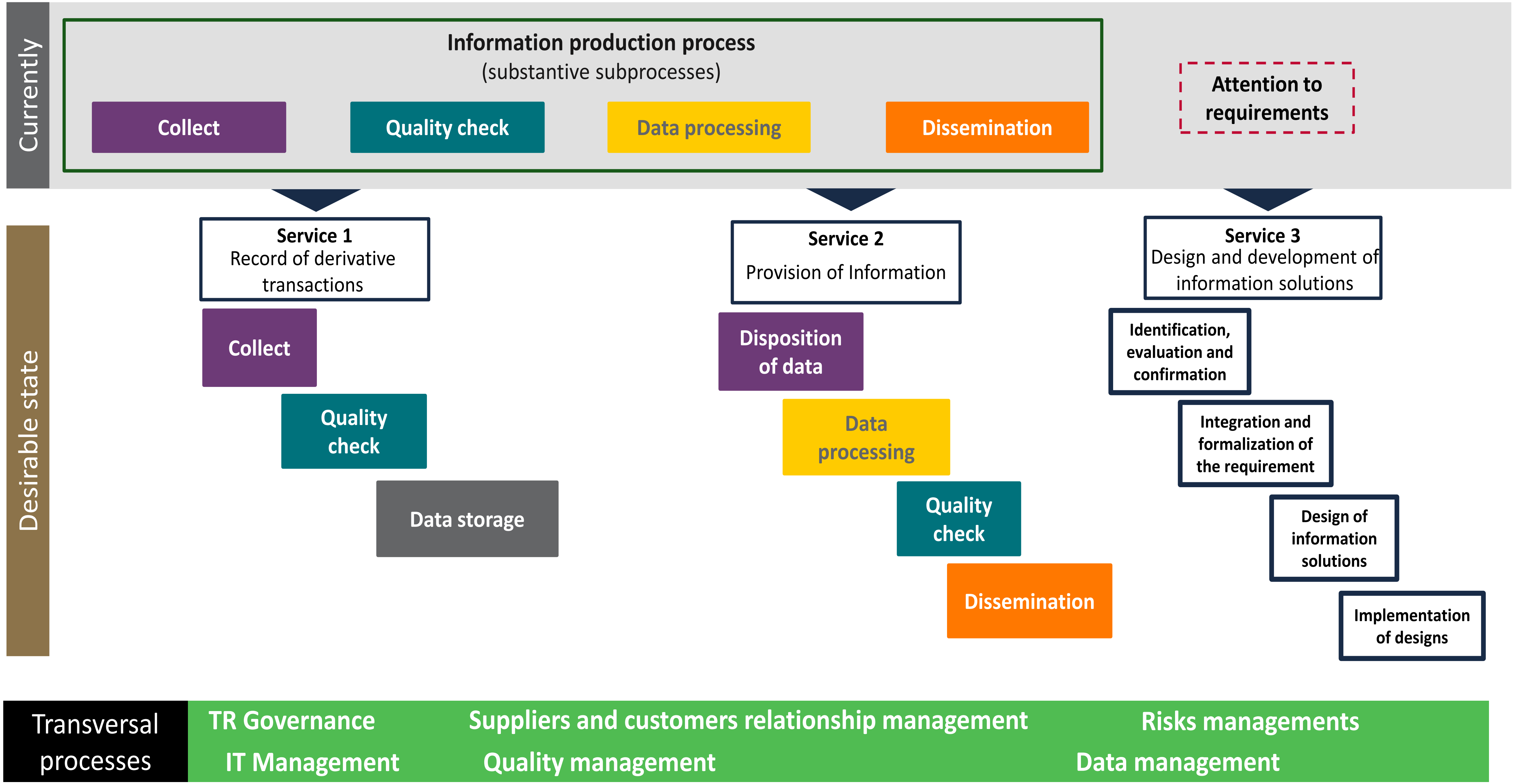
- Banco de Mexico has been working on improving its model of information of financial system.
  - Market credit:
    - Collecting microdata reported by credit bureaus,
    - Enhancements on information requirements of consumer credits and,
    - Utilizing the improvements in the information requirements on commercial credit and mortgages (CNBV).
  - Regulatory information:
    - Collecting data to calculate the Liquidity Coverage Ratio (monthly basis 2014 and daily basis 2017),
    - Collecting information to calculate the Net Stable Funding Ratio on monthly basis and,
    - Incorporation of all changes for capital adequacy proposed in Basel III.
  - Payments:
    - Improvements in the information requirement to “Switches” (transactions with credit or debit cards),
    - Collecting information about confirmation messages of each transaction done with credit or debit cards,
    - Improvements in the information requirement in microdata on checks, transfers and direct debit and,
    - Collecting information about cross-border transactions.

Recent Improvements on Model of Financial Information

- In 2015 a key change in the information requirements was made to improve the information of derivative operations, having as result a more complete model information.



Trade Repository Operative Model



Recent Improvements on Sharing and Dissemination of Microdata

- Over the last few years, Banco de Mexico has promoted a broad interchange of information with other Mexican financial authorities through MoU's, in particular with the Financial Services Protection Agency (CONDUSEF) in 2015 and with the Pension Funds Supervisor (CONSAR) in 2017.

- In 2016, the Interactive Application for Financial Graphs (PIIF) was launched. The PIIF is a tool that disseminates through graphics and tables, data of the main relevant aspects of some financial markets. Currently data on derivatives and securities outstanding by sector is available.

- Since 2017, Banco de Mexico has an inventory of "information products", it includes metadata to identify main characteristics of data, main topics of each product, sources of information used to generate each "information product", among others. Revision and expansion of metadata is an undergoing process for improving the use of microdata bases managed by Banco de Mexico.

Final Remarks

- Banco de Mexico has a large experience on collecting microdata on financial markets. Over the last few years we have done improvements on scope of the model of information.

- In our view, one of the main objectives of enhancements in the model of information at Central Banks is to maximize the potential social value of data. According to the experience of Banco de Mexico, in order to maximize the social value of information it is necessary to improve: i) efficiency in the generation of information, ii) accuracy of information and, iii) dissemination of information.

- This will increase the amount and quality of information in order to do better analysis and to take better decisions, and as result will maximize the social value of information.

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BANK FOR INTERNATIONAL SETTLEMENTS

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ECB data for analysis and decision-making: data governance and technology[1]

Emily Witt and Jannick Blaschke,
European Central Bank

[1] This paper was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

ECB data for analysis and decision-making: Data Governance and technology

Emily Witt, Jannick Blaschke

Abstract

Data are necessary to enable analysis and support decision-making. But the use of data raises many questions: How can we best exploit the wealth of data available within the ECB whilst safeguarding confidentiality? And how can we best leverage the data expertise available across business areas? This paper outlines how the Data Intelligence Service Centre (DISC) project will provide a high performant technical platform that supports users to easily access and experiment with data and deliver new analysis in a speedy manner. But even more important is to have a good data governance structure, which fosters strategic alignment, standardisation, as well as collaboration, data and knowledge exchange across business areas.

Keywords: data governance, data-driven decision making, central banking, data access, data sharing,

JEL classification: C80, D70, E50, M14, O30

Contents

Exponentially increasing availability of data calls for a holistic approach

Benoît Cœuré, Member of the Executive Board of the European Central Bank (ECB), outlined many examples how granular data can support policy making in his speech "Policy analysis with big data"[1] on 24 November 2017. He concluded that "*Central banks have made considerable progress in recent years in integrating big new datasets into their policy analysis and decision-making. Granular data collected by central banks themselves have, in particular, become an indispensable source of information for policymakers. … The potential of such data to enrich central bank analysis in the future is considerable, however, as are the challenges that come along with it.*"

This paper describes how the ECB addresses these data related challenges with a focus on technology and organisational themes.

The ECB has a 20 year history in preparing jointly with the National Central Banks (NCBs) and Eurostat macroeconomic statistics to prepare policy measures and assess their impact.

The financial crisis, and the euro area sovereign debt crisis that followed, were characterised by periods of increased heterogeneity, market fragmentation and sudden turns in economic activity. Recent data-related ECB and EU regulations paved the way for the ECB to get an encompassing view on the developments in EU financial market and instruments like loans (AnaCredit), money markets (MMSR)[2], security holdings (SHSDB), derivatives (EMIR), secure financed transactions (SFT-DS) and banks (COREP/FINREP). Such data will help to analyse diverse economic signals in a timely manner. They can be used to assess the underlying forces driving economic behaviour and understand the interconnectedness between financial institutions to better assess risks and to calibrate policy measures, e.g. by analysing how changes in the volume and price of central bank money impacted the monetary policy transmission mechanism or understanding how decisions in the asset purchasing programme impact the credit and funding behaviour of banks.

The exploitation of granular data poses various challenges to statisticians and users:

- The increasing volume and speed of the data
- The heterogeneity and complexity of the data
- Data confidentiality.

To address these challenges, the ECB applies a holistic approach, covering technology, governance, standardisation and collaboration.

[1] Speech given at the conference on "Economic and Financial Regulation in the Era of Big Data", organised by the Banque de France, Paris, 24 November 2017.

[2] For example, MMSR and AnaCredit are based respectively on regulations (EU) No 1333/2014 and No 2016/867 of the ECB. MMSR data contain confidential daily information on the individual euro-denominated loans in the euro money market from the 52 largest euro area banks, accounting for approximately 80-85% of the total balance sheet of euro area banks. AnaCredit will deliver loan-by-loan information, mostly on a monthly basis, on credit to around 8 million companies and other legal entities extended by about 4,500 euro area banks, comprising almost 100 different attributes.

DISC facilitates data usage, collaboration, automation

The ECB uses a Forecasting Analysis and Modeling Environment (FAME) for the production of time series and macroeconomic statistics and the Statistical Data Warehouse (SDW) for their dissemination to internal and external users.

However, FAME is not suitable for the production of granular data sets. For this reason, several IT systems were developed next to each other to fulfil specific data processing and business reporting needs resulting from the recent data-related ECB and EU regulations. The requirements of these systems were focused on answering particular business questions. Each of these systems has its own distribution channel and separate areas where users could get access to these granular data sources. Thus, the need emerged for data analysts to have a common environment to work with data in a secure and performant fashion.

Complementing the efforts by the ECB Directorate General (DG) Statistics to collect micro data and establish sound processes with the NCBs to ensure an appropriate level of quality, the ECB's IT department (DG Information Systems) established the Data Intelligence Service Centre (DISC). The DISC data platform project was initiated in March 2016 to provide a single shared platform for (i) business centric analytical capabilities, (ii) data integration and ETL services[3], and (iii) metadata management based on the Single Data Dictionary (SDD) and Data Inventory (see explanation in section *The Single Data Dictionary (SDD)*).

The DISC data platform is the central secure place for organising, storing, analysing data and related collaboration within the ECB. It aims to make large data volumes and the variety of data structures usable by employing the latest big data technologies available, such as Hadoop, Oracle Exadata, complemented with products from Cloudera and Informatica. It offers (connections to) tools such as Matlab, Python, R, SAS, Stata, Tableau for statistical analysis and visualisation purposes.

The central place for users to access data will be the DISC corporate store, which will contain the "golden copy" of relevant data from the statistical production processes and from other systems or sources for further usage by the end users. Currently, several micro data, such as statistics on the securities issued (CSDB) and the securities held (SHSDB), as well as the Register of Institutions and Affiliates Data (RIAD) are being on-boarded into the DISC corporate store. In a next phase, data sets from the SDW will be made available via DISC.

Business areas can request so-called data labs, which are self-service spaces within the DISC platform in which users can independently store and analyse data. They can manage the access rights to their data labs and thereby decide with whom to collaborate or share results.

DISC also provides data management components, which will technically enable activities to control, protect, deliver and enhance the value of data and information assets within the ECB.

[3] The term Extract, transform, load (ETL) refers to a process where data is first processed and then disseminated (usually via a data warehouse).

The service offering is complemented with a data factory, which allows automating the loading of data and make it available in a ready-to-use format.

DISC thus offers a highly performant environment, which has great potential to help exploiting large volumes of data sets and fostering collaboration between business areas.

But like any technology, the technical platform and services can only be successful if they are complemented with sound governance and the organisational willingness to share data, knowledge and results and to prioritise related work.

Strong ECB data governance ensures alignment

"Support[ing] analysis and decision-making through high quality, timely, integrated and relevant data" is part of the ECB Business Strategy 2018-2020.

In October 2016, the Executive Board approved a new ECB-wide data governance structure of a federalised type: data management is steered by a single Data Committee, and is jointly performed by a dedicated central team (DG Statistics) and dedicated roles in the business areas (data stewards and data owners) with a clear split of responsibilities. This approach shall ensure that data is governed and managed centrally whenever it is effective and efficient, without slowing down business areas' local data management and core business.

ECB Data Committee steers data management

The Data Committee is the overarching steering and coordination body for the management of data at the ECB. It is chaired by the Chief Services Officer and comprises area heads from the data providing and data using business areas as well as the technology provider.

The Data Committee proposes the data management strategy, data related policies and organisational changes to the Executive Board, decides on requirements for new internal data collections and steers the purchasing and provision of market data. It coordinates ECB-wide data standardisation activities and steers the implementation of the data management strategy and roadmap.

Data Steward Group fosters collaboration and operational alignment

The Data Steward Group comprises data representatives at senior expert level per business area to ensure cross-business area and conceptual alignment regarding data management. The data stewards act as sounding board for the data integration section in DG Statistics and contribute to the development of the data strategy, data policies, standards and prioritisation representing their business area specific activities and needs. The data stewards support the maintenance of the Data Inventory and the SDD. They strongly foster collaboration and the overcoming of silos, by sharing related experiences, issues and needs of their business area in the data steward group. They brief their business area representatives in the Data Committee and support the local implementation of the data management strategy and policies in their business area.

Directorate General Statistics adjusts its organisation to new needs

DG Statistics develops, collects, compiles and disseminates data, master data, statistics, statistical indicators, and metadata, and provides related user support services required for monetary policy, financial stability, banking supervision, the other ECB and the European System of Central Banks (ESCB) tasks, and for the support of the European Systemic Risk Board (ESRB). It thereby defines the concepts and methods and determines the master data for entities and transactions. DG Statistics also provides centralised market data services and develops financial market databases, e.g. for yields and credit risk. It makes non-confidential data available to market participants and the public, and shares confidential data in line with legal and contractual provisions. DG Statistics contributes in all fields to European and international standards related to statistics and data.

In June 2017 the DG Statistics adjusted its organisation to the new needs of the various internal and external stakeholders. It now comprises three divisions focussing on micro data, two divisions focussing on macro data, and two horizontal functions, namely one division responsible for statistical applications and tools, and a data integration and services section.

Micro data divisions deal with analytical credit data, financial market data, banking supervision data and centralised market data services. They strengthen the process-oriented clustering of micro data, with a focus on database development, data integration and supervisory services and enable innovative solutions. They also develop and manage RIAD and the SDD and work towards the reconciliation of statistical reporting requirements of credit institutions in particular through the Banks' Integrated Reporting Dictionary (BIRD) and Integrated European Reporting Framework (IReF) for reducing banks' reporting burden (see related section *Standardisation is essential for efficiency and integration*).

The two macro data divisions focus on monetary and general economic statistics, and macroeconomic statistics such as balance of payments and sector accounts including government finance statistics. They cluster well-established statistics with a strategic focus on a closer connection between external statistics and sector accounts capturing better the phenomenon of globalisation.

The statistical applications and tools division develops and maintains the ECB's statistical production environment (e.g. FAME) for collecting, producing and managing the ECB's macro-economic statistical databases, and the supervisory banking database. It is in charge of the SDW for disseminating macro-economic statistics and coordinates the on-boarding of data sets to the DISC corporate store. It contributes to the definition and implementation of analytical tools for accessing supervisory and statistical data and implements best practices and optimises data exchange processes and standards (SDMX, XBRL). It produces statistical publications and supports internal and external stakeholders with the visualisation of macro and micro data.

The newly established Data Integration and Services Section provides a focal point for the data integration within the ECB and offers ECB shared data services coordinated by the Data Committee. The section supports the Data Committee in defining and implementing the data management strategy and work program, ensuring existence and implementation of respective ECB-internal data policies, standards and processes (in particular data access and quality). It also coordinates the design and maintenance of a comprehensive data inventory covering all data sets available within the ECB to increase transparency for users and foster multi-purpose usage of data. The section closely collaborates with the Data Stewards, with other DG Statistics functions as main data provider and with DG Information Systems who is responsible for the implementation of technical solutions, such as DISC. In addition, the section offers a shared data services pilot, which is co-funded by business areas (see below).

Overall, DG Statistics contributes to high data quality, efficiencies and less operational risks by promoting best practices across the ECB (quality and methodology), ensuring optimal (re-)use of existing data, methods and code, exploiting synergies between similar business area needs.

Standardisation is essential for efficiency and integration

Global identifiers will facilitate data integration and reduce reporting burden

Whilst DISC provides a common platform, data inefficiencies and inconsistencies continue to be caused by a lack of harmonisation and standardisation. Standardisation efforts are critical to ensure national, regional and global aggregation where needed and for data integration to gain a consistent overview of inter linkages and concentration risks in the banking sector and other parts of the financial system. They will also help to consolidate reporting and lighten the burden on banks.

Standardisation and harmonisation efforts have been stepped up, as demonstrated by the ongoing work of the Committee on Payments and Market Infrastructures (CPMI) and the International Organization of Securities Commissions (IOSCO). Progress has been made in developing globally harmonised identifiers, such as the Legal Entity Identifier (LEI) for banks and their counterparts, Unique Transaction Identifiers (UTIs) and Unique Product Identifiers (UPIs), relying wherever possible, on data standards that already exist (e.g. ISO standards).

Eurosystem initiatives foster standards implementation

However, where harmonised identifiers exist, they have not yet been globally implemented. Therefore, in addition to promoting data standardisation at international and European level, the ECB pursues three further initiatives to facilitate the integration of different data sets for analytical purposes and to reduce the reporting burden for banks[4]: IReF, BIRD and SDD. Moreover, it has established RIAD, an important reference data bases for entities, and a Centralised Securities Database (CSDB).

[4] See also '*The ESCB's long-term approach to banks' data reporting*': http://www.ecb.europa.eu/stats/ecb_statistics/co-operation_and_standards/reporting/html/index.en.html

ESCB Integrated Reporting Framework (IReF)[5]

The long-term approach of the ESCB and its Statistics Committee (STC) to data collection from banks aims at standardising and integrating the existing ESCB statistical frameworks, as far as possible, across domains and countries[6]. The main objective is increasing the efficiency of the reporting and reducing the burden for banks, while continuing to provide users with high quality data.

One element of the approach is the ESCB IReF, which is intended to integrate banks' statistical reporting requirements. The other element is the Banks' Integrated Reporting Dictionary (BIRD), which aims at supporting reporting agents in optimising the organisation of the information stored in their internal systems to fulfil reporting requirements.

The IReF aims at integrating the existing ESCB statistical data requirements related to banks, as far as possible, into a unique and standardised reporting framework that would be applicable across the euro area and might also be adopted by other European countries. The main focus of the project is on the requirements of the ECB regulations on balance sheet items (BSI) and interest rates (MIR) statistics of monetary financial institutions (MFIs), the securities holdings statistics (SHSDB) of MFIs, and granular credit and credit risk data (AnaCredit).

The ESCB has initiated a cost-benefit analysis to assess the impact of the IReF on the supply and demand sides, in close cooperation with the banking industry. This will help to identify the most appropriate approach for the banking industry and the ESCB to take.

Banks' Integrated Reporting Dictionary (BIRD)[7]

The BIRD is a recommended tool that helps banks to organise their data by providing a harmonised data model (so called *input layer*), describing the data to be extracted from banks' internal IT systems, and a common set of transformation rules to derive the specific final regulatory figures. The BIRD offers a transposition of the legal requirements at a more operational level. It facilitates the implementation, in a uniform manner, of reporting requirements by banks and software companies in their internal operational systems (e.g. for accounting, risk management, securities or deposits), also helping to report data to the required level of granularity.

The BIRD is being developed thanks to the joint efforts and close collaboration by banking institutions, NCBs and the ECB. Based on harmonised concepts and using clear classifications (i.e. a data dictionary), the input layer provides an accurate, standardised and unique means of defining and identifying individual business positions and transactions, together with their corresponding attributes.

5 See also The ESCB Integrated Reporting Framework (IReF) – An overview http://www.ecb.europa.eu/pub/pdf/other/ecb.escb_integrated_reporting_framework201804.en.pdf

6 See also Par. 2.12 of the "Medium term work programme of the ESCB Statistics Committee": https://www.ecb.europa.eu/stats/pdf/stcworkprogramme2019.en.pdf.

7 See also the BIRD website at: http://banks-integrated-reporting-dictionary.eu/.

The Single Data Dictionary (SDD)

The SDD contains metadata with definitions and concepts for describing ECB datasets and their content, which aims at enhancing the harmonisation of the description of datasets content and, thus, data integration within the ECB[8]. The final goal of the SDD is to have a unique metadata dictionary that can serve the ECB in defining its reporting requirements, as well as in fully exploiting already available data. The SDD started as a home-made stand-alone application and is now being implemented in the DISC infrastructure.

Users will benefit by having all data sets described following the same standard. In addition, producers will benefit when using different data sets in compilation procedures or for checking the consistency between different data sets. The SDD also serves BIRD.

A dedicated team in DG Statistics defines and maintains the reference dictionary and the process for direct semantic integration. Other concepts, which are defined using terminologies different from the SDD (e.g. under responsibility of entities outside the ECB) can be mapped to the SDD terminology.

The decision of which data frameworks are to be included in the SDD in the next years will depend on requests by ECB business areas coordinated by the Data Committee. DG Statistics will propose to the Data Committee a migration plan of the current metadata dictionaries to the SDD, taking into consideration also the input provided by the Data Stewards ensuring that datasets managed by all ECB business areas are properly taken into consideration, and following a cost-benefit assessment. The migration plan will describe the "whether", "how", and "when" existing datasets get included in the SDD.

In case a new reporting framework is defined or an existing reporting framework is amended, DG Statistics will propose an integration strategy to the Data Committee following the same approach described above.

Register of Institutions and Affiliates Data (RIAD)

RIAD is an ESCB-wide unique master dataset covering reference data on legal and other statistical institutional units and the relationships between them, relevant for statistical and several other business processes in the ESCB and the Single Supervisory Mechanism (SSM).

RIAD is pivotal for the collection, joint management and provision of reference data needed for all ESCB granular data collections and enables the integration of a variety of datasets, via a shared identification of the counterparties. This holistic approach avoids maintaining parallel reference datasets in different business areas and allows for a harmonised view of counterparties within the ECB and in associated institutions (NCBs, National Competent Authorities (NCAs)). In RIAD group structures are derived using a wide range of attributes on individual entities and relationships between them. This approach offers a wide flexibility in modelling different group structures according to different business needs.

Different stakeholders update and enrich the RIAD dataset, perform the necessary data quality management and deliver the up-to-date information to end-

8 See also http://www.ecb.europa.eu/stats/ecb_statistics/co-operation_and_standards/smcube/html/index.en.html.

users (which may be individuals or other client systems). For this, a network of "hubs" has been set up for some years. Hubs are in place in NCBs (or NCAs) to coordinate the work at country level and ensure that high quality standards are met. The national hubs meet in the "RIAD Hub Network" under the auspices of the STC, which sets out principles on how to proceed, prepares instructions – including via guidelines and agreements with stakeholders –, and monitors all new requests and developments to ensure a high quality of service and data.

Centralised Securities Data Base (CSDB)

The CSDB is jointly operated by the ESCB and contains timely and high-quality security-by-security reference data on around 7 million debt securities, equity shares and investment fund units issued worldwide. This includes securities issued by EU residents; securities likely to be held and transacted in by EU residents; and securities denominated in euro, whoever the issuer is and wherever they are held.

CSDB processes input from multiple data sources (several commercial data providers and NCBs) with overlapping and even conflicting information. Based on this input, the system compounds a consistent 'golden copy' data set in a fully automated way, taking into account all information available and relying on pre-set compounding priorities and statistical compounding algorithms. The system benefits from an efficient shared data quality management by NCBs and the ECB.

A shift in working culture with closer collaboration is required to leverage the data potential

Make data fit for use whilst protecting confidentiality

The Data Inventory creates transparency of all data sets that exist in the ECB, documents the confidentiality of the data and the access request procedures to be followed. The data integration section in DG Statistics has defined the requirements for the Data Inventory, which will be migrated from an interim access database to DISC. It is also performing a quality control on the content. The Data Stewards coordinate the population of the inventory for their business areas.

The ECB aims to maximise the use of available data whilst safeguarding the confidentiality. It has established clear access approval and reconciliation processes. Users are trained in awareness sessions to understand their responsibilities and apply appropriate measures to ensure data protection. The current access approach is rather restrictive and user needs are assessed on a case-by-case basis. The combination of granular data sets creates new challenges for the protection of confidential information. Work is ongoing at technical and organisational level to reduce the complexity and the effort spent to manage and reconcile access rights and perform output controls.

International initiatives, such as the G-20 Data Gaps Initiative (DGI-2)[9] and the International Network for Exchanging Experience on Statistical Handling of Granular Data (INEXDA) are expected to contribute to these endeavours[10].

Clear guidance for publications and reports ensures consistency

The efforts by the DISC team and DG Statistics will give users more flexibility to use the granular data, apply own models and methods and easily create reports using tools like Tableau.

It is therefore essential that users fully document which data they used, which methods and codes they applied to ensure the traceability and reproducibility of their results. This is a prerequisite to ensure the soundness of decision making and understand the potentially different results based on the same data. Likewise, it is important that users, often coming from different business areas, share their knowledge, codes and methods to avoid duplication of efforts and reach results even faster. DISC will therefore provide functionalities to easily document the data related processes, provide versioning and historisation of data and of codes.

The Statistical Application and Tools Division has created a Tableau user guide jointly with the Communications and the IT department. They take into account existing practices and needs in the business areas, and provide corporate standards to ensure a harmonised look and feel for dashboards and reports produced across the organisation.

Create multidisciplinary teams and share knowledge

Multidisciplinary teams are best suited to exploit the potential of the granular data, new technologies and new methods and techniques. It is impossible for a single expert, even for a single division to master the complexity of the data. Therefore, the ECB started a few projects analysing data combining expertise from different fields, e.g. economists, financial stability experts, statisticians, data scientists and IT experts to jointly work on concrete questions.

These teams have demonstrated creativity by leveraging on the different skill sets and expertise, experimenting with machine learning and exchanging knowledge, code and output. Especially the co-ordinated feedback to data producers will help both data users and data producers.

9 As stated in the report "Update on the Data Gaps Initiative and the Outcome of the Workshop on Data Sharing" by the Inter-Agency Group on Economic and Financial Statistics, dated March 2017 "The G-20 economies are also encouraged to increase the sharing and accessibility of granular data, if needed by revisiting existing confidentiality constraints" … "Every overhaul of existing or introduction of new legislations (or legal texts to the extent possible) which may have implications for data collection (including for administrative uses) should address data sharing and accessibility at national and potentially regional levels to prevent duplicated information requests by different authorities."

10 INEXDA was launched by five central banks in 2017 (Banca d'Italia, Banco de Portugal, Bank of England, Banque de France and Deutsche Bundesbank), and the ECB and Banco de España joined in 2018.

Example: Shared data services pilot on funding and assets of banks

One of such projects is the shared data services project on the funding and assets of banks. Colleagues from various business areas are collaborating with the help of the DISC environment to combine security data with the objective to create a high quality integrated data set and conduct further analysis. They provide feedback to the DISC team on performance and user friendliness. They discuss with the data producers data quality questions and they work closely with user areas to provide reports containing answers to specific policy relevant questions.

The project combines data from RIAD, CSDB, SHS, several commercial data providers and CEPH[11]. With this concrete business case, it is performing a proof of concept of DISC. It started with the on-boarding of the data sets into the corporate store. This included the optimisation of table structures, which dramatically improved the performance of queries, which took hours in the CSDB environment and then was tuned from minutes to seconds in the DISC environment. The team is testing a new solution to ensure secure access. It is harmonising definitions and codes via the SDD and using a rule based approach to integrate the different data sets using the ISIN and LEI and other identifiers where available.

Conclusion

We are in the middle of a journey to exploit the potential of granular data for analytical and policy making purposes. The compass has been set right, but we will require persistence and continued collaboration at global, European and business area level to further progress on standardisation, optimise the use of technology, improve the legal framework for sharing data and develop appropriate methods to preserve confidentiality without unduly impacting the usability of the data. New business processes will emerge and statisticians and users will enter into new modes of cooperation, for which the rules need to be fine-tuned along the process.

Abbreviations used

BIRD	Banks' Integrated Reporting Dictionary
CEPH	Common Eurosystem Pricing Hub
CSDB	Centralised Securities Database
DG	Directorate General
DISC	Data Intelligence Service Centre

[11] CSDB contains reference and price information for around 10 mio securities at monthly frequency. The commercial suppliers cover 4,000 to 5,000 securities from different number of issuers in different ways, either from large banks or EU sovereign bonds, daily or tick-by-tick. The Common Eurosystem Pricing Hub (CEPH) provides daily data for around 40,000 securities, and provides all NCBs on a daily basis with a unique price "Final Eurosystem Price" for each marketable asset eligible as collateral for Eurosystem monetary policy operations.

ECB	European Central Bank
ESCB	European System of Central Banks
IReF	ESCB Integrated Reporting Framework
MFIs	monetary financial institutions
NCA	National Competent Authority
NCB	National Central Bank,
RIAD	Register of Institutions and Affiliates Data
SDD	Single Data Dictionary
SHSDB	Securities Holdings Statistics Data Base
SSM	Single Supervisory Mechanism
STC	Statistics Committee
MMSR	Money Market Statistical Reporting
FAME	Forecasting Analysis and Modeling Environment

Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

Ninth IFC Conference on “Are post-crisis statistical initiatives completed?”

Basel, 30-31 August 2018

ECB data for analysis and decision-making: data governance and technology[1]

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[1] This presentation was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

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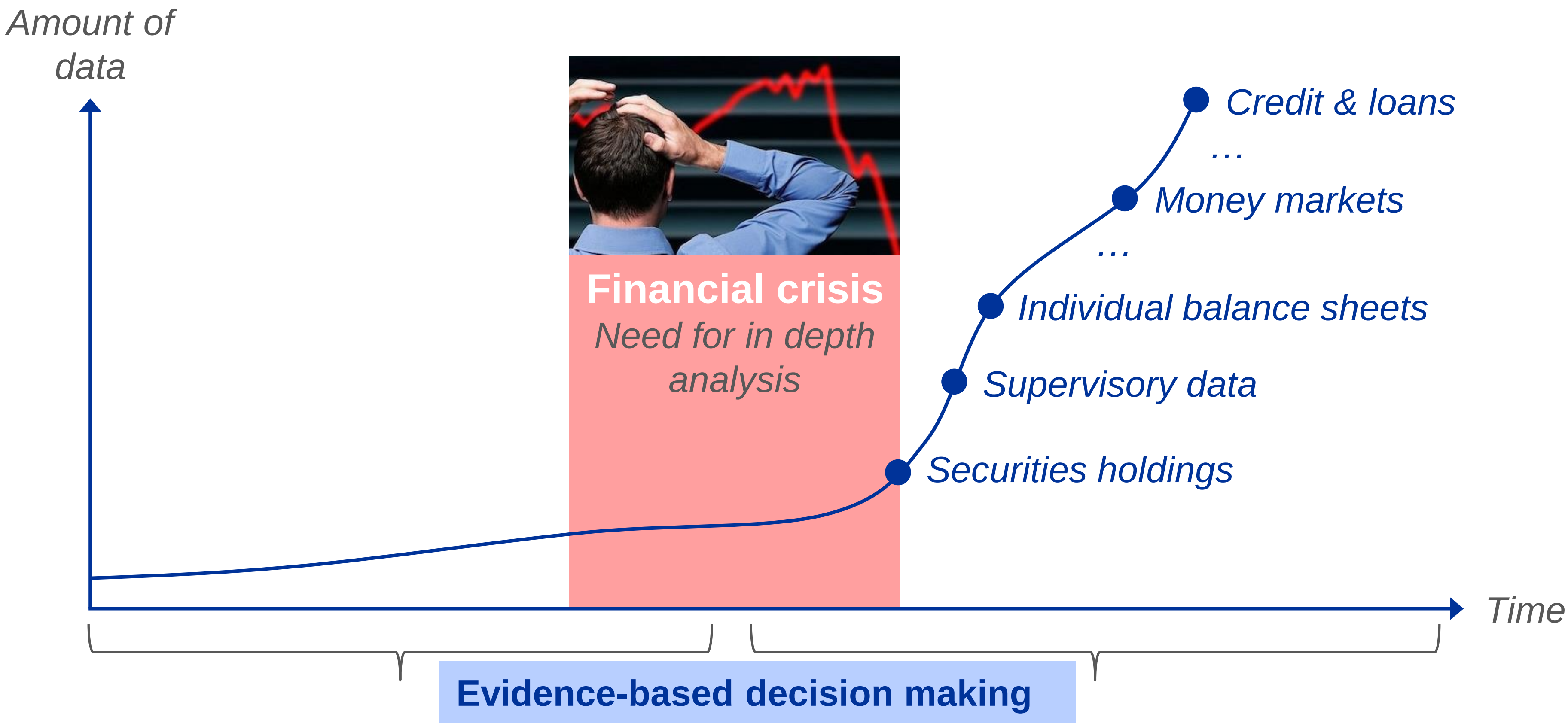
ECB data for analysis and decision-making: Data Governance and technology

9th IFC Conference
"Are post-crisis statistical initiatives completed?"

Basel, 31 August 2018

Exponentially increasing availability of data



Macroeconomic statistics
to analyse

- economic signals
- macroeconomic forecasts
- economic linkages

Micro data (in addition to macroeconomic statistics) to analyse

- timely and diverse economic signals
- risk concentration and distributional effects
- flexibly new questions

New challenges call for a holistic approach

To exploit the increasing availability of micro data challenges have to be addressed:

Increasing volume and speed

Heterogeneity of data

Complexity of data

Data confidentiality

DISC facilitates data usage, collaboration, automation

Macro data

FAME

Statistical Data Warehouse

Micro data

- Credit & loans
- Securities
- Derivatives
- Money markets
- …

DISC

Central, secure data platform to store, analyse and collaborate on large data volumes

- Secure infrastructure
  cloudera informatica
- Analytical tools
  sas
- Data labs and workbench
- Metadata tools
- Data management
- Data factory

Strong ECB data governance ensures alignment

Data Committee

Area heads from data producing/consuming BAs

Decide and steer …

- data management strategy, policies and work
- data standardization
- data collection and access requests
- purchase and provision of market data

DG Statistics

Data integration team and others

Develop and provide…

- data strategy, policies, standards
- shared data services pilot
- master data, single data dictionary, data inventory

In addition to regular statistical production

Data Steward Group

Experts from data producing/using BAs

Raise, discuss, contribute…

- data related experiences, needs and issues of the BAs
- data strategy/ policies/ standards/ management
- data inventory/ single data dictionary

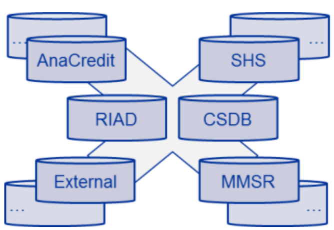
Standardisation for efficiency gains and integration

ISIN

- **Global standardisation of identifiers**
  - Entity
  - product
  - transaction

SDD

- **Joint initiatives with European banks**
  - Banks' Integrated Reporting Dictionary (BIRD)
  - Integrated Reporting Framework (IReF)
- **ECB Single Data Dictionary**



- **Reference data for entities and securities**
  - Register of Institutes and Affiliates Data (RIAD)
  - Centralised Securities DataBase (CSDB)

Shift in working culture to optimise data usage

Make data fit for use whilst protecting confidentiality

- Create transparency of data and data needs
- Make data access clear and efficient within legal boundaries
- Apply appropriate measures to protect data
- Adhere to clear rules for data usage and output control

Document guides, methodologies and code

- Use metadata and document methods and code to reproduce results
- Apply corporate standards for visualisation (Tableau user guide)

Create multidisciplinary teams and share knowledge

- Combine expertise from different fields e.g. economics, statistics, data science, legal, IT
- Define concrete projects to jointly analyse data for multiple purposes
- Exchange knowledge, code and output
- Provide quality feedback for data producers
- Learn new skills and experiment with e.g. machine learning, AI

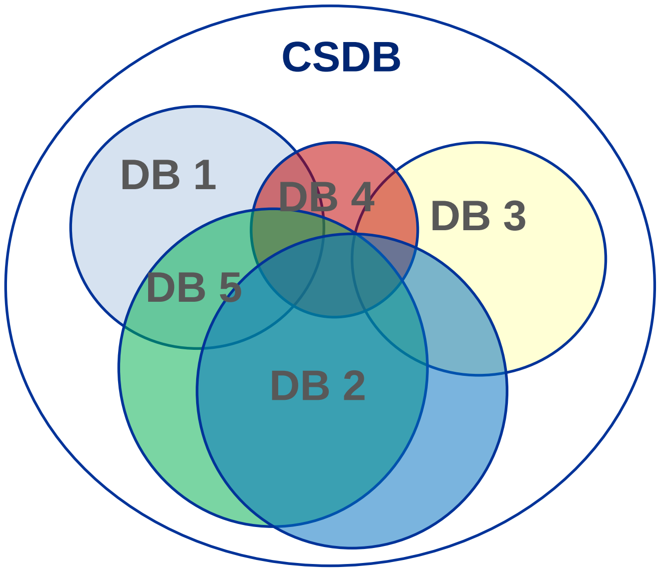
Joint project to leverage expertise and data

High quality integrated security data on assets and liabilities of banks

Joint team

- Economics
- Statistics
- Financial Stability
- IT

Security data



- **On-board** all relevant data sets to DISC, optimise table structures
- Harmonise definitions and codes via **SDD, comparable identifier**, etc.
- Ensure **secure access** (Jumphost)
- Use **DISC workbench** for storing, distributing and analysing data
- Manage and collaborate on code (BitBucket)
- Use **Tableau** for data visualisation
- Interact with **production teams** to clarify quality issues

7. Time to conclude and ask questions

- ❑ **The journey is going into the right direction**
- ❑ **Persistence and collaboration are required**

Time for questions and comments

Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

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New electronic data delivery system of Central Bank of the Republic of Turkey[1]

Adnan Eken, Aycan Ozek, Burcu Cakmak and Seyma Serdengecti,
Central Bank of the Republic of Turkey

[1] This paper was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

New Electronic Data Delivery System of Central Bank of the Republic of Turkey

Adnan Eken, Aycan Ozek, Burcu Cakmak, Seyma Serdengecti

Abstract

Statistical authorities are now more concerned about better dissemination, communication and correct use of official statistics. Dissemination of statistical products through tailored services of electronic data delivery systems allows computer-to-computer exchange in an easily accessible, understandable, interactive and reusable manner. Central Bank of the Republic of Turkey (CBRT) started electronic data dissemination system in 1995. The so-called Electronic Data Delivery System (EVDS) is a dynamic and interactive system that presents statistical time series data produced by the Bank and/or data produced by other institutions and compiled by the Bank. Widely used EVDS provides a rich range of economic and financial data to support economic education and foster economic research. Its technical infrastructure and visual design was revised in October 2017. The system is upgraded to better fulfill user requirements and catch up information technologies. Significant progress has been made to re-construct and renew the dissemination process. The new EVDS offers time series, info graphs and dashboards for users in a personalized manner. Users can build up their own database, graphs, maps and dashboards. The purpose of this paper is to present the Bank's renewal process of the data delivery system and show how EVDS used for communicating statistics. To that extent, Section 1, describes the importance of data dissemination services in communicating statistics and enhancing financial inclusion and literacy, Section 2 underlines historical background and the decisions and motivations behind the renewal process of the EVDS. Section 3, continues with a description of the new EVDS and main features. Section 4, includes next strategic steps over the long term and the conclusions.

Keywords: Central bank statistics, data delivery system, communicating statistics

Contents

Introduction

Official statistics are for the benefit of the whole economy, it serves data mainly for government policy making but also for other economic entities to create a base for decision making. In today's world, data is a part of management; central banks use data that they already have collected with the purpose of carrying out their own business and transactions. Central bank statistics used in the field of monetary policy decisions as well as in financial stability, payment systems and international reporting. Moreover, professionals, academicians and the public use statistics for various purposes. While the concept of dissemination of data is acknowledged as important in the fields of economic and statistical analysis, most central banks are still trying to catch up with this development. It is essential to make statistics more accessible to public, because statistics play a key role in educating public about the economy and enhance their awareness of data.

Electronic Data Delivery System (EVDS) of the Central Bank of the Republic of Turkey (hereinafter referred as the Bank) is not a new system; it dates back to 90's and served up to now. However, the need for renewal of EVDS in line with new technologies and user needs has arisen and the new EVDS has been designed to meet these needs. In this paper, we will focus on the updated electronic data dissemination system and its features.

Importance of Data Dissemination Services in Communicating Statistics

Central bank statistics around the world face significant challenges as new trends in statistics and communicating statistics have emerged. Statistics give guidance from the past, help you to understand the present, and make inferences about the future. Moreover, statistical data are essential input into monetary and financial policy decisions.

The Bank is aware of the dynamic structure of the statistical world and its repercussions on evolving needs of the both policy makers and public. It assigns the utmost importance to raising public awareness in matters of using EVDS. Therefore, EVDS will play a central role in supporting our key central bank functions.

The mission of the Bank in the field of statistics is to produce high quality statistics in line with international standards and in timely manner. Coherence, comparability, transparency and accessibility are the other key elements of our statistics mission. EVDS is the Bank's official platform to meet these statistics with the public. By doing this, EVDS plays a key role in informing public about main economic and financial statistics.

The United Nations Economic Commission for Europe (UNECE) mentioned in the Making Data Meaningful (2005), that with the growth of social media, multimedia tools and new communication channels, it has become apparent that the central banks are faced with the imperative need to upgrade their communication skills and tools. It is also related with how to find most suitable tool for communication to different users. The Bank change the culture of communicating statistics by disseminating the data in a more user-friendly system. New EVDS improved the practices, which was established in the first version to make the data accessible and assist both professionals and public decision-making.

The central banks around the world allocate significant resources to promote economic education and financial literacy. As the Bank, we aim to reach out to different audiences with the financial literacy and economics education programs. EVDS serves exactly to this purpose. In this line, the Bank publishes many informative documents, videos, organizes training programs for different target groups. Cude (2010) stated that increasing financial literacy serves as an important channel to improve the capability of the people in managing their money. In this respect, EVDS assists public in using statistics in their daily life and financial decisions.

Historical Background and Renewal Process of the EVDS

Historical Background

The duty of the Bank, to collect statistical information relating to the financial system and publish the statistical information is established in the "The Law on the Central Bank of the Republic of Turkey". In line with this; basic principles and standards dealing with the production and dissemination of official statistics and to produce reliable, timely, transparent and impartial data required at national and international level are determined by the Statistics Law of Turkey No 5429. Within the scope of this legal framework, the Bank collects, compile and disseminate monetary, financial, real sector, foreign exchange and balance of payments statistics. For this purpose, the functional division of the Bank, responsible for compiling and dissemination of statistics is the Statistics Department.

Until the early 1990s, the statistics, reports and bulletin produced by our Bank were distributed in paper format. Ongoing data sharing with printed bulletins and reports was carried out from paper to electronic media with the technological advances. The electronic data distribution project started in 1992. Implementation and development studies were completed in 1993, and the first version of EVDS, which was a character-based operation, has been opened to the users. There were 500 time series. In 1994, with the setting up of the Bank's internet access, the system was revised to serve as a telnet application and the new system was opened on 4 January 1995. Over time, the number of registered users for access to the system has exceeded 2.500.

Due to the difficulties in using the character-based application, the increasing requirements over time, and the developments in technology, the system has been redeveloped with web-based features and graph feature has been added in June 1998. The number of time series reached 1800 in this period.

Need for Update of the EVDS

The first version of the EVDS was heavily used, but to keeping up to date with technical innovations, a revised version was needed. The enrichment of data within the Bank increased the demand for information from the public. Increasing requests made it necessary to renew the EVDS to improve the efficiency and quality of our statistical service. To meet new challenges in dissemination of data, the Bank took this initiative. In 2016, project work for the renewal of EVDS began. Beginning from April 2017, an intensive study has been conducted by the Statistics Department (SD), the Information Technologies Department and the outsourcing company. After this intensive work, the new EVDS has been opened to public on 20th of October 2017.

The Bank has been working actively in the field of statistical dissemination and communication with the introduction of the new EVDS. Having carried out a major public service in monitoring the Turkish economy, EVDS meets the needs of many users. Policy makers use EVDS for decision making, academicians use for research, domestic and foreign professionals use for analyzing Turkish economy and lastly students use EVDS for their assignments. In addition to the existing services provided by EVDS, it was aimed to create more user-friendly system, taking into account the needs of the above-mentioned users.

The New EVDS

EVDS is a dynamic and interactive system that presents statistical time series data produced by the Bank and/or data produced by other institutions. These data are published on dynamic web pages. They can also be reported in the xls format or through the web service client (json, csv, xml), viewed in the graphics format.

The EVDS is available in Turkish and English. The system provides a rich range of economic data and information to support economic education and foster economic research.

Figure 1. EVDS Website

Main Features

Timely and comprehensive data

The Bank collects and compiles a wide range of statistics for its ongoing work and external users. There are approximately 26.000 time series from internal and external sources. The data is freely available to all. Recently updated data groups are listed on the main page. Now, there are twenty-two data groups: (Table 1)

List of Data Groups	Table 1
Exchange Rates	Market Statistics
Balance of Payments and International Investment Position	Deposits and Participation Funds Subject to Required Reserves
Foreign Trade Indices	External Debt
Money and Banking Statistics	Securities Statistics
Financial Accounts	Central Bank Balance Sheet Data
Surveys	Payment Systems
Price Indices	Production Statistics
Employment Statistics	Public Finance
Privatization Implementations	BIS Comparative Country Statistics
Gold Statistics	Interest Rates
Housing and Construction Statistics	Financial Statistics

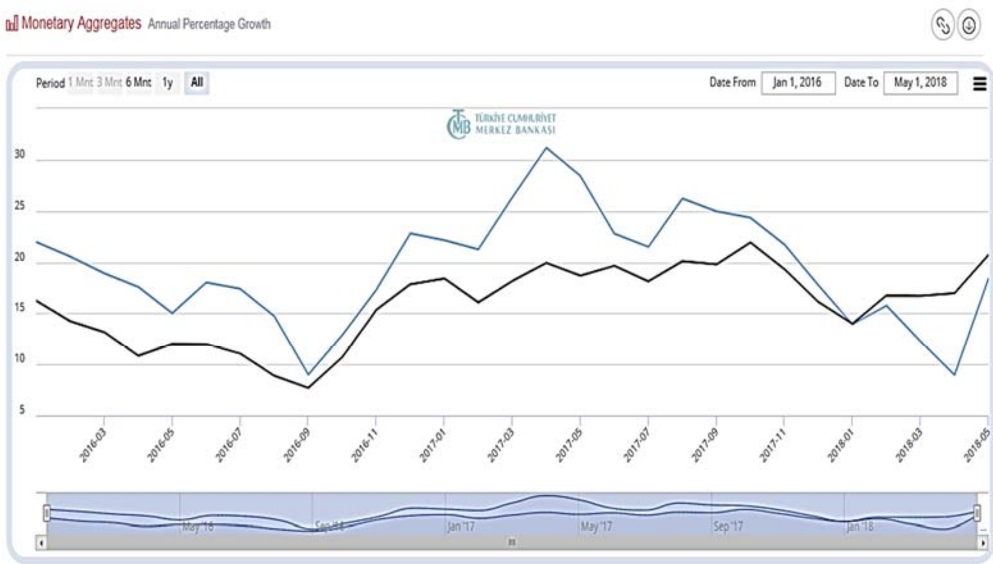
Create report, graph, and map

For the all series, users can easily create reports and graphs. Users can draw charts in six graphic types. Graphics can be printed and saved in different formats. The map display is available for eligible data sets (geographical distribution, house price index, etc.)

Dashboards

Dashboards disseminated by the Bank contains a graph and short explanatory notes about the graph and the data. Users can also create their own dashboards, save and share them.

Figure 2. Dashboard, Monetary Developments



The graph presents the annual growth rates of M1 and M3 money supply. M1 is composed of currency in circulation and demand deposits. Broad money supply M3 is derived by adding time deposits, funds received from repo transactions, money market funds and debt securities issued with a maturity up to 2 years to the M1. The graph shows that M3 growth rate exceeds the M1 growth rate recently.
The series used in the graph are taken from Money Supply and Counterpart Items table under the Money and Banking Statistics available at EVDS.
Prepared by: CBRT Statistic Department, Monetary and Financial Statistics Data Division (Contact: parasal.veriler@tcmb.gov.tr).

Subscriptions

By subscribing to the selected series or data, the system shares information by sending an e-mail to the user at the previously scheduled date and time when the data groups or series are updated.

Using formulas

There are eight different formula options in time series. Formula box contains: level, percentage change, difference, year to year percentage change, year to year differences, percentage change compared to end-of-previous year, difference compared to end-of-previous year, moving average and moving sum. With the latest update of the EVDS, registered users can create customized formulas by performing four operations between the time series. This feature allows users to add, subtract, multiply and divide the selected time series.

REST web service usage

The data in EVDS are updated most frequently in daily frequency. Therefore, data collection once a day is very important in terms of overall system performance with Web service method. It may also be useful to encode the data for the same data group together with the data needed by a single call.

Search tool

The search box on the EVDS home page can provide users to search anything about EVDS such as categories, data groups, series and metadata. This search box also directs the user to the search results screen by searching through the metadata and dashboards.

Help desk

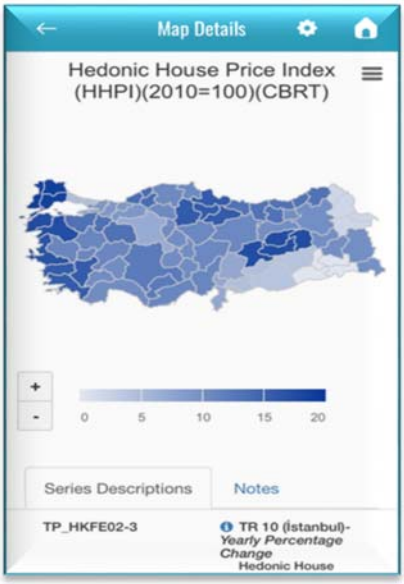
General public is one of the priorities of EVDS. If users find data access challenging, the main objective of the EVDS will be damaged. In this context, the SD built a call center for dealing directly with phone calls from the public. It helped us to have a better understanding of the users' difficulties. In addition, the public can communicate directly and receive assistance via e-mail.

Mobile Application

EVDS Mobile App is a mobile application that allows you to access and display the statistics disseminated by the Bank. The app offers dashboards and predefined graphs on topics such as external debt, weekly securities statistics and hedonic house price index. Users can access the latest available statistics and display them in tables, charts and maps and export data in various formats (such as .csv or .png). In brief, users can use all the features of the website over the application. Users can tweet, mail, or post their favorite graph or dashboards. Registered users can manage and share their subscriptions and dashboards.

Figure 3. Mobile Application homepage

Figure 4. Dashboard



Increasing Public Awareness about the EVDS

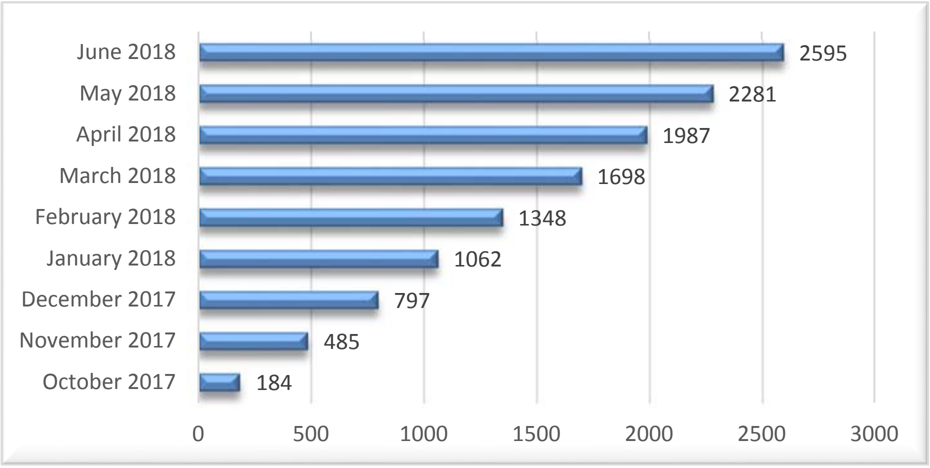
The Bank, assigns the utmost importance to raising public awareness in matters of using EVDS. First, general public should be grouped by their interest and level of financial literacy. In this way, targeted communication policies can be implied to different groups. In this line, the Bank publishes brochures, videos, organizes training programs for different target groups.

Firstly, there are many informative user documents in both written format and video format. Second, the Bank organizes practical training activities both for bank staff and outside users. The CBRT hosts university students at the CBRT Headquarters to inform them on the core functions of the CBRT. EVDS is one of the important topics in these events. Trainings have been organized for students, journalists and economists up to now. Moreover, a video has been released in the CBRT Blog- which is one of the Bank's official communication tools- to make it accessible to a larger audience

Use of EVDS: Immediate Results

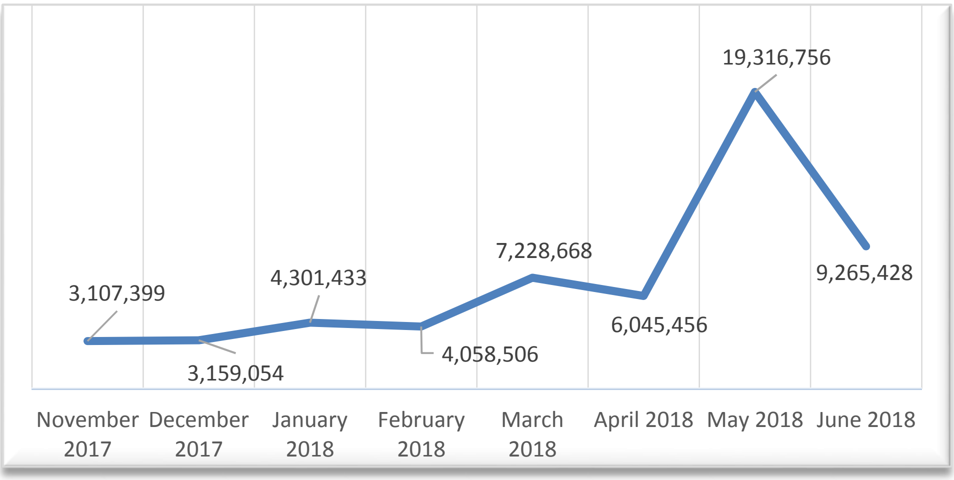
It is important to measure and monitor the system. By analyzing the indicators, behavior of the users and effectiveness of the communication strategy can be inferred. All the internal quantitative indicators show that EVDS is heavily used. For instance: total number of registered users is 2,595 as end of June 2018 and growing.

Graph 1. Number of registered users

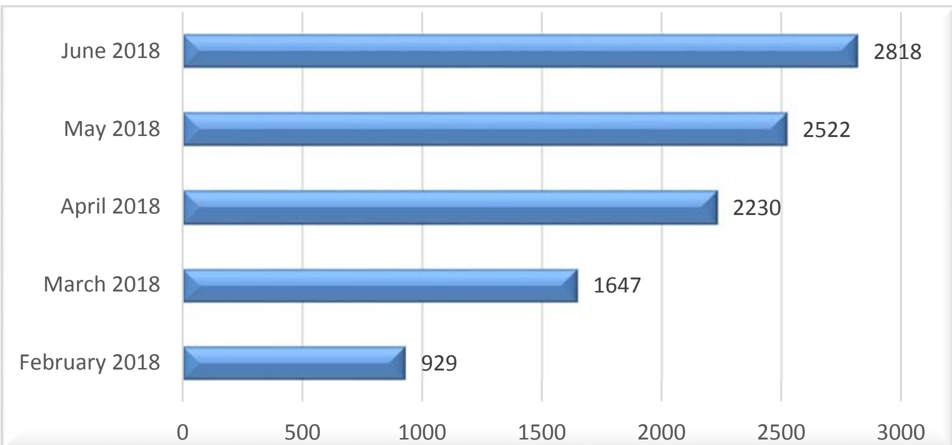


Other indicators, e.g. the number of "clicks" in EVDS is increasing at a fast pace - e.g., in June the number of total clicks is 9,265,428. The number of mobile application downloads is 2,818.

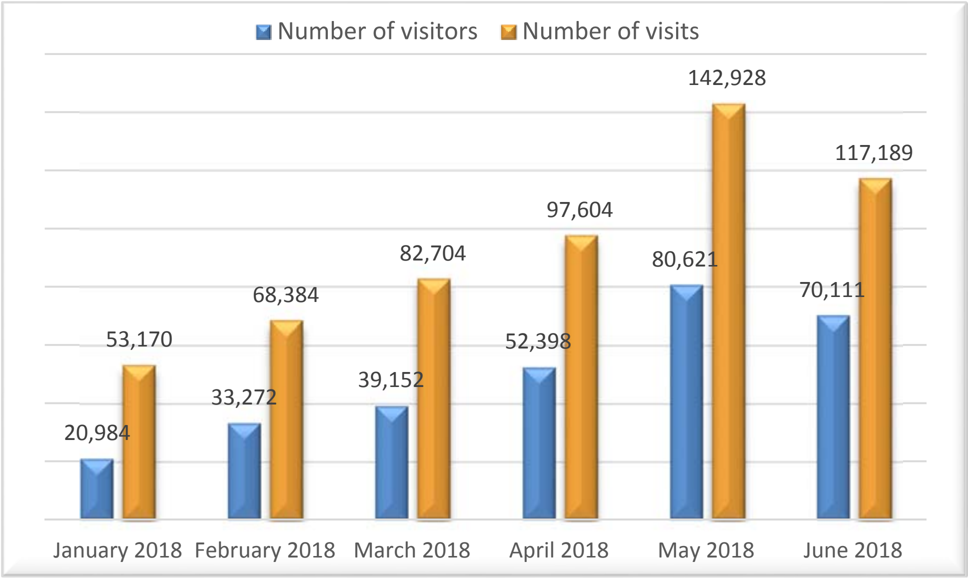
Graph 2. Number of total clicks



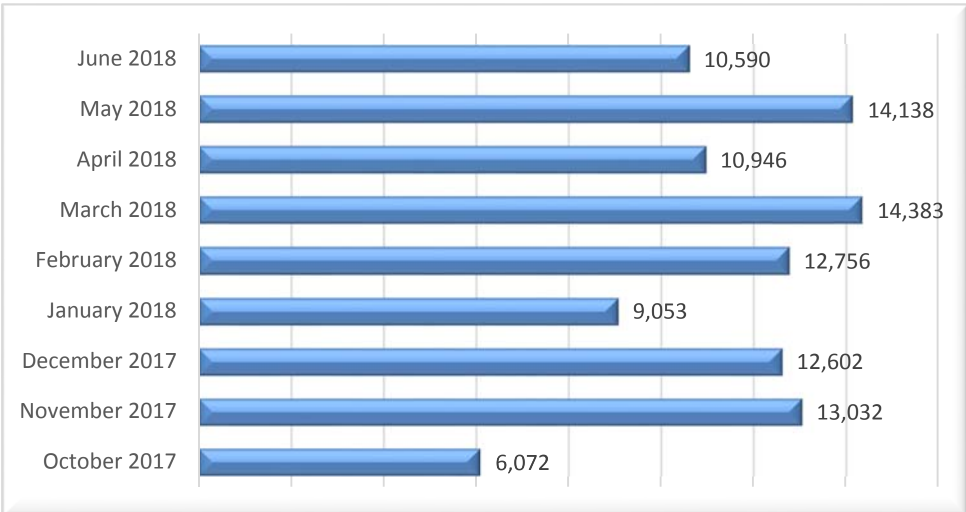
Graph 3. Number of mobile application users



Graph 4. Number of visitors and visits



Graph 5. Number of dashboard view



Next Strategic Steps

The EVDS is a dynamic database. The Bank, works in collaboration with the domestic and foreign institutions to increase economic data available in the EVDS. As a first step, the SD negotiated with the Bank for International Settlements (BIS) to extend EVDS data set by adding BIS series in which Turkey takes part.

To increase the analytical power of the system new functions such as mathematical operations between the series will be added.

To increase the functionality of the dashboards it is planned to re-design them as micro blog pages so that they not only to present formal data but also tell a story about the data.

Last but not least, a statistical portal is planned to be established. The platform will play an essential role in discussing statistics.

Conclusion

Central bank statistics around the world face significant challenges as new trends in statistics and communicating statistics have emerged. With the growth of social media, multimedia tools and new communication channels, the central banks are need to upgrade their communication skills and tools. With the new EVDS, the Bank change the culture of communicating statistics by disseminating the data in a more user-friendly system. The positive feedback from the public and the users statistics indicate EVDS has up to a good start in this direction.

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Basel, 30-31 August 2018

New electronic data delivery system of Central Bank of the Republic of Turkey[1]

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Central Bank of the Republic of Turkey

[1] This presentation was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

New Electronic Data Delivery System (EVDS) of Central Bank of the Republic of Turkey

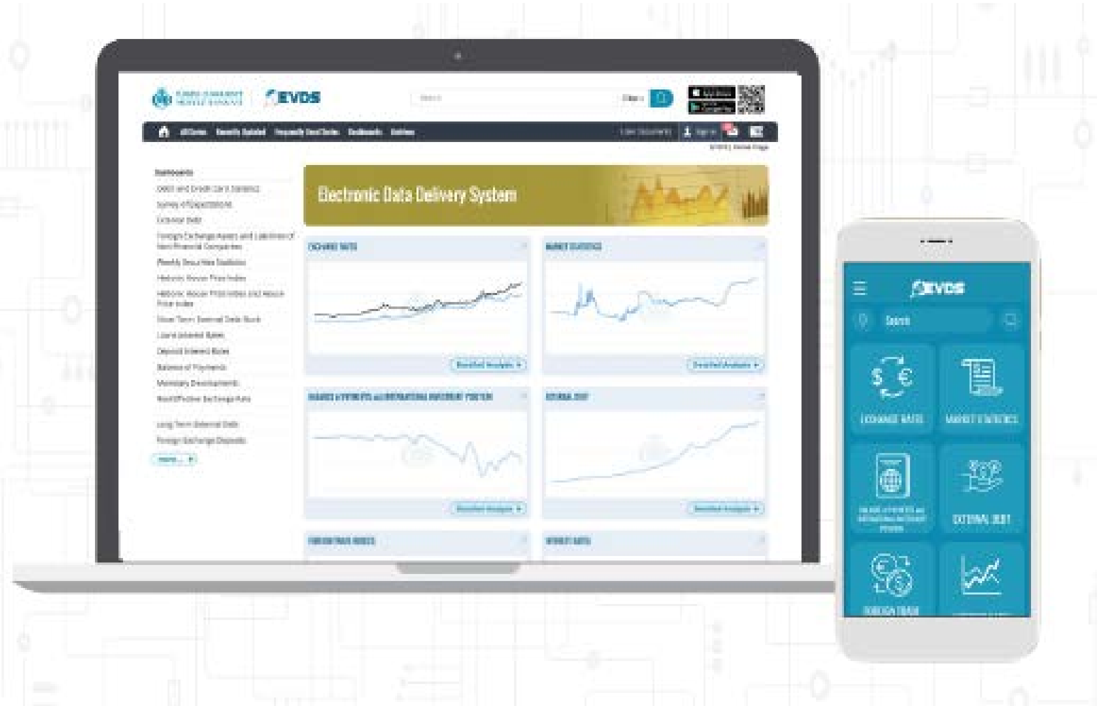
Seyma SERDENGECTI

30-31 AUGUST, 2018 | BASEL

Outline:

- What is EVDS?
- Features
- Dashboards
- Mobile Application
- Increasing Public Awareness
- Use of EVDS: Immediate Results
- Next Strategic Steps

What is EVDS?



- Data Delivery System of Central Bank of Turkey
- Dynamic and interactive
- Covers data produced by Bank and by other insitutions.
- Since 1995
- Renewed in 2017
- Opened to public on 20th of October 2017
- in Turkish and English

https://evds2.tcmb.gov.tr/

Features

22 Subject Titles , 315 Datagroups, 26 000 Time Series

8 formula options for every time series

Customized formulas

Get quick information on key economic indicators via dashboards

Search within data groups

Create dynamic tables and graphs

Dynamic map display for data groups containing locations

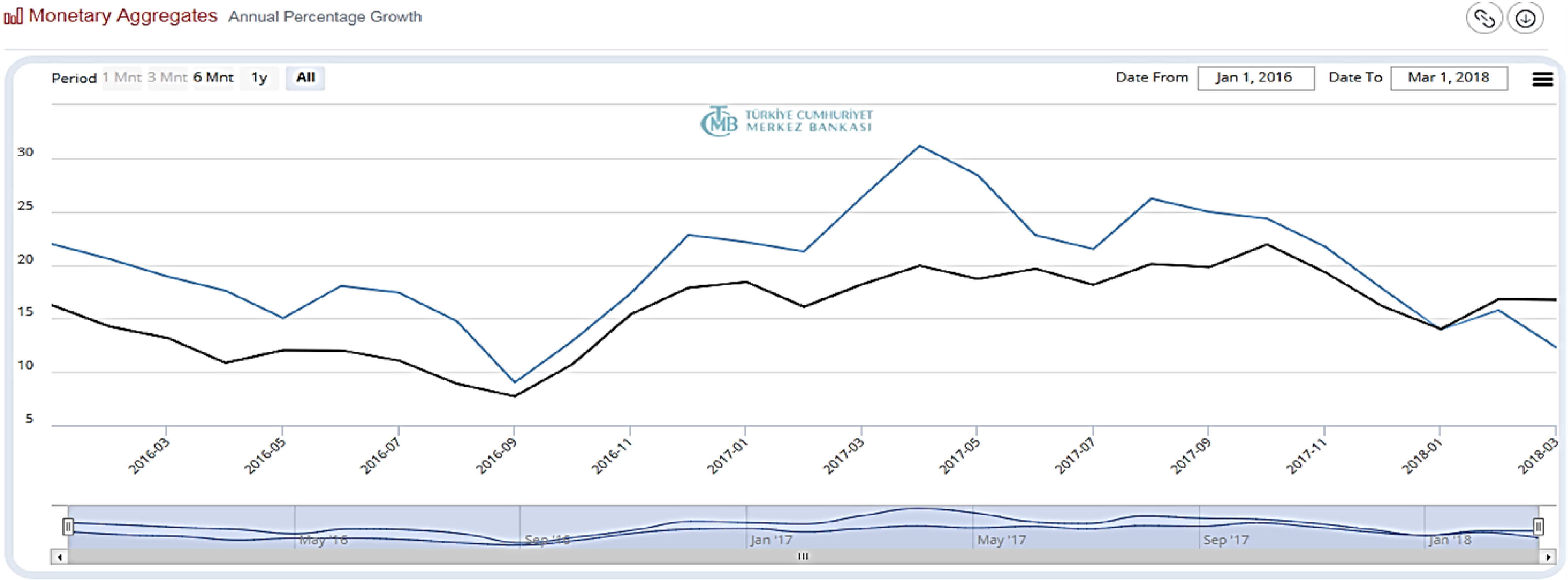
Personal dashboards that can be saved, linked and shared

Subscription

Help desk

REST web service usage

Dashboards

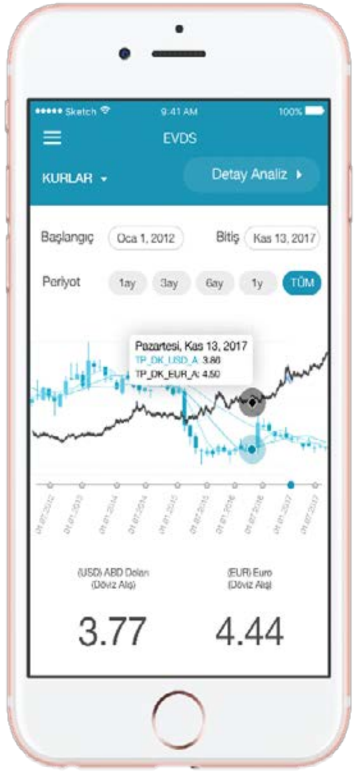


The graph presents the annual growth rates of M1 and M3 money supply. M1 is composed of currency in circulation and demand deposits. Broad money supply M3 is derived by adding time deposits, funds received from repo transactions, money market funds and debt securities issued with a maturity up to 2 years to the M1.The graph shows that M3 growth rate exceeds the M1 growth rate recently.

The series used in the graph are taken from Money Supply and Counterpart Items table under the Money and Banking Statistics available at EVDS.

Prepared by: CBRT Statistic Department, Monetary and Financial Statistics Data Division (Contact: parasal.veriler@tcmb.gov.tr).

Mobile Application



- Access the latest available statistics and display them in tables, charts and maps and export data in various formats (such as .csv or .png)
- Access, download and/or share your dashboards and predefined graphs
- Users can tweet, mail, or post their favorite graph or dashboards

Download on the App Store
GET IT ON Google Play

Increasing Public Awareness

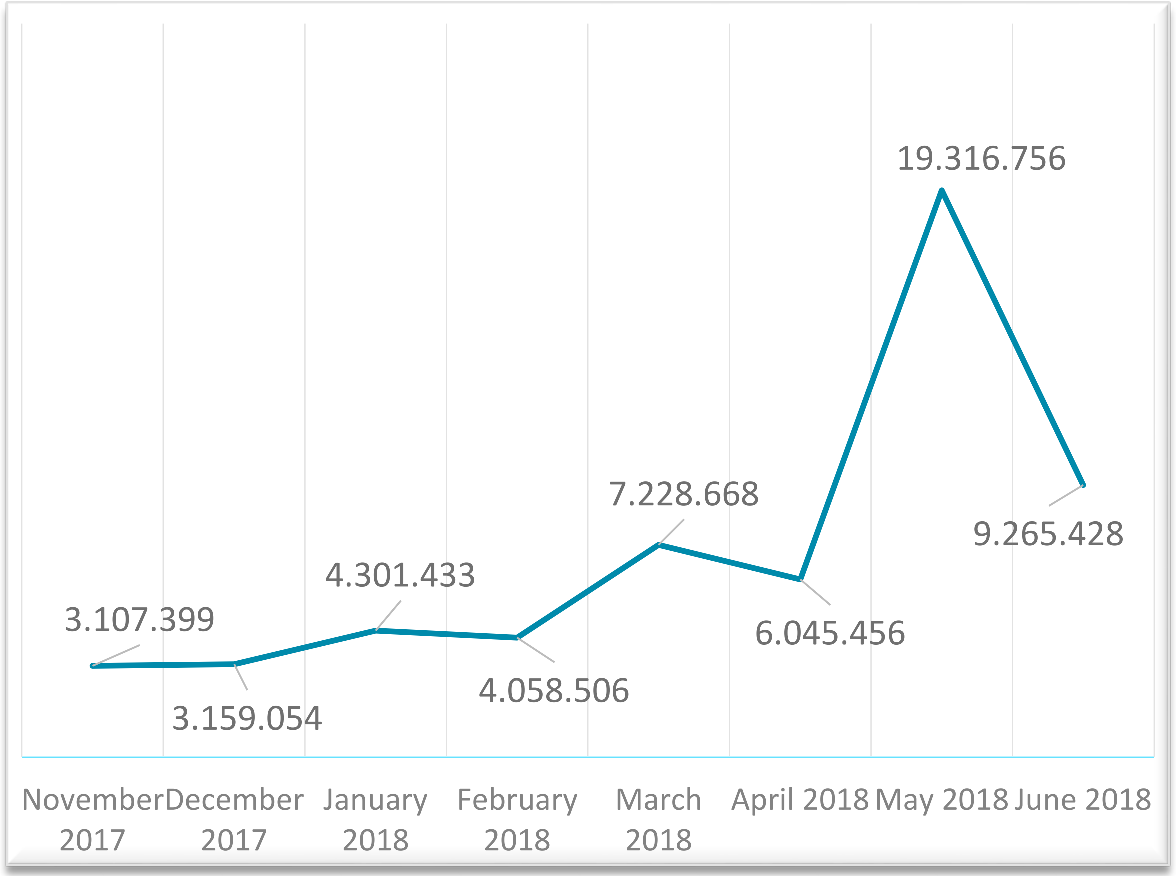
The Bank publishes brochures, videos, organizes training programs for different target groups.

The Bank organizes practical training activities both for bank staff and outside users.

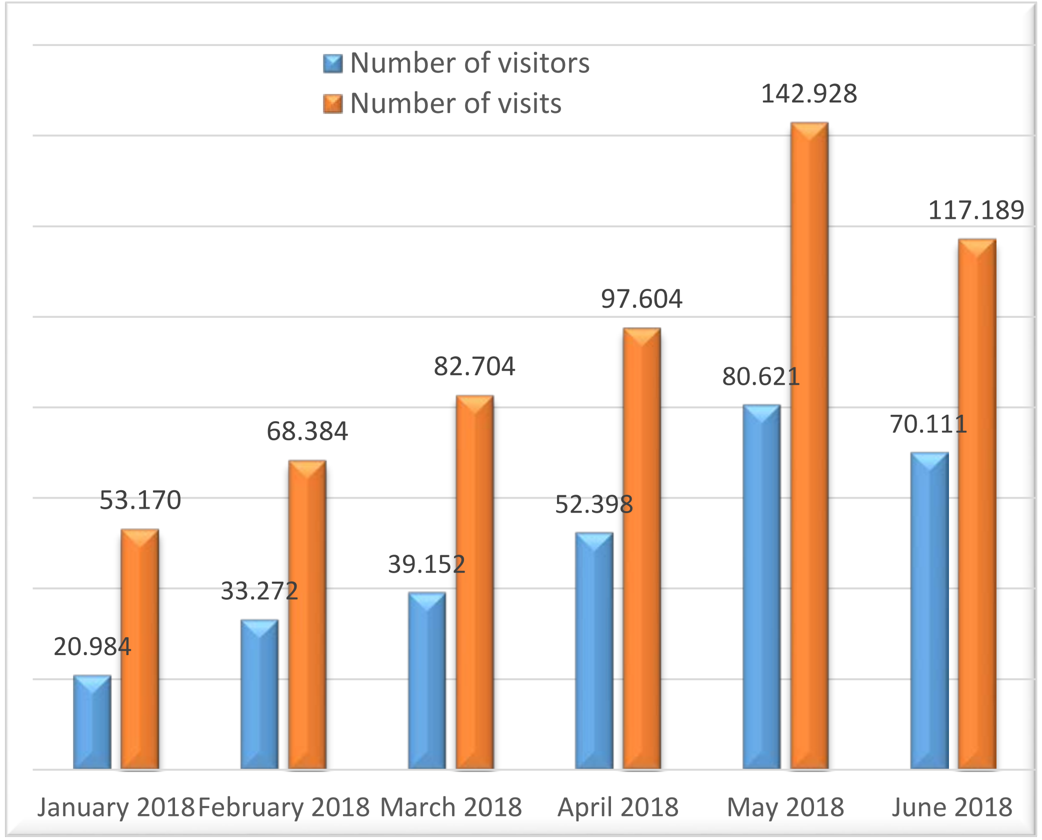
A video has been released by the CBRT to make it accessible to a larger audience.

Use of EVDS: Immediate Results

Number of total clicks



Number of visitors and visits



Next Strategic Steps

Increase the number of economic and financial data available in the EVDS

Add new functions (mathematical operations between the time series)

Build a statistical portal

Focus more on increasing financial literacy

Increasing public awareness

Thank you!

yeniEVDS@tcmb.gov.tr

EVDS DATA CENTRAL

TÜRKİYE CUMHURİYET MERKEZ BANKASI

Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

Enriching disclosures:
The Bank Financial Strength Dashboard [1]

Tobias Irrcher,

Reserve Bank of New Zealand

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Enriching disclosures: The Bank Financial Strength Dashboard

Tobias Irrcher

Abstract

On 29 May 2018, the Reserve Bank of New Zealand launched a new online and interactive disclosure tool called the Bank Financial Strength Dashboard (the Dashboard). The Dashboard aims to enhance market discipline by making regulatory disclosures more timely, accessible and comparable. It provides key financial and prudential information on all banks incorporated in New Zealand, including the four major banks owned by Australian parents. Effective disclosures are particularly important for New Zealand because its regulatory settings emphasize market discipline relatively more than many other jurisdictions, and market discipline works best if supported by comprehensive and timely disclosure. The Dashboard has a strong focus on the presentation and communication of quantitative disclosures to a broad audience, ranging from sophisticated analysts through to the typical depositor. A layered design and various interactive features not only make the Dashboard easy to use, but will also provide a rich source of information on the demand for and use of prudential disclosures going forward.

Alongside the development of the Dashboard, the Reserve Bank has conducted what we believe to be the first quantitative analysis of the strength of market discipline in New Zealand, by measuring the extent to which market participants monitor and influence the risk profile of banks. The concentrated nature of the New Zealand banking sector means we are able to explore the impact of public commentary along with the standard market monitoring of financial information. We find evidence that market participants, especially bond holders, monitor and react to risk information in the expect way (i.e. bond spreads rise when these indicators signal an increase in risk and vice versa) and it appears that media and other public commentary plays a role in drawing the market's attention to specific risk events.

Keywords: prudential disclosures, market discipline, bank risk-taking, financial stability, reg tech

JEL classification: G21, G28, G32, G38

Contents

1. Introduction

This paper discusses the role of public disclosures in New Zealand as it relates to the prudential supervision of banks and how the Reserve Bank's new online and interactive disclosure tool (the 'Dashboard') is expected to contribute to financial stability by enhancing market discipline. The paper also discusses recent Reserve Bank efforts to measure how market discipline operates in New Zealand.

Public disclosures have long played a prominent role in the Reserve Bank's approach to prudential supervision of banks. This is especially true since the mid-1990s when the Reserve Bank introduced a requirement for banks to publish quarterly disclosure statements and at the same time reduced the extent of prudential regulations that applied to banks (Mortlock, 1996). The disclosure statement regime aimed to improve information for investors, strengthen the role of bank directors and promote sound banking practices. A key focus of disclosure statements was to increase transparency about the financial condition and risk profile of banks. New Zealand was somewhat of a pioneer in raising the profile and importance of disclosures in prudential supervision in the mid-1990s. The prominence of disclosures remains a distinguishing feature of prudential settings for banks in New Zealand even though regulatory prudential requirements have been strengthened in the wake of the Global Financial Crisis (Fiennes, 2016b).

The relative importance of public disclosures in New Zealand is reflected in the Reserve Bank's three pillars approach to prudential supervision of banks. The three pillars are: market discipline; self-discipline and regulatory discipline. Market discipline reflects the influence that investors and other stakeholders can have on an institution's behaviour and risk profile. The requirement for public disclosures is intended to support the ability of investors and other stakeholders to exert market discipline. Self-discipline is aimed at supporting firms' internal risk management and governance systems. Regulatory discipline involves setting rules and requirements.

Today, public disclosures are an important element of prudential settings in many jurisdictions and disclosures have been a prominent feature of international best practice for the supervision of banks since at least the mid-2000s under the Basel II accord. International best practice is an important benchmark for policy settings in New Zealand but these are tailored to fit the domestic context. An example of this is when the Reserve Bank simplified its disclosure regime in 2011.

There has been a fair amount of academic interest in measuring the effectiveness of market discipline (Eling, 2010). Due to data limitations, much of this analytical work has focused on a narrow segment of the target audience for disclosures, principally the holders of market traded debt and equity instruments. Data limitations are somewhat more pronounced in New Zealand compared to other jurisdictions because there are few bank issued securities traded on secondary markets. That said, data sources have improved somewhat over time and the Reserve Bank has recently taken some early steps to replicate international studies and extend the state of knowledge on how market discipline operates in New Zealand (Haworth, Irrcher and Gillies, 2018). The calibration of prudential settings in New Zealand is such that market discipline is expected to be somewhat stronger in New Zealand compared to other jurisdictions. These settings include the lack of an explicit deposit guarantee scheme, recent enhancements to the bank resolution framework and the prominence of disclosures.

The relative scarcity of data on how market participants use information such as public disclosures has been noted in the literature and in a somewhat prophetic statement, (Eling, 2010) comments that:

> "[an] instrument to enhance market discipline could be a standardized information platform, perhaps to be posted on a regulator webpage."

The Reserve Bank's tradition of innovation in the area of disclosures is followed up with the recent introduction of its Dashboard, a new online and interactive public disclosure tool that aims to enhance the timeliness, accessibility and comparability of information about the financial and prudential condition of banks in New Zealand. The Dashboard uses information technology to enhance the regulatory process of disclosures and can therefore be considered Reg Tech, or regulatory technology.

The Dashboard concept was born out of a broad review of prudential regulatory settings in 2015 called the Regulatory Stocktake. The stocktake identified an opportunity to significantly enhance the effectiveness of prudential disclosures through an online and interactive central repository of disclosure data – this is the Dashboard concept. The Dashboard concept was refined through public consultation in 2016 and was launched in May 2018. Early usage statistics indicate that the new disclosure tool is reaching a significantly larger audience than its predecessor. We have also received positive feedback on the design and usability of the new disclosure tool from the analyst community, media and various government agencies.

The Dashboard sits alongside disclosure statements as a source of information about the financial condition of banks and was developed with a strong focus on meeting the needs of a diverse target audience. This includes an easy to use website, the production of educational materials and running a public awareness campaign to support the launch of the Dashboard. A by-product of building an interactive disclosure tool with wide appeal (like the Dashboard) is that it will provide an illuminating source of information on the use and demand for disclosure data over time. This type of information could help shed light on how market discipline operates in New Zealand and guide further refinements to the disclosure regime for banks.

Recently revised disclosure requirements in Basel III (i.e. the 2015 update) also makes reference to a 'Dashboard' approach. The Basel III Dashboard is a set of key prudential metrics that are reported in prescribed tabular format that aims to improve the accessibility and comparability of data across banks and across jurisdictions. The Reserve Bank's disclosure Dashboard has similar overarching objectives as the Basel IIII Dashboard but there are several important points of difference in the mechanics. For instance, the Reserve Bank's Dashboard is a centralized online repository with a strong focus on making information accessible to a general audience. By contrast there is no requirement for the Basel III Dashboard to be prominently displayed or easily accessible to users. Another point of difference is that the Reserve Bank's Dashboard also contains a lot more data items than the Basel III Dashboard. That said, the full set of Basel III disclosure requirements (i.e. in addition to those in the Basel III Dashboard) go beyond what is available on the Reserve Bank's Dashboard but this is largely because some regulatory requirements are not in place in New Zealand (e.g. there is no minimum leverage ratio requirement).

The rest of this paper is organized as follows; Section 2 discusses the Dashboard in more detail including early indications of its impact and some thoughts on possible next steps. Section 3 presents some results from recent analytical work at the Reserve Bank on measuring market discipline.

2. The Bank Financial Strength Dashboard

New Zealand context for disclosures

The Reserve Bank maintains a three pillar approach to prudential supervision of banks. The three pillars are: market discipline; self-discipline and regulatory discipline. As noted previously, market discipline reflects the influence that investors and other stakeholders can have on an institution's behaviour and risk profile. Self-discipline is aimed at supporting firms' internal risk management and governance systems. Regulatory discipline involves setting rules and requirements. The basic economic rationale for imposing prudential interventions is to mitigate the financial stability risks arising from market failures by aligning the interests of financial institutions with their customers and wider society. In comparison to other jurisdictions, New Zealand is an outlier in that the Reserve Bank does not do detailed on-site checking and instead relies relatively more on self and market discipline to achieve its financial stability objectives (Fiennes, 2016b).

Calibration of the three pillars is adjusted from time to time to reflect developments in international best practice and changes in domestic circumstances. As an example, the Reserve Bank simplified its disclosure regime in 2011. The 2011 changes were mainly focused on reducing compliance costs and improving the accessibility of disclosures for key users. The changes included dropping some components like the Key Information Summary because the costs outweighed the benefits. The remaining component, the quarterly General Disclosure Statement, was streamlined and simplified to lower costs and improve accessibility for sophisticated users. Also, the role of regulatory discipline has increased over the last 15 years, especially since the global financial crisis but market discipline remains a cornerstone of the Reserve Bank's regulatory approach.

Disclosure requirements naturally support the self and market discipline pillars through the scrutiny provided by market participants and other interested parties. The fact that no financial institution is guaranteed by the New Zealand government places additional market pressure on banks to emphasise safety. Another feature of New Zealand's disclosure regime is that bank directors are required to attest (i.e. sign statements) that, among other things, the bank has appropriate risk management controls in place, and that it has met its conditions of registration (or explained the extent of non-compliance, if any). These attestations by bank directors place additional weight on the importance of disclosure statements because there are stiff penalties on directors for attesting to false or misleading information and because the attestations are included in the disclosure statements themselves.

The Dashboard disclosure tool

The Dashboard is an online and interactive central repository of disclosure data that is updated quarterly. It is a tool designed to enhance the effectiveness of prudential disclosures, boost market discipline and thereby support the Reserve Bank's financial stability mandate. The Dashboard disclosure tool was born out of a broad review of prudential regulatory settings in 2015 called the Regulatory Stocktake, which identified stakeholder appetite for timelier, more accessible and more comparable prudential disclosures. The Dashboard concept was refined through public consultation in 2016 and was launched in May 2018 starting with one quarter of data.

The set of Dashboard data will become increasingly useful for trend analysis as the time series develops.

The Dashboard sits alongside disclosure statements as a source of meaningful information for investors and other interested users to better understand and compare a bank's business and its risks. As a result of the Dashboard, the frequency of disclosure statement publications was reduced from quarterly to six-monthly. The main rationale for retaining annual and half-yearly disclosure statements is that they remain useful for users and because they contain directors' attestation statements. There are a few important differences between the two types of disclosure that are summarised in Table 1.

The Dashboard data is sourced from private reporting that banks provide to the Reserve Bank whereas the disclosure data is prepared and published by banks themselves. The use of private reporting for the Dashboard minimises additional compliance costs for banks and contributes significantly to the comparability of data across banks because the information is based on definitions provided by the Reserve Bank. This is especially important for financial statement information, where the accounting standards can allow for discretion that adversely affects comparability of data. That said, banks have an incentive to achieve as much consistency as possible between the Dashboard and their disclosure statements so it is reasonable to expect banks to adjust their disclosure statements or provide reconciliations to minimise the impact of any remaining differences. Where disclosure statements are required to publish data related to prudential requirements, the data should be comparable between the Dashboard and disclosure statements, since the terms are defined by the Reserve Bank.

Another noteworthy difference is that the six-monthly disclosure statement information is subject to varying degrees of auditor scrutiny, whereas dashboard data is not. The lack of auditor scrutiny is one factor that allows the Dashboard to be published up to four weeks sooner than disclosure statements. Banks are able to revise their historical Dashboard data to maintain consistency across the different forms of disclosure. Finally, banks have different year-ends so financial flow data is much easier to compare on the Dashboard because the information is presented as quarterly flows rather than year-to-date as is done in disclosure statements.

Structural features of the Dashboard and Disclosure Statements		Table 1:
	Dashboard	**Disclosure Statements (from March 2018)**
Similarities		
Information content	Financial & prudential	Financial & prudential
Points of difference		
Source of information	Banks - Private prudential reporting to Reserve Bank.	Banks – self-published
Layout/ organisation	Unified	Significant variation allowed.
Director attestations	No	Yes
Audit / auditor review	No	Yes
Frequency	Quarterly	Six-monthly
Publication timing (clarify) Time lag after end of period	8 weeks	8-12 weeks
Publication location	RBNZ website	Banks' own websites
Commentary	Focused (provided by RBNZ?)	Extensive (provided by banks)
Revisions history	Yes	No
Reporting period for financial flow data	Calendar quarters	Year-to-date (from balance date)

Dashboard contents

The Dashboard data is organised in a layered format and contains over 100 individual metrics (see Table 2 for details). The first level of detail is the 'key metrics summary' page that presents seven key metrics (one for each subject area) in a visual format and is intended to provide users with quick insights. These charts are interactive and contain plain English descriptions of what the metric is about. A second level of information provides more granular data in a number of areas. A third level of information is a page for each bank that includes all their data in one place. Each bank's profile page also includes details of any recent data revisions and supplementary commentary that is provided directly by banks. Users who are interested in getting access to the underlying data will be able to download a file by clicking the 'just give me all the data' link.

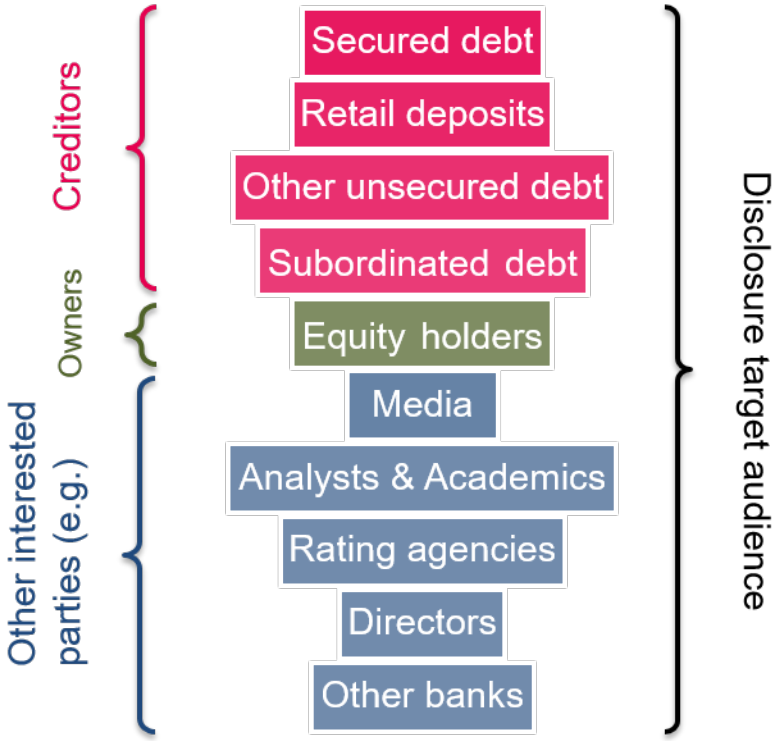
The Dashboard content can be categorised as either 'prudential' or 'financial'. Prudential information provides users with the ability to assess and monitor a bank's compliance with minimum risk-based requirements on regulatory capital and liquidity management and other important risk areas like credit concentration and asset quality. Financial information, which includes balance sheet and income statement data, allows users to gain a better understanding of a bank's business and provides context to some of the more prudential-oriented metrics. Some information, like asset quality, can be considered as both prudential and financial in nature.

Dashboard metrics			Table 2
Subject area	**Type of information**	**Key metric**	**Number of detailed metrics**
Credit rating	Prudential	Credit rating	3
Capital adequacy	Prudential	Total capital ratio & regulatory minimum	27
Asset quality	Prudential & Financial	Non-performing loans ratio	44
Profitability	Financial	Return on assets	14
Balance sheet	Financial	Total assets	14
Liquidity	Prudential	Core funding ratio	3
Credit concentration	Prudential	Sum of top 5 non-bank exposures relative to CET1 capital	4

Accommodating diverse users

The target audience for prudential disclosures is quite diverse and includes creditors, owners and other interested parties like the media, rating agencies and the banks themselves (see Figure 1). These users differ in a number of ways such as their financial literacy and preferences for different information presentation formats (i.e. raw data, written text and visualisations). It is reasonable to expect a large gap in financial literacy between some user groups, especially between the typical retail depositor and frequent users of disclosures like academics, financial journalists and professional investors. These types of differences were taken account of in the design and implementation of the Dashboard.

Figure 1: Target audience for prudential disclosures:



The starting point for the design of the Dashboard user interface was its predecessor, a little used data table (called the G1 table) prepared by the Reserve Bank and assembled from individual bank disclosure statements. A number of design iterations and some user experience testing revealed that a very graphics forward design, along with plain English explanatory materials and education videos were needed to adequately accommodate the range of expected users. The Reserve Bank reached out to other government agencies and financial journalists to help support the development of understandable explanatory materials and educational videos.

Good public disclosures are a shared responsibility

Basel III disclosure requirements note the five principles of effective disclosures: 1) clear; 2) comprehensive; 3) meaningful to users; 4) consistent over time and 5) comparable. In addition to this list, the Reserve Bank considers that market participants must have incentives to monitor banks and mechanisms to exercise discipline, such as reasonable alternative investment options provided by a competitive marketplace [Fiennes 2016]. Another equally important element of effective disclosures is that stakeholders must have confidence in the information being disclosed (Bascand (2018)). Indeed, there are quite a few ingredients needed to ensure that disclosures work as intended and many of these fall to the regulator but other stakeholders also share some responsibility in making sure disclosures work effectively. Banks are responsible for providing quality data and users are responsible for engaging with the data and engaging with the regulator about their needs.

Simply stating that good disclosures is a shared responsibility is of little value unless the appropriate incentives are also in place. For banks, disclosures are a regulatory requirement but banks also benefit from disclosures because the information they provide is useful for benchmarking risks and performance. The Dashboard has been welcomed by a number of banks because they see benefits in the data for themselves. Some stakeholders, such as journalists and rating agencies, have fairly clear professional or business incentives to monitor disclosures. Bank creditors and owners also have quite clear incentives to monitor disclosures because they care about the safety of their money.

While creditors have vested interests in disclosures, the Reserve Bank recognises that engaging with certain creditors, like retail depositors, is a challenge because they are a large group of people with varying levels of financial literacy. For this reason, the Dashboard was developed with a strong focus on presentation and communications. For example, the layered design and graphics presentation was specifically developed with a general audience in mind. Incidentally, this layered design and the various interactive features on the Dashboard will also provide a rich source of information on the demand for and use of prudential disclosures going forward. This information could shed light on how market discipline operates in New Zealand and provide useful guidance on how to further enhance prudential disclosures. Another benefit of the Dashboard for the Reserve Bank comes from the use of private reporting as the data source - the need to publish revisions places additional incentives on banks to focus on the quality of their private reporting.

Launch and reception of the Dashboard

The Dashboard was launched on 29 May and was accompanied by significant promotional efforts. The Dashboard was featured in the May Financial Stability Report (FSR) and was mentioned at the FSR press briefing on 30 May. An online and social media paid promotion campaign was run for about two weeks following launch date. There was a lot of very positive feedback on the understandability and ease of use from a number of sources including financial journalists, academics, and government agencies. Early usage statistics were quite positive but we are uncertain of the steady state interest in the Dashboard due to several one-off factors associated with the first publication including large promotional efforts and the novelty effect. Nonetheless, the Dashboard received more visits in its first 24 hours than its predecessor (the G1 table) typically receives in an entire year. The vast majority of these visits are from New Zealanders. An interesting observation is that about 15% of users to date are return visitors, which is an indication that a number of users view the Dashboard as a resource rather than just a one-off curiosity.

The Dashboard is Reg Tech (regulatory technology)

The Dashboard is the Reserve Bank's first native cloud application, which means that it lives in the cloud (Amazon Web Services to be precise). The Dashboard IT solution combines a user interface that draws data from a database that is also hosted in the cloud via an application programming interface (API). This configuration of applications and the use of cloud computing services is new for the Reserve Bank but is fairly common by modern IT standards. The benefits of this approach include enabling the Reserve Bank to focus its resources to build and run application and services without having to manage IT infrastructure (i.e. server-less architecture). External users benefit from high performance and high availability offered by the cloud. In this way, the Dashboard uses information technology to enhance a regulatory process, prudential disclosures in this case, and can therefore be considered an example of Reg Tech or regulatory technology.

The Reserve Bank is committed to further developing the Dashboard over time to reflect the evolving needs of users, changes in domestic regulatory policy settings and updates to international best practice. There is a short list of developments currently underway. The most immediate of these is the development of a public API to allow more flexible and efficient use of disclosure data. The public API would be particularly useful for users who want to make regular use of disclosure data for analytical or reporting purposes. Further down the track, users will likely benefit from being able to see trends on the Dashboard. Trend information won't be available for some time because the Dashboard was launched with one quarter of data and it will take time for trend information to accumulate. Finally, the Reserve Bank has made previous public statements about its interest in exploring disclosure dashboards for other sectors like insurance and non-bank deposit takers.

3. Better understanding how market discipline operates in New Zealand.

The Reserve Bank has an interest in better understanding how market discipline operates because it features prominently in New Zealand's regulatory settings for banks. As noted previously, the Dashboard will, over time, provide a rich source of information on the use of disclosure data. It will be interesting to observe how the demand for disclosure data correlates with macroeconomic developments and idiosyncratic risk events for specific banks. The usefulness of the Dashboard in this regard will depend on how much use the Dashboard gets but early indications on uptake and usage are encouraging.

Another stream of work by the Reserve Bank, separate from the Dashboard, has focused on replicating empirical studies that try to measure market discipline in other jurisdictions to see if the typical findings are also applicable in New Zealand, which has not been included in any studies that we are aware of. The existing literature identifies two elements of market discipline, a monitoring dimension and an influencing dimension. Monitoring involves market participants assessing disclosed information and reacting by affecting the cost of funding or by withdrawing funding. Influencing is when the actions of market participants alter the risk profile of a bank. The existing literature is almost entirely focused on the market monitoring dimension due to the lack of information on how bank management is influenced by market participants. This distinction between monitoring and influencing is conceptually useful but perhaps less relevant in practice because the cost and availability of funding can have a direct impact on the ability of a bank to take on certain risks and therefore influence their risk profile.

The market monitoring studies focus on a fairly narrow set of stakeholders, mainly creditors and owners, to measure market disciplines because there is readily available data on the price of funding from secondary markets. Recalling Figure 1, which describes a diverse range of stakeholders, the narrow focus of existing empirical work, where stakeholders with the most at stake are the subject of study, can be thought of as a 'canary in the coal mine' approach. The broad finding from this literature is that market participants, especially subordinated debt holders, are monitoring the risk profile of banks via public disclosures of financial information. The results for other stakeholders like retail depositors are less conclusive, in part because the available data on retail depositors is not ideal (e.g. no data on the movement of deposits).

Data limitations are more acute in New Zealand because there are only a few equity and debt securities listed by New Zealand banks on secondary markets. Nonetheless, the broad finding that market participants, especially bond and equity holders, monitor bank risks is confirmed in New Zealand. On the other hand, the concentrated nature of the New Zealand banking sector means we are able to explore other dimensions of market discipline that do not appear to be featured in other studies. In particular, we have developed a comprehensive, list of idiosyncratic risk events that go beyond the standard information set used to measure the magnitude of market discipline in other jurisdictions. These risk events include things like credit rating changes, changes in capital requirements and other one-off announcements like a change in senior management. An interesting question is whether market participants are paying attention to these types of developments and whether the media and other commentators play a role in drawing the attention of the market to them. The results suggest that media and other commentators can have an amplifying effect on the market's awareness of and reactions to risk events (Haworth, Irrcher and Gillies 2018).

Looking ahead, the Reserve Bank plans to continue looking for opportunities to further develop its understanding of market discipline. In addition to the rich analytics we expect to get from the Dashboard tool itself, further empirical work is a possibility but data limitations are an inherent barrier. Another opportunity lies in focusing on stakeholders that have not featured prominently in the existing studies on measuring market discipline. This includes professional investors and other interested parties like rating agencies and the broader analyst community (see Figure 1). In terms of understanding how the actions of these stakeholders might influence the risk profile of banks it could be instructive to consider a more qualitative approach through questionnaires or interviews. Insights from this type of qualitative analysis would not provide a measurement of market discipline per se but would shed light on how the broader community of disclosure stakeholders contribute to market discipline.

4. Conclusion

The Dashboard is a new online and interactive prudential disclosure tool that represents an important step forward in responding to user needs for timely, comparable and accessible information on the financial and prudential condition of New Zealand incorporated banks. The Dashboard tool also marks the Reserve Bank's entry into Reg Tech, or regulatory technology, because it is built with an up to date IT approach that leverages the advantages of cloud computing to deliver a more efficient and effective regulatory process – that of prudential disclosures.

Better prudential disclosures, from the Dashboard, provide a number of benefits. Disclosure users benefit directly from easier access to better data. The banks benefit from better benchmark information. The Reserve Bank benefits from higher quality private reporting due to the additional incentives placed on banks to invest in quality assurance of their private reporting which is the source of the Dashboard data. There are also financial system stability benefits from enhanced market discipline enabled by the Dashboard. Finally, compliance costs are minimized because the Dashboard contents is drawn from existing data that banks provide and because the Dashboard enabled a reduction in the frequency of disclosure statement publications from quarterly to semi-annually.

Since the launch of the Dashboard on 29 May, the usage statistics suggest that we have succeeded in reaching a broader audience for prudential disclosures. The Reserve Bank is committed to further building on this early success in a number of ways. First, it will continue to invest in building awareness of the Dashboard and educating users on prudential disclosures. The Reserve Bank is also committed to improving the Dashboard in response to user needs. An example of this is our plan to develop a Dashboard public API, which will make it easier for interested parties to access and use the data for further analysis or reporting purposes.

Recent Reserve Bank empirical work broadly confirms that market participants, especially bond holders, are monitoring and reacting to public disclosures by banks, which is what we would expect to see and matches the general findings from other jurisdictions. Also, the research appears to support to the idea that media and other public commentators can have an amplifying effect on the market's awareness of risk events.

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Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

Enriching disclosures: The Bank Financial Strength Dashboard [1]

Tobias Irrcher,

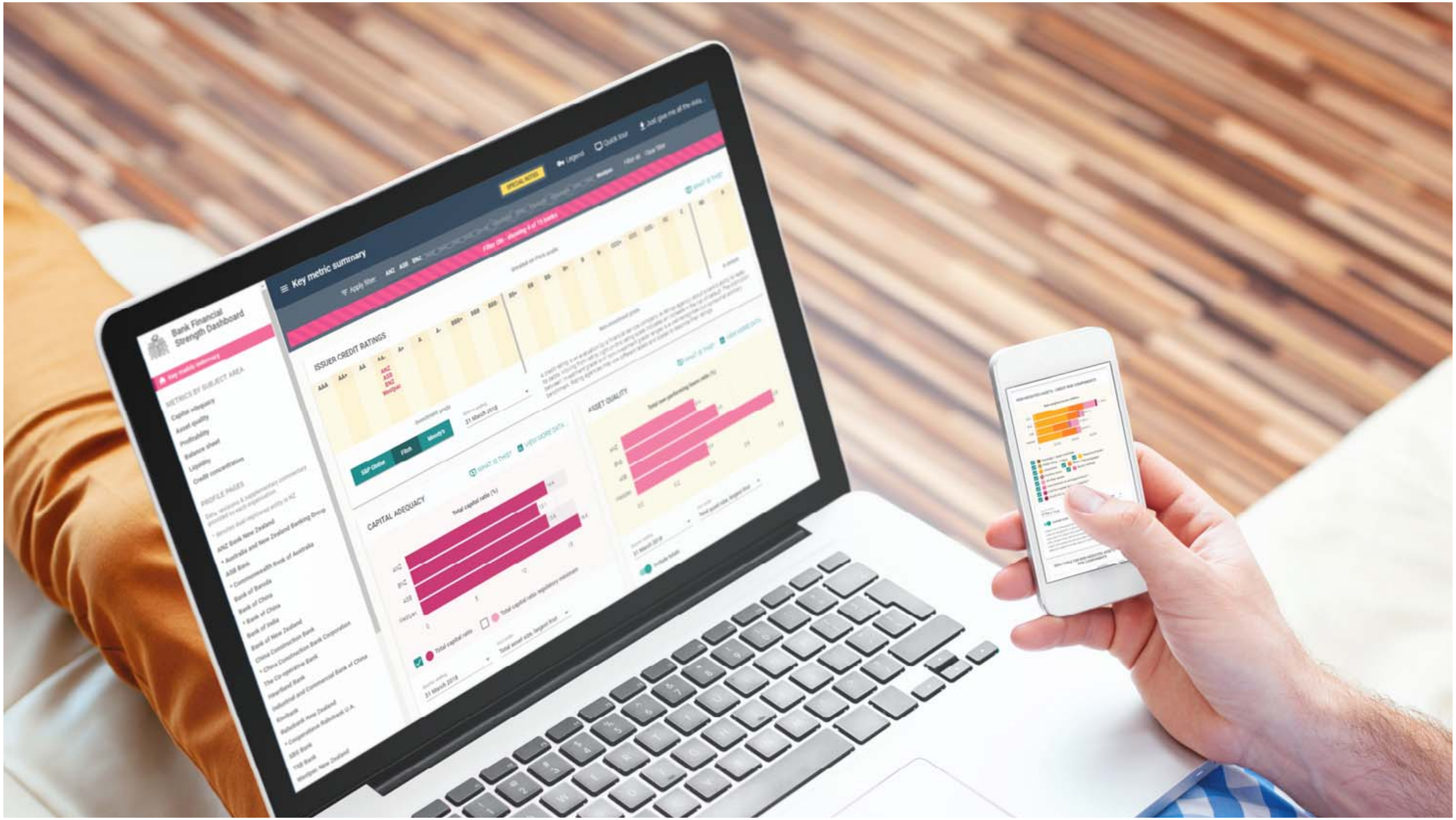
Reserve Bank of New Zealand

[1] This presentation was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

Bank Financial Strength Dashboard

Tobias Irrcher

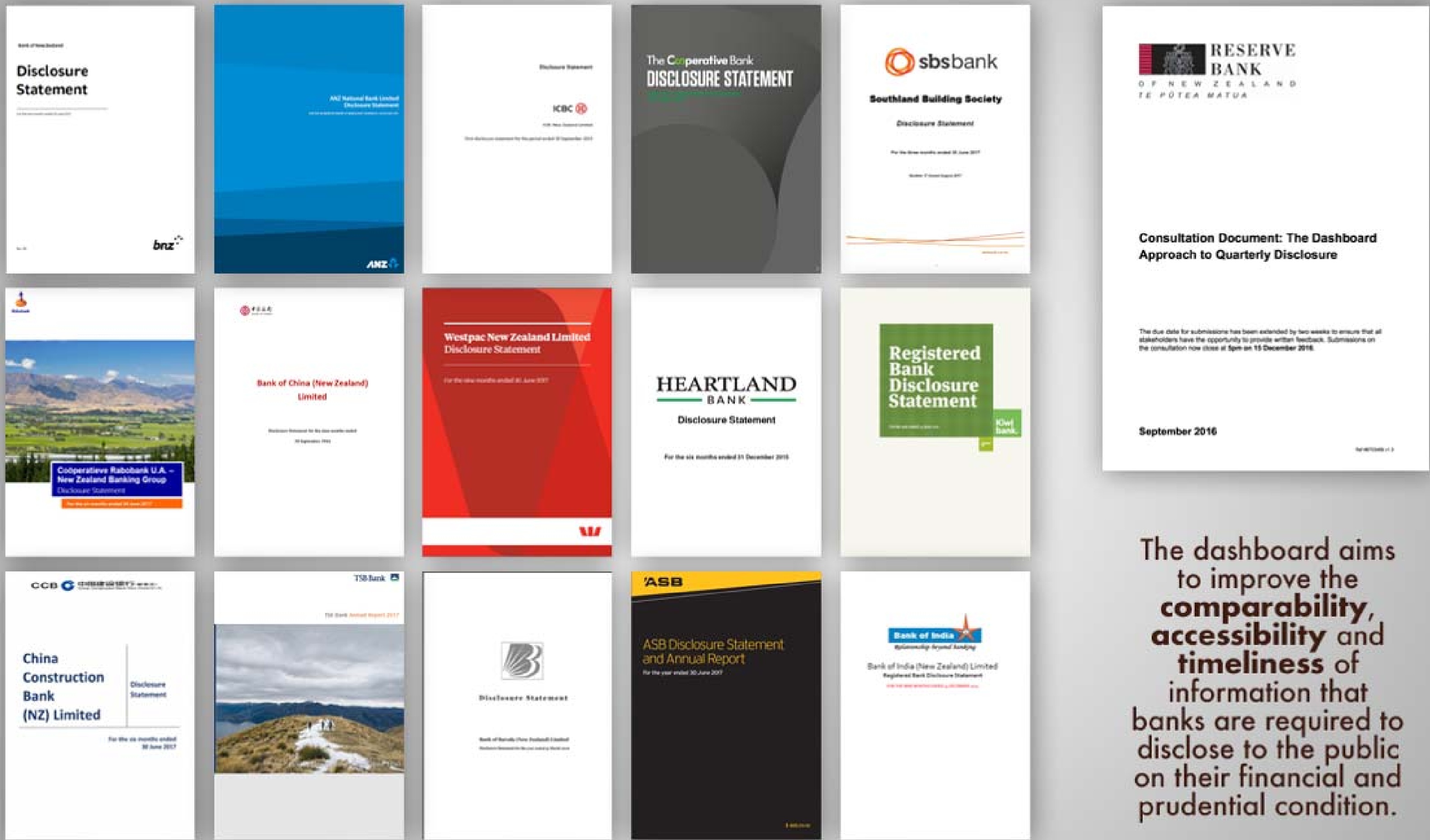
RESERVE BANK
OF NEW ZEALAND
TE PŪTEA MATUA


Bank Financial Strength Dashboard
Key metric summary
ISSUER CREDIT RATINGS
CAPITAL ADEQUACY
ASSET QUALITY

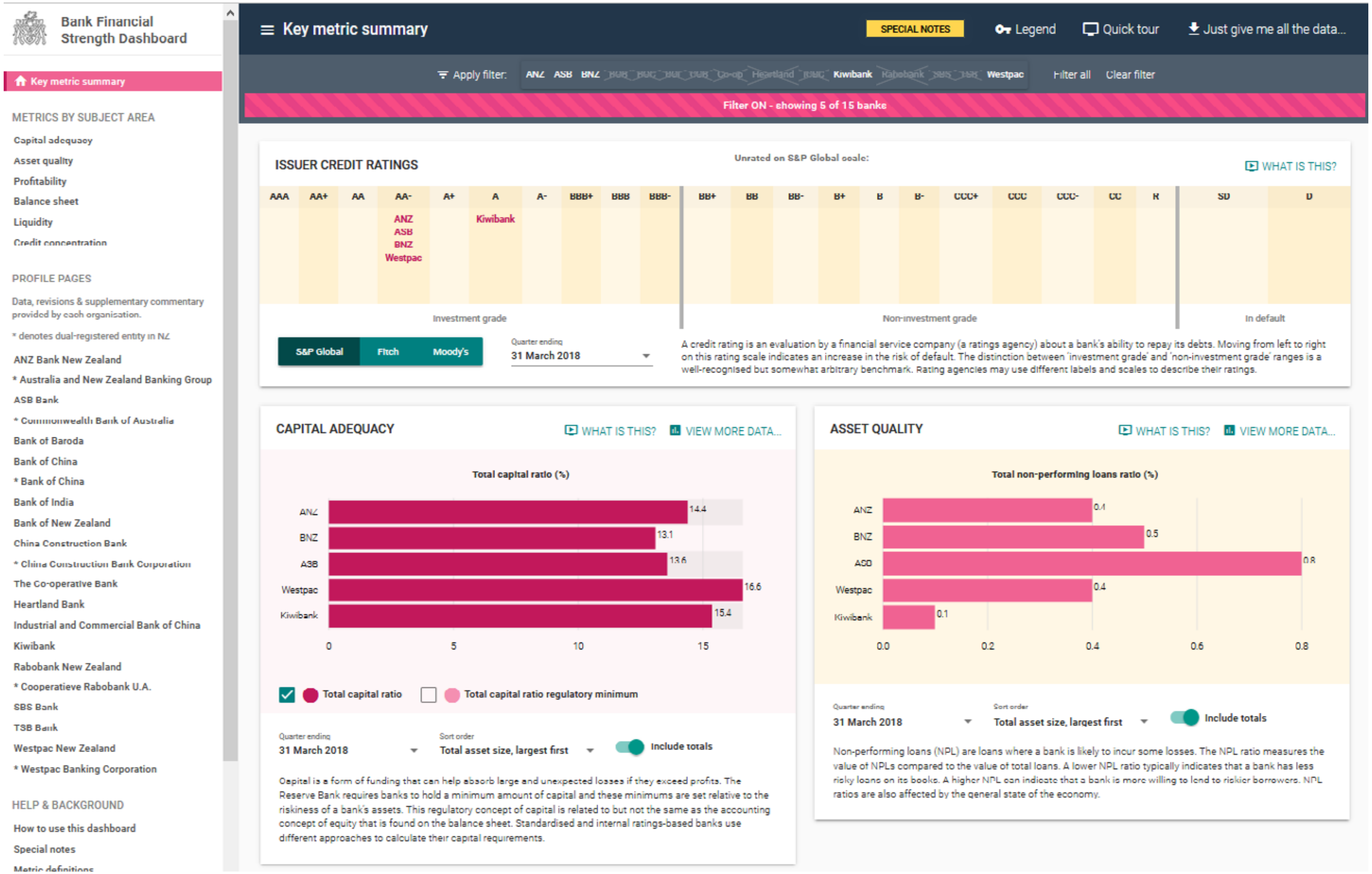

Self-
discipline
Market
discipline
Regulatory
discipline

Background on prudential disclosures

- Public disclosure is a cornerstone of prudential supervision
- NZ disclosure regime for banks introduced in 1996 (pioneering)
- NZ disclosure regime reviewed and simplified in 2011 with a focus on sophisticated audience
- Basel updated disclosure standards in 2006, 2012, 2015 and 2017
  - Guiding principles: Clear, comprehensive, meaningful, consistent and comparable
  - Post GFC updates - more prescriptive & more detailed



The dashboard aims to improve the **comparability**, **accessibility** and **timeliness** of information that banks are required to disclose to the public on their financial and prudential condition.



Bank Financial Strength Dashboard
Key metric summary
METRICS BY SUBJECT AREA
Capital adequacy
Asset quality
Profitability
Balance sheet
Liquidity
Credit concentration
PROFILE PAGES
Data, revisions & supplementary commentary provided by each organisation.
* denotes dual-registered entity in NZ
ANZ Bank New Zealand
* Australia and New Zealand Banking Group
ASB Bank
* Commonwealth Bank of Australia
Bank of Baroda
Bank of China
* Bank of China
Bank of India
Bank of New Zealand
China Construction Bank
* China Construction Bank Corporation
The Co-operative Bank
Heartland Bank
Industrial and Commercial Bank of China
Kiwibank
Rabobank New Zealand
* Cooperatieve Rabobank U.A.
SBS Bank
TSB Bank
Westpac New Zealand
* Westpac Banking Corporation
HELP & BACKGROUND
How to use this dashboard
Special notes
Key metric summary
SPECIAL NOTES
Legend
Quick tour
Just give me all the data...
Apply filter:
Filter all
Clear filter
Filter ON - showing 5 of 15 banks
ISSUER CREDIT RATINGS
Unrated on S&P Global scale:
WHAT IS THIS?
AAA AA+ AA AA- A+ A A- BBB+ BBB BBB- BB+ BB BB- B+ B B- CCC+ CCC CCC- CC R SD D
ANZ
ASB
BNZ
Westpac
Kiwibank
Investment grade
Non-investment grade
In default
S&P Global
Fitch
Moody's
Quarter ending
31 March 2018
A credit rating is an evaluation by a financial service company (a ratings agency) about a bank's ability to repay its debts. Moving from left to right on this rating scale indicates an increase in the risk of default. The distinction between 'investment grade' and 'non-investment grade' ranges is a well-recognised but somewhat arbitrary benchmark. Rating agencies may use different labels and scales to describe their ratings.
CAPITAL ADEQUACY
WHAT IS THIS?
VIEW MORE DATA...
Total capital ratio (%)
ANZ 14.4
BNZ 13.1
ASB 13.6
Westpac 16.6
Kiwibank 15.4
0 5 10 15
Total capital ratio
Total capital ratio regulatory minimum
Quarter ending
31 March 2018
Sort order
Total asset size, largest first
Include totals
Capital is a form of funding that can help absorb large and unexpected losses if they exceed profits. The Reserve Bank requires banks to hold a minimum amount of capital and these minimums are set relative to the riskiness of a bank's assets. This regulatory concept of capital is related to but not the same as the accounting concept of equity that is found on the balance sheet. Standardised and internal ratings-based banks use different approaches to calculate their capital requirements.
ASSET QUALITY
WHAT IS THIS?
VIEW MORE DATA...
Total non-performing loans ratio (%)
ANZ 0.4
BNZ 0.5
ASB 0.8
Westpac 0.4
Kiwibank 0.1
0.0 0.2 0.4 0.6 0.8
Quarter ending
31 March 2018
Sort order
Total asset size, largest first
Include totals
Non-performing loans (NPL) are loans where a bank is likely to incur some losses. The NPL ratio measures the value of NPLs compared to the value of total loans. A lower NPL ratio typically indicates that a bank has less risky loans on its books. A higher NPL can indicate that a bank is more willing to lend to riskier borrowers. NPL ratios are also affected by the general state of the economy.

Expected benefits

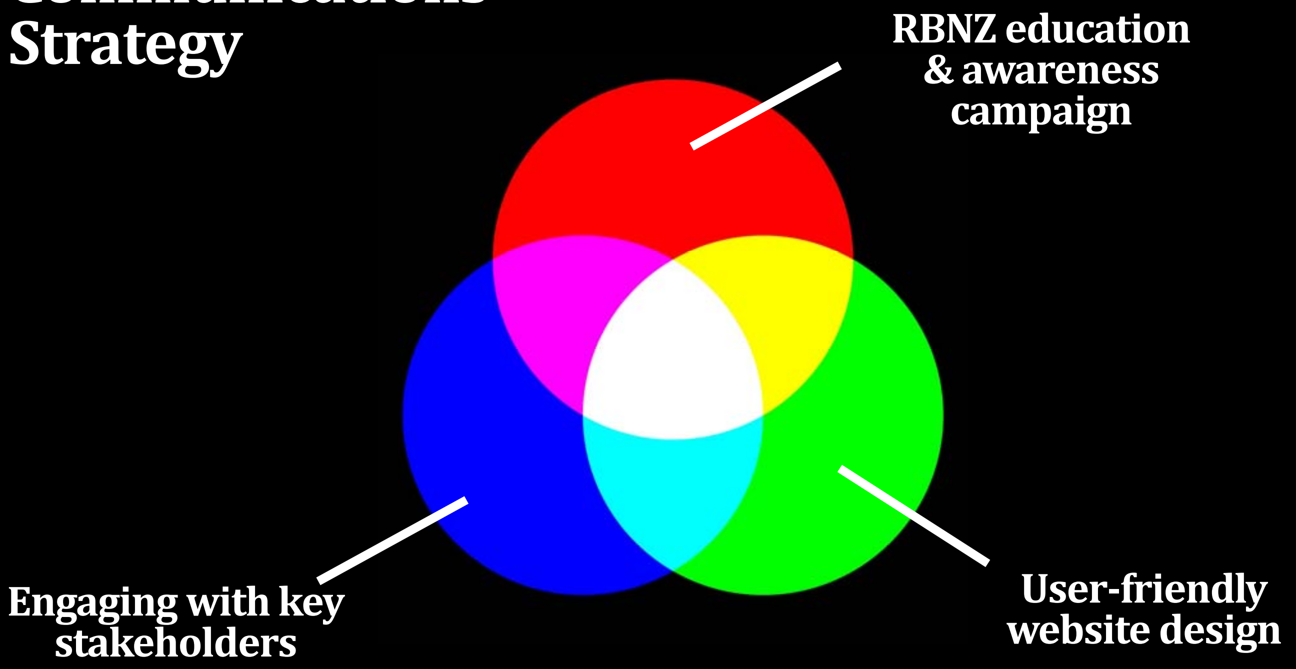
Enhanced market discipline

Better public benchmark data

Learning and research

Better quality data

Communications Strategy



Disclosure target audience

Creditors
- Secured debt
- Retail deposits
- Other unsecured debt
- Subordinated debt

Owners
- Equity holders

Other interested parties (e.g.)
- Media
- Analysts / Academics
- Rating agencies
- Directors
- Other banks

What is next

- Continue to promote and build awareness of the Dashboard
- Possibly other disclosure dashboards (e.g. insurance and NBDTs)
- Develop new features to meet user needs:
  - Public API's for flexible and efficient use of data
  - Print / share image feature
- Further analytical work on market discipline
  - Quantitative and qualitative
  - Dashboard monitoring

Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

The establishment of a central credit register at the Bank of Israel and its statistical disclosure control processes[1]

Ariel Mantzura,
Bank of Israel

[1] This paper was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

The Establishment of a Central Credit Register at the Bank of Israel and its Statistical disclosure Control Processes

Ariel Mantzura

Abstract

The Information and Statistics Department at the Bank of Israel collects and produces economic statistics and manages databases that contain granular data in various fields: the equity market, foreign exchange, banking, credit, and more. The Bank of Israel is now intensively engaged in the building of a central credit register containing granular and personal information regarding the credit history of individuals, which will serve credit agencies in the building of models for credit scoring. On the basis of this credit register the Information and Statistics Department at the Bank of Israel will manage an anonymized database where the private information is unidentified. This system is built for in-house use in order to support some of the tasks assigned to the central bank by law. This work will describe the credit register's statistical disclosure control processes.

1. INTRODUCTION

Following the Global Financial Crisis of 2008, central banks, including the Bank of Israel, began managing macroprudential policy, the aim of which is to identify systemic risks at the formative stage and to advance actions that will deal with them and limit their effect on the financial stability of the economy. The new challenges are motivating the central banks to manage consistent and integrative databases that will support this policy. Alongside technological development, which makes it possible to store and process very large quantities of information, there is an increasing need for databases of itemized data, which will enable the completion of information on the flow of capital in the economy, and on which bases it will be possible to obtain a detailed and available picture of the state of financial stability and robustness.

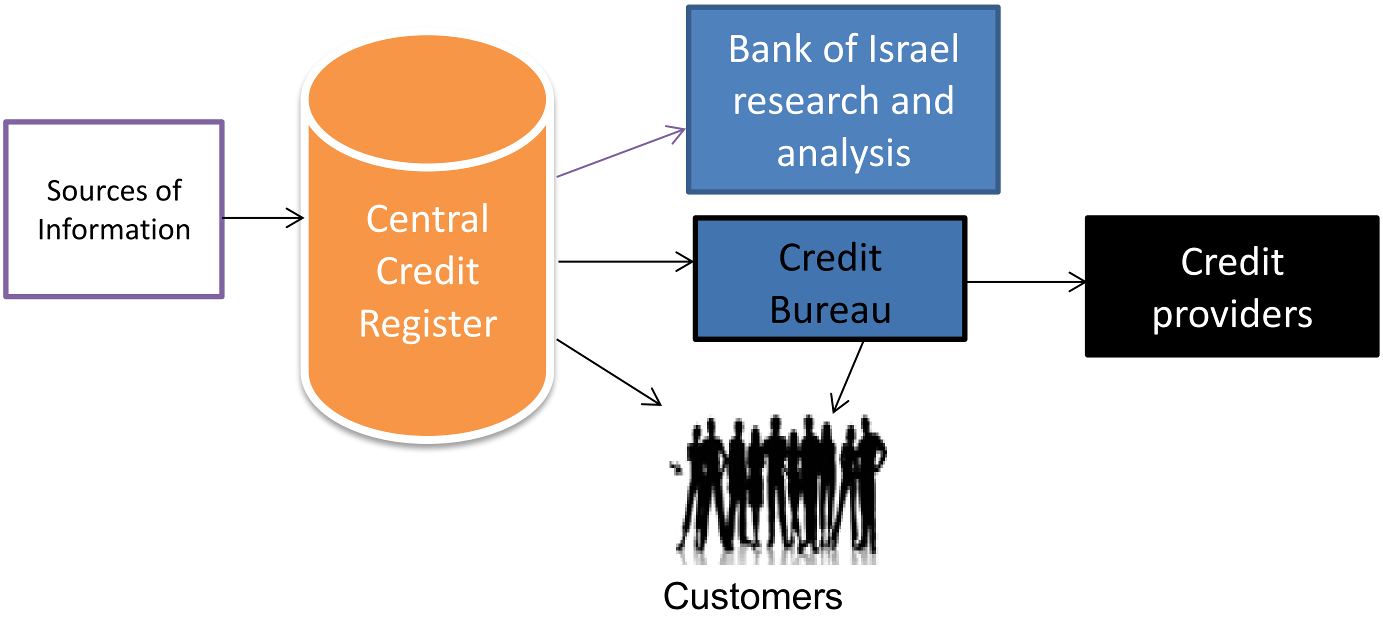
Against the background of these trends, and in parallel with the development of freedom of information laws that emphasize the importance of increased transparency and sharing of information, various entities that manage statistical information tend to enable access to itemized information as well, for the purposes of managing policy, economic analysis, and research. In order to allow access to such information within the organization or outside it, the Protection of Privacy Law requires that the confidentiality of the information be maintained, as the information relates to individual persons. In addition, the law requires that the commercial confidentiality of business entities be maintained—a complex task, particularly when dealing with financial information that is sometimes characterized by high concentration.

The Information and Statistics Department at the Bank of Israel, which collects and creates financial statistics, manages databases that include, among other things, itemized information on various topics: the capital market, the foreign exchange market, banking, the credit market, and more. In this context, the Bank of Israel is currently building a credit register that includes itemized information on the credit history of borrowers in the economy, and which will help the credit bureaus[1] in building models for the credit rating of borrowers. Based on this register, the

[1] The Credit Data Law, Section 16. This law will soon come into force.

Information and Statistics Department will manage a statistical database where the itemized information contained in it is not identified, for the Bank of Israel's internal uses in order to fulfill its legally mandated functions.

Main players



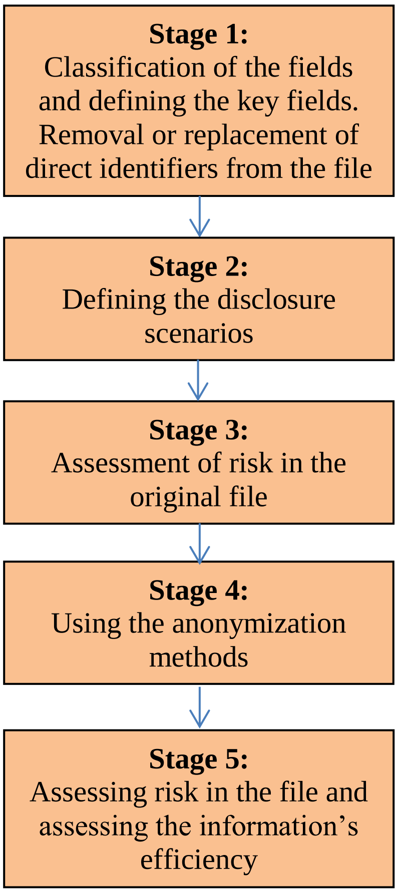
In order to enable access to this database, while also maintaining its confidentiality, the Bank of Israel is designing a process called "anonymization". The objective of the anonymization process is to protect the information so that it will not be possible to identify or expose the individuals whose data appear in the files, particularly information about them that is sensitive or confidential. This process will relate to both data intended for use within the Bank—even though only a few economists within the Bank will be permitted to access them—and information that is permitted to be accessible to the credit agencies, subject to the privacy protection restrictions and maintaining commercial confidentiality.

A database containing itemized information naturally includes information that directly identifies the individual—a field that on its own exposes the identity of the individual even without needing additional information located in other fields. Examples of this include the identification number and full name of the individual. Therefore, a necessary condition for anonymizing the database is the deletion of all direct identifiers. However, this condition is not sufficient to protect the database, because even without this information, it is sometimes possible to discover information on individuals by connecting a number of fields, or cross-referencing them with information from other databases the access to which is permitted. An individual can also be identified by searching for combinations that are not common among the relevant population, which are characteristic only of a particular individual or a small group of individuals.

The anonymization process begins with a precise definition of disclosure scenarios. These scenarios include the possibilities available to users in order to expose information on individuals, and against which we want to be protected. With the given scenarios, we can use methods to blur the identification and protect the information. At the end of the process, we will have to assess the remaining risk and quantify the information that was lost as a result of the process. It is clear that there is a tradeoff between the extent of anonymization, meaning the extent of protection of the file, and the extent of usability of the data, since there is a loss of information.

2. DESCRIPTION OF THE STAGES IN THE ANONYMIZATION PROCESS

Flowchart of the anonymization process



Stage 1: Classification of the fields and defining the key fields

Types of field—It is common to divide the fields in a file into three types. This division is not necessarily exclusive: A field can belong to more than one type.

- **Direct identifiers**—Fields that identify individuals in the file without using other fields. Examples of such fields are the identification number, the full name, and the precise address. Fields of this type are deleted from the file in the first stage of the anonymization process, or are replaced on a one-to-one basis with other fields that are not identifiers.
- **Key fields**[2]—Fields that can be cross-referenced with external information, such as those in the published or partially published census file, thereby exposing the identity of the individuals behind certain records in the file.

[2] See, for instance, [7].

- **Sensitive fields**—Fields where, due to their sensitivity, it is prohibited that their values, regarding each of the individuals whose identity is known in the file, be disclosed. An example of such a field is a person's income.

In addition to this division, the fields can be divided into two other types:

- **Categorical fields**—Fields that include a finite number (generally a low number) of categories or values.
- **Continuous fields**—Numerical fields that can be the subject of arithmetical actions. These fields can obtain a large number of values.

Stage 2: Defining disclosure scenarios

Disclosure scenarios[3] are a group of assumptions that describe how a user, or another person exposed to the file, can expose information on individuals from within the file. For instance: A user can cross-reference the information from the file with other information he has through a number of common characteristics or through information on an individual that he knows and he is aware that this individual is in the file. In that way, he can disclose additional sensitive information about that individual through the characteristics he knows.

The disclosure scenario can for the most part be summed up by determining groups of key fields through which information in the file can be cross-referenced with other external information (a file or personal knowledge), to discover information on individuals through combinations that are characteristic of only a few individuals in the file.

Setting disclosure scenarios is necessary to the anonymization process, since we are trying to protect the information from them. The assessment of the level of risk of information disclosure is also dependent on setting these scenarios, because it is not general, but relates to certain disclosure scenarios. The disclosure scenarios are determined with the help of experts in the relevant content worlds, who know how and through what means a user, or anyone with access to the information, can disclose information on individuals in the file. Even so, even experts in the content worlds do not know all of the information disclosure possibilities, and in certain cases, the tendency is therefore to assume the worst case scenario.

The disclosure scenarios can be less or more severe than the objective information disclosure possibilities, according to the disclosure policy that depends on how the data are used, the purpose of the use, the identity of the users, the severity of the damage inherent in disclosure, and so forth. In this context, it is common to distinguish between scientific use files, which are used by researchers under contract, subject to permissions and restrictions such as working within a physical research room or a virtual research room through remote access, and public use files that have no restriction or control. The policy regarding the information files issued to the public is generally very strict, and requires significant data processing.

In the context of the credit register, a designated committee composed of domain experts, statisticians, the supervisor of privacy protection and legalists determined together the disclosure scenarios regarding the internal uses of the credit register. These disclosure scenarios sum up to the construction of a three column table with the following structure (example):

[3] See, for instance, [7].

Database that can be cross-referenced	Type of data in credit register that can be cross referenced	Who has access to both databases?
Personal information	• Direct identifiers • Exact numeric values	• Credit register users
Employees file	• Income • Payment to Income • Statistical area	• Research, Data and Statistics, IT
Real-estate transactions file	• Statistical area • Loan to Value • Loan date	• Research, Data and Statistics, IT

Stage 3: Assessing the risk of disclosure in the file

As stated, the risk of disclosure relates directly to disclosure scenarios, meaning to groups of key fields (categorical or continuous) that are defined for a certain file. After the key field groups are defined, a number of risk indices can be addressed.

- **The risk of a record in a file**—the likelihood that it will be possible to connect a certain record in a file and a certain individual whose identity is known. In this context, a distinction should be made between categorical key fields and continuous key fields. In terms of a scenario in which categorical key fields are cross-referenced, there are two common requirements.
    - **K-anonymity requirement**[4]—a requirement that in each combination of categorical key fields in groups that are defined in the disclosure scenario, there shall be at least *k* records with the same combination. In order to check this, a multi-dimensional table (or tables for each disclosure scenario) can be built, in which the number of cells is equal to the number of possible combinations. Based on this table, the likelihood of risk of each record can be calculated. The purpose of this requirement is to protect against the disclosure of identity, because if a certain combination from the table relates to only one individual, that combination can be cross-referenced with the same combination in a different table with the same key fields, thereby disclosing the identity of the individual.
    - **L-diversity requirement**[5]—another requirement that is meant to protect against disclosure of characteristics. Each cell in the frequency table may have enough records, but regarding a particular sensitive field, there is no variance among those records that belong to the same combination. The l-diversity requirement is that in all possible combinations there should be at least *l* different values. In a situation where there is no variance, it is enough to know which combination relates to an individual in order to identify that characteristic with certainty, even without knowing that the record relates to him.

- **Risk in continuous key fields**—regarding continuous key fields, we cannot build a frequency table, since most of the values appear only once. It is generally customary to

[4] See, for instance, [7].
[5] See [5].

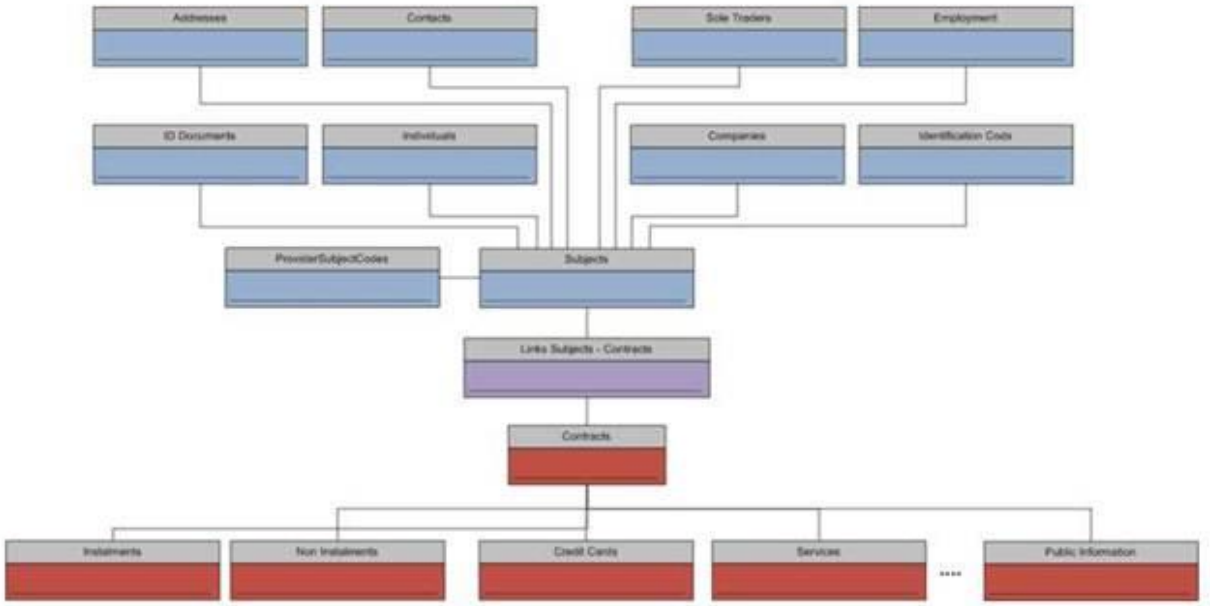
assess the risk in these variables based on the extent to which record linkage is possible between the file where we changed the data on continuous variables, such as by adding noise, and the original file.

- **Global risk of each file**—an index that grades the risk level of the entire file, which is calculated on the basis of an aggregation of the likelihoods of identification of the records in the file. An example of such an index is the total likelihood of identification in the file, which is equal to the incidence of the number of identities in it.

<u>Structure of database</u>

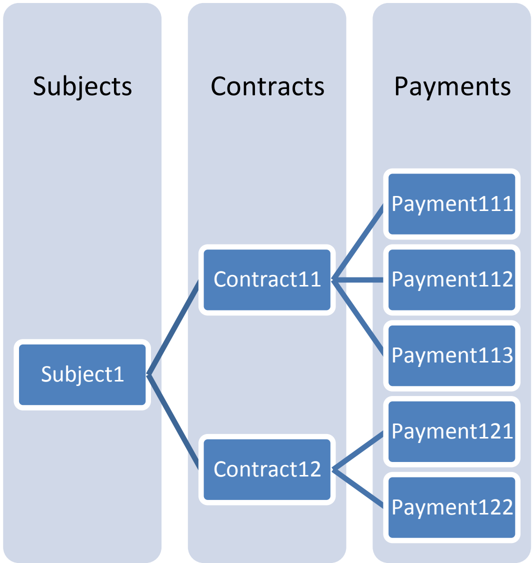
Assessing the risk of the database via the concept of k-anonymity requires a 2- dimension structure of the data, i.e. rows and columns. However, the primary structure of the database consists of linked tables which does not enable assessing risk in the k-anonymity sense.

Structure of linked tables



Evaluating the risk via the concept of k-anonymity requires us to flatten the linked tables structure to a 2-dimensional table with rows and columns. The columns must of course contain key fields. The following figure is an example of a flat structure.

<u>Flat structure</u>



Stage 4: Using the anonymization methods

The following is an outline of a number of common anonymization methods that were considered (among others) in the anonymization of the credit register:

- **Global recoding**—a method that lowers the level of information in the field and adjusts it to categorical fields and to continuous fields. For a categorical field, global recoding means attaching a number of categories to the common category. Global recoding in a continuous field is basically replacing a continuous field with a categorical field. For instance, a field that is a loan amount can be replaced by a number of categories that are in ranges of NIS 100,000. The following table shows an example of global recoding of the income field (continuous).

Record number	Monthly income in shekels	Monthly income after recoding
1	8,365	Up to 10,000
2	16,569	10,000–20,000
3	100,200	100,000–200,000
4	5,750	Up to 10,000

- **Upper and lower recoding**—This method is an individual case of global recoding, and deals with the ends of the distribution. For a continuous field, it gathers the extreme categories beyond the upper bound of one category, and the same can be done regarding low categories. In a continuous field, the method gathers all the values beyond the upper and/or lower bound of two categories—upper and lower—and in the rest of the range, the data are gathered as in the previous section. This method is appropriate for fields where there are few instances beyond a certain bound.
- **Local suppression**—This method inserts missing values into certain fields of certain records, and is appropriate for categorical fields and not for continuous fields. When there are combinations of key fields where there are few records, a missing value can be inserted in one of the fields. The advantage of this method is that it deals only with records at risk. On the other hand, it creates a lack of uniformity in a certain field, because a missing value appears in certain records in that field.

- **Adding noise (additive)**[6]—This method changes the numeric values in the field, and is appropriate for continuous fields but not categorical fields. There are a number of accepted paths, two of which are presented below.
  - **Adding white noise (unadjusted)**—In this method, unadjusted noise is added to a particular field, which we will label as *X*, as follows:

    $Z=X+\varepsilon$

    where ε is a vector of noises broken down numerically and unadjusted (white noise). It can be shown that this method maintains (proximately) the common incidence and variance between every pair of variables, but does not maintain the variance or correlation coefficients. In particular, it increases the variance of the variables, while reducing the correlation, in absolute value, between each pair of variables, due to the added noise element.
  - **Adding adjusted noise**—In this method, we randomize adjusted noise regarding a number of variables. It can be shown that in this method, the correlations between each pair of variables are maintained.

Stage 5: Assessing disclosure risk in the file and maintaining information efficiency

Maintaining information efficiency and minimizing risk—The objective of the anonymization process is to make a protected file of data accessible so that it embodies a low risk of identification of the individuals, while at the same time, subject to that limitation, it maintains maximum information in the file (information efficiency/usability). There is a tradeoff between the level of information protection and its usability. The higher the level of protection, the greater the information loss (Figure 2).[7] The objective is to find the methods that will lead to the optimum tradeoff given the importance of information use and the damage that may be caused from identification. There are a number of methods for measuring the maintenance of information efficiency in the file, including a direct comparison between the data in the original file and the data after anonymization, and a comparison of calculated statistics (average, standard deviation, and so forth) between them.

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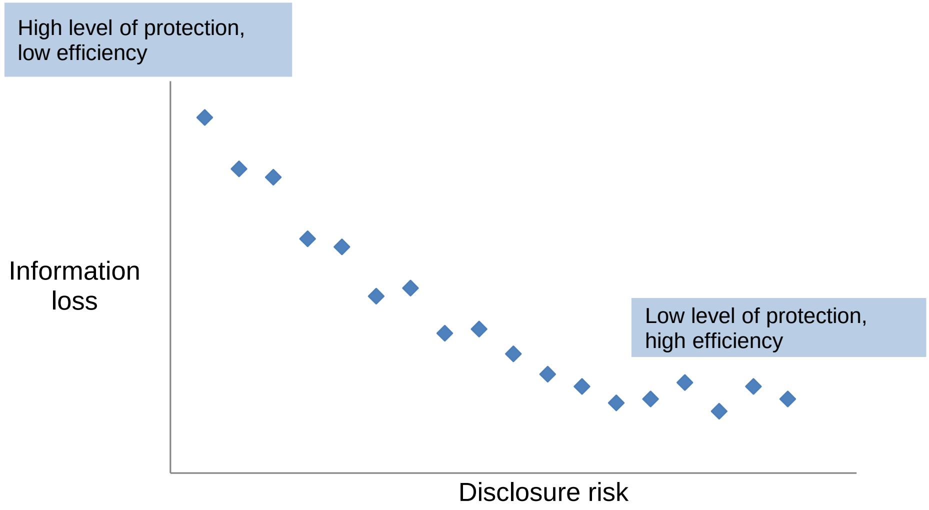
[6] See, for instance, [8].
[7] See [4]

Figure 2
Information Efficiency vs. Risk



3. CONCLUSION

The Information and Statistics Department uses various complex methods, described above, to anonymize itemized the data of the central credit register. An effective anonymization process protects the itemized data, while also maintaining the usability of the information even after some of it is lost. The extent of anonymization is determined in accordance with information disclosure scenarios that we want to protect against. Building these scenarios is a complex process that requires expertise in content and also takes into account the existence of complementary databases that are available to users and enable cross-referencing of information and identification of the individuals.

In an era in which information analysis is based more and more on powerful databases of itemized data, the Bank of Israel will have to continue conducting complex anonymization processes in order to allow for freedom of information for policy and economic research needs, while at the same time maintaining the confidentiality of the itemized information as required by law.

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Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

The establishment of a central credit register at the Bank of Israel and its statistical disclosure control processes[1]

Ariel Mantzura,

Bank of Israel

1 This presentation was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

The establishment of a Central Credit Register at the Bank of Israel and its Statistical Disclosure Control processes

Ariel Mantzura
Bank of Israel

August 31, 2018

Credit Data Law - Objectives

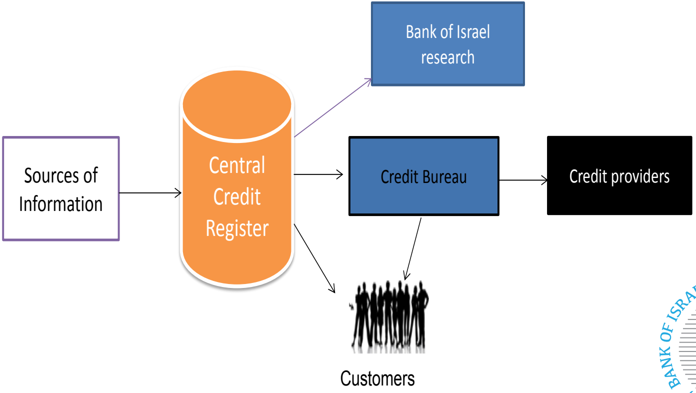
The objective of this law is to establish an overall arrangement for sharing credit data...for the following purposes:

- Enhancing competition in the retail credit market.
- Expanding access to credit.
- Reducing of discrimination in the granting of credit and of economic gaps.
- Creating an anonymous database for use by the Bank of Israel in carrying out its functions.

Backround - Protection of Privacy Law

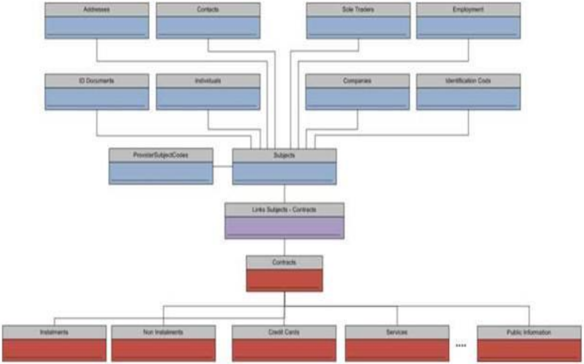
- In order to allow access to such information within the organization or outside it, the Protection of Privacy Law requires that the confidentiality of the information be maintained, as the information relates to individual persons.
- In addition, the law requires that the commercial confidentiality of business entities be maintained, a complex task, particularly when dealing with financial information that is sometimes characterized by high concentration.

Backround - Central Credit Register



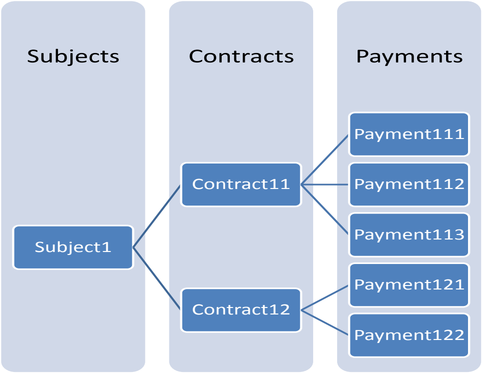
Backround - Credit register structure

Linked tables structure



Backround - Credit register structure

Flat structure



Flow chart of anonymization process

Stage 1:
Classification of the fields and defining the key fields.
Removal or replacement of direct identifiers from the file

↓

Stage 2:
Defining the disclosure scenarios

↓

Stage 3:
Assessment of risk in the original file

↓

Stage 4:
Using the anonymization methods

↓

Stage 5:
Assessing risk in the file and assessing the information's efficiency

Defining disclosure scenerios

- Disclosure scenarios are a group of assumptions that describe how a user, or another person exposed to the file, can expose information on individuals from within the file.
- For instance: A user can cross-reference the information from the file with other information he has through a number of common characteristics.
- The disclosure scenario can for the most part be summed up by determining groups of key fields through which information in the file can be cross-referenced with other external information.

Defining disclosure scenerios

- Setting disclosure scenarios is necessary to the anonymization process, since we are trying to protect the information from them.
- The assessment of the level of risk of information disclosure is also dependent on setting these scenarios.
- The disclosure scenarios are determined with the help of experts in the relevant content worlds.

Defining disclosure scenerios

Database that can be cross-referenced	**Type of data in credit register that can be cross referenced**	**Who has access to both databases?**
Personal information	• Direct identifiers • Exact numeric values	Credit register users
Mortgage file data	•	•
Employees file	•	•
Real-estate transactions file	•	•

Defining disclosure scenerios

- The disclosure scenarios can be less or more severe than the objective information disclosure possibilities.
- The disclosure policy depends on how the data are used, the purpose of the use, the identity of the users, the severity of the damage inherent in disclosure, and so forth.

Defining disclosure scenerios

- It is common to distinguish between **scientific use files** and **public use files**.
- **scientific use files (SUF)** are used by researchers under contract, subject to permissions and restrictions such as working within a physical research room or a virtual research room through remote access.
- **public use files (PUF)** have no restriction or control. The policy regarding the information files issued to the public is generally very strict.

Assessing the risk of disclosure in the file

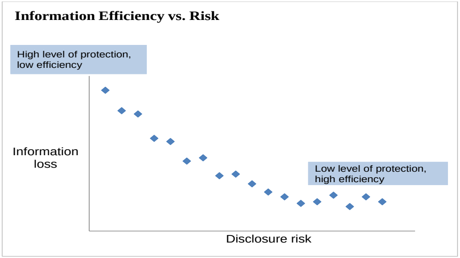
- There are two common requirements:
- **K-anonymity** - a requirement that in each combination of categorical key fields in groups that are defined in the disclosure scenario, there shall be at least k records with the same combination.
- **l - diversity** - The l-diversity requirement is that in all possible combinations there should be at least l different values.

Information efficiency vs minimizing risk

- The objective of the anonymization process is to make a protected file of data accessible so that it embodies a low risk of identification of the individuals.
- At the same time, subject to that limitation, it maintains maximum information in the file.
- There is a tradeoff between the level of information protection and its usability.
- The higher the level of protection, the greater the information loss.

Information efficiency vs minimizing risk

Figure: Risk Utility Map



Thank you!

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Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

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Making available data more useable: compilation and publication of break-adjusted (historical) time series[1]

Ruben van der Helm and Jan Bartman,
Netherlands Bank

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[1] This paper was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

Making available data more useable: Compilation and publication of break-adjusted (historical) time series[1]

Ruben van der Helm and Jan Bartman[*]

Abstract

Time series are key for policy analysis and policy making. However their use can in practice be severely hampered by breaks. This is especially the case for data on outstanding amounts (or stocks, positions), for which break-adjusted time series are rarely published by central banks. This paper shows the policy towards and methodology for compiling break-adjusted monetary statistics at De Nederlandsche Bank (Netherlands Bank; DNB). DNB has recently increased its publication of such time series, as part of a wider program to increase the accessibility and value-added of its data to users. Breaks are mainly adjusted using a set of automated rules that do not require manual intervention. In specific cases, however, expert judgement is applied to increase quality and provide longer historical time series.

Keywords: Time series, break-adjusted, positions, mortgage loans

JEL codes: C82, G21

Introduction:

For statisticians, breaks in statistical time series are a *fact of life*. For users, however, they can severely hamper the use of statistics for analytical, policy making and forecasting purposes.

Many statistical publications, amongst which those published by De Nederlandsche Bank (Netherlands Bank; DNB), are characterised by breaks. Breaks stem from updates of statistical frameworks and guidelines, changes in population and erroneous reporting. Put differently, breaks are caused by everything but real economic developments. Trend breaks in collected data reflecting such real economic developments, for example political or (monetary) policy announcements, are thus outside the scope of the breaks we focus on in this paper.

In the monetary statistics compiled and published by DNB, the most impactful breaks in time series stem from structural changes in the underlying data. For instance the largest breaks in balance sheet total stem from changing frameworks (e.g. December 1997, June 2010, December 2014), changing supervisory or accounting guidelines (e.g. March 2000, December 2016) and changing reporting population or consolidation scope (June 2005, June 2014). For these breaks reporting agents are generally not required to provide corrections in the preceding reference periods.

More numerous, but typically less significant are breaks involving erroneous reporting and the inability of reporting agents to revise their returns for all errors made in the past. One could think of an investment portfolio missing from the returns for some years, for which source data (e.g. the ledger) have already been moved to 'inactive' databases. The impact of such breaks on aggregated statistical figures is generally rather limited.

[1] The views expressed are those of the authors and do not necessarily reflect those of De Nederlandsche Bank.

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Statisticians face the question whether they should adjust their data for such breaks, or leave such adjustments to users. This question involves a trade-off between actual observed data points and developments on the one hand and usability of the time series on the other hand. When source data (i.e. revised returns from reporting agents) are not available for all reference periods concerned, any break adjustment means another processing step of the observed data and, thus, an additional deviation between source data and output. The larger the difference between the observed data and published statistics, the more prone the data are to misinterpretation.

However, as stated by Dembiermont et al. (2013), 'both unadjusted and break-adjusted series are imperfect measures'. The unadjusted series are, prior to a break, implicitly incorrect or not in line with the framework used for recent periods (otherwise there would not be a break in the series), while the adjusted series assume the unobserved data develops in a similar fashion to the data collected for the respective periods. Hence, the chances of misinterpretation are (probably) comparable.

Moreover, the usability and user friendliness of statistics increase substantially when they are corrected for breaks. In principle, having more (detailed) information on specific breaks, statisticians should be better equipped to correct for breaks and, hence, break corrections by statisticians will probably increase the overall quality of the time series. This is especially the case when users will likely need to adjust time series for breaks anyway – and would do this by means of less sophisticated measures when left to their own devices.[2]

At the juncture of the introduction of its new statistics website, DNB's Statistics Division launched a project to extend the publication of time series adjusted for breaks. In this paper we elaborate on the policy behind the compilation and publication of break-adjusted monetary statistics and we demonstrate the methodology used to compile break-adjusted historical time series for one of our key monetary indicators: loans granted for house purchase to Dutch households.

The paper is structured as follows. Section 1 describes DNB-statistics' policy of publishing break-adjusted monetary statistics. In section 2 we focus on historical time series for mortgage loans granted to Dutch households. Finally, conclusions are drawn and the way forward is set out in section 3.

Section 1: Towards a new policy

Policies towards the publication of monetary statistics adjusted for breaks vary between organisations. A stock-taking in 2017 amongst some peer institutions[3] shows that in general these institutions publish derived transactions (or flows)[4] only, while the positions are not corrected for breaks. Some institutions publish growth rates for selected series, which they calculate on the basis of derived transactions and observed positions. Break adjusted (notional) positions, are rarely published by central banks, some examples are the Banque de France (loans to NFC and households) and the Bank of England (monetary aggregates).

Reasons provided for the limited publication of break-corrected positions are, first, to avoid confusion amongst users, because there will be two different figures for one 'phenomenon' (e.g. mortgage loans to households or M3). Second, the arbitrary nature of break adjustment. Not all users will agree on the methodology used for the adjustments, the way to treat inconsistencies or the base period. Third, the adjustment for breaks requires considerable resources, more in particular when i) a very sophisticated (econometric) model is used or ii) breaks are revised on the basis of qualitative research and (fully) integrated by staff members (like in national/sector accounts).

Despite the (potential) drawbacks, in 2017 DNB's Statistics Division launched a project to compile and publish statistical series adjusted for breaks, as part of a wider program to increase the accessibility and

[2] Such as multiplicative corrections or – as has been witnessed in some cases – by removing double observations marking breaks and thus assuming implicitly that these breaks do not exist.
[3] NCBs of Austria, Belgium, Germany, Spain, France, Italy and the United Kingdom as well as the ECB and the BIS.
[4] Transactions are calculated as the difference between the positions in period T and T-1, adjusted for revaluations, exchange rate variation, write-off/write-downs and other changes in volume (e.g. breaks).

value-added of its data to users. In the trade-off between the usability and user friendliness of statistics on the one hand and the reported data on the other hand the former prevailed. Besides break-adjusted tables for regular statistical publications, also the publication of key indicators for monetary statistics was introduced. [5]

To maximise value-added of the adjusted series and align with the unadjusted publications, it was ultimately decided to publish the break-adjusted positions rather than break-adjusted flows or (observed) growth rates. The publication of flows and growth rates, still requires users to compile adjusted time series for (notional) positions. Moreover, users encounter similar problems (e.g. inconsistencies) statisticians do when compiling the time series.

The quality of the break-adjusted positions should equal at least the quality of time series adjusted by users on the basis of statistics published by DNB. In addition, if available, detailed (source) information of breaks is used to make more precise adjustments for past periods. This leads to three basic principles when eliminating breaks.

First, the quality of the adjustment is weighted against its complexity and cost. The following ranking applies for the approach taken:

1. Adjustments based on resubmissions from reporting institutions are preferred. From a quality perspective this is the preferred option, however it is relatively expensive (i.e. reporting burden and compilation) or (close to) impossible for the whole time series. Therefore resubmissions from reporting institutions are, in general required for some periods, resulting in a break in another period.
2. If resubmissions are not available or too expensive, adjustments based on additional qualitative information (e.g. from reporting institutions, literature or the market) are the second best option. Quality is probably a bit lower than under approach 1, but there is little (or no) additional reporting burden. In contrast, it is probably more costly in terms of resources from the statistics department.
3. If the first two approaches are not an option, we apply multiplicative adjustment (i.e. backward calculation applying growth rates or proportional up- or down scaling of data in earlier periods). The overall quality is most probably lower than the adjustments resulting from approaches 1 and 2, however the application is relatively cheap and also often employed by users. The technicalities behind the multiplicative break-adjustment are available in Annex I.[6]
4. In specific cases, for example where user demand or quality requirements are especially high, tailored solutions may be employed. Such solutions can entail a combination of the approaches mentioned above for specific series (e.g. historical time series for key monetary indicators).

Second, in principle, no adjustments are made for inconsistencies arising from multiplicative adjustments. The example provided in Annex II demonstrates the inconsistencies that arise from the methodology used (i.e. multiplicative backward calculation on the basis of the most recent observation). Maintaining the growth factors observed prevails and users can, if needs be, allocate inconsistencies in accordance with their own preferences.

Third, the most recent available (reference) period is used as base period for the adjustments. In other words, the past is aligned with the latest frameworks, definitions, reporting population and methodology.

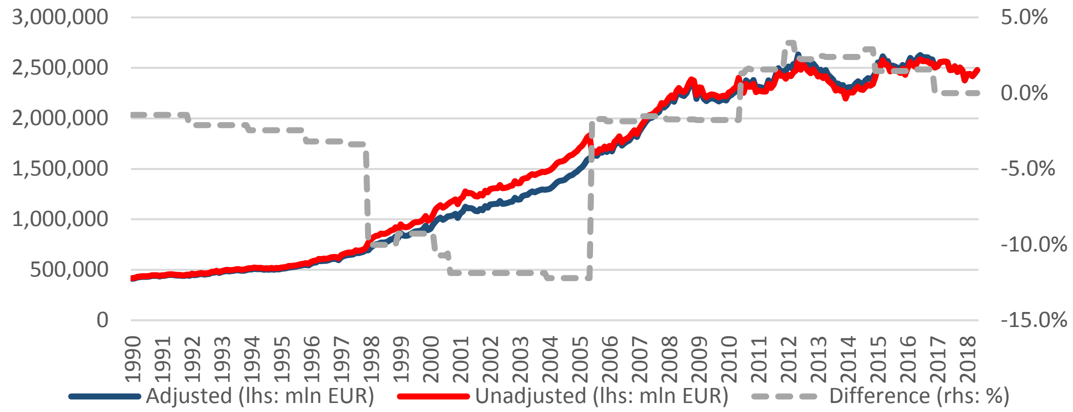
Chart 1 presents the break-adjusted and unadjusted time series for Dutch MFI's total assets, as well as the difference (percentage points) between both series. In contrast to the findings for most series in Dembiermont *et al.* (2013), the differences become smaller again in the earlier periods after reaching its

[5] https://statistiek.dnb.nl/en/downloads/index.aspx#/details/key-indicators-monetary-statistics-month/dataset/b698ca40-9cae-435b-954e-4fe2c5651370/resource/6c3650d4-3631-4964-9ef9-4d0505aeb48a.

[6] Except for the exclusion of 'other changes' from the up and down scaling of the adjusted series, the method is similar to the adjustment described in Dembiermont *et al.* (2013). We exclude 'other changes' such as securitisations to mitigate the multiplier effect of the break factor on (significant) other changes which are (very likely) to be correct. Securitisation transactions are for example made known to the public at large (e.g. by means of investor reports).

maximum (-12.2 %) between December 2003 and May 2005. The divergence of the series in the earlier periods mainly comes from the fact that the substantial breaks in December 1997 (+EUR 52.745 mln) and June 2005 (-EUR 196.420 mln) as well as some –relatively smaller- breaks in between more or less balance each other.

Chart 1: Total assets of Dutch MFI, break-adjusted and unadjusted (monthly)



Source: DNB, authors' own calculations

At the current stage the main tables[7] are adjusted for breaks, while work is still in progress for the more disaggregated tables. For some sector statistics (e.g. insurance companies and pension funds) more recent breaks have been eliminated and adjusted balance sheet data are available from 2002 onward. In the next stage the time series will be adjusted back to 1986. The ultimate goal is to adjust all tables for which break adjustments is deemed feasible, if needs be on a higher level of aggregation.

Besides the compilation and publication of adjusted series (and tables), DNB continues providing statistics to (inter)national organisations (i.e. the ECB, BIS, IMF and Statistics Netherlands) in accordance with the frameworks, formats and methodologies agreed.

Section 2: Historical time series for mortgage loans granted by MFI to Dutch households

Besides break-adjusted tables for regular statistical publications, DNB's Statistics Division also started the publication of key indicators for monetary statistics, amongst which the *loans granted for house purchases*.[8] The aim is, provided the availability of source data, to compile and publish historical time series for these indicators. This section deals with the compilation and publication of time series at monthly frequency for mortgage loans granted by MFI[9] to Dutch households from December 1956 onward, for which a tailor made approach (method) was taken.

2.1 Data availability and preparation

DNB has been collecting data from financial institutions for the purpose of monetary analysis following the implementation of the banking law ('Bankwet') in 1948. Information was mostly collected by means of the returns for the purpose of prudential supervision, but additional monetary (or 'social-economic)

[7] E.g. *Balance sheet of De Nederlandsche Bank (monetary presentation), Balance sheet of Dutch-based MFI (not including DNB), Combined balance sheet of DNB and Dutch based MFI and Dutch contribution to monetary aggregates in the euro area, Securities issue statistics.*
[8] https://statistiek.dnb.nl/en/downloads/index.aspx#/details/key-indicators-monetary-statistics-month/dataset/b698ca40-9cae-435b-954e-4fe2c5651370/resource/6c3650d4-3631-4964-9ef9-4d0505aeb48a.
[9] For the purpose of this paper, more in particular section 2 on historical time series for mortgage loans granted by MFI to Dutch households, the scope of MFI is limited to the 'other MFI' (i.e. deposit taking corporations), excluding the Central Bank.

data were collected from reporting agents via dedicated appendices. In 1982 DNB started the collection of complete balance sheets using the so-called 'social-economic reports', with more detailed counterparties and instruments (Van Straaten, 1989).

Currently the social-economic reports are collected from MFI. The MFI sector more or less consists of what used to be the *money creating sector* and *savings banks*.[10] Monthly and quarterly statistics for money creating institutions are available from 1957 onward, while yearly statistics go back to 1900. In contrast, savings banks had to submit their returns each quarter and, hence, no monthly source data is available. Historical time series, in accordance with the social-economic reports, were published on several occasions (DNB, 1973; 1980; 1985; 1987; 2000; 2003). Annex III provides an overview of the data we use to compile the monthly time series for mortgage loans granted by MFI to Dutch households.[11]

Between 1998 and 2003 data for mortgage loans for house purchases were collected on a quarterly basis only. For that period we assumed equal growth rates for all consecutive months in the respective quarter, in order to perform temporal disaggregation. For the compilation of monthly positions of mortgages granted by savings banks we apply Chow-Lin (1971) temporal disaggregation of the quarterly data from savings banks on the basis of the monthly developments of mortgage loans granted by money creating institutions.

Provided the substantial securitisations of Dutch mortgage loans in the past, reaching record high in November 2010 (EUR 168.060 mln), DNB adjusts MFI mortgage loans for true sale securitisation transactions[12] in some of its publications (see also section 2.2). Information on securitisation transactions and total amounts outstanding have been collected from January 2003 onward. Additional information on true sale securitisation transactions was collected from external sources (e.g. annual reports) to extend the time series back to the first true sale securitisation in September 1997. The positions on Special Purpose Vehicles' (SPV) balance sheets from September 1997 till December 2002 were estimated accumulating the securitisation transactions in that period. The break observed in January 2003 (see also Annex IV), at the juncture of the introduction of a new framework that allowed for the collection of more detailed information on securitisation transactions and SPV's balance sheets, is assumed to equal repayments of derecognised loans in the past.[13] These 'repayments' are deducted from the estimated positions.

Besides the time series, breaks in the series are in general well documented. Not only is the value of the break made available to the user, also (some) background information of the nature of the respective breaks is presented. Annex IV provides an overview of all breaks in the time series. Most of them are present within a specific source (or time series) used, except for the breaks in December 1982 (-EUR 12.755 mln), December 1997 (-EUR 3.392 mln) and December 1998 (-EUR 992 mln).

2.2 Methodology and assumptions

Similarly to the approach described by the ECB (2015) we aggregate the MFI and SPV balance sheets to capture total loans granted by MFI. The aggregation takes place before the break-adjustment in both balance sheets. Rational behind is the fact that some (significant) breaks on MFI balance sheets relate to securitisation and, hence, are balanced by breaks of similar or the same size on the SPVs' balance sheets. The pre-adjustment aggregation mitigates the impact on breaks originating from 'incorrectly allocated'

[10] Money creating institutions include the central bank, general government, 'universal' banks, cooperative banks, trade banks, post office giro institutions and, from 1986 onward, savings banks. Section 2.2 provides more details for the classification of savings banks.
[11] More time series on mortgage loans are available in our database, but they usually have a lower frequency, cover only a short period or represent only a part of the population (e.g. trade banks, cooperative banks, specific individual institutions).
[12] True sale securitisations, involving loans or loan packages from the MFI balance sheet being sold and transferred (i.e. derecognized) to a non-banking entity specifically established for this purpose, i.e. an SPV. In addition to selling loans, MFIs may also repurchase previously securitised loans and add them to their balance sheet. Usually the MFI still services the loans, in other words, the costumers will not be able to tell whether or not their loans have been securitised.
[13] A repayment rate of 0.05% completely eliminates the break in 2009.

(true sale) securitisations, broadly in line with the ideas underlying the break-adjustment of other DNB monetary statistics publications.

For years DNB used multiplicative adjustment for its external publication of loans granted to households and non-financial corporations adjusted for breaks and securitisations.[14] For adjustment of the positions, the method is fully in line with Dembiermont *et al.* (2013), which also uses break factors to eliminate breaks in the past, aligning the level to the latest observation.[15]

Lastly, we combine the developments of the mortgage loans granted by savings banks and money creating institutions to calculate backward the positions from 1982 to 1956. Until 1986 savings banks were not part of the money creating sector, because they used to take savings deposits and make investments mainly on the capital market (Van Straaten, 1989). The kind of activities savings banks were allowed to engage in was restricted, it was for example by law forbidden for them to grant loans to business enterprises ('T Hart *et al.*, 1997). As a result of that, their balance sheet was –on the asset side- dominated by long term (government) securities and loans extended to government entities until mid-1970's. The need for i) flexibility to adjust (credit) interest rates and ii) alternative sources of income, lead savings banks to start servicing private households, amongst which by increasingly granting mortgages (Van Straaten, 1989; 'T Hart *et al.*, 1997). The increase of 'regular banking activities' lead to the reclassification of savings banks into the money creating sector in January 1986, the break was however calculated backward to 1982 and published as such.

Adjusting the break stemming from the reclassification of savings banks into the money creating sector (hereafter MFI sector) in December 1982, implies we assume the savings banks were part of the MFI sector. Provided they took deposits or other repayable funds from the public and granted credits for their own accounts, nowadays they would classify as credit institutions and, hence, be part of the MFI sector. For that reason we include them in our adjusted series, using the reported data (with its own specific developments).[16]

Table 2 in Annex III provides an overview of the data sources used for specific periods. In general we use only data collected by reporting agents, except for the securities transactions mentioned under 'G'. Most data are available at monthly frequency, for those reference periods for which only quarterly source data are available, we made adjustments (see section 2.1).

2.3 Results and application

Chart 2 shows the historical developments of both the positions and corresponding annualised growth rates between December 1956 and May 2018.[17] Except for the period between 1983 and mid-1993, mortgage loans granted by MFI to Dutch households have grown considerably since the 1950's. The considerable increase (and level) of mortgage debt of Dutch households can to a large extend be explained by the policy instruments to stimulate home ownership in the Netherlands: the mortgage interest tax relief. The way it is designed, stimulates higher debt levels rather than repayments. Also the economic growth, demographic factors (e.g. higher employments rates, double income and more households) relatively generous borrowing limits play a role (Kakes *et al.*, 2017).

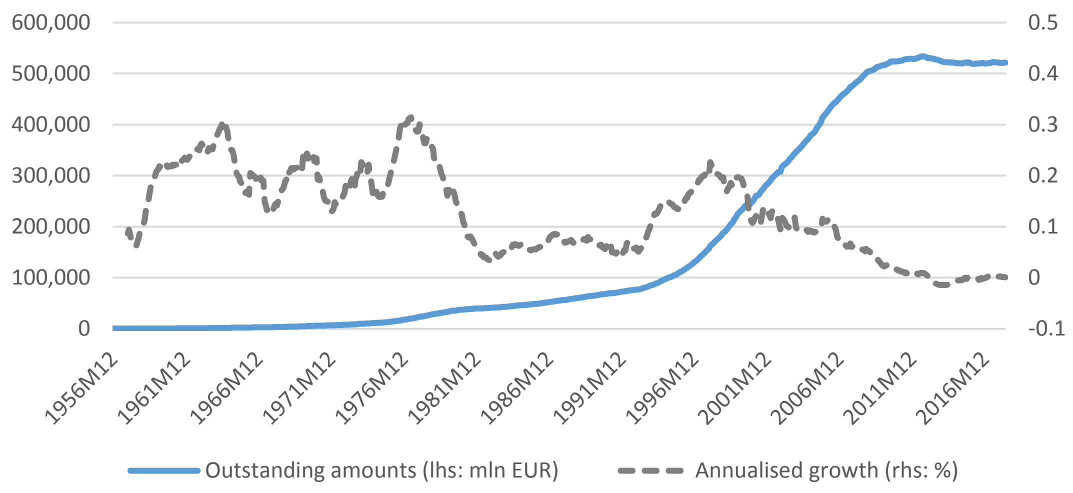
Kakes *et al.* (2017) provide also some explanations for the growth of MFI's balance sheets (rather than other financial institutions). First, the strict delineation between activities of 'specialised' banks disappeared over time. All 'types of banks' increasingly competed on each other's markets and inter-sectoral takeovers and mergers took place, resulting in very comparable bank institutions. Second, against the background of increased demand for loans, banks were able to adjust trends easier than

[14] https://statistiek.dnb.nl/en/downloads/index.aspx#/details/residential-mortgages-extended-by-dutch-mfis-to-dutch-households-adjusted-for-securitisations-month.
[15] The break factor is defined as: 1 + (Break value T/position T)
[16] Mortgage banks also granted mortgage loans to households, but they mainly financed their activities issuing bonds. Second, mortgage banks were not reclassified like savings banks (except when they merged with/were taken over by banks). For that reason they remain out of scope and, hence, their data are not used for the backward calculation.
[17] Vintage 23 July 2018.

their competitors on the mortgage market (i.e. institutional investors). The latter also started to look for new opportunities abroad (after bans on investments abroad by pension funds were lifted) or on other markets (e.g. commercial real estate). Last but not least, financial deregulation. Rules for loan-to-value (LTV) and loan-to-income (LTI) limits became less stringent (De Haas et al., 2000), the policy on credit restrictions was discontinued in the 1990's and over time the capital requirements for mortgage loans decreased.

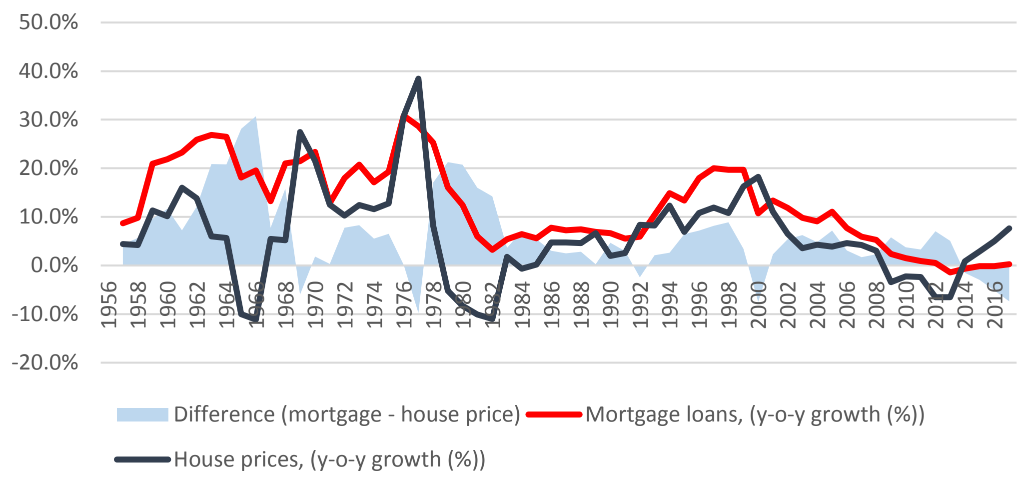
When comparing annual growth rates of mortgage loans granted by MFI to Dutch households with house prices developments (see chart 3), we find the developments follow –overall- a similar pattern. However, mortgage growth is significantly higher until 1969 and between 1978 and 1982 (following the housing bubble in 1977 (ESB, 2017)). Against the back of the second oil crisis, high interest rates and economic recession (in 1981 and 1982), both mortgage growth and house prices deteriorate, the latter turning negative. In contrast, financial deregulation, relatively high real economic growth and demographic changes boast both mortgage growth and house prices again until 2000. After 2000 mortgage growth gradually declines, followed by the start of the financial crisis in 2007. In 2013, for the first time since 1956, the annual growth rates are negative, where house prices dropped already in 2009.

Chart 2: Mortgage loans granted by MFI to Dutch households: adjusted for breaks and securitisations



Source: Refer to table 1 and Annex III, authors' own calculations

Chart 3: Mortgage loans and house prices developments (annual growth (%))



Source: Refer to table 1 and Annex III, CBS Statline[18], Jordà et al. (2017), Knoll et al., authors' own calculations

However, a user should note that the multiplicative adjustment have two (potential) drawbacks. First, as mentioned in section 1 and Annex II, the method causes inconsistencies between individual series and aggregates. Second, depending on the numerator/denominator used, the adjustment will impact on ratio's that are calculated on the basis of the adjusted series. For example, if we use the adjusted positions to calculate Dutch households' mortgage debt as a percentage of GDP, a break of 10% of the outstanding amount not equalled by a similar revision of GDP, will have a significant impact on the respective ratio.

Table 2 provides an overview of the average differences between the adjusted and unadjusted figures for specific periods. The periods are chosen in such way that the differences within the period are 'homogeneous'. For example, between 1975 and 1982 the difference (defined as adjusted *minus* unadjusted) is negative for all periods concerned, while between 1982 and 2000 the difference is at least double digit positive.

Table 2: Average, maximum and minimum difference (%) between break-adjusted and unadjusted figures

Period	Dec 1956 - Sep 1975	Oct 1975 - Sep 1982	Dec 1982 - Aug 2000	Sep 2000 - Sep 2010	Oct 2010 - May 2018
Average	2.05%	-12.43%	20.30%	4.16%	0.49%
Maximum	2.87%	-8.84%	25.71%	5.74%	1.31%
Minimum	-0.02%	-13.25%	12.42%	2.50%	0.00%

Sources: see annex III, authors' own calculations

Section 3: Conclusions and way forward

Breaks in statistical time series are a *fact of life*, but they hamper severely the use of statistics for analytical, policy making and forecasting purposes. This paper describes DNB-statistics' policy of publishing break-adjusted statistics. Despite the possible drawbacks of compiling and publishing break-adjusted series, DNB has recently increased its publication of such time series, primarily to improve the usability of its statistics.

To decide on an approach to eliminate breaks, the costs (e.g. reporting burden for reporting agents and resources required at DNB's Statistics Division) are weighted against the benefits. Users were for example queried after their preferences and priorities. Following these principles, breaks are mainly adjusted using an automated procedure that scales up or down the observed data on the basis of break factors. In specific cases, however, a tailor made solution is applied to increase quality and provide historical time series.

Besides adjusting regular statistical publications for breaks, DNB's Monetary and Banking Statistics department also started the publication of key indicators for monetary statistics, amongst which mortgage loans granted by MFI to Dutch households. In the paper we demonstrated the (tailor made) methodology and assumptions underlying the compilation of a time series for mortgage loans granted by MFI to Dutch households at monthly frequency along with the results.

In line with other publications on the historical development of mortgage loans granted to households, we find that mortgage loans granted by MFI to Dutch households have grown considerably since the 1950's. Growth was exceptionally high before 1982 and during the 1990's, while it was fairly stable (ranging between 4 and 10% annually) between 1982 and 1990. Following the financial and sovereign

[18] Statistics Netherlands' online database (https://opendata.cbs.nl/statline/#/CBS/en/)

debt crisis (2007-2014) and the considerably dropping house prices in the Netherlands, the annual growth rates turned negative for the first time since 1956.

In future we plan to publish a broader set of extended historic time series on DNB's statistics website, prioritizing time series included in the set of key indicators. Furthermore we plan to reach out to a broader group of users, by including those that are harder to interact with – e.g. users downloading data from the DNB Statistics website. This way we can take their preferences and priorities on break-adjusted time series into account in our follow-up work.

On the methodology, where available we see merits to adjust breaks on the individual institution level. The current (aggregated) approach implies that i) errors made by, ii) the impact of framework changeovers on and iii) mergers/acquisitions involving bank A impact total banks' balance sheet and, thus, other banks' balance sheets in periods preceding the break.

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Annex I: Technical annex to breaks adjustments under 'approach 3' (multiplicative adjustments)

To determine a position change (SM), the following applies:

$$SM_t = S_t - S_{t-1} \qquad (1)$$

Where:
S = position observed

To determine the break (B) and the break factor (BF), the following applies[19]:

$$B_t = S_t - SB_t \qquad (2)$$

$$BF_t = \frac{S_t}{SB_t} \cdot BF_{t+1} \qquad (3)$$

Where:
S = position observed after the break[20]
SB = position observed before the break

To determine the derived transaction (T), the following applies:

$$T_t = SM_t + OM_t - HW_t - B_t \qquad (4)$$

Where:
SM = position change
OM = other change (e.g. securitisations)
HW = revaluation[21]
B = Break

To calculate adjusted transactions (T'), the following applies:

$$T' = T \cdot BF_t \qquad (5)$$

Where:
T = derived transaction
BF = break factor (for t = most recent observation, the following applies: BF = 1)

To calculate adjusted positions (S'), the following applies:

$$S'_t = S'_{t+1} - T'_{t+1} + OM_{t+1} \qquad (6)$$

Where:
S' = adjusted position
T' = derived transaction
OM = other change

[19] Note: For the most recently observed period, BFt+1 equals 1, and for periods where no breaks are observed the following applies: S = SB
[20] In other words, there is a double observation for period T, and the difference equals the size of the break.
[21] Revaluations are not included in the adjustment to allow the "price index" (revaluation as a percentage of positions outstanding) to be maintained.

Annex II: Inconsistencies arising from break-adjustments

DNB use the introduction of the new monetary framework in December 2014 to enforce the gross reporting of *notional cash pooling activities.*[22] For most positions vis-à-vis counterparty sectors, amongst which the insurance corporations and pension funds, gross treatment meant a substantial upward revision (see table 3). The break value (difference between figures for 2014-12B and 2014-12) for both the short term maturity and the total equals around EUR 16.500 mln. After multiplicative break-adjustment, keeping the original growth rates, the periods preceding the December 2014 break show significant inconsistencies between the directly (total) and indirectly (sum of maturity breakdown) adjusted series (see table 4).

Table 3: MFI positions vis-à-vis insurance corporations and pension funds before break-adjustment

mln EUR	< 1 year	1-5 year(s)	>5 years	Total	*Of which Notional cash pooling*
2014-07	1.137	788	1.755	3.680	
2014-08	1.129	873	1.780	3.782	
2014-09	1.370	755	1.900	4.025	
2014-10	1.253	869	1.817	3.939	
2014-11	1.203	955	1.840	3.998	
2014-12	2.706	418	1.519	4.643	
2014-12B	19.286			21.223	*17.455*
2015-01	24.913	419	1.506	26.838	*22.698*
2015-02	21.551	419	1.532	23.502	*19.369*
2015-03	24.911	419	1.638	26.968	*22.271*

Table 4: MFI positions vis-à-vis insurance corporations and pension funds after break-adjustment

mln EUR	< 1 year	1-5 year(s)	>5 years	Total	Sum of maturities	*Difference*
2014-07	8.103	788	1.755	16.821	10.646	*6.175*
2014-08	8.046	873	1.780	17.287	10.699	*6.588*
2014-09	9.764	755	1.900	18.398	12.419	*5.979*
2014-10	8.930	869	1.817	18.005	11.616	*6.389*
2014-11	8.574	955	1.840	18.275	11.369	*6.906*
2014-12	19.286	418	1.519	21.223	21.223	*0*
2015-01	24.913	419	1.506	26.838	26.838	*0*
2015-02	21.551	419	1.532	23.502	23.502	*0*
2015-03	24.911	419	1.638	26.968	26.968	*0*

[22] More information on the 'The statistical classification of cash pooling activities' is available in Colangelo (2016)

Annex III: Data availability and sources

Table 1: Data availability and features of mortgage loans and securitisations

Code	Time series	Instrument	Reporting agents	Counterparty sector	Framework	Frequency	Source
A	1956M12 - 1997M12	Mortgage loans	Money creating sector (e.g. trading banks, cooperative banks)	All sectors	Supervisory / Monetary*	M	Monthly returns from reporting agents. Time series (quarterly) are also published in DNB (1985).
B	1956M12 - 1982M12	Mortgage loans	Savings banks (until 1986 not part of the money creating sector, corrected backward to 1982)	All sectors	Supervisory / Monetary**	Q	Quarterly returns from savings banks received and compiled by DNB and Statistics Netherlands (1957 figures partly estimated). Time series are also published in DNB (1985).
C	1982M12 - 1997M12	Housing mortgages (with or without government guarantee)	Total banks (money creating sector incl. savings banks)	Private households	Monetary	M	Monthly returns from reporting agents. Regular publication in DNB's '*Jaarverslag*' and from 1969 in '*Kwartaalbericht*'
D	1997M12 - 1998M12	Housing mortgages	Monetary Financial Institutions (MFI: excluding the central bank)	Households	Monetary	M	Monthly returns from reporting agents. Regular publication in DNB's '*Jaarverslag*' and from 1969 in '*Kwartaalbericht*'
E	1998M12 - 2002M12	Housing mortgages	Monetary Financial Institutions (MFI: excluding the central bank)	Households	Monetary	Q	Quarterly returns from reporting agents. Regular publication on DNB's statistics website ***
F	2002M12 - 2018M06	Housing mortgages	Monetary Financial Institutions (MFI: excluding the central bank)	Households	Monetary	M	Monthly returns from reporting agents. Regular publication on DNB's statistics website.
G	1996M09 - 2009M12	Securitisations (true sale) of loans for house purchases	Special Purpose Vehicles (SPV)/ MFI	MFI	Monetary	M	Internal data: time series of securitisation transactions and (from 2003 onward) amounts outstanding on the SPV's balance sheets
H	2009M12 - 2018M06	Securitisations (true sale) of loans for house purchases	Special Purpose Vehicles (SPV)/ MFI	MFI	Monetary	M	Monthly returns from reporting agents. Regular publication on DNB's statistics website.

* In 1982 the social-economic reporting (for 'monetary supervision' purposes was fully implemented, before 1982 key series were collected besides prudential supervisory data (Van Straaten, 1989)
** In 1983 the social-economic reporting (for 'monetary supervision' purposes was fully implemented, before 1982 key series were collected besides prudential supervisory data (Van Straaten, 1989)
*** DNB Statistics website: https://statistiek.dnb.nl/en/statistics/index.aspx

Table 2: Overview of data sources used for the compilation of adjusted positions for mortgage loans granted by MFI to Dutch households

Reference period	1956 - 1982	1983 - 1996	1997	1998	1999 - 2002	2003-2009	2010 - 2018
Data sources	A, **B**	C	C, G	D, G	**E**, G	F, G	F, H

Codes (capital letters) refer to the overview of sources presented in table 1, bold capitals indicate quarterly frequency

Annex IV: Overview of the breaks (size and background) in the time series

Period	Amount (mln EUR)	MFI (including savings banks prior to 1982) Explanation	Amount (mln EUR)	Special Purpose Vehicle (SPV) Explanation
1965-Dec	23			
1967-Sep	25			
1975-Dec	1617			
1976-Dec	978			
1979-Mar	-274			
1979-Dec	-7			
1980-Dec	364			
1982-Dec	-12755	New framework/methodology/change in the reporting population		
1985-May	-1966			
1985-Dec	-11			
1986-Jun	2			
1987-Mar	-272			
1990-Dec	1112	New framework/methodology		
1991-Dec	724	Change in the reporting population/bank's restructuring		
1993-Dec	1766	Change in the reporting population/bank's restructuring		
1995-Nov	4148	Change in the reporting population/bank's restructuring		
1997-Mar	1268	Change in the reporting population/bank's restructuring		
1997-Sep	-908	Reclassification: first true sale securitisation	908	Reclassification: first true sale securitisation
1997-Dec	-3392	New framework/methodology		
1998-Dec	-992	Change in the reporting population/bank's restructuring		
2000-Sep	23253	Change in the reporting population/bank's restructuring		
2002-Dec	5270	Reclassification		
2003-Jan			-1976	Start of a new series owing to a change in the reporting framework
2003-Oct	-375	Reclassification		
2004-Dec	-1266	Reclassification		
2005-Nov	-425	Reclassification		
2005-Dec	-7367	New methodology and reclassification		
2006-Mar	455	Reclassification		
2006-Dec	-3624	New methodology and reclassification		
2007-Sep	1100	Change in the reporting population/bank's restructuring		
2007-Dec	2315	New methodology and reclassification		
2009-Dec			1360	Start of a new series owing to a change in the reporting framework
2010-Jun	-46304	New framework/methodology and reclassification	43819	Reclassification
2010-Aug	2831	Change in the reporting population/bank's restructuring	4740	Reclassification
2010-Sep	6	Change in the reporting population/bank's restructuring		
2010-Oct	6885	Change in the reporting population/bank's restructuring	4568	Reclassification
2011-Mar	380	Change in the reporting population/bank's restructuring	2019	Reclassification
2011-Nov	1229	Reclassification		
2012-Apr	-560	Change in the reporting population/bank's restructuring		
2012-Jul			-60	Reclassification
2012-Dec	-1054	Reclassification	1055	Reclassification
2014-Dec	2512	New framework/methodology		
2016-Dec	37417	Reclassification	-36168	Reclassification

Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

Making available data more useable: compilation and publication of break-adjusted (historical) time series[1]

Ruben van der Helm and Jan Bartman,

Netherlands Bank

[1] This presentation was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

Making available data more useable: Compilation and publication of break-adjusted (historical) time series

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DeNederlandscheBank

EUROSYSTEEM

Motivation and objectives

A break is *'**an interruption of continuity or uniformity**'*

(https://en.oxforddictionaries.com)

- Direct request from internal users to adjust for breaks
- Strong wish to improve the value added of DNB's statistics

The objectives of our paper are to:

- Describe DNB's policy for the publication of break-adjusted data
- Present the methodology underlying break-adjusted data
- Show results for break-adjusted (historical) time series

Way towards a new policy

- Some important issues for discussion
  - Scope
  - Methodology
  - Quality
  - Publication
  - Resourcing

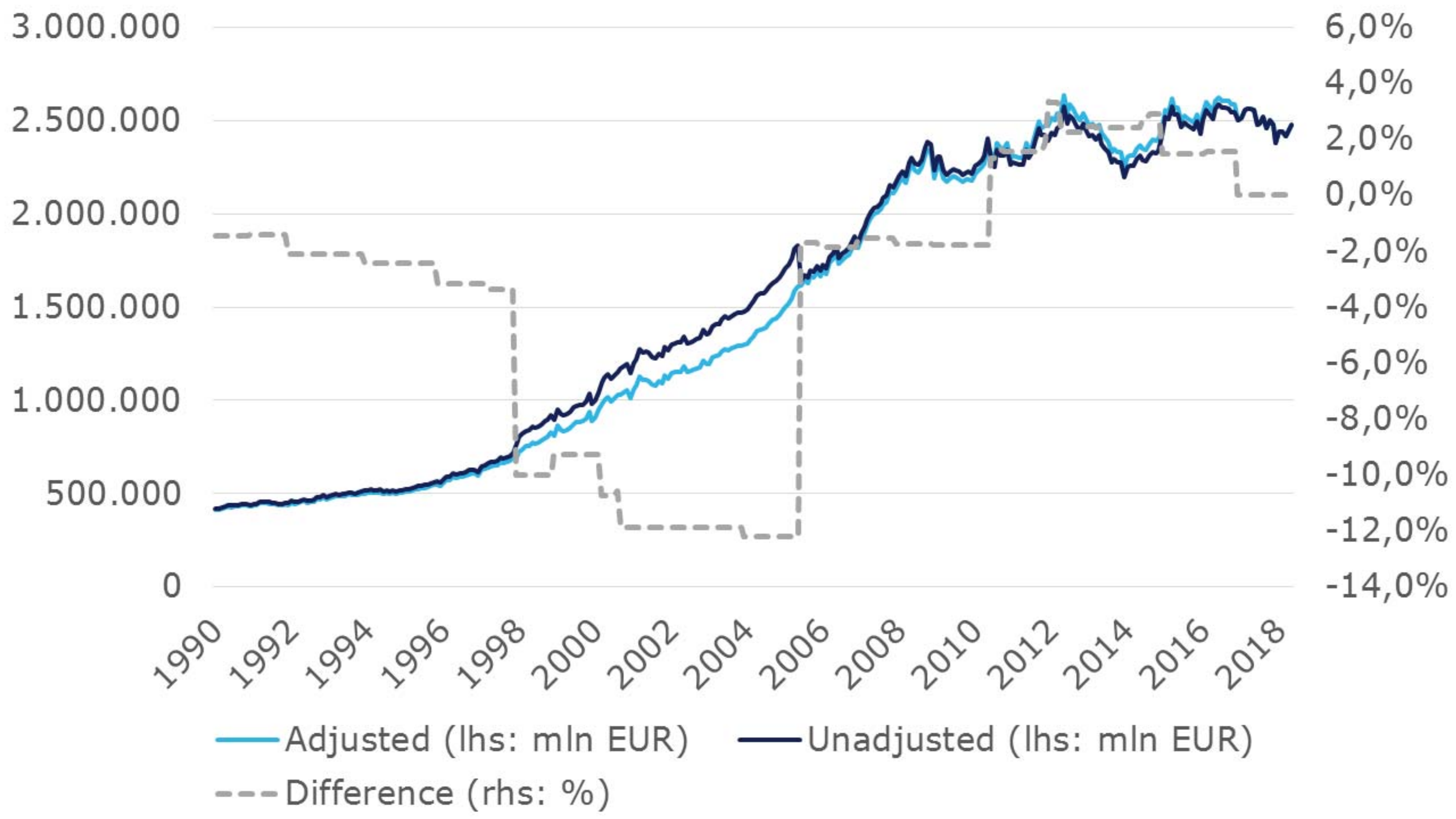
New policy for break-adjusted data

- Costs and benefits weighted: ranking of methods/approaches
  1. Adjustments based on data adjusted by reporting institutions
  2. Adjustments based on additional qualitative information
  3. Automated (i.e. multiplicative) adjustment for positions and flows
  4. Tailored solutions

- Minimal viable product: what could a user achieve?
- No adjustment for inconsistencies
- Publication of both adjusted and unadjusted series
- Start publication of *key monetary indicators*

Break-adjusted series: MFI’s total assets

Break-adjusted and unadjusted data for MFI’s total assets; a comparison

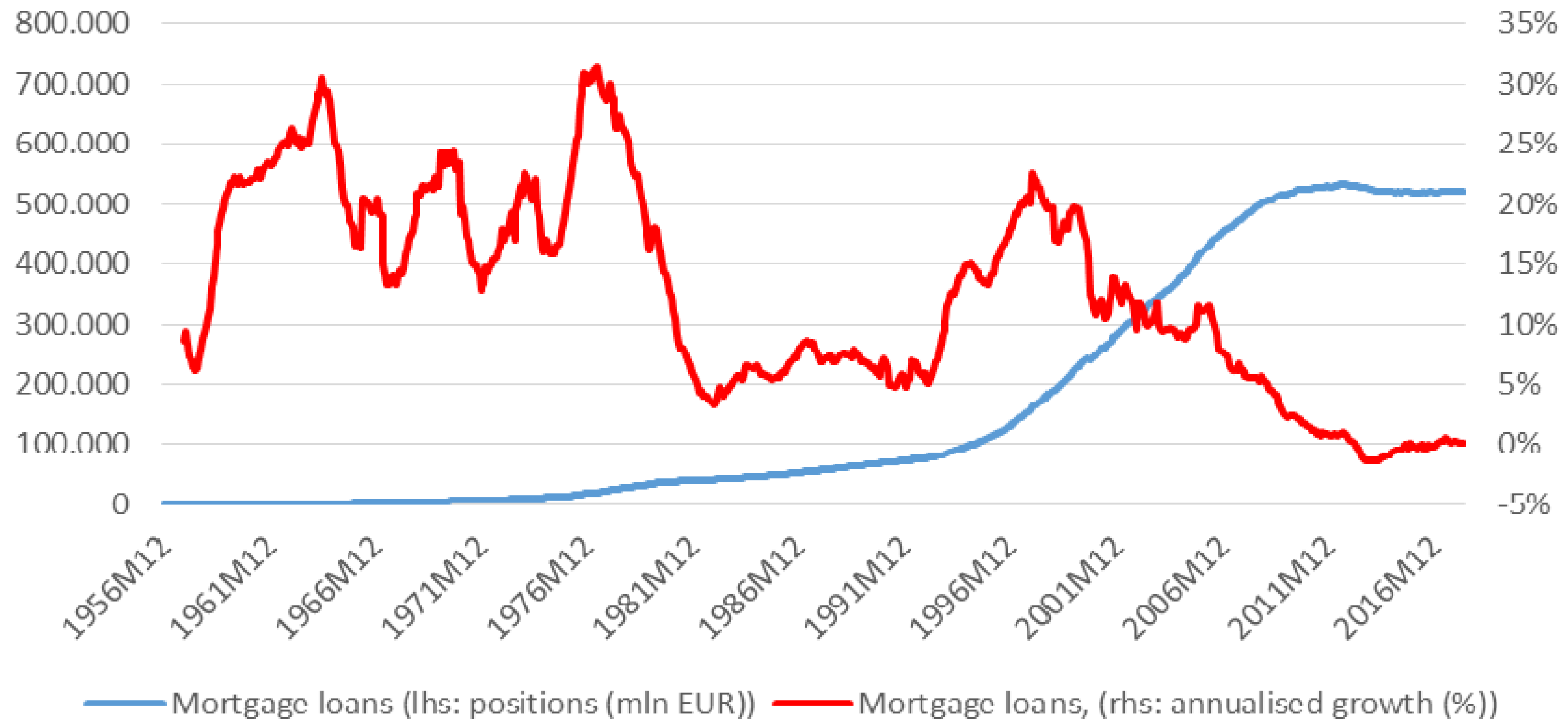


Historical time series for mortgage loans (1)

- Data availability
  - ‘Social-economic reporting’
  - Publication of historical time series
  - External sources (securitisations)
- Tailor-made approach: combination of different approaches
- Adjustment for securitisations and savings banks’ balance sheets developments

Historical time series for mortgage loans (2)

Break-adjusted data for MFI mortgage loans granted to Dutch households



Conclusions and way forward

- Break-adjusted statistics increase the value added of data
- The policy recently introduced fosters the compilation and publication of break-adjusted data
- Breaks are mainly adjusted automatically, historical time series require more tailor-made solutions

- Way forward:
    - Assess 'unknown users' preferences
    - Develop and assess adjustment on individual institution level
    - Extend the publication of historical time series

Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

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Reporting practices of Islamic financial institutions in the BIS locational banking statistics[1]

Siew Koon Goh,

Bank for International Settlements

[1] This paper was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

25 June 2018

Reporting practices of Islamic financial institutions in the BIS locational banking statistics

Siew Koon Goh[1]

In the implementation of the *System of National Accounts* 2008 (2008 SNA), statisticians raised some concerns related to Islamic banking. One concern is related to the measurement of financial intermediation services indirectly measured (FISIM) provided by Islamic bank. The 2008 SNA and the sixth edition of the *Balance of Payments and International Investment Position Manual* (BPM6) recognize FISIM produced only by financial corporations and only on their loan assets and deposit liabilities. For this reason, the mapping of Islamic financial instruments to conventional financial instruments becomes very important. For those instruments which stay out from the categories of "loan assets and deposit liabilities", they will not be included in FISIM calculation. Another concern is whether an "Islamic bank" should be considered as a bank. If the balance sheet structure and the risk profile of an Islamic bank is very different from that of a conventional bank, should it be considered as a bank? To address these concerns, the UN Working Group on National Accounts set up a task force on Islamic finance to formulate recommendations concerning the treatment of Islamic banking transactions in national accounts.[2] As part of its contribution to the work of the task force, the BIS collected information about the reporting practices of Islamic banks in the BIS locational banking statistics (LBS).[3] This paper summarises these practices.

Islamic banking

Islamic banking is a system of banking that is based on the principles of Shariah law. Shariah law prohibits the receipt and payment of interest, known as "riba". It also prohibits undertaking excessive uncertainty, gambling and short sales or financing activities that it considers harmful to society. The fundamental concept of Islamic banking is that money itself has no intrinsic value; it is simply a medium of exchange.

1 Siew Koon Goh, Senior Statistical Analyst, Monetary and Economic Department, Bank for Inaternational Settlements, e-mail: SiewKoon.Goh@bis.org. The author thanks Bruno Tissot, Philip Wooldridge, Benjamin Cohen, Catherine Koch and members of the UN task force on Islamic finance for their helpful comments and suggestions. The views expressed in this paper are those of the author and do not necessarily reflect those of the BIS.

2 This paper was originally prepared for a meeting of the Task Force on Islamic Finance held in Beirut, Lebanon, 24-26 October 2017. For information about the task force, see https://unstats.un.org/unsd/nationalaccount/ud-IF.asp.

3 The LBS capture the outstanding claims and liabilities of banks located in 47 reporting countries on counterparties resident in each of over 200 countries, including intragroup positions between offices of the same banking group. The LBS are collected based on the residence of entities, meaning that they follow the same principles as national accounts and balance of payments.

Therefore, profit cannot be made by exchanging money with another person. In other words, a Muslim is not allowed to benefit from lending money or receiving money from someone.

Islamic banks use either a trading model or a profit-and-loss sharing model in their business to make profits. As a result, financial instruments issued by Islamic bank may be recorded differently than those issued by conventional bank in its balance sheet. As discussed in H van Greuning and Z Iqbal (2009), IMF (2015) and IMF (2017), the balance sheet structure as well as the risk profile of an Islamic bank is different from that of a conventional bank. First, the 'pass-through' nature of the balance sheet of an Islamic bank. An Islamic bank's customers' return is linked to the return on the assets of the bank. This feature removes the typical asset-liability mismatch exposure of a conventional bank. Second, the assets of an Islamic bank contain financing assets where the tangible goods and commodities are purchased and sold to the customers. This practice creates distinct exposures. For example, in a conventional car financing a car is financed by a loan from the bank to the customer. But in case of an Islamic bank, the asset and the financing are coupled together. Therefore, an Islamic bank is not limited to the exposure as a "banker", but may develop additional exposures resulting from dealing with physical assets. Finally, due to prohibition of interest, an Islamic bank cannot issue debt to finance the assets. This discourages the creation of leverage in the balance sheet. As a result, an Islamic bank is considered less risky. The conventional banking system may develop multiple layers of intermediaries, which result in the financing becoming remote from the underlying assets. In an Islamic bank, the financial intermediary is always closely associated with the asset. Therefore, an Islamic bank is able to perform better monitoring of the asset as well as the customers.

Reporting practices

The remainder of this paper summarises the responses to a questionnaire sent by the BIS to LBS reporting countries with significant Islamic banking activities. The questionnaire asked how Islamic institutions are treated in LBS, as well as how they currently report financial claims and liabilities, including derivatives. Six countries responded to the questionnaire: Bahrain, Indonesia, Malaysia, Saudi Arabia[4], Turkey and United Kingdom.

a. Type and size of Islamic banking institutions

The questionnaire showed that, in terms of the business model, different countries allow different models for Islamic banking business to take place (Table 1). Some countries permit conventional banks to offer Islamic banking business through a "window" concept, others require the establishment of a separate entity to engage in the Islamic banking activities, ie through dedicated standalone Islamic banks, or through subsidiaries. Table 1 also showed approximate size of assets held by Islamic banking institutions as a percentage of total assets of the domestic banking system. Annex A provides an overview of the global Islamic financial sector in these countries.

4 Saudi Arabia is preparing to join the LBS reporting population.

Table 1

Country	Type of Islamic banking institutions[1]			Assets of Islamic banking assets as a percentage of total assets of the domestic banking system (approximate size, %)
	Stand-alone institutions not affiliated with conventional banks	Islamic banking subsidiaries affiliated with conventional banks	Islamic windows that are part of conventional banks	
Bahrain	Yes			≈17
Indonesia	Yes	Yes	Yes	≈6
Malaysia	Yes	Yes	Yes	≈24
Saudi Arabia	Yes		Yes	≈26
Turkey	Yes			≈5
United Kingdom	Yes		Yes	<0.1

[1] "Yes" indicates types of Islamic banking institutions that are available in respective LBS reporting country.

b. Classification of financial institutions

In the BIS's Guidelines for reporting BIS international banking statistics, Section B.2.2 explains the definition for LBS reporting institutions:

> Reporting institutions cover mainly internationally active banks. In particular, they cover institutions located in each reporting country whose business it is to receive deposits (and/or close substitutes for deposits) and to grant credits or invest in securities on their own account ("banks" or "banking offices" in these Guidelines). Thus, the reporting institutions include not only commercial banks but also savings banks, savings and loan associations, credit unions or cooperative credit banks, building societies, and post office giro institutions, other government-controlled savings banks and other financial institutions if they take deposits or issue close substitutes for deposits.

The BIS's Guidelines also clarify that reporting institutions generally should not include money market funds. Money market funds are included in the reporting population only when their liabilities (ie the shares and units issued) are treated as close substitutes for deposits or as deposits.

This definition of "banks" in LBS is fully consistent with the harmonised definition in macroeconomic statistical guidance. Banks in the LBS conform with terms such as:

(i) "deposit-taking corporations, except the central bank" used in 2008 SNA, code S.122 and BPM6, paragraph 4.71-4.73;

(ii) "Other depository corporations excluding money market funds" in the IMF's *Monetary and Financial Statistics Manual and Compilation Guide 2016* (MFSMCG); and

(iii) "Other monetary financial institutions excluding money market funds" as used in the new *European System of National and Regional Accounts* (ESA 2010).

The BIS's current Guidelines do not discuss the treatment of Islamic banking institutions. Nevertheless, for statistical purposes, countries reporting to the LBS treat Islamic banking institutions as conventional banking institutions. Responses to the questionnaire showed that, even though their operation and accounting recording concepts are different, **Islamic banking institutions are treated as "deposit-taking corporations, except the central bank" and are included in the current LBS reporting population**. The questionnaire, however, did not collect information on factors that determine these institutions be classified as "deposit-taking corporations, except the central bank" in these countries.

c. Classification of financial instruments

The BIS Guidelines, Section B.3.1 describes the scope and coverage for instruments in LBS. There are three types of instrument classifications in LBS: loans and deposits, debt securities and other instruments, ie those not included under loans and deposits and debt securities.

The banks' financial assets, or claims, should be broken down into:

(i) loans and deposits, which comprise interbank deposits and loans and advances (to banks or non-banks), including reverse repurchase agreements;

(ii) holdings of debt securities; and

(iii) other claims, including financial derivatives with a positive market value.

Similarly, banks' liabilities should be broken down into:

(i) loans and deposits, which comprise interbank loans received and deposits (from banks or non-banks), including repurchase agreements;

(ii) own issues of debt securities; and

(iii) other liabilities, including financial derivatives with a negative market value and equity.

Arrears and accrued interest as well as principal in arrears should be included in the claims and liabilities under the respective instruments, whenever possible.

The LBS does not distinguish between loans and deposits. In contrast, in national accounts and balance of payments statistics (BOP) loans are distinguished from deposits on the basis of the representation in the documents that evidence them. Annex B maps the three instrument classifications in the LBS to six broad categories in BOP.

Responses to the questionnaire showed that **Islamic banking institutions in each country follow different practices for reporting financial assets and liabilities in the LBS**. Taking Murabaha[5] as an example, some Islamic banking

[5] An Islamic financing structure (also known as mark-up financing) that is done in two stages. First, the bank buys a specific good that a customer is requesting from a third party (a supplier). Second, the

institutions considered it a “deposit” on the understanding that extending loan to earn interest is not permitted, while others classified it as a “loan” because its characteristics are similar to those in conventional banking business. There are also countries that considered Murabaha financing structures as “debt securities”, “trade credits” or even “other instruments”. Annex C summarises the reporting practices in the selected LBS reporting countries. While Islamic banking institutions generally do not report financial derivatives because Islamic transactions must not involve trading of excessive uncertainty (gharar), or speculative behaviour (maysir), the questionnaire showed that one country reports Islamic instruments with derivative-like features, ie Bai bil-Istighlal, under the derivative category. This indicates that there are already some Islamic financial instruments that partially resemble conventional derivatives being reported in LBS and BOP.

Notably, the diversity of reporting practices cannot be explained by accounting practices. In terms of the accounting framework, the accounting standards that are adopted by countries with significant Islamic transactions are either International Financial Reporting Standards (IFRS) or national standards that converge toward IFRS. These standards can fundamentally reflect Islamic finance without compromising Shariah principle, and therefore are being applied to Islamic finance in a number of territories including Saudi Arabia and Malaysia. Annex D summarises the accounting standards in LBS reporting countries with significant Islamic banking activities.

Instead, the diversity of reporting practices can be explained by the absence of international statistical guidelines for reporting Islamic financial instruments. Different countries apply different concepts when it comes to mapping the Islamic financial instruments within the conventional statistical categorisation. To address this, developing international guidance on the statistical treatment of Islamic financial products is important to facilitate cross-country comparison.

Developing international guidance

The growing importance of Islamic financial institutions across the world calls for increased attention to the appropriate statistical treatment of Islamic financial instruments to effectively monitor economic and financial developments and facilitate cross-country comparison of data. The IMF has taken important steps in this direction. The Annex 4.3 of the MFSMCG provides guidance on the classification of Islamic financial institutions and instruments in the context of compiling monetary statistics. The guideline focuses on various types of Islamic financial instruments in comparison with conventional ones in the context of macroeconomic and financial statistics.

Moving forward, the following may be considered when developing a guideline for statistical reporting of Islamic financial instruments:

- focus on the characteristics of underlying Islamic financial products (including discussion on Islamic instruments with derivative-like features) when providing

bank resells the good to the customer with both parties agree to a payment schedule (ie the payment covers both costs and the agreed upon profit margin). The customer made a deferred payment to the bank, where the good serves as collateral until the agreed payment is paid in full. The bank takes risk between the purchase of the goods from the seller and the sale of the assets to the customer requiring the goods. The bank is compensated for the time value of its money in the form of profit margin.

guidance to Islamic banks for reporting financial instruments. To have an exhaustive list may become impossible as there are continued product innovations in the financial markets.

- add a comparison of balance sheet structure between Islamic banks and conventional banks in guidelines, such as system of national accounts, balance of payments manual, monetary and financial statistics manual to highlight the differences in statistical treatment of different instruments.

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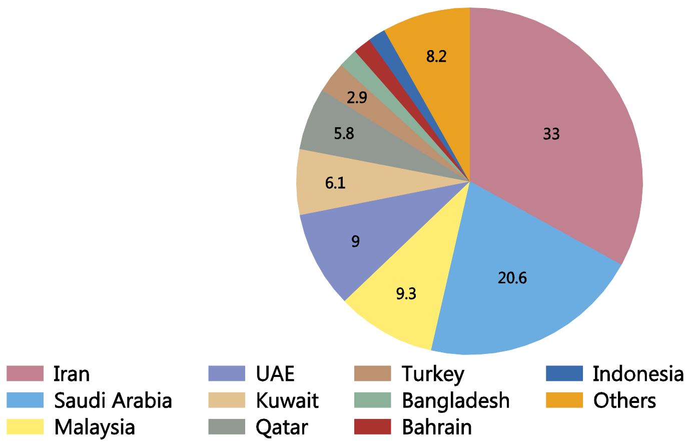
Annex A: Islamic financial sector globally

In the *Islamic Financial Services Industry Stability Report*, with data as of end-June 2016, global Islamic banking assets amounted to US$1.5 trillion. By jurisdiction (Graph 1), Iran is the largest market, accounting for 33% of the global Islamic banking industry. The Gulf Cooperation Council countries accounted for a total share of 43.2% (Saudi Arabia: 20.6%; UAE: 9%; Kuwait: 6.1%; Qatar: 5.8%; and Bahrain: 1.7%). The shares of Malaysia, Turkey and Indonesia were 9.3%, 2.9% and 1.4%, respectively.

Global Islamic banking assets[1]

Percentage share, as of end-June 2016 — Graph 1



[1] Shares are apportioned in US dollar terms.

Source: Islamic Financial Services Industry Stability Report 2017 (Chart 1.1.6)

The following summaries of Islamic business activities in selected LBS reporting countries are based on information in the IMF's Country Report on Ensuring Financial Stability in Countries with Islamic Banking, published in June 2017:

Bahrain: Bahrain operates a dual system where Islamic financial institutions operate in parallel with conventional banks. Bahrain, with 22 Islamic banks, has the largest concentration of Islamic banking operations among the countries that operates dual banking systems. While Bahrain accounts for less than 2% of the global Islamic banking assets, the market share of Islamic banks is 13.2% of the banking industry assets.

Indonesia: The Islamic banking sector in Indonesia, comprising 12 standalone banks and 22 Islamic windows of conventional banks, accounts for 7% of the domestic Islamic finance industry and 5% of the total banking system assets.

Malaysia: In Malaysia, Islamic financial institutions operate in parallel with conventional financial institutions, both offering a full range of financial products and services and often using the same infrastructure. The Islamic finance industry is dominated by the Islamic banking sector, which accounts for 42% percent of industry assets. Nine of the 16 Islamic banks are part of banking groups that also operate as commercial banks in Malaysia.

Turkey: Participation finance is a term that used in Turkey for financial practices structured in accordance with Shariah law. The participation finance institutions operate alongside conventional financial institutions in Turkey. The participation banking segment dominates with a market share of 83% of the total participation finance industry assets, but this accounts for only 5.2% of Turkey's banking industry.

Annex B: Instrument classifications between LBS and Balance of Payments (BPM6)

LBS financial assets and liabilities classification	**Balance of Payments - broad category**
Assets	
▪ Loans and deposits	▪ Currency and deposits ▪ Loans (including financial lease)
▪ Debt securities holdings	▪ Debt securities
▪ Other assets (*ie equity investment, equity securities, participations, derivatives instruments, any other residual on-balance sheet financial claims*)	▪ Other accounts receivable ▪ Equity ▪ Financial derivatives
Liabilities	
▪ Loans and deposits	▪ Currency and deposits ▪ Loans (including financial lease)
▪ Debt securities issuance	▪ Debt securities
▪ Other liabilities (*ie equity capital, retained earnings, equity securities, derivatives instruments, any other residual on-balance sheet liabilities*)	▪ Other accounts payable ▪ Equity ▪ Financial derivatives

Annex C: Reporting practices in LBS countries with significant Islamic banking activities

The tables below show how some commonly used (ie list is not exhaustive) Islamic financial instruments are categorised within the conventional statistical categorisation in LBS reporting countries with significant Islamic banking activities. The numbers in the parentheses indicate the number of reporting countries that categorise a particular Islamic financial instrument under the conventional statistical categorisation. Countries are allowed to indicate more than one category in each type of instrument.

A. Categorisation of Islamic financial assets

	Islamic financial instrument	Equity	Debt	Derivatives	Non-financial assets
1	Bai bil-Istighlal (eg option-like instrument)			Option (1)	
2	Bai Muajjal (eg deferred payment contract)		Loans (1) Trade credits (2) Others (2)		
3	Bai Salam (eg advanced payment contract)		Loans (2) Trade credits (2) Others (1)		(1)
4	Bail bil-wafa (eg repo-like instrument)		Debt securities (2)		
5	Ijarah (eg leasing or renting contract)		Debt securities (1) Loans (4) Deposits (1) Trade credits (1) Others (2)		
6	Istisnaa (eg progressive financing)		Loans (3) Trade credits (1) Others (1)		
7	Joala (eg derivatives-like instrument)		Others (1)		
8	Mudaraba (eg profit sharing)		Debt securities (1) Loans (2) Deposits (3) Others (2)		
9	Murabaha (eg cost plus)		Debt securities (1) Loans (3) Deposits (2) Trade credits (1) Others (2)		
10	Musharaka (eg joint venture)	(1)	Debt securities (1) Loans (3) Deposits (1) Trade credits (1) Others (2)		
11	Qard-hasan (eg deposit with no interest)		Loans (3) Deposits (1) Trade credits (1) Others (1)		
12	Mushtarakah (eg a combination between Musharakah and Mudarabah)		Loans (1)		

B. Categorisation of Islamic financial liabilities

	Islamic financial instrument	Equity	Debt	Derivatives
1	Amanah (eg trust)		Deposits (1) Others (1)	
2	Ijarah (eg leasing or renting contract)		Loans (2) Trade credits (1) Others (2)	
3	Istijrar (eg leasing or renting contract)		Loans (1) Deposits (2) Trade credits (1) Others (2)	
4	Mudaraba (eg profit sharing)		Loans (2) Deposits (1) Others (2)	
5	Mudaraba Sukuk (certificate on the basis of mudaraba)		Debt securities (2) Loans (2) Deposits (1) Others (1)	
6	Qard (eg deposit with no interest)		Loans (2) Deposits (2) Others (1)	
7	Qard-hasan (eg deposit with no interest)		Loans (3) Trade credits (1)	
8	Restricted Mudaraba	(2)	Deposits (1) Trade credits (1) Others (1)	
9	Sukuk (eg Islamic bonds)		Debt securities (4) Loans (2) Deposits (1) Others (1)	
10	Wadiah (eg custody of fund)		Deposits (3) Others (2)	

Annex D: Accounting standards in LBS countries with significant Islamic banking activities

An excerpt from IFRS official website (http://www.ifrs.org/)

- Are IFRS Standards required for domestic public companies in these countries?

Country	Description
Bahrain	IFRS Standards are required.
Indonesia	Indonesia has not adopted IFRS Standards for reporting by domestic companies. Indonesia has been converging its national standards toward IFRS Standards, but without a plan for full adoption of IFRS Standards.
Malaysia	Public companies are required to use the MFRS Framework, which is substantively equivalent to IFRS Standards.
Saudi Arabia	IFRS Standards are required for all listed companies, banks, and insurance companies.
Turkey	IFRS Standards adopted as Turkish Accounting Standards are required for listed companies, financial institutions, and other public interest entities.
United Kingdom	All domestic companies whose securities trade in a regulated market are required to use IFRS Standards as adopted by the EU in their consolidated financial statements.

Irving Fisher Committee on
Central Bank Statistics
BANK FOR INTERNATIONAL SETTLEMENTS

Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

Reporting practices of Islamic financial institutions in the BIS locational banking statistics[1]

Siew Koon Goh,

Bank for International Settlements

[1] This presentation was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

BANK FOR INTERNATIONAL SETTLEMENTS

Reporting practices of Islamic financial institutions in the BIS locational banking statistics

Siew Koon Goh

Bank for International Settlements

9th IFC Conference

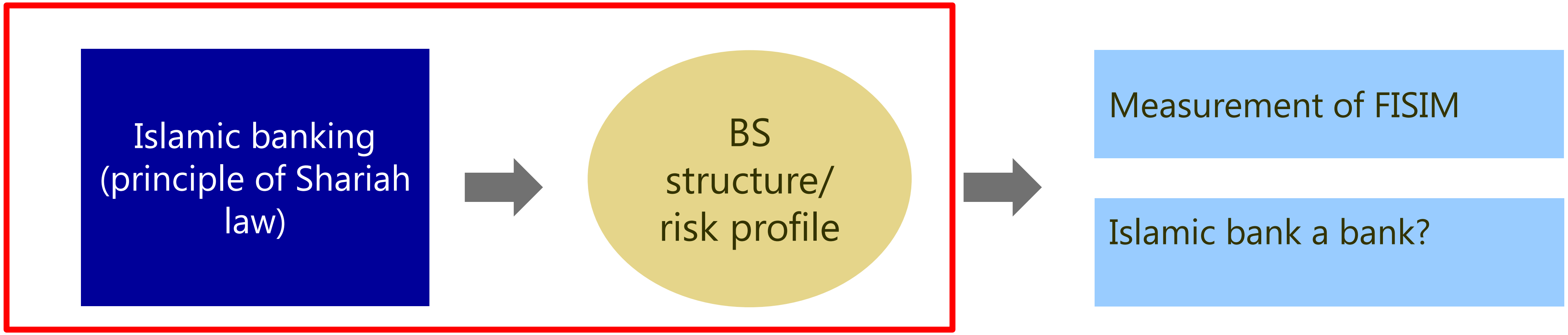
Basel, 30-31 August 2018

Introduction

- Implementation of 2008 SNA recommendations

1. Measurement of FISIM	• Mapping of Islamic financial instruments to conventional financial instruments, ie loan assets and deposit liabilities
2. Islamic bank a bank?	• Balance sheet structure • Risk profile

Islamic Banking (Shariah law)



- Balance sheet structure is different
- Risk profile
  - Customers' return is linked to the return on the assets of the bank
  - Assets contain financing physical assets
  - Discourage creation of leverage

Questionnaire on reporting practices of Islamic financial institutions

LBS-reporting countries	Coverage of questionnaire
• Bahrain • Indonesia • Malaysia • Saudi Arabia • Turkey • United Kingdom	• Islamic banking business models in different countries • How central banks treat IFIs • How transactions of Islamic financial instruments are captured in statistical reporting

Response to the questionnaire

- Islamic banking business models in different countries

Country	Type of Islamic banking institutions[1]			Assets of Islamic banking assets as a percentage of total assets of the domestic banking system (approximate size, %)
	Stand-alone institutions not affiliated with conventional banks	Islamic banking subsidiaries affiliated with conventional banks	Islamic windows that are part of conventional banks	
Bahrain	Yes			≈17
Indonesia	Yes	Yes	Yes	≈6
Malaysia	Yes	Yes	Yes	≈24
Saudi Arabia	Yes		Yes	≈26
Turkey	Yes			≈5
United Kingdom	Yes		Yes	<0.1

[1] "Yes" indicates types of Islamic banking institutions that are available in respective LBS reporting country

Response to the questionnaire (cont'd)

- How central banks treat IFIs
  - IFIs are treated as "deposit-taking corporations except the central bank" (S.122) in LBS
- How Islamic financial instruments are captured
  - Islamic banks in each country follow different practices for reporting financial assets and liabilities in the LBS
  - Accounting standards fundamentally reflect Islamic finance without compromising Shariah principle

What‘s next step

- Develop an international statistical guidelines for reporting Islamic instruments
  - Characteristics of underlying Islamic financial products
  - Differences in statistical treatment of different instruments

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Demystifying big data in official statistics – it's not rocket science![1]

Jens Mehrhoff,
Eurostat

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Demystifying big data in official statistics – it's not rocket science!

Jens Mehrhoff, Eurostat

Abstract

The talk will initially define big data and discuss the interpretation in the area of official statistics. We will then focus on the use of big data in the production of official statistics, referring to the case study of 'scanner data'. Simple classification rules and similarity measures are introduced, which help in grouping items together. An empirical example shows how a price index can be calculated from this new data source. At all stages of the presentation two things are key: demystifying machine learning and the like, while, at the same time, highlighting the limits of what is technically possible.

Keywords: big data; machine learning; classification; record linkage; scanner data

JEL classification: C43; C55; C81

Contents

1. Definition of big data

Big data usually includes data sets with sizes beyond the ability of commonly used software tools to capture, curate, manage, and process data within a tolerable elapsed time. The '3 Vs' definition of big data according to Gartner (2001) comprises:

- Volume: amount of data ('found/organic' data);
- Velocity: speed of data in and out (real time); and
- Variety: range of data types and sources ('data lake').

But large data are not necessarily big data. The Square Kilometre Array (SKA) radio telescope, on the other hand, will ultimately be the largest scientific instrument on Earth, both in physical scale and in terms of volume of data it will generate. Just in its first phase, the telescope will produce some 160 terabytes of raw data per second – more than 4 times the 2016 global internet traffic. These data are no longer analysable by humans.

This is a massive amount of data. If a byte of data is equivalent to a small grain of rice, 160 terabytes per second would take

- half a second to cover Basel 10 cm high in rice,
- one day to cover the entire European Union 10 cm high in rice,
- three-and-a-half weeks to cover the whole surface of the Atlantic Ocean 10 cm high in rice, and
- two millennia to fill up the Atlantic Ocean with rice from its seabed to the surface.

More often than not, big data in official statistics are simply large data sets or the IT architecture handling them. There are, at least, four possible interpretations of big data in the area of official statistics:

- 'Data science': e.g. linking micro data;
- New data sources: e.g. Google or social media;
- IT architecture: e.g. distributed computing; and
- Large data sets: e.g. granular/administrative data.

2. Use of big data in the production of official statistics

As a case study for the use of big data in the production of official statistics we refer to electronic transactions data ('scanner data') for measuring the average change in prices. This is a large but structured data set. Simple classification rules and similarity measures are introduced, which help in grouping items together. An empirical example shows how a price index can be calculated from this new data source.

The process is split into three parts:

1. Classification of individual products into homogeneous groups via supervised machine learning;
2. Treatment of re-launches via probabilistic record linkage (fuzzy matching); and
3. Index calculation via multilateral methods (here: time-product dummy).

2.1 Classification of individual products

According to Mitchell (1997) 'a computer program is said to learn from experience *E* with respect to some class of tasks *T* and performance measure *P* if its performance at tasks in *T*, as measured by *P*, improves with experience *E*.' The task in our setting is the classification of individual products into homogeneous groups, the performance measure is accuracy, i.e. the proportion of automatically correctly classified products, and the experience is training data.

Supervised learning is where the computer is presented with example inputs and their desired outputs and the goal is to learn a general rule that maps inputs to outputs. Classification is an example with the aim of identifying to which of a set of categories a new observation belongs, on the basis of a training set. In contrast to this is unsupervised learning, where no labels are given to the learning algorithm, leaving it on its own to find structure in its input. An application is clustering with the objective of grouping a set of objects in such a way that objects in the same group are more similar to each other than to those in other groups.

Example: Is a *yellow* and *firm* orange ripe? Table 1

Orange	Colour	Softness	Ripeness	Orange	Colour	Softness	Ripeness
1	Green	Firm	Unripe	**9**	Orange	Firm	Ripe
2	Green	Firm	Unripe	**10**	Orange	Firm	Ripe
3	Orange	Soft	Ripe	**11**	Orange	Soft	Unripe
4	Yellow	Firm	Unripe	**12**	Orange	Firm	Ripe
5	Yellow	Firm	Ripe	**13**	Green	Firm	Unripe
6	Orange	Soft	Ripe	**14**	Orange	Firm	Ripe
7	Green	Firm	Ripe	**(end of training data)**			
8	Yellow	Soft	Ripe	**15**	Yellow	Firm	**?**

The naïve Bayes classifier relies on the assumption that every feature being classified is independent of all other features:

$$\begin{aligned} P(\text{ripe}|\text{yellow,firm}) &= \frac{P(\text{yellow,firm}|\text{ripe}) \cdot P(\text{ripe})}{\mathrm{P}(\text{yellow,firm})} \\ &= \frac{P(\text{yellow}|\text{ripe}) \cdot P(\text{firm}|\text{ripe}) \cdot P(\text{ripe})}{P(\text{yellow}) \cdot P(\text{firm})}. \end{aligned}$$

Unlike in Bayesian econometrics, the prior information, i.e. *P*(ripe), actually exists. Plugging in the numbers derived from a cross-tabulation of colour and softness with ripeness, one gets

$$
\begin{aligned}
P(\text{ripe}|\text{yellow,firm}) &= \frac{P(\text{yellow}|\text{ripe}) \cdot P(\text{firm}|\text{ripe}) \cdot P(\text{ripe})}{P(\text{yellow}) \cdot P(\text{firm})} \\
&= \frac{(2/9) \cdot (6/9) \cdot (9/14)}{(3/14) \cdot (10/14)} \\
&= \frac{28}{45} = 0.62.
\end{aligned}
$$

The accuracy of supervised machine learning, i.e. the proportion of automatically correctly classified products, is around 80% for supermarket scanner data. That means that one out of five products is misclassified. Hence, while machine learning can give reasonable suggestions for the classification, it eventually needs to be assisted by human beings; it is no panacea!

2.2 Treatment of re-launches

A relaunch is a new attempt to sell a product or service, often by advertising it in a different way or making it available in a different form, e.g. different packaging and different GTIN (Global Trade Item Number, 'barcode').

Record linkage has the task of finding records in a data set that refer to the same entity across entities that may not share a common identifier. In our case the entity is the product or service and the identifier is the GTIN.

The Levenshtein (1965) distance is defined as the minimum number of operations needed to turn one string into another. Operations are insertion, deletion, or substitution of a character:

- 'car' → '**s**car' (insertion of 's' at the beginning);
- '**s**can' → 'can' (deletion of 's' at the beginning); and
- 'sca~~r~~' → 'sca**n**' (substitution of 'r' for 'n').

Example: Which products are the same? Table 2

Product description (or GTIN text)	Size of the string	Levenshtein distance	Levenshtein similarity
'Whole Milk 1L' (*original*)	13	0	100%
'whole milk 1L'	13	2	85%
'whole milk 1 liter'	18	8	56%
'whole milk 1 litre'	18	8	56%
'Whole milk 1 ltr'	26	15	42%
'Whole Milk 2L'	13	1	92%
'1L Whole Milk'	13	6	54%

Levenshtein similarity is calculated as (1 – Levenshtein distance / length of the longer string) · 100%.

The last string leads to horrible results because language allows us to swap the order of words. There are still plenty of other ways to improve: capitalisation, trimming, character encoding, et cetera.

However, 1 litre of milk is different from 2 litres; while '1L', '1 liter', '1 litre', and '1 ltr' are all the same. Hence, do not trust the results blindly! They would be the input into a user interface, for a computer-assisted classification – so use them as suggestions (and look also at second and third best results).

2.3 Index calculation

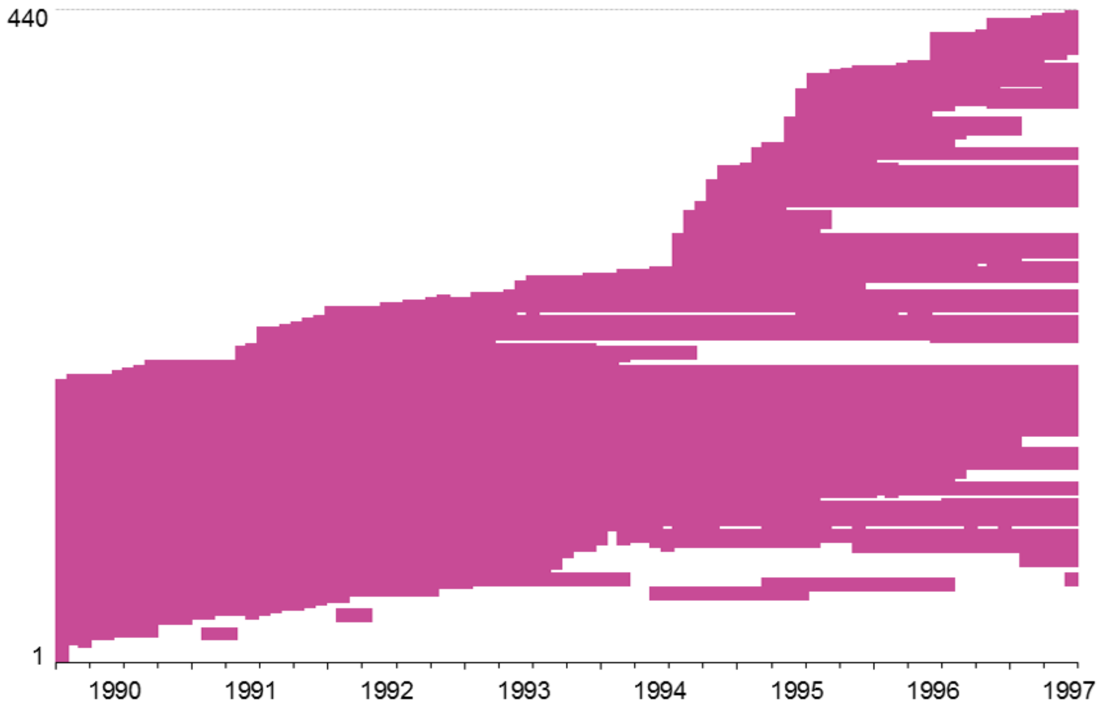
The purpose of a price index is measuring the average rate of change in consumer prices going from a base period 0 to a comparison period *t*. Traditional bilateral indices would be drifting when chain-linked due to effect of sale prices and stockpiling. Hence, multilateral indices are applied instead. We exemplify this by the time-product dummy (TPD) method, where the index $P^t = \exp \delta^t$ ($P^{t=0} = 1$) from an expenditure share-weighted regression of the logarithmic prices on time and product dummies:

$$\ln p_i^t = \alpha + \sum_{t=1}^{T} \delta^t D_i^t + \sum_{i=1}^{N-1} \gamma_i D_i + \varepsilon_i^t.$$

The data are taken from the Dominick's database of the James M. Kilts Center at the University of Chicago Booth School of Business.[1] Dominick's Finer Foods was a Chicago-area grocery store chain and historic data are provided for academic research purposes. The data set covers 93 stores for 399 weeks from 14 September 1989 to 7 May 1997 and totals 98,884,285 observations (after cleansing) of 13,845 products (excluding re-launches) in 29 categories (from analgesics to toothpastes).

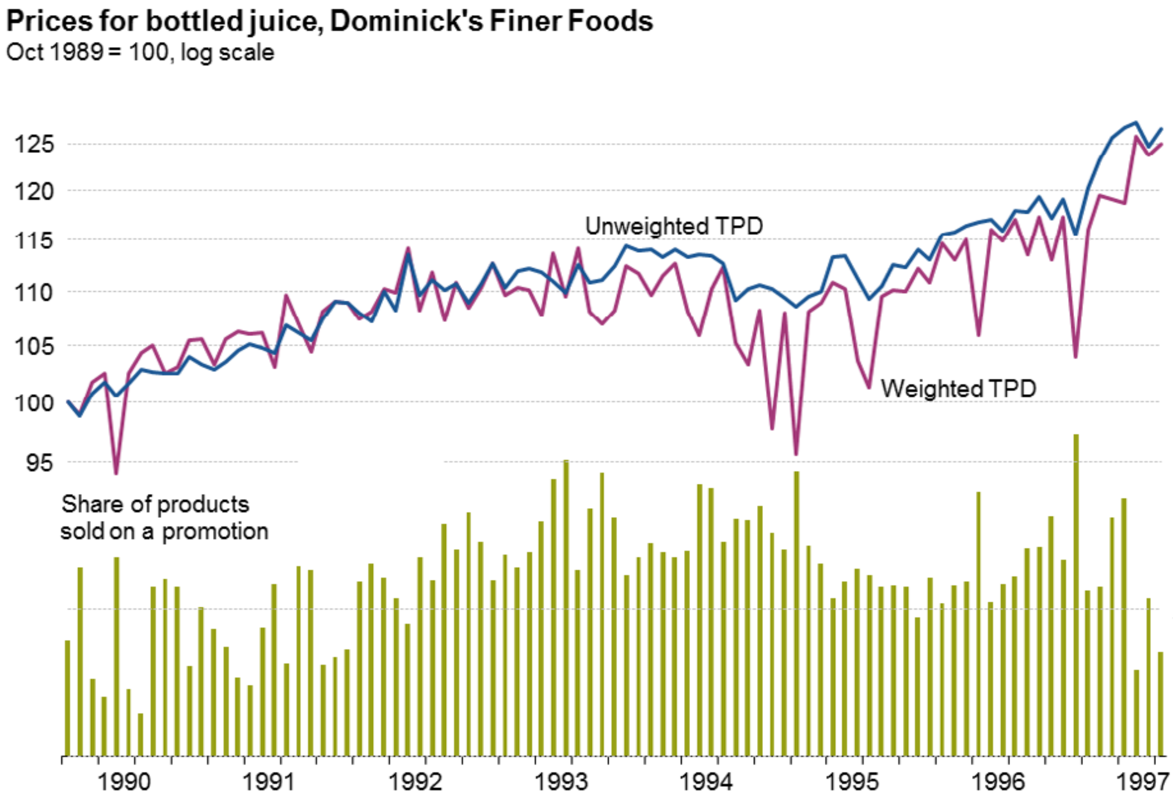
For the sake of exposition we aggregate the weekly store-level Universal Product Code (UPC, incorporated by GTIN) data to chain-wide item codes (tracking the same product across multiple UPCs) at monthly frequency using the month in which the week ends (weeks run from Thursday to Wednesday), covering the period from October 1989 to April 1997 (91 months; 467,605 observations of 13,818 products). Below we present the results for bottled juice as an example.

Product churn by item code, bottled juice



[1] Mehrhoff, J. (2018), *Promoting the use of a publically available scanner data set in price index research and for capacity building*, available from https://ec.europa.eu/eurostat/web/hicp/overview

The within-category average duration of bottled juice products in the sample is 37 months (average over all categories: 34 months). Notably, more than 10% (5%) of products are available throughout the 91 months studied. On the other hand, 3½% (2½%) of products are available in just one month. Compared to the first month, half of the initial products are still sold after 82 months.



As it can be seen from a comparison of the weighted and the unweighted TPD index, where the latter is less affected by quantity increases due to price decreases – very much like web-scraped data –, the troughs are highly correlated to sale periods. But the stronger signal in the weighted TPD index comes at a cost: there is now also much more noise in the time series than in the unweighted version.

3. Discussion and outlook

Big data can be very precise – but at the same time may have limited accuracy. Not more data are better, better data are better! The paradox: the 'bigger' the data, the surer we will miss our target (Meng, 2016). Big, or 'organic', data is not capturing all behaviours in the society, just some; and we might not know which ones are missing. The combination of survey and census data with big data is the ticket to the future (Groves, 2016).

The future direction, after the hype, is more like big data will be supplementing rather than replacing official statistics; a genuine change in paradigm is rather doubtful in the short to medium term. This has to been seen not least against the background of the lower quality (keyword: coverage bias) of such experimental statistics. Just one question: Will the lower production costs outweigh the potentially considerably higher non-monetary costs of misguided policy decisions?

The Irving Fisher Committee on Central Bank Statistics revealed other issues including managing legal, financial and ethical risks (data governance), huge implications for information systems (IT resources), and that necessary skills may not be available in-house (staff resources). A fundamental change in institutions' business models, though, is not (yet) in sight.

Irving Fisher Committee on
Central Bank Statistics

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1. Definition of big data

- **Four possible interpretations of *big data*** – at least:
    - **'Data science'**: e.g. linking micro data
    - **New data sources**: e.g. Google or social media
    - **IT architecture**: e.g. distributed computing
    - **Large data sets**: e.g. granular/administrative data
- More often than not, ***big data* in official statistics are simply large data sets or the IT architecture handling them**.

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2. Use of big data in the production of official statistics

- **Case study: Electronic transactions data** ('scanner data') for measuring the average change in prices → large but structured data set
    1. **Classification of individual products into *homogeneous* groups**: supervised machine learning
    2. **Treatment of *re-launches***: probabilistic record linkage (fuzzy matching)
    3. **Index calculation**: multilateral methods (here: time-product dummy) – *time will not allow, please see*: https://www.youtube.com/watch?v=4zHpD5jzMMM

2. Use of big data in the production

2.1 Classification of individual products

Example: Is a *yellow* and *firm* orange ripe?

Orange	Colour	Softness	Ripeness	Orange	Colour	Softness	Ripeness
1	Green	Firm	Unripe	**9**	Orange	Firm	Ripe
2	Green	Firm	Unripe	**10**	Orange	Firm	Ripe
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8	Yellow	Soft	Ripe	**15**	Yellow	Firm	**?**

European Commission

2. Use of big data in the production

2.1 Classification of individual products

- **Naïve Bayes classification:**

$$P(\text{ripe}|\text{yellow,firm}) = \frac{P(\text{yellow,firm}|\text{ripe}) \cdot P(\text{ripe})}{P(\text{yellow,firm})}$$

$$= \frac{P(\text{yellow}|\text{ripe}) \cdot P(\text{firm}|\text{ripe}) \cdot P(\text{ripe})}{P(\text{yellow}) \cdot P(\text{firm})}$$

- Relies on the **assumption** that every feature being classified is **independent of all other features**.

2. Use of big data in the production
2.1 Classification of individual products

Cross-tabulation of colour and ripeness

Colour	Ripe	Unripe	Total
Green			
Yellow	*P*(yellow|ripe)		*P*(yellow)
Orange			

NB: *P*(ripe) = proportion of ripe oranges (independent of colour and softness).

Cross-tabulation of softness and ripeness

Softness	Ripe	Unripe	Total
Soft			
Firm	*P*(firm|ripe)		*P*(firm)

2. Use of big data in the production

2.1 Classification of individual products

Cross-tabulation of colour and ripeness

Colour	Ripe	Unripe	Total
Green	1/9	3/5	4/14
Yellow	***2/9***	1/5	***3/14***
Orange	6/9	1/5	7/14

NB: *P*(ripe) = ***9/14***.

Cross-tabulation of softness and ripeness

Softness	Ripe	Unripe	Total
Soft	3/9	1/5	4/14
Firm	***6/9***	4/5	***10/14***

2. Use of big data in the production

2.1 Classification of individual products

- **Naïve Bayes classification:**

$$
\begin{aligned}
P(\text{ripe}|\text{yellow,firm}) &= \frac{P(\text{yellow}|\text{ripe}) \cdot P(\text{firm}|\text{ripe}) \cdot P(\text{ripe})}{P(\text{yellow}) \cdot P(\text{firm})} \\
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&= \frac{28}{45} = 0.62
\end{aligned}
$$

2. Use of big data in the production
2.1 Classification of individual products

- The **accuracy of supervised machine learning**, i.e. the proportion of automatically correctly classified products, is **around 80% for supermarket scanner data**. That means that **one out of five products is misclassified**.
- Hence, while machine learning can give **reasonable suggestions for the classification**, it eventually **needs to be assisted by human beings**; it is no panacea!

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2. Use of big data in the production
2.2 Treatment of re-launches

- **Re-launch**: A new attempt to sell a product or service, often by **advertising it in a different way or making it available in a different form**, e.g. different packaging → different GTIN.
- **Record linkage**: The task of **finding records** in a data set that **refer to the same entity** across entities that **may not share a common identifier**.
  - **Entity**: product or service; **Identifier**: GTIN ('barcode')

2. Use of big data in the production
2.2 Treatment of re-launches

- **Levenshtein (1965) distance**: Minimum number of operations needed to **turn one string into another**.
  - **Operations**: insertion, deletion, or substitution of a character
- **Examples:**
  - 'car' → '**s**car' (**insertion** of 's' at the beginning)
  - '**~~s~~**can' → 'can' (**deletion** of 's' at the beginning)
  - 'sca**~~r~~**' → 'sca**n**' (**substitution** of 'r' for 'n')

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2. Use of big data in the production

2.2 Treatment of re-launches

Product description (or GTIN text)	Size of the string	Levenshtein distance	Levenshtein similarity[1]
'Whole Milk 1L' (*original*)	13	0	100%
'whole milk 1L'	13	2	85%
'whole milk 1 liter'	18	8	56%
'whole milk 1 litre'	18	8	56%
'Whole milk 1 ltr'	26	15	42%
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'1L Whole Milk'	13	6	54%

[1] Calculated as (1 – Levenshtein distance / length of the longer string) · 100%.

2. Use of big data in the production

2.2 Treatment of re-launches

- The **last string** leads to horrible results because language allows us to **swap the order of words**.
  - There are still **plenty of other ways to improve**: capitalisation, trimming, character encoding, et cetera.
- However, **1 litre of milk is different from 2 litres**; while '1L', '1 liter', '1 litre', and '1 ltr' are all the same.
  - Hence, **do not trust the results blindly**! They would be the input into a user interface, for a **computer-assisted classification** – so use them as suggestions.

3. Other potential uses of big data

- A recent survey by the Irving Fisher Committee on Central Bank Statistics (IFC) showed that there is **strong interest in big data in the central banking community**.
(http://www.bis.org/ifc/publ/ifc-report-bigdata.pdf)
- The IFC Executive decided to select a **few case studies** for piloting the usefulness of big data:
  - **1. Administrative data; 2. Internet data; 3. Commercial data; 4. Financial market data**
- The **IFC / Bank Indonesia Satellite Seminar** to the ISI RSC 2017 explored the topic of big data from a central banking perspective (see *IFC Bulletin No 44*).
(http://www.bis.org/ifc/publ/ifcb44.htm)

4. Discussion and outlook

- The future direction, after the hype, is more like **big data will be supplementing rather than replacing official statistics**; a **genuine change in paradigm is rather doubtful** in the short to medium term.
- This has to been seen not least against the background of the **lower quality (keyword: coverage bias) of such *experimental* statistics**.
- Just one question: Will the lower production costs outweigh the potentially considerably higher **non-monetary costs of misguided policy decisions**? (Others include **governance and resource issues**.)

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Liquidity in the JGB cash market: an evaluation from detailed transaction data[1]

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[1] This paper was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

Liquidity in the JGB Cash Market

An Evaluation from Detailed Transaction Data

Toshiyuki Sakiyama   Shun Kobayashi[1]

Abstract

We create new liquidity indicators for the JGB cash market based on "big data," i.e. detailed inter-dealer transaction data. Since it has become necessary to grasp JGB market liquidity in more detail, we compile indicators from multifaceted perspectives such as volume, tightness, depth and resiliency.

An examination of indicators suggests that they have generally improved gradually since autumn of 2016, after having deteriorated at the beginning of 2016, when the "Negative Interest Rate" policy was introduced. However, we must continue to monitor future developments in liquidity, because transaction volume has not increased. We have also found that improvements in short-term and off-the-run bonds are relatively delayed.

Keywords: JGB cash market, market liquidity, detailed transaction data, transaction volume, tightness, depth, resiliency

JEL classification: E43, E52, E58, C80

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Contents

Introduction

Interest in liquidity in government bond markets continues to rise at home and abroad. Strengthening of financial regulations after the Lehmann crisis, increasing presence of High Frequency Trading, and unconventional monetary policies by major central banks in advanced countries—especially the purchase of government bonds—may have effects on liquidity in the government bond markets. Especially, in Japan, it is heard that the Bank of Japan purchases massive amounts of government bonds, which affects the liquidity in the JGB markets.

Against this background, the Bank of Japan examines the liquidity in the JGB markets from a broader range of perspectives by utilizing both qualitative and quantitative information, such as comments heard at meetings and survey results from market participants, as well as liquidity indicators compiled with individual transaction data. Regarding liquidity indicators which have started to release from August 2015, it is characterized that these indicators include not only indicators for the JGB futures market (which was often taken up in past research) but also those for the JGB cash market, which had few prior studies even overseas because of data limitation. At that time, we focused on the relatively stagnant dealer-to-client transactions and compiled some indicators for dealer-to-client transactions in the JGB cash market.[2]

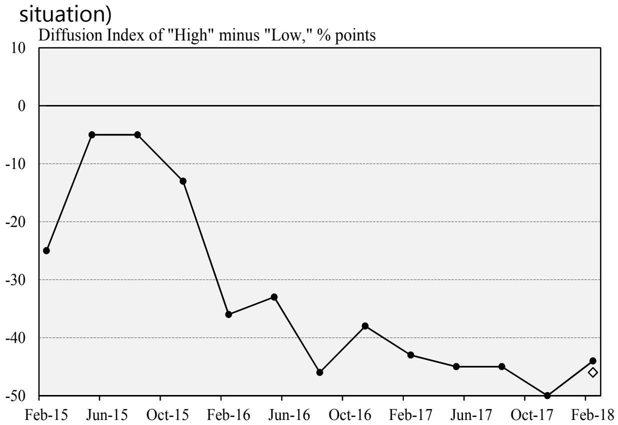
To expand existing liquidity indicators, the Bank of Japan decided to compile new indicators of inter-dealer transactions in the JGB cash market with newly acquired data. For two primary reasons, the need to finely grasp liquidity in the JGB markets is increasing, particularly within the JGB cash market (dealer-to-client transactions and inter-dealer transactions). First, the Bank of Japan is purchasing massive amounts of cash JGBs after the introduction of "Quantitative and Qualitative Monetary Easing (QQE)" in April 2013. In September 2016, the Bank introduced a new framework, "QQE with Yield Curve Control," and now operates purchase of cash JGBs to control yield curve. As a result, the Bank holds over 40% of all JGB issuances. Therefore, it is important to grasp in more detail the situation of liquidity in the JGB cash market, specifically where the Bank is purchasing JGBs under monetary operation.

Second, interest in liquidity and functioning of the JGB cash market by market participants is rising. For example, results from Bond Market Survey on the JGB cash market reveal a considerably large portion of responses claiming that market function is "low" (Chart 1). In addition, in Bond Market Group meetings, opinions on difficulty of transactions were expressed, especially concerning the difference in liquidity by issue. For this reason, it is important to compile liquidity indicators in the JGB cash market and to examine whether evaluation of market participants can be explained with objective data.

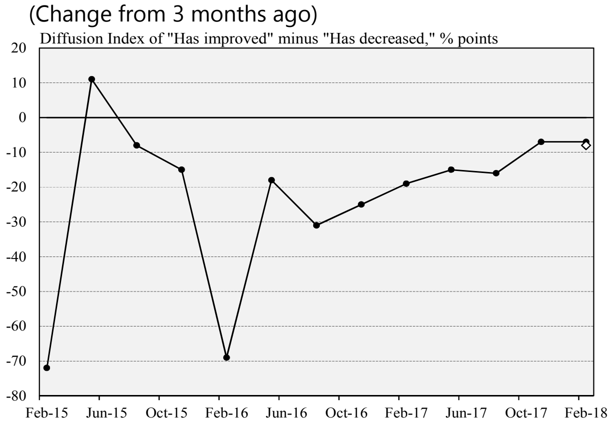
2 Transactions of cash JGBs can be roughly divided into inter-dealer, dealer-to-client, and government bidding/purchase under the Bank of Japan market operation.

Bond Market Survey	Chart 1

Degree of bond market functioning (Current situation)



Degree of bond market functioning (Change from 3 months ago)



1. The survey from February 2018 onward includes responses from major insurance companies, asset management companies, etc., in addition to those from eligible institutions for the Bank's outright purchases and sales of JGBs. 2. Regarding the figures for February 2018, the filled circle indicates the reference data which are based on responses only from eligible institutions for the Bank's outright purchases and sales of JGBs, and the hollow square indicates the data which include responses from major insurance companies, asset management companies, etc.

Source: Bank of Japan

The structure of this paper is as follows: Section 2 briefly presents initiatives by the Bank of Japan to capture the situation of liquidity in the JGB markets; Section 3 explains the details of newly acquired data, and then examines the situation of liquidity in the JGB cash market after the fall of 2015 with new liquidity indicators compiled by this data; Section 4 concludes with a summary of this paper.

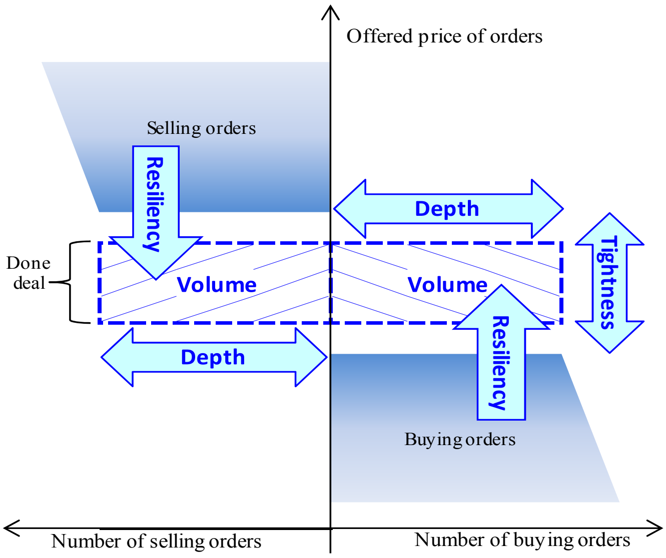
Grasping market liquidity in the JGB cash market

The situation of high market liquidity is thought as one in which "market participants are able to smoothly buy and sell their intended amount at a price close to the market price," or "purchases and sales by each market participant have little impact on the market price." The definition of "market liquidity" is not necessarily uniform and its quantitative measurement is not simple.[3] Therefore, the Bank of Japan is trying to capture market liquidity from a broader range of perspectives by utilizing liquidity indicators, market surveys and dialogues with market participants, while remaining conscious of several limitations about definition and measurement of market liquidity.

[3] Concerning definition discrepancies and measurement of market liquidity, see Nishizaki, Tsuchikawa, and Yagi (2013) and Kurosaki *et al.* (2015).

Liquidity indicators in the JGB markets

The Bank of Japan has been releasing "Liquidity Indicators in the JGB Markets" each quarter since August 2015. In compiling liquidity indicators, we focus on four evaluation axes: volume, tightness, depth, and resiliency. These four evaluation axes are visually captured as shown in the below chart.[4]



Source: Nishizaki, Tsuchikawa, and Yagi (2013).

- Volume: Frequent transactions and large amount transactions become easier with larger transaction volume.
- Tightness: The narrower the price range (the spread between selling and buying prices) is, the traders can execute transactions at a price closer to their intended prices, resulting in a smaller transaction cost.
- Depth: The deeper the market (larger volume of orders at the current price level) is, the smaller the difference between the investors' intended prices and the actual prices. Prices do not easily change even with large amount transactions.
- Resiliency: The more resilient the market (the speed at which prices revert to the equilibrium prices when there are shocks to prices) is, the more smoothly and rapidly traders can execute transactions, therefore less impact on prices.

Regarding the JGB futures market, we grasped market liquidity in detail by compiling indicators with individual transaction data of JGB futures listed on the Osaka Exchange from the viewpoint of the four evaluation axes mentioned above.[5]

4 Measurement from a multiple evaluation axes is also proposed in Kyle (1985), which is a classic study on market liquidity.

5 Tick data provided by Nikkei NEEDS.

Here, individual transaction data of the JGB futures market specifically indicate (1) quotation and volume of bid-ask data per minute and (2) price and volume of transaction data per transaction. Characteristically, such high frequency and granular data (sometimes called detailed transaction data) have much more information than data with only one point per day or aggregate data. On the other hand, regarding the JGB cash market, there are limitations in obtaining such detailed transaction data because most transactions of cash JGBs are bilateral among market participants. Therefore, by using daily and monthly data, we worked on compiling indicators related to volume, tightness, and depth for dealer-to-client transactions of cash JGBs in addition to an indicator related to volume for inter-dealer transactions of cash JGBs. Then we released them in “Liquidity Indicators in the JGB Markets” (Table 1).

Compiling indicators for the JGB cash market

Table 1

“Liquidity Indicators in the JGB Markets” released by the Bank of Japan

	JGB futures market	JGB cash market	
		Dealer–to–client	Inter–dealer
Volume	◎ Transaction volume	△ Transaction volume	○ Transaction volume
Tightness	◎ Bid–ask spread	○ Bid–ask spread	
Depth	◎ Volume of orders at the best–ask price	△ Best–worst quote spread	
Resiliency	◎ Price impact		

Newly compiled liquidity indicators

	JGB cash market
	Inter–dealer
Volume	◎ Transaction volume
Tightness	◎ Bid–ask spread
	◎ Total observation time of bid–ask spreads
Depth	◎ Volume of orders at the best–ask (best–bid) price
	◎ Ratio of issues by total observation time of the best–ask (best–bid) price
Resiliency	◎ Price impact

1. ◎ : compiled with detailed transaction data, ○ : compiled with daily data, △ : compiled with monthly data.

“Bond Market Survey” and “Bond Market Group” meetings

The Bank of Japan introduced the quarterly Bond Market Survey in February 2015 to continuously understand market participants’ views on the functioning of the bond market and outlook of long-term interest rates. In addition, the Bank has held Bond Market Group meetings twice per year since June 2015 to enhance dialogue with market participants in reference to the survey results.

Regarding Bond Market Survey, major institutional investors were added to eligible institutions for the Bank’s outright purchases and sales of JGBs in February 2018. As a result, we are able to capture a wider coverage of market participants. The discussions at the meetings were lively, and following comments were heard at December 2017 meeting: “It has become difficult to deal off-the-run bonds,” and “number and volume of bidding and offering have decreased recently,” and “there is a movement to make dealing lots for transactions smaller beforehand in order to trade smoothly.” These voices suggest that there are rising interests in liquidity of the JGB cash market for market participants.

Expansion of liquidity indicators in the JGB cash market — recent situation of market liquidity

Although the Bank of Japan tried to grasp liquidity in the JGB markets from a broader range of perspectives, compilation of liquidity indicators in the JGB cash market is not enough due to difficulty of obtaining detailed transaction data. Some indicators of dealer-to-client transactions are compiled from daily and monthly data, but it is not possible to comprehend situations in intraday market liquidity in detail. Furthermore, it is difficult to construct indicators of inter-dealer transactions other than transaction volume.

Hence, we decided to acquire tick data from the Japan Bond Trading, the largest company for intermediation of inter-dealer transactions, and expand liquidity indicators of inter-dealer transactions in the JGB cash market. In this section, we compile new liquidity indicators related to tightness, depth, and resiliency on the basis of detailed transaction data of inter-dealer transactions. Then, adding them to current indicators related to volume, we can examine situations about market liquidity of inter-dealer transactions in the JGB cash market using the four evaluation axes. These indicators allow us to capture market liquidity in more detail, i.e., liquidity in intraday market and of all JGB issues. In addition, we expect to evaluate some comments voiced at Bond Market Group meetings based on the indicators compiled with objective data.

Details of newly acquired detailed transaction data

The Bank of Japan compiled new liquidity indicators by using tick data provided by the Japan Bond Trading, such as that of bonds traded and/or ordered at the electric trading system. Tick data acquired from the Japan Bond Trading consists of information related to both (1) execution such as price and amount per transaction and (2) orders such as best-bid and best-ask prices presented during intraday—best prices presented by buyers and sellers—as well as the amount of these orders (we call this information detailed transaction data). In this study, we analyzed 2-year, 5-year, 10-year, 20-year, 30-year, and 40-year JGBs; Further, we took into consideration seven hours per day.[6]

Volume

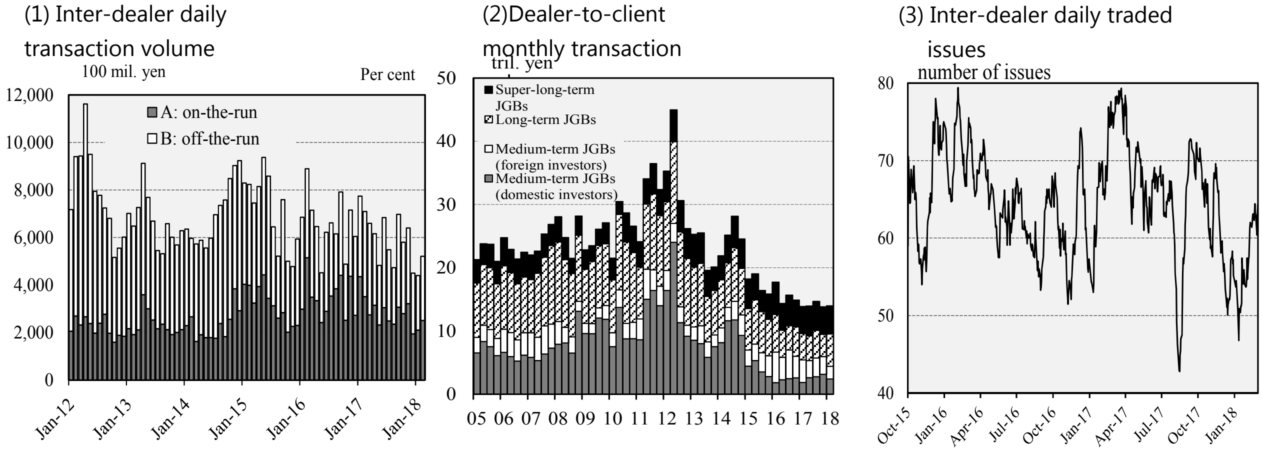
Concerning volume in the JGB cash market, we release information for both dealer-to-client and inter-dealer transactions in the current "Liquidity Indicators in the JGB Markets." From the trend of inter-dealer transactions since 2016, we found that transaction volume remained close to the same level. The ratio of transactions of on-the-run bonds to total transactions seemed to gradually increase, and the fluctuation of transaction volume became somewhat larger than before. However, from the assessment of dealer-to-client transactions in the JGB cash market,

[6] There are about 300 issues of cash JGBs as at January 2018.

transaction volume decreased primarily because of a decrease in transactions of long-term and medium-term bonds traded by domestic investors. The volume of transactions has remained generally flat since mid-2016 (Chart 2).

Transaction volume

Chart 2



(1) is the sum of 2-year, 5-year, 10-year, 20-year, 30-year, and 40-year JGBs via Japan Bond Trading. 2. Treasury Discount Bills, etc. are excluded from (2). 3. "Clients" include city banks, regional financial institutions, investors, and foreigners. Other institutions (government, Bank of Japan, Japan Post Bank, Japan Post Insurance, business corporations, other financial institutions, etc.) are excluded from "clients." 4. 10-day backward moving average is applied to (3). Latest data as at end-February 2018.

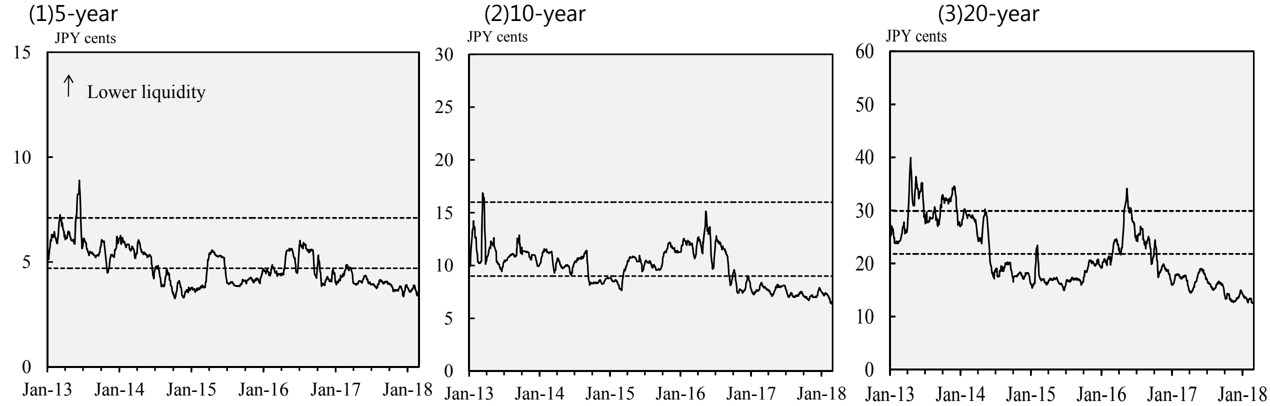
Sources: QUICK; Japan Bond Trading; Japan Securities Dealers Association.

Recently, we have been able to examine the number of issues of cash JGBs traded with detailed transactional data, which amounted to 50–80 each day since the fall of 2015, and then decreased several times to less than 50 in the second half of 2017 (Chart 2).

Tightness

We release bid-ask spreads based on the data of dealer-to-client transactions of on-the-run bonds at 15:00 each day in the current "Liquidity Indicators in the JGB Markets" to understand tightness in the JGB cash market. These bid-ask spreads, once widened in the summer of 2016, gradually shrank from the fall of 2016, and were recently at the lowest level in the past five years (Chart 3).

Bid-ask spreads of dealer-to-client transactions (tightness) Chart 3



1. Quotations through Trade web as of 3:00 p.m. Dotted lines indicate the first/third quartile spreads between January 2010 and March 2013. 2. 10-day backward moving average. Latest data as at end-February 2018.

Source: Thomson Reuters.

In addition to the bid-ask spreads, we compiled new bid-ask spreads of inter-dealer transactions as an indicator to enable analysis of liquidity in intraday market by issue. Furthermore, we will compile a new indicator named total observation time of bid-ask spreads for inter-dealer transactions to complement bid-ask spreads, because, unlike in JGB futures transactions, there are time periods during which bid and/or ask prices are not submitted.

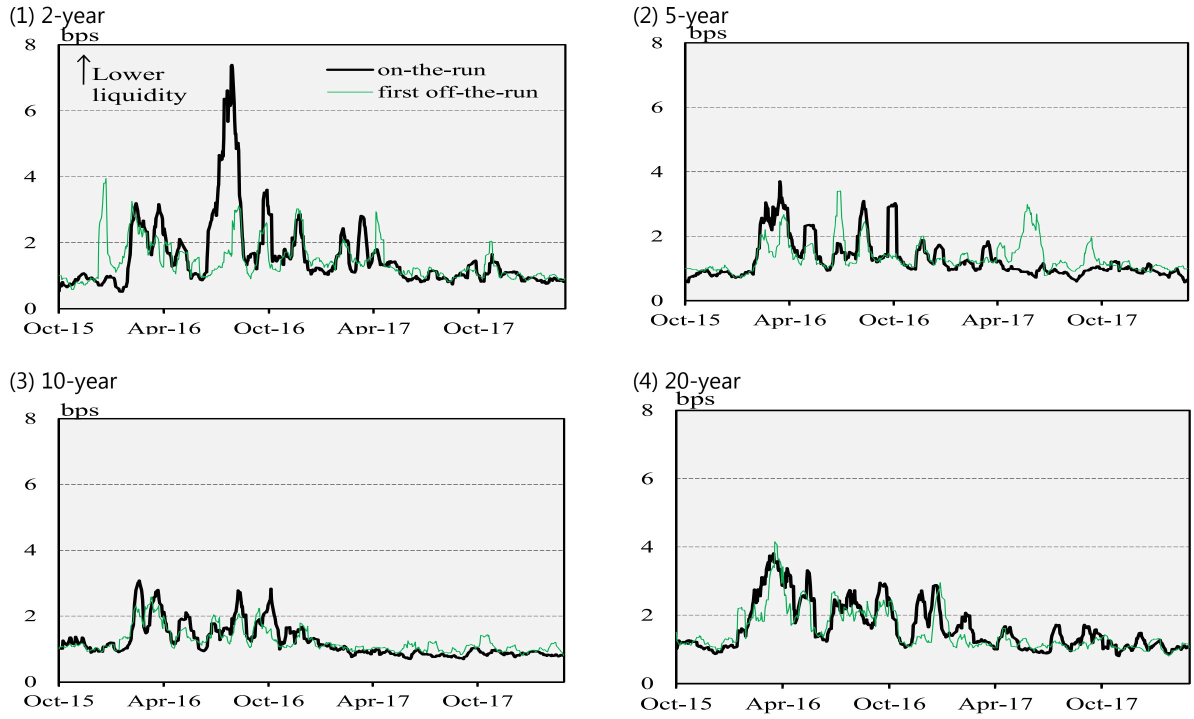
Bid-ask spread

The bid-ask spreads (average of the widest 10 percent) of both on-the-run and first off-the-run bonds were compiled with detailed transaction data of inter-dealer transactions.[7] Once they widened in the summer of 2016, then gradually shrank from the fall of 2016; however, recently they were the same or less compared to those in the latter half of 2015, similar to the development of bid-ask spreads of dealer-to-client transactions (Chart 4). This suggests that trading as a whole is easier now than during the last few years, considering the difference between prices submitted by sellers and buyers. Comments by market participants, such as "based on close communication between the BoJ and market participants, predictability about future interest rates is high, and therefore trading is easy to do," support the evidence from Chart 4. However, we must pay attention to the observation that

[7] Average of the widest 10 percent is calculated by averaging the widest 10 percent of bid-ask spreads with a 1-second frequency. It is possible to compile an indicator with different levels of percentile and/or simple average.

there have been occasional events where bid-ask spreads have widened since the beginning of 2016 (e.g., 5-year first off-the-run bond).

Bid-ask spreads of inter-dealer transactions (tightness) Chart 4



1. Figures indicate the average of the widest 10 percent of bid-ask spreads with a 1-second frequency. 2. Bid-ask spreads are calculated only for time periods in which both best-bid and best-ask prices were submitted. 3. 10-day backward moving average. Latest data as at end-February 2018.

Sources: Japan Bond Trading.

Total observation time of bid-ask spreads

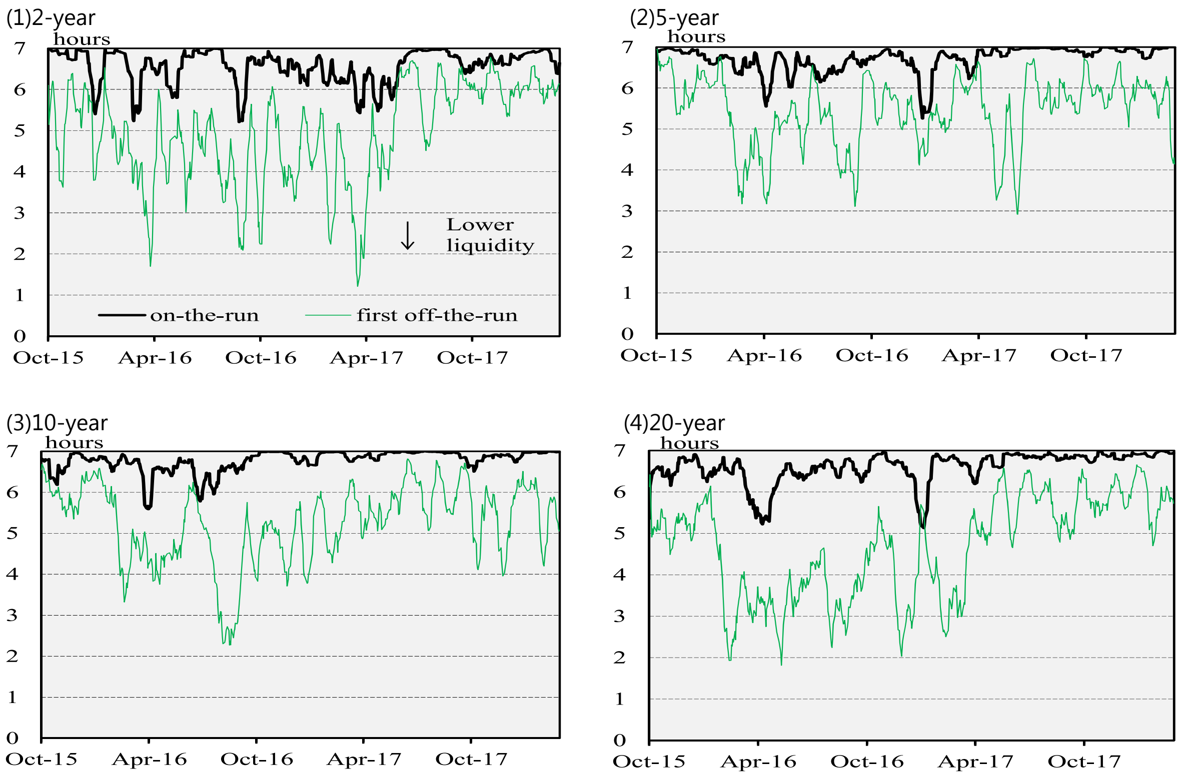
Regarding bid-ask spreads of inter-dealer transactions compiled and explained above, we first calculated spreads over each time period in which both bid and ask prices are submitted, and then filtered out 10 percent of the widest spreads and calculated the average. However, it should be noted that there are times when bid and/or ask prices are not submitted in inter-dealer transactions, differing from the fact that prices are submitted almost all the time in the JGB futures market, owing to the market-maker system. Thus, a reduction in bid-ask spreads does not necessarily mean an improvement of liquidity conditions, if bid and/or ask prices are not submitted. To compensate for this, we also compiled a new indicator of total observation time of bid-ask spreads in addition to bid-ask spreads.

The indicator we call total observation time of bid-ask spreads indicates a length of hours when both bid and ask prices were submitted within a day. First, the indicators of first off-the-run bonds are lower and the swing width of the indicators are larger compared with on-the-run bonds. Second, the indicators of both on-the-run bonds and first off-the-run bonds decreased considerably at the beginning of 2016, then gradually improved from during the fall of 2016 to the spring of 2017.

However, long- and super-long-term first off-the-run bonds had some days in which there is not enough observation time of bid-ask spreads (Chart 5). These results coincide with voices from market participants such that “with the increase of the proportion of the JGB amounts which the Bank of Japan holds, trading is difficult, especially for off-the-run issues,” and “there are situations where neither bid nor ask prices are seen.”

Total observation time of bid-ask spreads of inter-dealer transactions (tightness)

Chart 5



1.Figures indicate the total length of time in which both best-bid and best-ask prices were submitted. 2. 10-day backward moving average. Latest data as at end-February 2018.

Source: Japan Bond Trading.

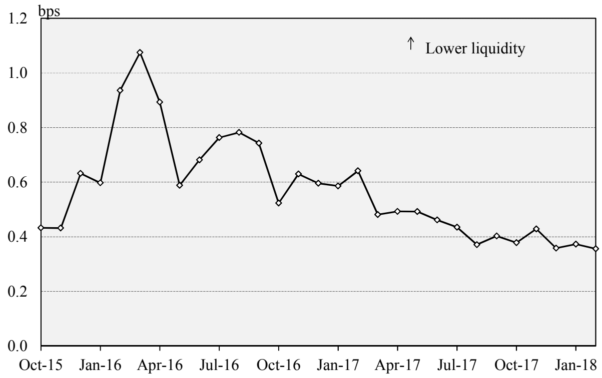
Depth

As for measuring depth in the JGB cash market, we release best-worst quote spreads (monthly basis) in the current "Liquidity Indicators in the JGB Markets."[8] The spread greatly expanded at the beginning of 2016, meaning that market liquidity decreased, then it gradually shrank, and recently fell below the level which was in the latter half of 2015 (Chart 6).

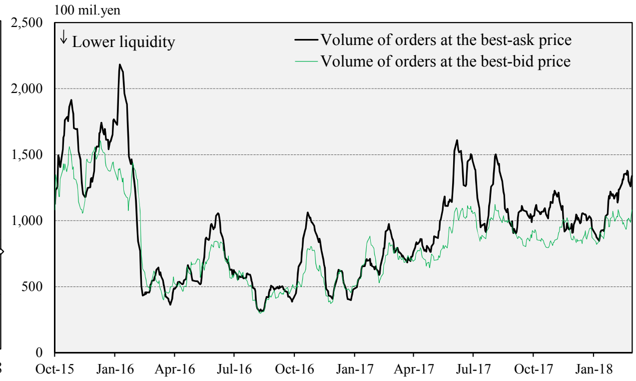
Market depth (depth)

Chart 6

(1) Best-worst quote spreads of dealer-to-client transactions



(2)Volume of orders at the best-ask(bid) price of inter-dealer transactions



(1) is calculated by averaging the spreads between the best and worst quotes offered by dealers against each client request. Transactions with spreads wider than 10 bps are excluded from the calculation. (2) is calculated by summing up the median of volume of orders at the best-ask (best-bid) price with a 1-second frequency per issue. 10-day backward moving average. 3. Latest data as at end-February 2018.

Sources: Yensai.com; Japan Bond Trading.

In addition to best-worst quote spreads, we compiled two new indicators for inter-dealer transactions with detailed transaction data. The volume of orders at the best-ask (best-bid) price enables us to capture liquidity in intraday market by issue, and the ratio of issues by total observation time of the best-ask (best-bid) price represents how orders are submitted.

Volume of orders at the best-ask (best-bid) price

The indicator we call volume of orders at the best-ask (best-bid) price in inter-dealer transactions greatly decreased at the beginning of 2016, meaning that market liquidity decreased, then has gradually increased since fall 2016, similar to best-

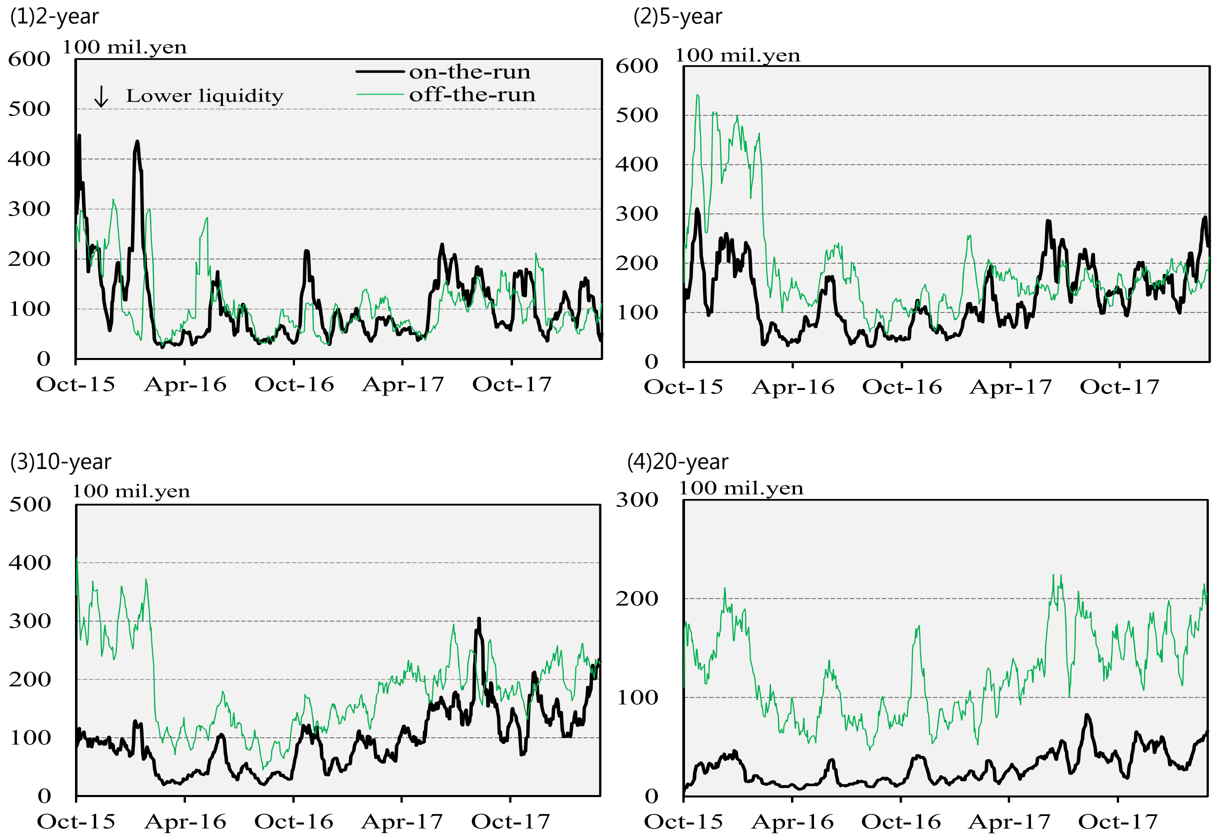
[8] The best-worst quote spread was calculated by averaging the spreads between the best and the worst quotes offered by dealers against each client request. This spread is close to the measure of market depth, in the sense that a tight best-worst quote spread means that a client has many dealers to make transactions at a price level near the best quote.

worst quote spreads in dealer-to-client transactions[9] (Chart 6). This suggests that trading as a whole is easier for dealers now than the last few years, reflecting that prospects for interest rates among market participants have converged since around the fall of 2016, consistent with the development of bid-ask spreads. However, we note that the volume of orders at the best-ask (best-bid) price does not recover to the level in the beginning of 2016, differing from best-worst quote spreads (monthly basis). By examining the volume of orders at the best-ask price in more detail, in terms of residual maturity per issue, we see that volumes of super-long-term bonds are recovering while short-term bonds and 10-year off-the-run bonds have a low degree of recovery (Chart 7). It is also noted that the volume of orders at the best-ask price is calculated by summing up all issues and therefore is not directly related to the ease of large amount transactions.

9 The volume of orders at the best-ask (best-bid) price is calculated by summing up the median of volume at the best-ask (best-bid) price with a 1-second frequency per issue.

Volume of orders at the best-ask price by residual maturity of inter-dealer transaction (depth)

Chart 7



1.Figures indicate the sum of the median of volume of orders at the best-ask price with a 1-second frequency per issue. 2. 10-day backward moving average. Latest data as at end-February 2018.

Source: Japan Bond Trading.

Ratio of issues by total observation time of best-ask (best-bid) price

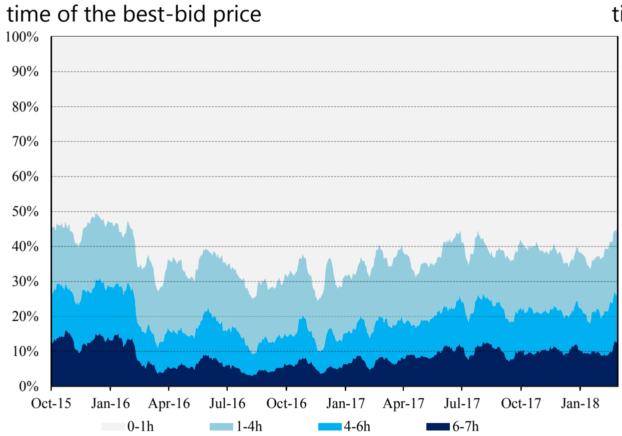
The volume of orders at the best-ask (best-bid) price shows market depth from the size of the order amount traded at the best price. Here, we tried to capture depth in the JGB cash market based on the number of issues with a lengthy observation time of the best-ask (best-bid) price. Specifically, we compiled a new indicator of ratio of issues by total observation time of the best-ask (best-bid) price, capturing the percentage of issues according to the length of time that the best-ask (best-bid) price is submitted. For example, if the ratio of issues with a lengthy observation time of the best-ask (best-bid) price is high in short-term maturity, prices of other issues with short maturities are unlikely to be affected even when supply and demand conditions for a certain issue in short-term maturity tightens. We can consider this as an indicator for market depth.

First, looking at the ratio of issues by total observation time of the best-ask price, we find that the proportion of issues whose prices were submitted for more than six hours per day (less than one hour) drastically decreased (increased) at the beginning of 2016, then gradually increased (decreased) from the fall of 2016. Recently, the proportion improved (declined) to the level it was at the beginning of 2016. Next, concerning the ratio of issues by total observation time of the best-bid price, we found that it is similar to the best-ask price, but the degree of improvement of the best-bid price has been smaller than that of the best-ask price since around fall 2016 (Chart 8).

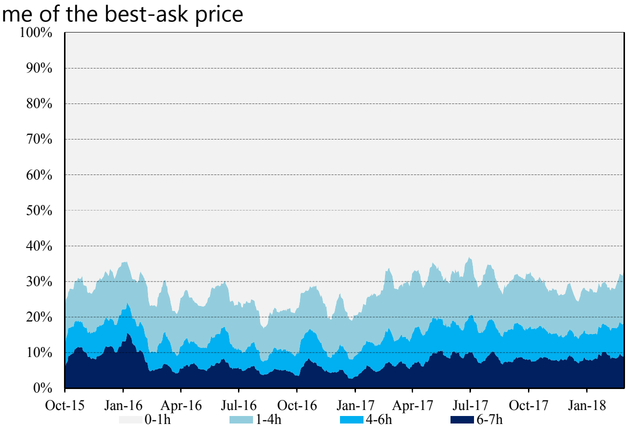
Ratio of issues by total observation time of the best-bid (best-ask) price of inter-dealer transactions (depth)

Chart 8

(1) Ratio of issues by total observation time of the best-bid price



(2) Ratio of issues by total observation time of the best-ask price



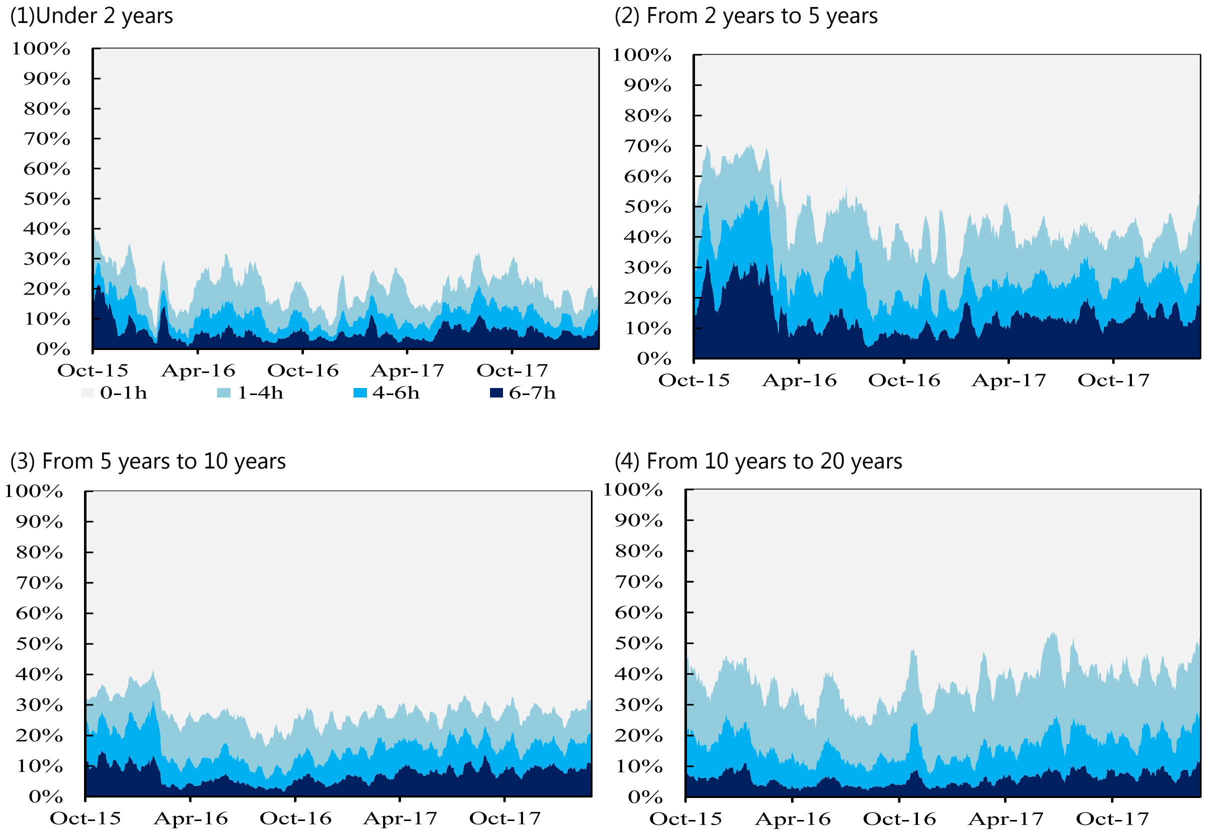
1.Figures indicate the percentage of issues by daily observation time, 0-1hours, 1-4hours, 4-6hours, 6-7 hours, of best-bid (best-ask) prices.
2. 10-day backward moving average. Latest data as at end-February 2018.

Source: Japan Bond Trading.

Thus, we observed the ratio of issues by total observation time of the best-bid price by residual maturity. We found that indicators for super-long-term maturity are recovering, while the indicator of more than six hours for short-term maturity is just slightly recovering and the indicator of less than one hour for short-term maturity is still high. This suggests a possibility that if large amount transactions of a certain bond in short-term maturity are conducted, prices of other bonds in short-term maturity are affected (Chart 9).

Ratio of issues by total observation time of the best-bid price by residual maturity of inter-dealer transactions (depth)

Chart 9



1. Figures indicate the percentage of issues by daily observation time, 0-1hours, 1-4hours, 4-6hours, 6-7 hours, of best-bid price.
2. 10-day backward moving average. Latest data as at end-February 2018.

Source: Japan Bond Trading.

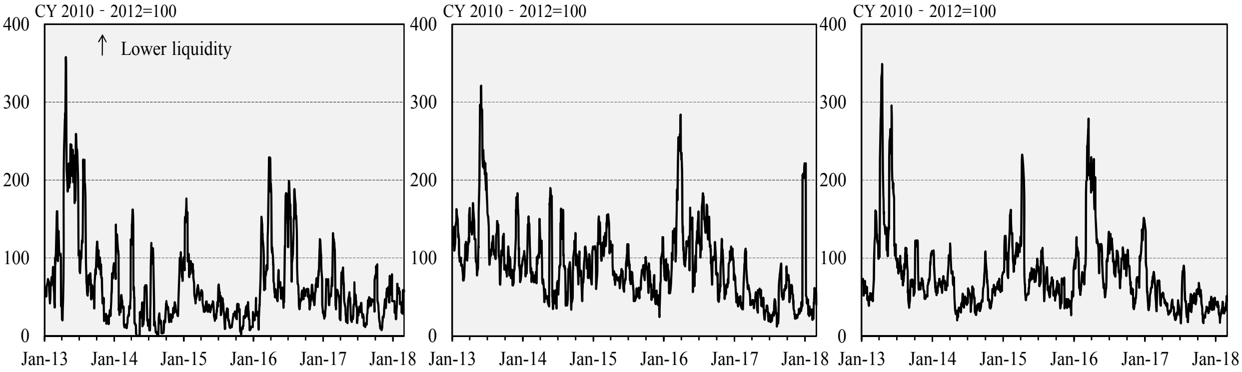
Resiliency

So far, we observed daily price range to transaction volume ratio as a proxy for resiliency of on-the-run bonds in inter-dealer transactions [10] (Chart 10). These indicators had large rises around the spring of 2016, and the indicator of 10-year on-the-run bond had a large increase in December 2017. However, this indicator was limited in that intraday developments cannot be grasped because it is not calculated with detailed transaction data but with only daily data.

[10] The daily price range to transaction volume ratio is defined as the difference between the highest and lowest transaction prices of the day divided by the transaction volume within the day.

Daily price range to transaction volume ratio of inter-dealer transactions (resiliency) Chart 10

(1) 5-year (2) 10-year (3) 20-year



1. 10-day backward moving average. Latest data as at end-February 2018.

Source: QUICK

To overcome this limitation, this paper references to Cont et al. (2014) in that price impact indicator—the influence of change per unit volume of orders on the market price—was compiled with information related to orders such as the best-bid(ask) prices, and is frequently updated rather than information related to execution. Assuming that order flow imbalances (OFI) for the following equations, and we measure the impact per unit of OFI on the market price (in the JGB cash market) by dividing change width of the best-bid (best-ask) prices by OFI.[11]

$$OFI_n^b = q_n^b I_{[P_n^b \geq P_{n-1}^b]} - q_{n-1}^b I_{[P_n^b \leq P_{n-1}^b]},$$

$$OFI_n^a = q_{n-1}^a I_{[P_n^a \geq P_{n-1}^a]} - q_n^a I_{[P_n^a \leq P_{n-1}^a]},$$

$$\beta_n^b = \Delta P_n^b (= P_n^b - P_{n-1}^b)/OFI_n^b,$$

$$\beta_n^a = \Delta P_n^a (= P_n^a - P_{n-1}^a)/OFI_n^a,$$

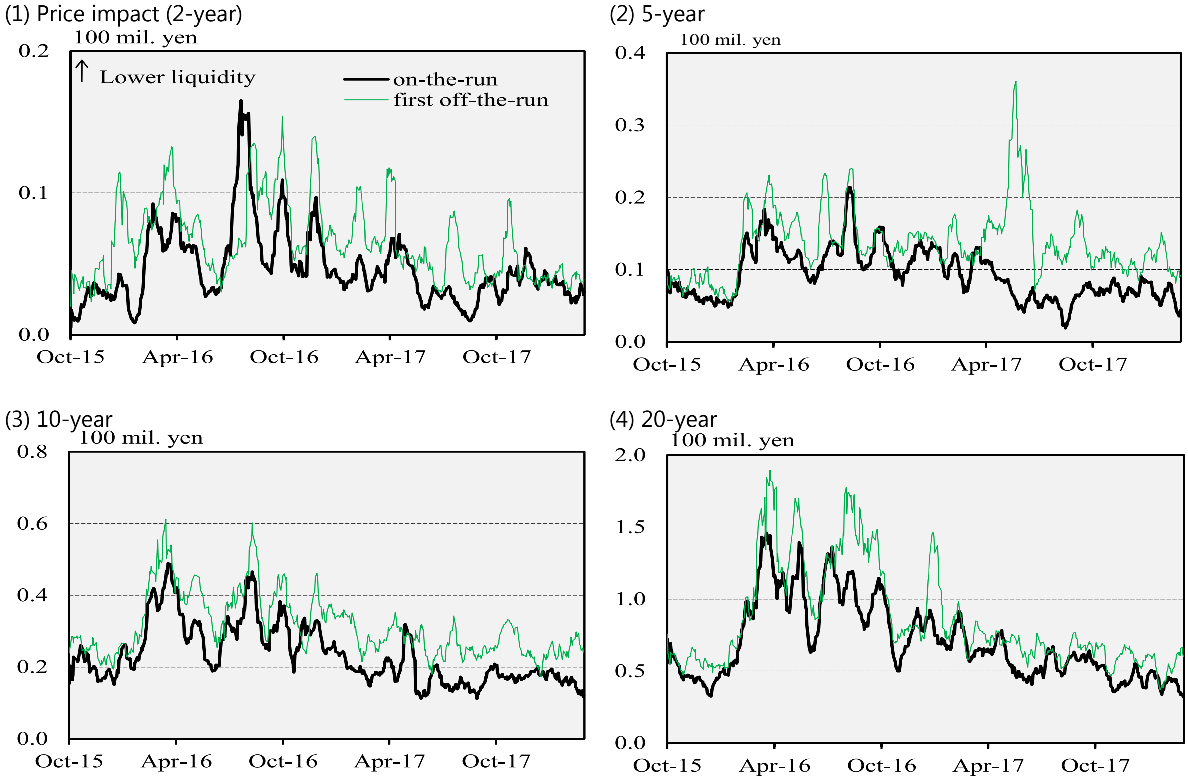
$$\beta = \left(\sum_{n=1}^{N_b} \beta_n^b + \sum_{n=1}^{N_a} \beta_n^a\right)/(N_b + N_a).$$

Here, N_b is a number representing the best-bid price updated on a day, N_a is a number for the best-ask price updated on a day, $P_n{}^b$ is the best-bid price, $P_n{}^a$ is the best-ask price, $q_n{}^b$ is the volume at the best-bid price, $q_n{}^a$ is the volume at the best-ask price. OFI is order flow imbalances. I [•] is a function that is 1 if the condition in [ ] is satisfied and 0 otherwise.

11 Consider, for example, a case where market participants strongly want to purchase cash JGBs and a new bid order (volume, q) is submitted at a price (P') higher than current best-bid price (P). In this case, OFI is q, the change width of the best-bid prices is ($P'–P$), and the price impact of this order becomes ($P'–P$)/q.

The price impacts (β) of on-the-run bonds largely increased in the spring and summer of 2016, then fell from the fall of 2016, and recently were lower than the levels in the spring and summer of 2016, which is similar to indicators of daily price range to transaction volume ratio. The improvement of market resiliency indicates the market price is hard to move drastically even with large amount transactions. However, it also suggests that market liquidity in short-term maturity is still relatively low because indicators of first off-the-run bonds in short-term maturity continue to greatly fluctuate (Chart 11). In addition, a spike in the daily price range to transaction volume ratio for 10-year on-the-run bond in December 2017 was not observed in the price impact for the same bond. This may suggest that daily price range to transaction volume ratio spiked because transaction volume of 10-year on-the-run bond at that time was low, yet the price impact (β) complied with detailed transaction data did not spike because the volume of orders was higher.

Price impact (*β*) of inter-dealer transactions (resiliency) Chart 11



1. 10-day backward moving average. Latest data as at end-February 2018. Sources: QUICK; Japan Bond Trading.

We note the voices from market participants that "based on transaction volume at the market, investors and securities companies reduce the amount to a range that can be transacted smoothly". It is important to understand that this behavior of reducing the amount may have the indicator of the price impact (β) to improve.

Conclusion

This paper explained new market liquidity indicators for tightness, depth, and resiliency with detailed transaction data of inter-dealer transactions in the JGB cash market. These indicators greatly expand upon the current indicators in "Liquidity Indicators in the JGB Markets," because they can grasp intraday market liquidity of all JGB issues.

New liquidity indicators for inter-dealer transactions in the JGB cash market considerably worsened at the beginning of 2016, and then have gradually improved since the fall of 2016, as confirmed in section 3. This development is similar to indicators for the JGB futures market and dealer-to-client transactions in the JGB cash market.

Observations about the JGB cash market suggested that, from the perspective of bid-ask spreads and volume of orders, we are in a better environment for trading than after the introduction of negative interest rate policy. These bid-ask spreads and volume of orders improve as prospects of market participants' interest rates converge under QQE with Yield Curve Control.

We must pay attention that such improvement of liquidity indicators is not accompanied by an increase in transaction volume. There is no major obstacle in executing each transaction when needs for transactions are relatively small, while it is possible that stabled liquidity indicators, such as bid-ask spreads and volume of orders, will deteriorate or destabilize if needs for transactions rapidly increase with change in future market conditions.

For this reason, it is important to carefully observe various liquidity indicators for a sign of deterioration or destabilization in market liquidity, and which type of transactions is more vulnerable to change in market conditions. According to newly compiled liquidity indicators with detailed transaction data, especially for short-term and off-the-run bonds, the improvement of indicators was delayed and indicators temporarily deteriorated during intraday. We have to continue to analyze market liquidity deeply. Thus, we can capture market liquidity in more detail with newly compiled liquidity indicators. It is beneficial to continue examining the JGB markets, including these indicators.

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Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

Liquidity in the JGB cash market: an evaluation from detailed transaction data[1]

Toshiyuki Sakiyama and Shun Kobayashi,
Bank of Japan

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[1] This presentation was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

Liquidity in the Cash Market:

An Evaluation from Detailed Transaction Data

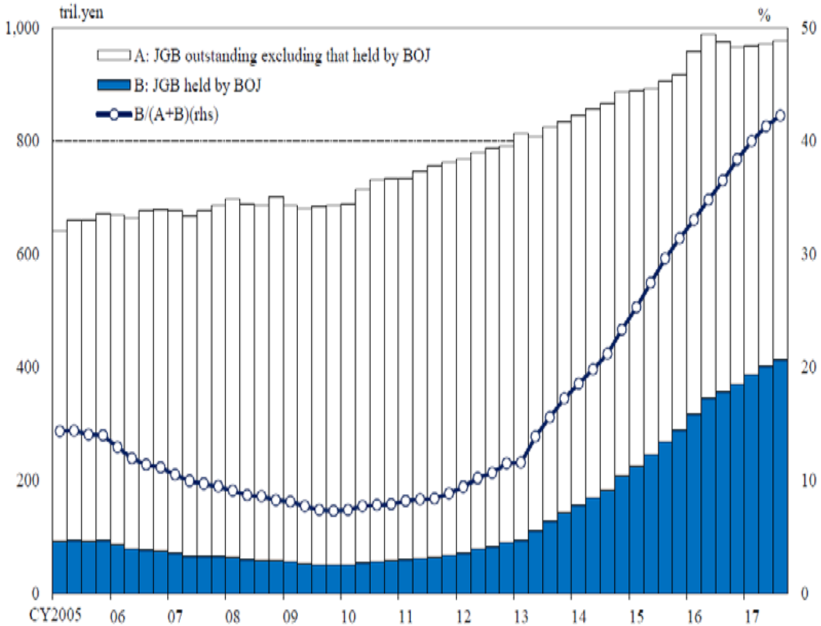
August 2018

Toshiyuki Sakiyama
Shun Kobayashi
Bank of Japan

Importance of grasping JGB cash market liquidity

- BoJ has been purchasing massive amounts of cash JGBs since the introduction of "Quantitative and Qualitative Monetary Easing (QQE)" in April 2013 (In September 2016, BoJ introduced a new framework, "QQE with Yield Curve Control"). As a result, BoJ holds over 40% of all JGB issuances. Therefore, it is important to grasp in more detail the liquidity in the JGB cash market, from which BoJ purchases JGBs in particular.
- The definition of "market liquidity" is not necessarily uniform and its quantitative measurement is not simple. Therefore, BoJ tries to capture market liquidity from a broader range of perspectives by utilizing liquidity indicators, market surveys and dialogues with market participants.

Share of JGB holdings by BoJ



Source: Bank of Japan

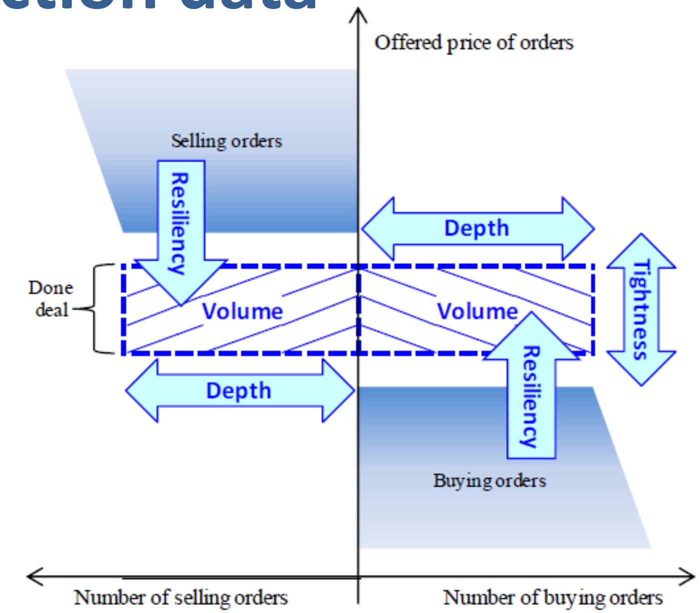
BoJ's initiative for grasping JGB market liquidity

	(i) Liquidity Indicators in the JGB Markets	(ii) Bond Market Survey
Contents	Liquidity indicators using individual transaction data to monitor liquidity in the JGB markets from multiple angles	Market participants' views on functioning of the bond market, outlook of interest rates
Focus	Indicators include both those for the JGB futures market and for the JGB cash market.	Respondents are banks, securities companies, insurance companies etc.

We expanded liquidity indicators by acquiring tick data

Expansion of Liquidity indicators based on detailed transaction data

- BoJ has been releasing "Liquidity Indicators in the JGB Markets" each quarter since 2015. In compiling indicators, we focus on four evaluation axes: volume, tightness, depth, and resiliency.
- However, compilation of liquidity indicators in the JGB cash market was inadequate due to difficulty of obtaining detailed transaction data. We decided to acquire tick data from Japan Bond Trading, the largest company for intermediation of inter-dealer transactions, and expand liquidity indicators.



Liquidity Indicators in the JGB Markets" released by the BoJ

	JGB futures market	JGB cash market	
		Dealer-to-client	Inter-dealer
Volume	◎ Transaction volume	△ Transaction volume	○ Transaction volume
Tightness	◎ Bid-ask spread	○ Bid-ask spread	
Depth	◎ Volume of orders at the best-ask price	△ Best-worst quote spread	
Resiliency	◎ Price impact		

Newly compiled liquidity indicators

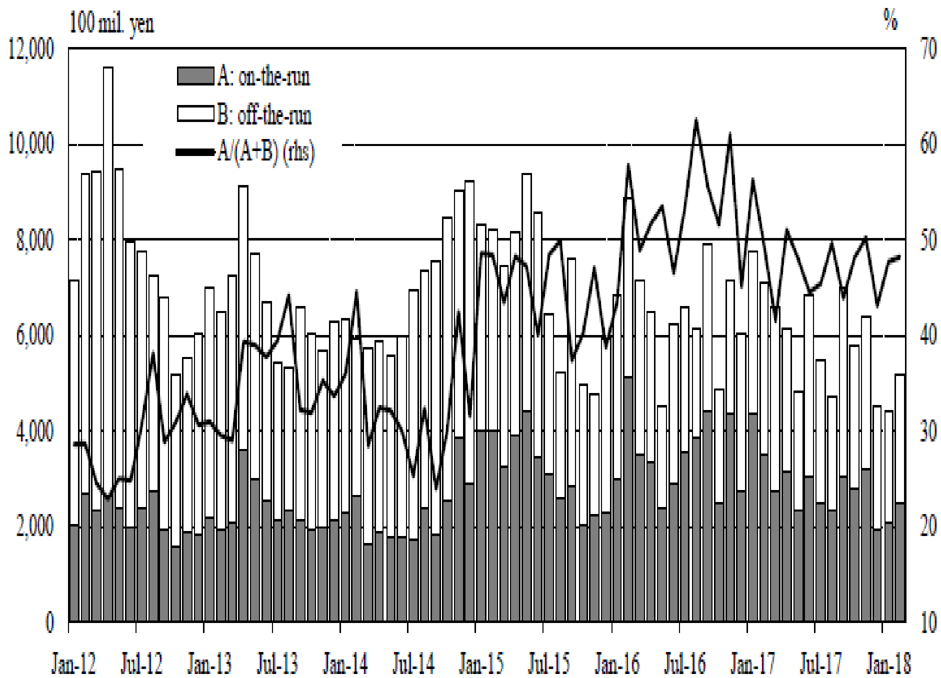
JGB cash market
Inter-dealer
◎ Transaction volume
◎ Bid-ask spread
◎ Total observation time of bid-ask spreads※
◎ Volume of orders at the best-ask (best-bid) price
◎ Ratio of issues by total observation time of the best-ask (best-bid) price※
◎ Price impact

Notes: 1. ◎ : compiled with detailed transaction data, ○ : compiled with daily data, △ : compiled with monthly data.
2. ※: compiled from new perspectives.

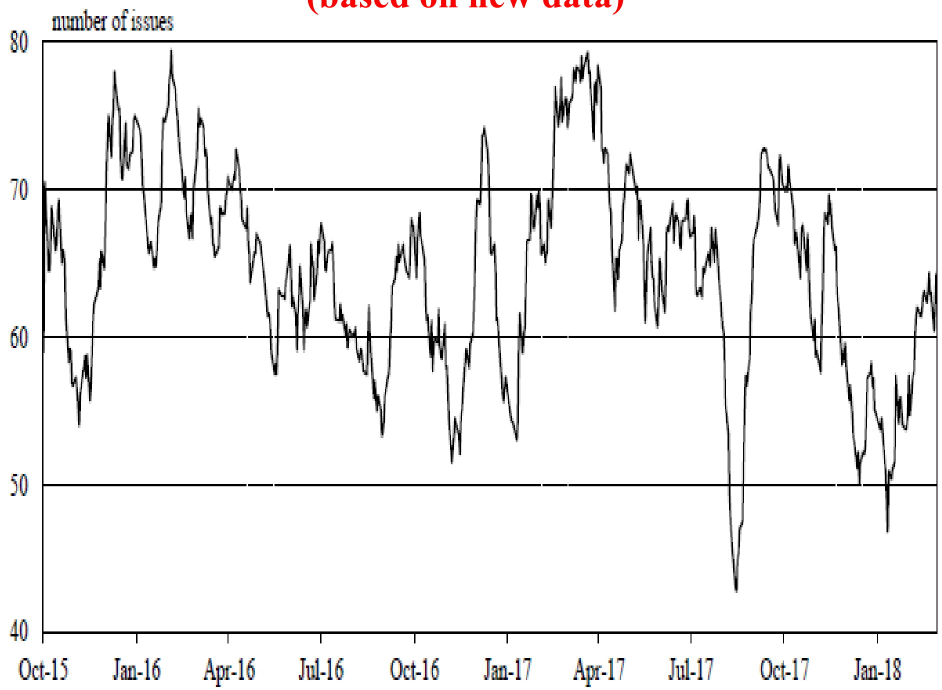
Liquidity indicators – transaction volume

- From the trend of inter-dealer transactions since 2016, we found that transaction volume remained close to the same level.
- However, with the newly acquired detailed transaction data, we have been able to examine the number of issues of cash JGBs traded each day, which amounted to 50–80 after fall 2015, and then decreased several times to less than 50 in the second half of 2017.

Inter-dealer daily transaction volume



Inter-dealer daily traded issues (based on new data)



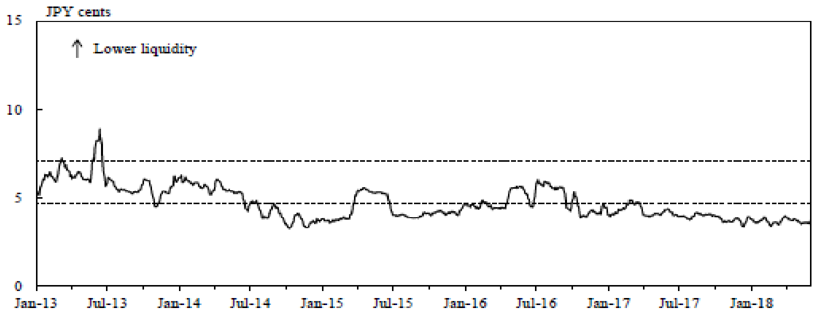
Notes: 1. Transaction volume is the sum of 2-year, 5-year, 10-year, 20-year, 30-year, and 40-year JGBs via Japan Bond Trading.
2. Number of issues indicates 10-day backward moving average. Latest data as at end-February 2018.
Sources: QUICK, the Japan Bond Trading

Liquidity indicators – tightness

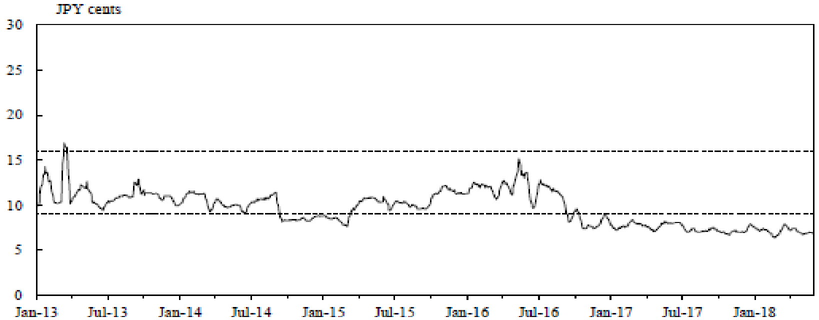
- By using new data, we can also check tightness (measured by bid-ask spreads) in more detail.

Bid-ask spreads of dealer-to-client transactions

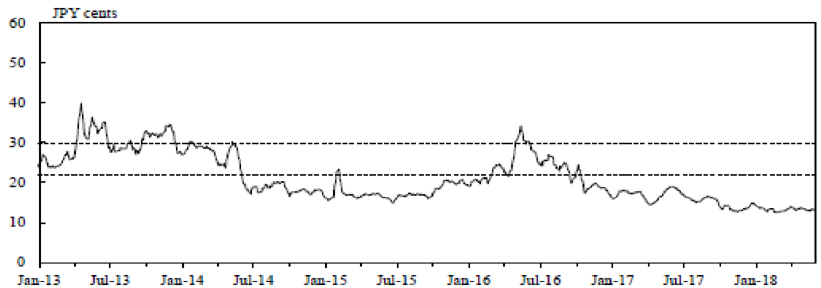
(1) 5-year JGBs



(2) 10-year JGBs



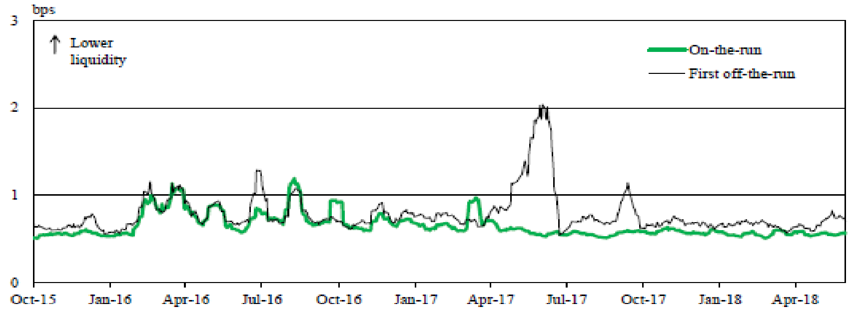
(3) 20-year JGBs



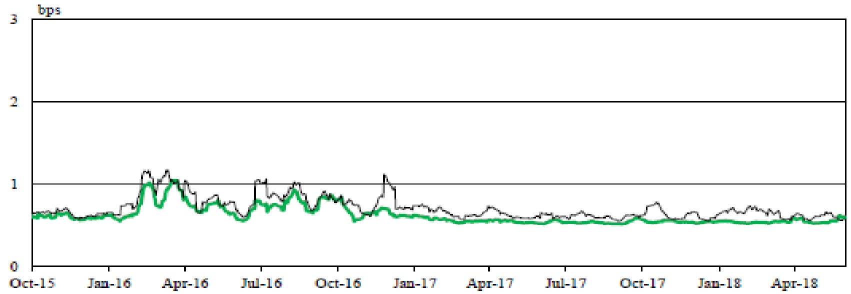
Note: Quotations through Trade web as of 3:00 p.m. Dotted lines indicate the first/third quartile spreads between January 2010 and March 2013. 10-day backward moving average. Latest data as at end-May 2018.
Source: Thomson Reuters

Bid-ask spreads of inter-dealer transactions (based on new data)

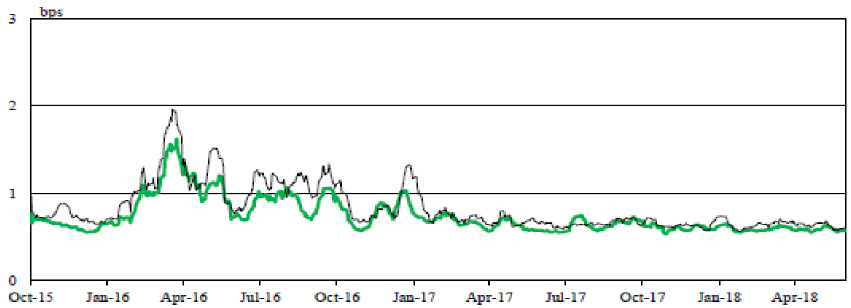
(1) 5-year JGBs



(2) 10-year JGBs



(3) 20-year JGBs

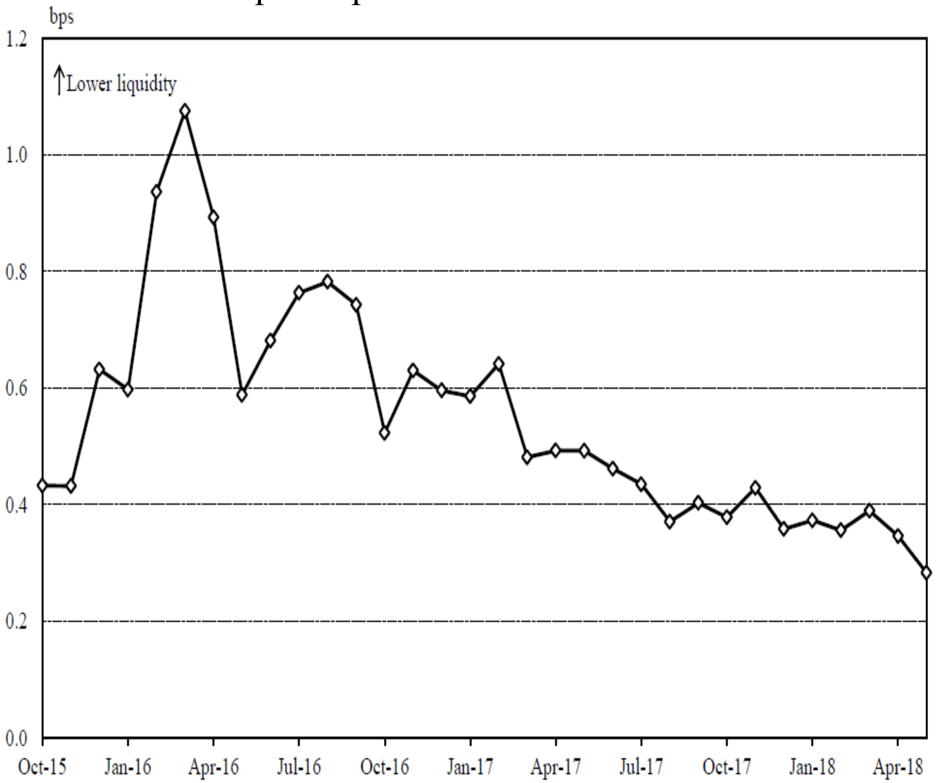


Notes: Figures indicate the average of bid-ask spreads with a 1-second frequency. Bid-ask spreads are calculated only for time periods in which both best-bid and best-ask prices were submitted. 10-day backward moving average. Latest data as at end-May 2018.
Source: Japan Bond Trading.

Liquidity indicators – depth

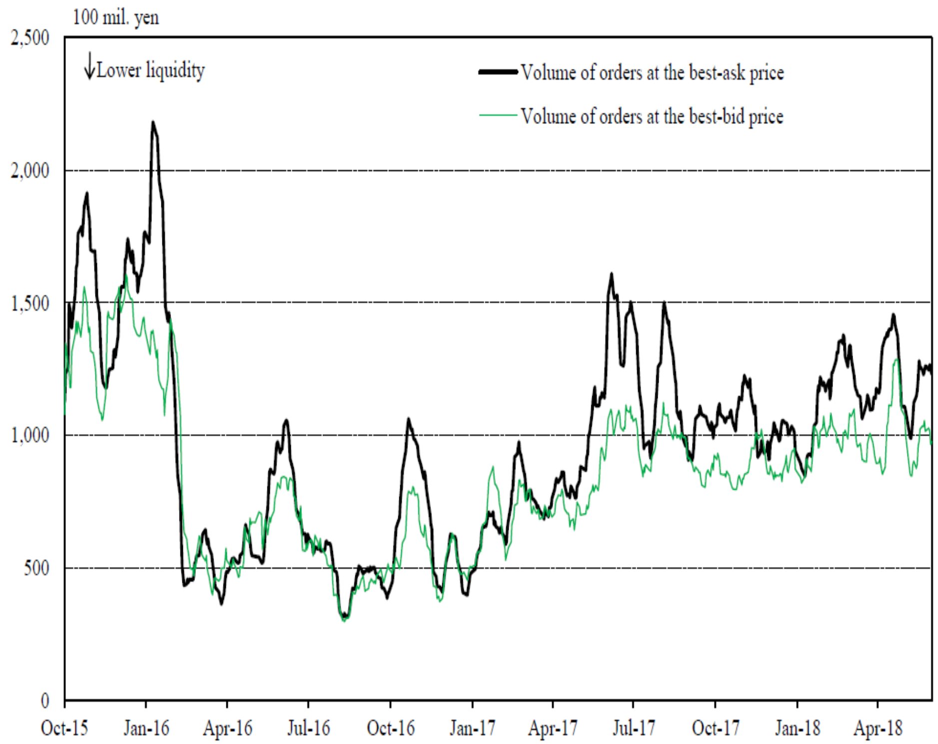
- Without newly acquired data, we couldn't construct a "depth" (The larger the volume of orders at the current price level, the smaller the difference between the investors' intended prices and the actual prices).
- Based on the new data, we can construct a new measure – "the volume of orders at the best-ask(bid) price"- which enables us to capture liquidity in the intraday market by issue.

Best-worst quote spreads of dealer-to-client transactions



Note: Calculated by averaging the spreads between the best and worst quotes offered by dealers against each client request. Transactions with spreads wider than 10 bps are excluded from the calculation. Latest data as at end-May 2018.
Source: Yensai.com

Volume of orders at the best-ask (best-bid) price of inter-dealer transactions (based on new data)



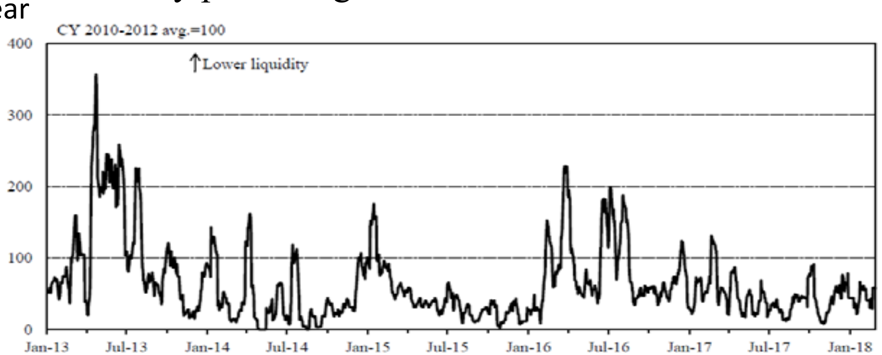
Note: Calculated by summing up the median of volume of orders at the best-ask (best-bid) price with a 1-second frequency per issue. 10-day backward moving average. Latest data as at end-May 2018.
Source: Japan Bond Trading.

Liquidity indicators – resiliency

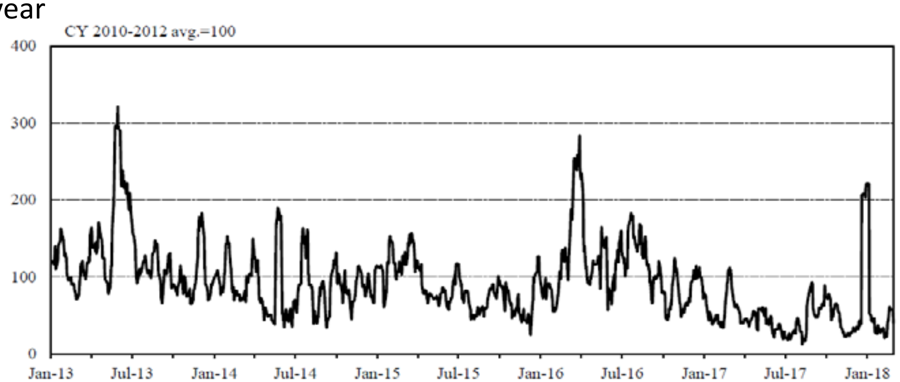
- So far, we depended on a crude measure – "daily price range to transaction volume ratio" – to grasp the resiliency of the JGB cash market.
- Based on the new data, we can construct a new resiliency measure. We have measured the impact of change per unit volume of orders on market prices with information related to orders such as the best-bid and best-ask prices, which is frequently updated rather than with information related to the execution of orders.

Daily price range to transaction volume ratio

5-year

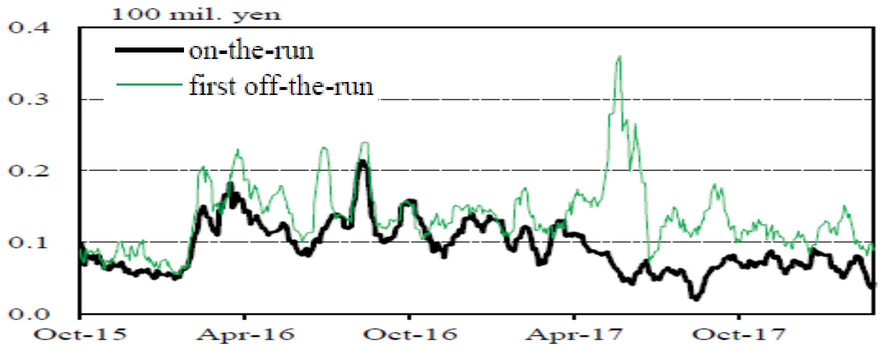


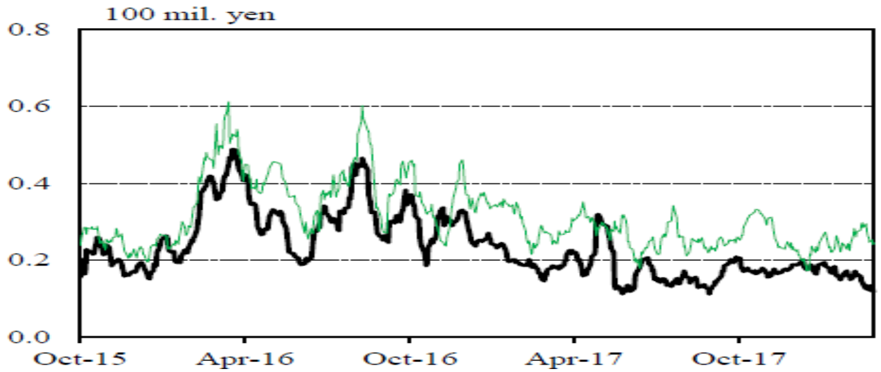
10-year



Note: Daily price range (the difference between the highest and lowest transaction prices of the day) divided by the transaction volume of the day. 10-day backward moving average. Latest data as at end-February 2018.
Source: QUICK.

Price impact of inter-dealer transactions (based on new data)



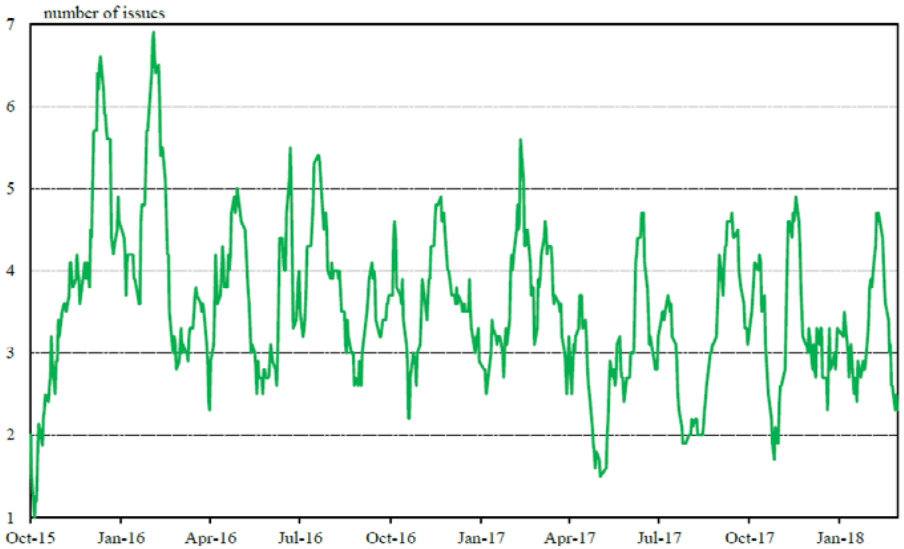


Note: The impact of change per unit of order flow imbalances (OFI, proposed by Cont, Kukanov, and Stoikov(2014)) on market prices measured by dividing change width of the best-bid (best-ask) prices by OFI. 10-day backward moving average. Latest data as at end-February 2018.
Sources: QUICK; Japan Bond Trading.

Conclusion

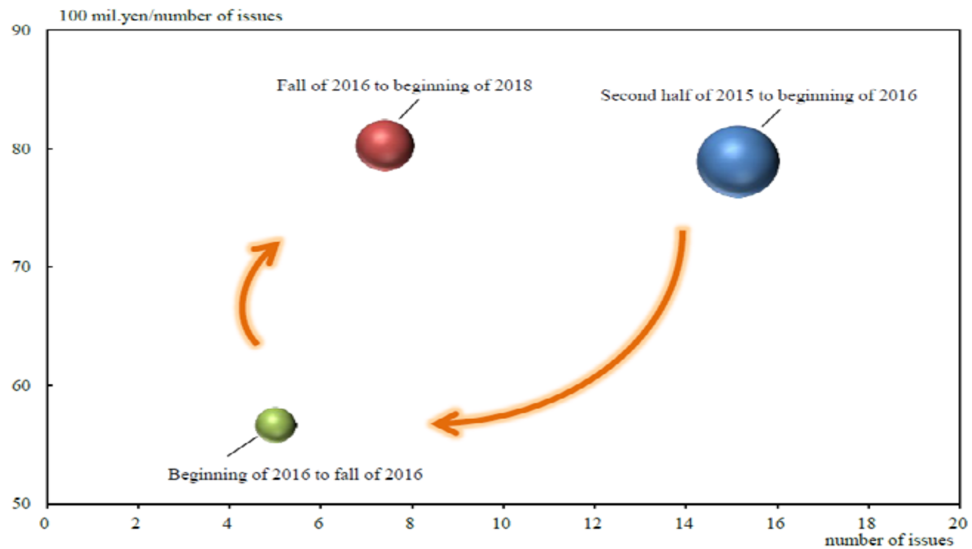
- Examining new liquidity indicators suggests that, as a whole, they have gradually improved since the fall of 2016, after worsening at the beginning of 2016. This suggests it is easier to trade now than it was following the introduction of “Negative Interest Rate.”
- However, we must continue to pay attention to future developments in market liquidity because transaction volume has not increased while some indicators have improved. We also found that improvement in short-term and off-the-run bonds is relatively delayed and have observed situations where liquidity temporarily deteriorates within a day.
- There are remaining points that we cannot grasp very well with indicators (e.g., difficulty in conducting large amount transactions). Thus, it is important to carefully examine these points by using communication with market participants as well as indicators.

Number of issues thought to be conducted as large amount transactions (based on new data)



Note: Large amount transactions are 5 billion yen. 10-day backward moving average. Latest data as at end-February 2018.
Source: Japan Bond Trading.

Number of issues and volume of orders assumed as large amount transactions (based on new data)



Note: Number of issues whose volume of orders at the best-ask exceeds 2.5 billion yen on average per day. Circle size represents the total volume of orders thought to be conducted as large amount transactions.
Source: Japan Bond Trading.

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Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

Can media and text analytics provide insights into labour market conditions in China?[1]

Jeannine Bailliu, Xinfen Han, Mark Kruger,
Yu-Hsien Liu and Sri Thanabalasingam,
Bank of Canada

[1] This paper was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

Can Media and Text Analytics Provide Insights into Labour Market Conditions in China?[1]

Jeannine Bailliu, Xinfen Han[2], Mark Kruger, Yu-Hsien Liu and Sri Thanabalasingam

Abstract

The official Chinese labour market indicators have been seen as problematic, given their small cyclical movement and their only partial capture of the labour force. In our paper, we build a monthly Chinese labour market conditions index (LMCI) using text analytics applied to mainland Chinese language newspapers over the period from 2003 to 2017. We use a supervised machine learning approach by training a support vector machine classification model. The information content and the forecast ability of our LMCI are tested against official labour market activity measures in wage and credit growth estimations. Surprisingly, one of our findings is that the much maligned official labour market indicators do contain information. However, their information content is not robust and, in many cases, our LMCI can provide forecasts that are significantly superior. Moreover, regional disaggregation of the LMCI illustrates that labour conditions in the export oriented coastal region are sensitive to export growth, while those in inland regions are not. This suggests that text analytics can, indeed, be used to extract useful labour market information from Chinese newspaper articles.

Keywords: China labour market, text mining in Chinese, text classification, SVM

JEL classification: C38, C55, E24, E27

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Contents

1 Introduction

Assessing labour market conditions is a prerequisite for careful analysis of macroeconomic dynamics. A reliable and regularly released labour market indicator can offer insights into an economy's cyclical position, supporting macroeconomic analysis and policymaking. Moreover, such an indicator is also essential for the design of appropriate labour market policies. In this paper, we construct a labour market conditions index (LMCI) using text analytics applied to mainland Chinese-language newspapers over the period from 2003 to 2017. More specifically, we apply a supervised machine learning approach by training a support vector machine (SVM) classification model. In this context, this paper seeks to answer the following questions: Can we train a classifier to discern labour market sentiment from Chinese newspaper articles? Can a news-based index of labour market sentiment reasonably track key historical developments in China's labour market? Compared with the official data, does this index have superior information content and forecasting ability in a Phillips curve framework for wage growth and a McCallum rule framework for credit growth?

Our paper yields several interesting findings. First, the comportment of our LMCI appears to be consistent with the economic shocks that have impacted the Chinese labour market. Second, the regional disaggregation of the LMCI illustrates that labour conditions in the export-oriented coastal region are sensitive to export growth, while those in inland regions are not. Third, while each of the official labour market indicators does contain some information either for wage or for credit growth, the information in our LMCI is more consistent. Only our LMCI provides significant information in the two wage and the credit estimations. Moreover, our LMCI provides wage and credit forecasts that are better than those from any single official labour market indicator. These results suggest that the text analytics can be used to extract useful labour market information from Chinese newspapers. This paper contributes to the literature in three ways. First, we create a novel dataset and use text analytics to develop a monthly LMCI for China that can be updated in real time. Second, we build on the methodology of Tobback et al. (2018) by applying a supervised machine learning technique to Chinese-language documents and by using a two-stage approach in training our SVM classification model. Third, we find that our LMCI is more robust in explaining and forecasting both wage and credit growth than any single official labour market indicator.

Our paper is structured as follows. A brief literature review is contained in Section 2. Section 3 presents our dataset and describes our methodology. In Section 4, we compare the information content of our LMCI to that of other labour market activity indicators in explaining and predicting wage growth in a Phillips curve framework. Section 5 compares the ability of our LMCI to explain and forecast credit growth in a McCallum rule framework against that of the official labour market indicators. Section 6 offers some concluding remarks.

2 Literature review

Our paper relates to two strands of literature. First, it focuses on developing alternative measures of the Chinese unemployment rate to address problems associated with the official data. Second, it adds to the growing literature on developing text-based indicators that can be useful proxies for economic and policy conditions. Most text-based indices are based on predefined keyword searches (for example, see Alexopoulos and Cohen (2009) and Baker et al. (2016)). Our paper builds on the methodology of Tobback et al. (2018), who use a supervised machine learning technique to develop an economic policy uncertainty index for Belgium. As Tobback et al. (2018) point out; their methodology is an improvement over simple keyword searches, as it avoids the human bias inherent in the keyword selection process.

Official labour statistics do not seem to reflect the actual employment situation in China. Indeed, Cai et al. (2013) propose comprehensively reforming the statistical system to improve the current set of labour market indicators so as to have better data to inform policy-making. It is generally agreed that the official unemployment rate underestimates the level of unemployment in China (Wang and Sun (2014)). Moreover, the official rate has remained fairly stable over time and does not appear to capture key historical labour market developments. For example, it did not increase by much during the period of state-owned enterprise (SOE) reform (1996-2002) despite the massive layoffs triggered by the reform. Moreover, it did not fluctuate appreciably during the 2008-2009 global financial crisis in spite of the significant employment loss over that period. Indeed, Lam et al. (2015) note that, compared with the unemployment rate in other major countries, the official unemployment rate has displayed considerably less sensitivity to changes in output.

Although issues have been raised with respect to many of China's official statistics, those pertaining to the labour market are seen as particularly problematic. Indeed, *The Economist* (2008) noted that "the prize for the dodgiest figures goes to the labour market." There are three sets of official Chinese labour market indicators of relatively high frequency. The first is the urban registered unemployment rate, which is published on a quarterly basis by the Chinese Ministry of Human Resources and Social Services (MOHRSS). The second is the urban demand-supply ratio, which is also published on a quarterly basis by MOHRSS. The third is the employment sub-component of the manufacturing and non-manufacturing Purchasing Managers Indices (PMIs), which are published on a monthly basis by China's National Bureau of Statistics. The main problem with the official statistics is that while they capture formal employment, they do not appear to include migrant workers, who are typically engaged on an informal basis.[3] The omission of migrant workers in Chinese labour statistics is problematic because they represent a large share of the labour force. Wang and Wan (2014) estimate that there were over 100 million migrant workers in China in 2010, which represented about 25% of urban employment.

The issues with the official unemployment rate have been acknowledged in the literature, and several papers have developed alternative measures of the Chinese unemployment rate that more closely follow international guidelines. Alternative unemployment rates, such as that estimated by Feng et al. (2017), are more variant and do capture these key developments. A summary of the key studies in this literature is presented in Table 1. Although these papers report a range of estimates for any given year, they all suggest that the actual unemployment rate was higher than the official rate. While these alternative indicators are very useful in identifying the problems associated with the official unemployment rate in China, they are of limited use for policy and analysis, given that they are not updated and thus unavailable on a high-frequency and timely basis. Our paper aims to bridge this gap in the literature by developing an LMCI for China that can be updated in real time.

[3] Migrant workers in China are those workers who do not have a *hukou* – an urban residence permit – for the jurisdiction in which they work.

3 Methodology

The methodology that we use in this paper builds on that of Tobback et al. (2018), who employ a supervised machine learning technique to develop an economic policy uncertainty index for Belgium. They do so by training a classifier using an SVM algorithm to predict whether an article addresses economic policy uncertainty. Our methodology differs from theirs in two important ways. First, we use Chinese-language documents, which present some challenges. Notably, text analytics involves finding relevant words, and what constitutes a "word" in Chinese is not obvious by simply looking at a selection of text. Therefore, we need to go through an additional step of "segmenting" Chinese characters into words. Second, after training their SVM classifier, Tobback et al. (2018) use a single-stage methodology to identify articles that are relevant for economic policy uncertainty. After considering alternative specifications, we use a two-stage approach. In the first stage, we train our SVM classifier to find articles that are relevant to the state of the Chinese labour market. In the second stage, we train the classifier to distinguish between articles that represent positive labour market sentiment and those that evoke negative sentiment.

While a number of methodologies exist for classifying text, we selected the SVM methodology, as the literature suggests that it is superior for classifying Chinese-language documents (Tan and Zhang (2008)).

Our methodology consists of the following steps:

1. Preselecting the articles;
2. Constructing the training and testing subset;
3. Preprocessing the articles for machine learning;
4. Transforming the text into a numerical matrix;
5. Training the classifier; and
6. Constructing the LMCI.

3.1 Preselecting the articles

In this paper, we create a novel dataset drawing on Chinese-language newspapers from mainland China provided by Wisers, a Hong Kong-based company. Wisers is the world's largest database of Chinese newspapers, beginning in late 1999 and consisting of 428 Chinese-language newspapers from mainland China. The newspapers cover both regional and national news.[4] We focus on a subset of 90 Chinese

[4] More information on Wisers can be found at www.wisers.com.

newspapers, which were continuously published over the period from January 2003 to June 2017 (this list of 90 newspapers is provided in Appendix A). As shown in Figure 1, this set of newspapers provides broad geographical coverage of China.

Millions of articles were published in the 90 Chinese newspapers between 2003 and 2017. They contain a mixture of news: central government policies, local companies' news, major events in the country, human interest stories, etc. To make our dataset more manageable, we preselected a subset of articles based on keywords most relevant for news about the labour market. We drew on Antenucci et al. (2014) and translated the keywords into Chinese (see Table 2 for a list of the keywords selected). Our keyword search of 90 newspapers for the period January 2003 to June 2017 resulted in more than eight million articles, or over 1600 articles per day. We then randomly selected one day for each month between January 2003 and June 2017 and downloaded all the articles published on that day that contained any of our keywords. This process resulted in a set of a little over 266,000 potentially relevant newspaper articles in our dataset.[5]

3.2 Constructing the training and testing subset

In machine learning, the classification problem, which maps input data into given categories, is one of the typical problems solved by supervised machine learning algorithms. The algorithms that solve the classification problems are called "classifiers." The supervised machine learning uses a training dataset and seeks the best algorithms that predict well out of sample (Mullainathan and Spiess (2017)).

To create a subset of articles to be used for both training and testing the classifier, we randomly selected just under 800 articles from the 266,000 in our dataset. We read all of them and then classified them using a two-step process. First, the articles were divided into two groups: (i) those that clearly contained either positive or negative sentiment with respect to the state of the Chinese labour market (relevant articles) and (ii) those that did not (irrelevant articles). In the second step, the first group was further subdivided into articles that contained positive sentiment and those that contained negative sentiment (the grouping of the articles in the training/testing subset is depicted in Table 3).

To frame our reading of the articles, we agreed upon general rules to help each author to classify articles in our training/testing set. Articles were labelled as relevant (positive/negative) if they met the following principles:

- Directly reported instances of companies hiring (positive) or cutting jobs (negative); individuals finding (positive) or losing jobs (negative).

- Indirectly reported labour market conditions. For example, national or regional policies have been implemented to help people to find jobs, which indicated the underlying labour market conditions were poor (negative).

5 In order to test the robustness of our sampling method, we randomly selected a different day from each month to construct our second sample set of articles. Using this sample set, we constructed LMCI using the same methodology outlined in the paper. The resulting index is similar to the index produced from the first sample set of articles.

To ensure that the manual selection process was robust, several of the authors read and independently scored each article for both relevance and sentiment. This was followed by a discussion of those articles upon which there was a disagreement until consensus was reached as to whether an article expressed sentiment and, if so, the nature of the sentiment. It is difficult to associate the positive or negative sentiment contained in the articles with specific economic indicators: employment, labour force participation, hours worked or wage growth. We assigned articles positive or negative sentiment based on our sense of whether the article contained “positive news” or “negative news” about general labour market conditions. In this way, we see labour market sentiment as akin to consumer confidence, which could rise because of increasing employment or rising wages or the expectation of better economic times ahead. While consumer sentiment is based on survey data, our labour market sentiment is a function of whether newspaper articles report positive or negative news.

3.3 Preprocessing the articles for machine learning

The goal of preprocessing is to break the Chinese text into small, meaningful units. In English, these units are typically words, and unique words are easy to identify in a document, since they are separated from other words by spaces. In contrast, Chinese text has no spaces between characters and a character, on its own, may not form a meaningful unit. Indeed, a large proportion of Chinese words are made up of two or more characters. Since the occurrence of a Chinese word in a document is not indicated by any sort of punctuation, the meaning of a sentence is potentially ambiguous.

To illustrate how the meaning of a sentence depends on how Chinese characters are segmented into words, consider the following example. The Chinese sentence below can have different meanings depending on how the characters are segmented.

Sentence: 乒乓球拍卖完了

Segmentation 1: 乒乓球拍/ 卖/ 完/ 了 (pingpangqiupai mai wan le)

Meaning: The ping pong paddles are sold out.

Segmentation 2: 乒乓球/ 拍卖/ 完/ 了 (pingpangqiu paimai wan le)

Meaning: The ping pong ball auction is over.

In order to sort Chinese characters into words, we relied on natural language processing software called Harbin LTP (Che et al. (2010)). We tested several software packages designed for the Chinese language and found that Harbin LTP outperformed the others in terms of word segmentation accuracy and speed. We also removed “stop words” from each article at this stage. Stop words are those that are important from a grammatical perspective but do not contain independent meaning. We did this with the assistance of the *Word List with Accumulated Word Frequency Sinica Corpus 3.0*. We eliminated 63 additional words, mostly adverbs, that we felt were not independently meaningful.

3.4 Transforming the text into a numerical matrix

The next step involves transforming the text from the articles into a numerical matrix.[6] Each article can be represented as a "bag-of-words" vector $[t_1, t_2, \ldots, t_j, \ldots t_m]$ that contains all m unique words that are present in the training set, where t indicates how often the jth word appears in the article.

The bag-of-words vector is then used to construct the term-frequency matrix $tf(n, m)$, where n is the number of articles and m is the number of unique words in the training set. The term-frequency matrix essentially presents the distribution of unique words across all the articles. To diminish the weight of words that occur frequently and increase the weight of those that appear rarely, the term-frequency matrix is multiplied by the inverse document frequency (*idf)* to obtain *tfidf* matrix. The inverse document frequency measures the importance of a word in all articles in the training set and is calculated as follows:

$$idf = log\frac{Number\ of\ articles\ n\ in\ the\ training\ set}{N umber\ of\ articles\ in\ training\ set\ in\ which\ term\ j\ occurs} \qquad (1)$$

The re-weight of *tf* by *idf* is to diminish the importance of words that occur very frequently in the articles but that carry little meaning. It increases the importance of words that appear rarely but contain a lot of meaning. It is these words that, potentially, give the classifier more power to discriminate between different categories of articles.

Given that there are over 3000 unique words in our training set, we applied a χ^2 feature selection method to avoid model over fit. We conducted this feature selection to select the 125 most important words to train our Stage I classifier and the 200 most important words to train our Stage II classifier – the *tfidf* matrix was thus transformed into an $n \times 125$ matrix for the Stage I classifier and into an $n \times 200$ matrix for the Stage II classifier.

3.5 Training the classifier

Having constructed the *tfidf* matrix, we can now use it as an input into the SVM algorithm. To solve any classification problem, the SVM searches for the decision boundary that maximizes the margin between the two classes. The classification problem is illustrated in Figure 2. The SVM selects two parallel hyperplanes to separate the two categories of data, so that the distance between the two hyperplanes (dashed lines) is maximized. The distance between the two hyperplanes is called the margin, and the decision boundary is the hyperplane in the middle (solid line). The circles and crosses that lie on the dashed lines are support vectors; these are the data points that are most difficult to classify. The intuition for the SVM algorithm is that if the classifier is able to separate the data points closest to the margin, it will be relatively easy to classify the data points that lie farther away.

As described in Fan et al. (2008), the linear SVM tries to solve the following optimization problem:

[6] To implement our methodology, we draw on scikit-learn, an open source machine learning library for the Python programming language (Pedregosa et al. (2011)).

$$min\frac{1}{2}\omega^T\omega + C\sum_{i=0}^{n} max(1 - y_i\omega^T x_i, 0)^2 \qquad (2)$$

Where x_i is defined as the vector of *ith* article in the training set of n articles, ω is the weight vector $[\omega_1,\omega_2, ..., \omega_j, ..., \omega_m]$ of unique words in the training set, and y_i represents the manual classification labels (i.e., 1 or −1) for *ith* article in the training set. The term $C\sum_{i=0}^{n} max(1 - y_i\omega^T x_i, 0)^2$ is added to cover the cases that the SVM is not able to perfectly clearly classify – i.e., this term is intended to penalize classifications that fall within the margin. We performed an in-sample grid search with cross-validation to find the optimal value of *C*, the cost parameter. It controls the trade-off between limiting misclassifications and maximizing the margin. If C is too large, the chance of misclassification is small, but the margin will be too narrow and the chance of over-fitting is great. If C is too small, the margin will be too big and there will be too many misclassifications. The best value for C optimizes this trade-off. In our case, we trained the SVM to find an optimal linear function for each stage. The linear function (classifier) is in the following form:

$$f(x_i) = \omega_0 + \omega_1 x_{i1} + \omega_2 x_{i2} + \cdots + \omega_j x_{ij} + \omega_m x_{im} \qquad (3)$$

Where x_i represents the vector of ith article in the training set, and x_{ij} represents the *tfidf* value of jth unique term in ith article in our training set. ω_j represents the weight of jth unique term in the training set. For each article x_i, if $f(x_i) > 0$ then the article will be classified into the category labelled 1, and if $f(x_i) < 0$ then it will be grouped into the category labelled -1.

Recall that we run the SVM twice: once to find articles that are relevant (Stage I) and a second time to differentiate between positive and negative news (Stage II). In the Stage I classification, we trained the SVM to correctly identify articles that we had manually classified as either being relevant to the state of the Chinese labour market or being irrelevant. Of our training/testing sample, 80% of the articles were used as a training set and 20% as a test set (to be used to measure the out-of-sample performance of the classification model). We used an 80/20 split between the training and testing sets to ensure that we had sufficient data to conduct the ten-fold cross-validation.[7]

Following Sokolova and Lapalme (2009), we evaluated the performance of the SVM according to three metrics:

$$\textit{Accuracy: } \frac{TP + TN}{TP + FP + TN + FN}$$

$$\textit{Specificity: } \frac{TN}{FP + TN}$$

$$\textit{Sensitivity: } \frac{TP}{TP+FN}$$

where:

[7] As an example, a three-fold cross-validation would involve splitting the training set into three equal-sized subsets. The classifier would then be trained using two of the subsets, and validated using the remaining subset. The cross-validation process would then be repeated three times (the folds), with each of the three subsets used once as the validation data.

$$TP = \text{True positives}$$

$$TN = \text{True negatives}$$

$$FP = \text{False positives}$$

$$FN = \text{False negatives.}$$

The results of our Stage I testing are shown in Table 4. The SVM could achieve a high accuracy rate with 85% of the articles classified correctly. The proportion of irrelevant articles correctly identified by the classifier (i.e., specificity) was also elevated at 89%, as was the share of relevant articles properly categorized by the classifier (i.e., sensitivity) at 82%. We followed the same procedure for the Stage II classification, where we trained the SVM to separate the articles identified as relevant in Stage I into those representing positive labour market sentiment and those reflecting negative sentiment. We split the 313 articles in this sample using the same 80/20 split between the training and testing sets; this yielded 250 articles in the training set and 63 in the testing set. As shown in Table 4, reported values for the metrics suggest that the classifier performed well in the Stage II classification as well.

In an ideal case, we would like the classifier to be able to distinguish between articles as accurately as human reading does. However, there is no established standard to define the acceptable classification error rate for the Accuracy, Specificity and Sensitivity metrics. Moreover, there are trade-offs between the metrics such that improving Specificity could reduce Sensitivity. This is akin to the trade-off between Type I and Type II errors. Our reading of the literature is that an acceptable error rate for the reported metrics is project-specific and subject to the discretion of the authors.

To further assess the accuracy of our two-stage methodology, we developed two alterative classifications. We trained a one-stage classifier that sought to divide the articles into three categories: positive labour market articles, negative labour market articles, and neutral labour market ones (Method 1).[8] And we trained a two-stage classifier, in which the Stage I classifier divided all the articles into relevant and irrelevant categories and the Stage II classifier divided the relevant articles into positive sentiment, negative sentiment, or sentiment neutral categories (Method 2). The performance of our preferred methodology (Method 3) against the two alternative methods is presented in Table 5. Our preferred methodology appears to be superior. Method 1 does well at identifying labour market-neutral articles, but not at identifying labour market relevant ones. Method 2 has the same Stage I classifier as our methodology, which performs reasonably well. However, its Stage II classifier does not perform as well.

There are clear differences between the articles that express negative sentiment and those that express positive sentiment. Figures 3 and 4 show the frequency of the top 30 words that only appear in either the negative or in the positive sentiment news articles. The terms "laid-off (下岗)", "unemployment (失业)", "unemployed (失业人员)", "laid-off/unemployed (下岗失业)", "laid-off workers (下岗职工)", and "laid-off staff (下岗失业人员)" feature prominently in the negative sentiment news stories.

[8] SVM is a binary classification algorithm. A three-category classification can be done as the result of three binary classifications undertaken in one stage. See scikit-learn's documentation (Pedregosa et al. (2011)).

3.6 Constructing the LMCI

We construct a composite LMCI that is intended to capture the relative frequency of positive sentiment articles to negative sentiment articles. As a first step, we create two sub-indices: one capturing positive labour market sentiment and one indicating negative sentiment. To do so, we follow the approach used by Baker et al. (2016) to create an economic policy uncertainty index. This procedure involves first creating a monthly series of the number of positive (negative) sentiment news articles in each newspaper. The raw counts are then scaled by the total number of articles in the same newspaper and month. The resulting series for each newspaper is then standardized to unit standard deviation and summed across all the papers by month. Finally, each multi-paper index is normalized to a mean of 100.

Once the two sub-indices are created, we construct our LMCI by dividing the positive sentiment index by the negative sentiment index. We then demean the series so that the index has a mean of zero. A value above (below) zero indicates that on net, Chinese labour market sentiment is positive (negative). The standard deviation of the series is 0.1. Our LMCI is depicted in Figure 5.

4 Evaluation: Can our Chinese LMCI explain and predict wage growth?

Before we compare the usefulness of our LCMI against that of official labour market indicators, we first check to see if its evolution is consistent with changing labour market conditions.

4.1 Does our LMCI capture the likely impact of key shocks on the Chinese labour market?

Our LMCI appears to capture the likely impact of key shocks on the Chinese labour market (Figure 5). The index dipped below zero during the 2003-2004 periods, suggesting that labour market sentiment was on net negative, likely reflecting two key events. First, the massive layoffs triggered by the SOE reforms (1996-2002) were probably still impacting the Chinese labour market in 2003-2004. It is estimated that about 45 million workers were laid off during the SOE reform period (Giles et al. (2005)) and it would have taken the labour market some time to recover from this large shock. In addition, the SARS outbreak, which started in late 2002 and went on for most of 2003, also had a negative effect on the Chinese labour market, particularly for workers in the services industry. Many migrant workers returned to their home villages during the SARS epidemic, some having been permanently laid off as their employers faced financial difficulties because of the SARS outbreak.

In the mid-2000s, the index was well above zero for several years, suggesting that labour market sentiment improved significantly and was on net positive. China's accession to the WTO (in December 2001) resulted in a rapid development in the export-oriented sector and a considerable increase in industrial employment.[9] This period of positive labour market sentiment was interrupted in 2007. This could be related to the new Labour Contract Law (LCL), which was enacted in June 2007 and became effective in January 2008. The purpose of this new law was to improve the Chinese labour contract system, clarify the rights and obligations

[9] Between 2000 and 2005, industrial employment in China increased by over 30% from 45 to 60 million workers (International Trade Organization (2011)).

of the parties, protect employees' lawful interests and strengthen labour relations (Chen and Funke (2009)). A key outcome of this law was to enforce written labour contracts. Anecdotal evidence suggests that some employers laid off informal workers in the period after the new LCL was announced but before it was implemented (i.e., in the second half of 2007) given that it became more difficult to lay off workers after the LCL became effective.

The decline in the index in 2007 was followed by a marked increase in 2008 reflecting employment gains that may be associated with the reconstruction after the Sichuan earthquake and the 2008 Olympics. In May 2008, a devastating earthquake of magnitude eight hit Sichuan province, killing more than 80,000 people and leaving more than 15 million homeless. The Chinese government responded rapidly with a reconstruction plan that involved building about 6.6 million houses, 3000 schools and 1100 medical facilities over a three-year period. Given the scope of the reconstruction effort, workers were drawn from both inside and outside the earthquake-affected area. Preparation for the 2008 Beijing Olympics is also associated with an increase in employment, particularly in the construction and transportation sectors (Wang and Zhang (2013)).

The index dipped precipitously during the global financial crisis (GFC) because of the significant employment loss over that period. It is estimated that around 23 million workers lost their jobs in China during the global financial crisis, as thousands of factories in the coastal region were closed when the number of orders filled by many export-oriented firms declined sharply (Cai and Chan (2009)). Most of these workers were migrants. In response to the GFC and to minimize its impact on the Chinese economy, the government announced a very large economic stimulus package (the headline number was US$586 billion or over 13% of GDP) in late 2008 to be invested in infrastructure and social welfare. Infrastructure-related employment helped mitigate the impact of job losses in the export-oriented sector. The recovery in the labour market is reflected in the evolution of the LMCI, which was back up to zero by mid-2010.

From 2011 onwards, the LMCI suggests that sentiment in the Chinese labour market tended to be on net positive. Several factors may account for this positive sentiment, including the solid performance of the Chinese economy over this period and the shrinking of the working-age population (starting in 2012). The index does dip below zero in late 2013 and into 2014, corresponding with the period when employment was reduced in overcapacity sectors (notably coal and steel). Although employment in the six main overcapacity sectors accounts for a small share of total employment (about 4% of total non-farming employment), companies in these sectors tend to be concentrated in certain regions/cities and hence job losses have been significant in some localities.[10] Another factor that may explain the decline in the index in 2013/2014 is the lack of job opportunities for university graduates – the Chinese media reported that 2013 was a very challenging year for university graduates seeking employment.

While the LMCI and official labour market indicators seem to follow similar trends as seen in Figures 6, 7 and 8, the LMCI captures events not observed in other indicators. For example, from around 2010 to 2013, the LMCI reflects strong growth in the Chinese economy, while the official unemployment rate displays no variation (Figure 6). Furthermore, the cuts to overcapacity sectors are not captured across the official indicators, whereas the LMCI falls sharply during this event.

[10] The Chinese government has highlighted the following six sectors as excess capacity industries: steel and iron, coal, cement, aluminium, ship building, and flat glass.

4.2 Regional LMCIs and export growth

Since we collect newspaper articles from a range of Chinese cities, we can undertake analysis to better understand how regional labour market conditions may vary. In particular, we would expect labour market conditions in the coastal region, which is more export-oriented than inland provinces, to be more sensitive to shocks emanating from abroad.

To test this, we construct two LMCI sub-indices: one for the coastal provinces (including Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan) and a second for the remaining inland provinces.[11] We then run a series of regressions in which the LMCI sub-indices are regressed on their first lag, a constant and export growth. The results are presented in Table 6. We find that exports are a predictor of labour market conditions in the coastal region (and for the country as a whole) but not for the inland region. This result not only sheds light on the difference between the coastal and inland labour markets, it also reinforces previous findings that the LMCI is, indeed, sensitive to actual labour market developments.

4.3 Wage movements

Ultimately, the usefulness of our LMCI will depend on the extent to which it allows us to capture direct measures of labour market outcomes. Moreover, the LMCI's value added needs to be assessed vis-a-vis the ability of the official measures of labour market activity discussed above to capture these outcomes.

A natural starting point for an indicator of labour market activity is its ability to predict wage movements. Thus, we estimate a set of Phillips curve-type equations in which wage movements are regressed on controls and various labour market indicators, including our LMCI. Our equations are of the following form:

$$w_t = \beta_0 + \beta_1 w_{t-1} + \beta_2 \pi^e + \beta_3 labour\ indicator_{t-1} + \varepsilon_t, \quad (4)$$

where w is wage growth (in year-over-year terms), π^e is CPI inflation expectations, $labour\ indicator$ represents one of the labour market indicators that we consider and ε is an error term.

Given the lack of availability of a quarterly Chinese wage series over our sample period, we use disposable income as a proxy for wages.[12] The inflation expectations measure we use is the quarterly diffusion index created by the People's Bank of China (PBOC), which compiles survey responses on the direction of the price level in the next quarter. We convert our LMCI from monthly to quarterly frequency by taking a five-month centred average of the index and then averaging the monthly index values in each quarter. To assess the relative information content of our LMCI, we compare it against the following labour market activity measures: the urban labour demand-supply ratio, the official unemployment rate and the employment sub-components of the PMIs. Figures 6, 7 and 8 graph the official labour market indicators against our LMCI. Note that there was a trend in the urban supply-

[11] We constructed two regional LMCI sub-indices because of the limited number of articles available for each province in our dataset.

[12] We use urban disposable income as a proxy for wages. Wages and salaries data only begin in 2013Q1. In contrast, urban disposable income data begin in 2001Q1. Wage and salaries made up around 60% of urban disposable income annually since 2013, making for a reasonable proxy.

demand ratio, which we removed by taking the four-quarter change. More details on variable construction and data sources are provided in Appendix B.

The results are presented in Table 7.[13] The results show that over the full sample period, our LMCI is the only labour market activity indicator that has explanatory information for wage growth.[14] It is the case that the employment sub-indices of the manufacturing and non-manufacturing PMIs also contain information relevant for wage growth. Note that these indicators are only available over a shorter time frame.

We next proceed to forecast wage growth and compare the forecasts using the LMCI against those using the official labour market activity measures. The forecasts were constructed as rolling four-quarter-ahead forecasts beginning in 2008Q2 and running to 2017Q1. The forecast results, which show the ratio of the root-mean-squared error (RMSE) of forecasts that use the other labour market activity variables to those using our LMCI, are presented in Table 9 (a number less than one indicates that our LMCI provides superior forecasts). The RMSEs of the forecasts are quite close. Indeed, only the four-quarter-ahead forecast using the employment sub-index of the non-manufacturing PMI is statistically superior to the others, as per the Diebold-Mariano test.

There appears to be a downward trend in wage growth beginning in 2007Q3 and continuing to the end of our sample (Figure 9). This downward trend suggests that there are longer-term structural changes affecting wage growth in addition to short-term cyclical pressures. In view of this, we estimate a second set of regressions in which the dependent variable and the lagged dependent variable are the deviations of wage growth from trend. All other variables are as defined in Equation 4. The results of these estimations are presented in Table 8. In this set up, only our LMCI and the official unemployment rate contain statistically significant information.[15] It is worth noting that the employment indices of the PMI are no longer significant in this formulation.

Once again, we undertake a forecast comparison exercise by conducting rolling four-quarter forecasts beginning in 2008Q2 and going to 2017Q1 and comparing the RMSE ratios. The results are presented in Table 10. They show that forecasts conducted with our LMCI are superior to those using other labour market activity indicators. Moreover, in about half the cases, the gain in accuracy from using our LMCI is statistically significant as per the Diebold-Mariano test.

5 Evaluation: Can our LMCI explain and predict credit growth?

In this section, we evaluate the usefulness of our labour market index by testing if it can help explain credit growth in the context of a McCallum-type monetary policy rule better than the official labour market indicators can.

[13] Unit root tests conducted using the Augmented Dickey-Fuller test suggested that all the series in equation (4) are stationary, as assumed.

[14] Our results were robust to the removal of the observations associated with the GFC (i.e., 2008Q3- 2009Q3).

[15] Here too, our results were robust to the removal of the observations associated with the GFC (i.e., 2008Q3-2009Q3).

5.1 Estimating and forecasting a McCallum-type rule

Understanding Chinese monetary policy, and attempting to represent its conduct using a monetary policy rule, is a challenging endeavour because the PBOC has many monetary policy instruments and multiple objectives. Over our sample period, the PBOC has used the following instruments to conduct monetary policy: reserve requirement ratios, benchmark interest rates, open market operations, targeted lending facilities and window guidance. Moreover, the importance accorded to individual instruments has changed over time, further complicating the task of representing the conduct of Chinese monetary policy with a rule. For instance, the PBOC relied heavily on reserve requirement ratios as a monetary policy instrument a few years ago but does less so now. More recently, it has put a bigger emphasis on the use of targeted lending facilities. While interest rates have been used as an instrument over the entire sample period, the preferred benchmark rate has changed over time: for many years, the PBOC used the one-year base lending rate but has recently been emphasizing the seven-day reverse repo rate.

Chinese monetary policy has also been guided by multiple objectives over our sample period: employment, GDP growth target, inflation target, monetary aggregate target, external balance, stable currency and financial stability.[16] Although it is likely that the importance of its different monetary objectives has also changed over time, its employment objective has been and continues to be very important. It is very difficult to assess the output gap in a dynamic economy like China's. The PBOC may have better information about the relationship between unemployment and it natural rate and target balance in the labour market so as to maintain aggregate demand in line with aggregate supply. Given the importance of employment as a monetary policy objective, we would expect monetary policy to adjust in a counter-cyclical fashion to labour market conditions: tighten when market conditions are buoyant and loosen when conditions deteriorate. With this hypothesis in mind, we test if our LMCI can help explain the conduct of Chinese monetary policy by modifying the following McCallum monetary policy rule to make it more applicable to the Chinese context:

$$\Delta m_t = \beta_0 + \beta_1(\Delta \mathrm{y}^* - \Delta \mathrm{y}_{t-1}) + \beta_2 \emptyset_t + \varepsilon_t, \qquad (5)$$

where Δm is monetary aggregate growth, $\Delta \mathrm{y}^*$ is the target of nominal GDP growth, $\Delta \mathrm{y}$ is nominal GDP growth, $\emptyset$ are additional relevant variables and ε is an error term. In this type of rule, a central bank is assumed to conduct monetary policy by responding to deviations in GDP growth from its target and to other additional relevant variables (for example, change in the velocity of money or deviations from an inflation target).[17]

We modified this rule so it better reflected monetary policy with "Chinese characteristics." We used deviations in credit growth from its trend instead of money growth as the dependent variable. In doing so, we are assuming that the impact of all the PBOC's monetary instruments was used to control credit growth. We took the PBOC's Total Social Financing as our broad credit measure.[18] We use deviations of

[16] "The single objective of maintaining price stability is an enviable arrangement, as it is simple and easy to measure and communicate. However, it is not yet realistic for China at this stage. For a long time, the annual objectives of the PBOC mandated by the Chinese government have been maintaining price stability, boosting economic growth, promoting employment, and broadly maintaining balance of payments" (Zhou (2016)).

[17] The McCallum rule is described in McCallum (1988). For the application of McCallum rule to the analysis of Chinese monetary policy see Burdekin and Siklos (2008) and Klingelhöfer and Sun (2018)

[18] Total Social Financing is seen as one of the PBOC's key monetary targets. "The PBOC will implement the prudent and neutral monetary policy, control total money supply, and use multiple monetary policy instruments to maintain reasonable growth of money, lending and social

real GDP growth from its target instead of nominal GDP growth because the Chinese central government has had a real rather than a nominal GDP growth target. Finally, we used deviations of inflation from target, where the inflation target comes from data compiled by Klingelhöfer and Sun (2018) for the period 2000-2015 and from press reports for subsequent years.

The estimation results for different specifications of the McCallum-type rule applied to China using OLS are presented in Table 11.[19] In the first column, we report the results of a basic McCallum rule. In subsequent columns, we add our labour market activity indicators. Our LMCI and the urban supply-demand ratio come in significantly at the 1% level, while the employment sub-index of the non-manufacturing PMI is significant at the 10% level but the sign on this variable is wrong.

Next, we undertake a rolling four-quarter out-of-sample forecasting exercise, like those conducted in Section 4 above. The results are reported in Table 12. For each of the forecast horizons, our LMCI provides forecasts of credit deviations that are significantly better than those from equations using the official unemployment rate and the manufacturing PMI employment sub-index, as per the Diebold-Mariano test. The forecast from the urban supply-demand ratio and the non-manufacturing PMI employment sub-index beat those of our LMCI, but the improvement in forecast accuracy is not significant.

6 Concluding Remarks

Building on the methodology of Tobback et al. (2018), we constructed a Chinese LMCI using text analytics applied to Chinese-language newspapers from the mainland over the period from 2003 to 2017. Visual inspection suggests that our news-based LMCI appears to track the key historical developments in China's labour market. Regional disaggregation illustrates that labour conditions in the export-oriented coastal regions are sensitive to export growth while those in inland regions are not.

We then formally test the information content and the forecast ability of our LMCI against four official labour market activity measures: the unemployment rate, the urban supply-demand ratio and the employment sub-indices of the non-manufacturing and manufacturing PMIs. Surprisingly, one of our findings is that the much-maligned official labour market indicators do contain information. However, their information content and their forecasting ability are not robust across the two wage growth and the credit estimations. Indeed, each of the official labour market activity variables is only significant (and properly signed) in one of the three estimations. In contrast, our LMCI does well in all three estimations. Moreover, in many instances, our LMCI is able to provide forecasts that are significantly superior to those of official labour market indicators.

Economists trying to understand the Chinese economy have to overcome a number of data challenges. Chinese data on many economic variables of interest either do not exist, or the time series are short. This leads researchers to create proxies. Indeed, this is what we had to do in this paper to get at wage

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financing to keep adequate and stable liquidity, improve the efficiency of financial operations and its capacity to serve the real economy, and constrain the overall leverage ratio at an acceptable level" (PBOC (2018)).

[19] Unit root tests conducted using the Augmented Dickey-Fuller test suggested that all the series used in these estimations are stationary.

growth. Since the Chinese economy is deeply dynamic, many popular proxies cease to be helpful. Consider the "Li Keqiang Index" which is made up of railway cargo volume, electricity consumption and loans disbursed by banks. It has been considered as an alternative to GDP for measuring economic activity. While this measure may have been useful in the past, China's transition to a more service-based economy and the advent of the shadow banking system makes it less relevant now. Our research suggests that text analytics can be used to extract useful labour market information from Chinese newspaper articles. More generally, the development of text analytics offers researchers the ability to turn newspapers into an alternative source of information about the Chinese economy.

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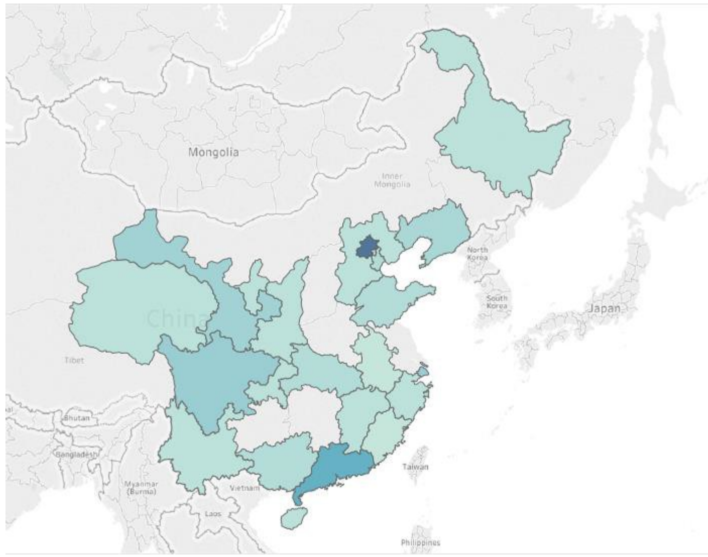
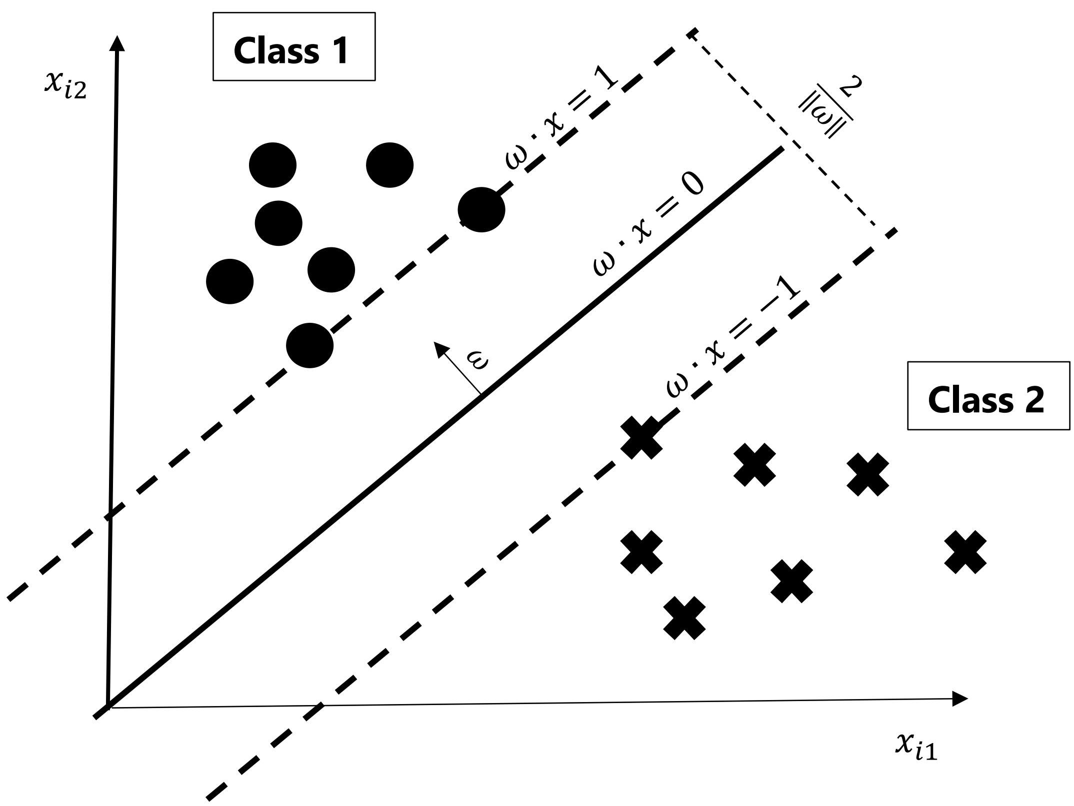


Note: There are between 1 and 23 newspapers in each region (the darker the colour, the larger the number of newspapers in that region)

Figure 1: Geographical distribution of newspapers



Source: Based on information retrieved on March 2, 2018, from https://en.wikipedia.org/wiki/Support vector machine.

Figure 2: Graphical representation of a support vector machine classifier

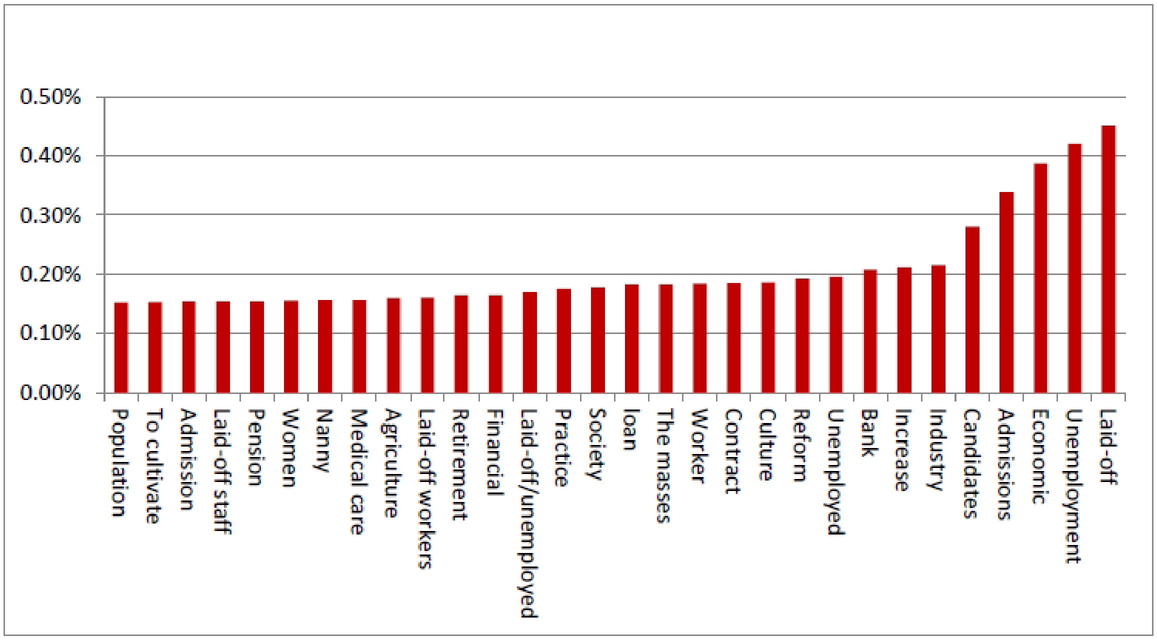


Figure 3: Negative sentiment news articles: word weights of top 30 words

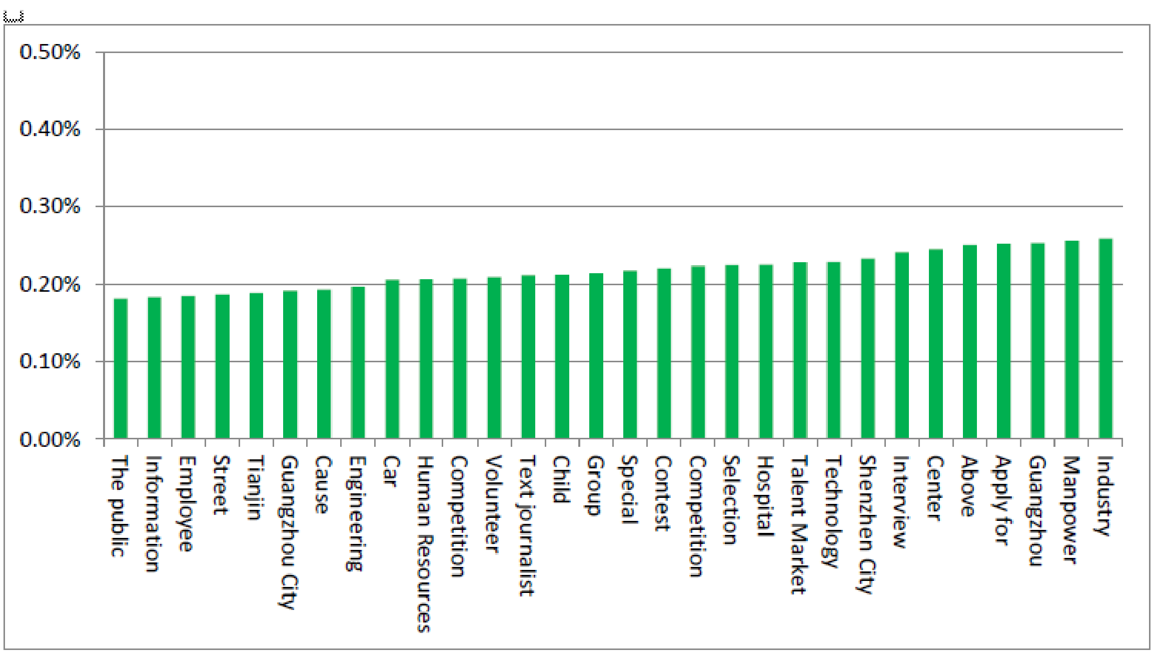


Figure 4: Positive sentiment news articles: word weights of top 30 words

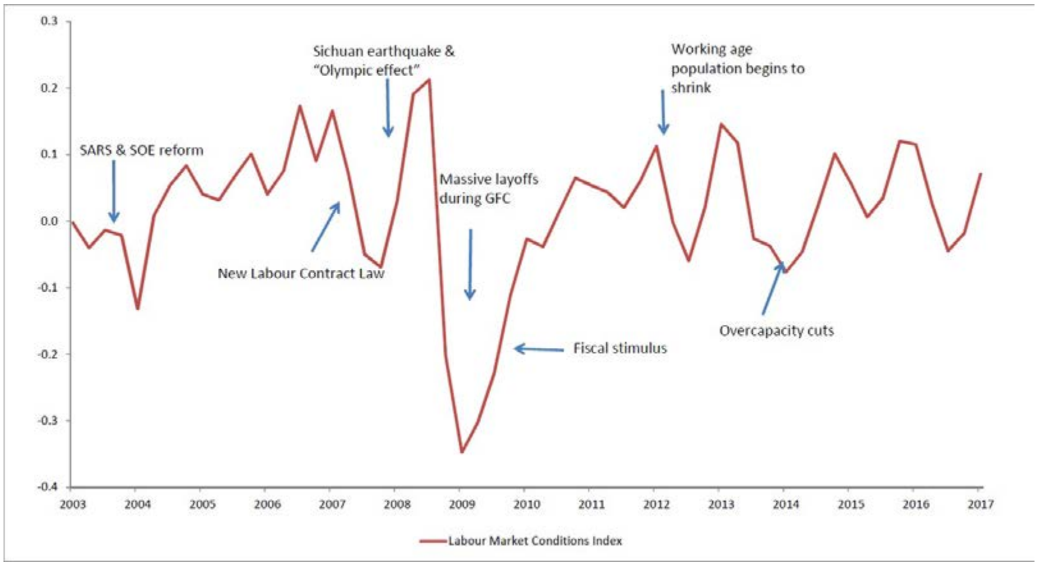


Figure 5: Key historical shocks and the labour market conditions index in China

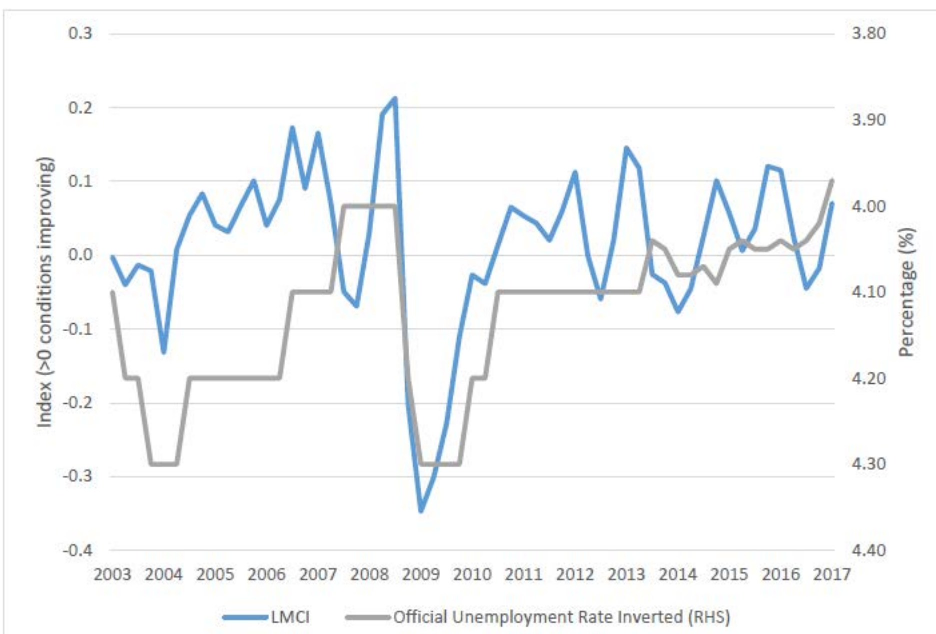


Figure 6: Labour market indicator comparisons (1)

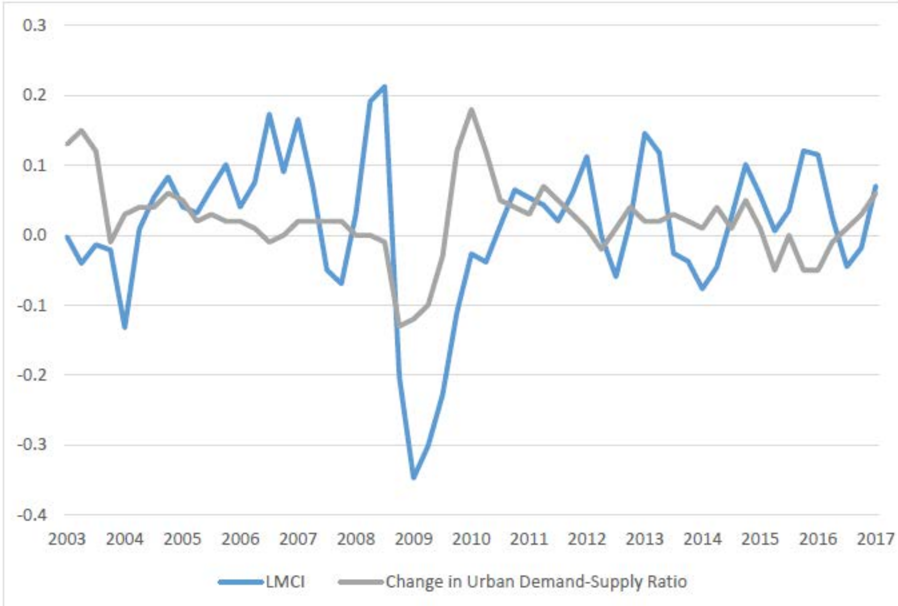


Figure 7: Labour market indicator comparisons (2)

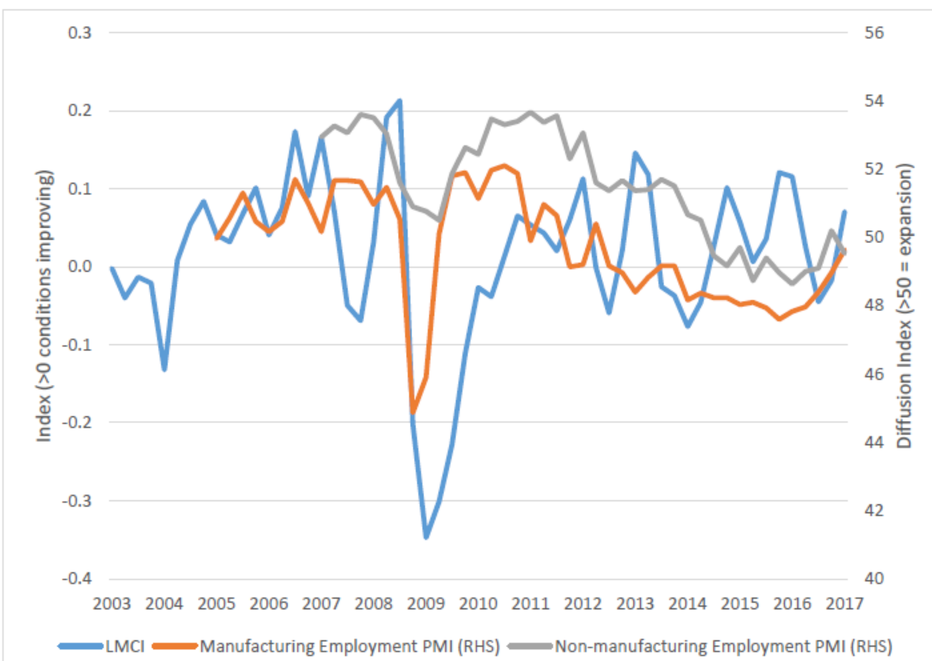


Figure 8: Labour market indicator comparisons (3)

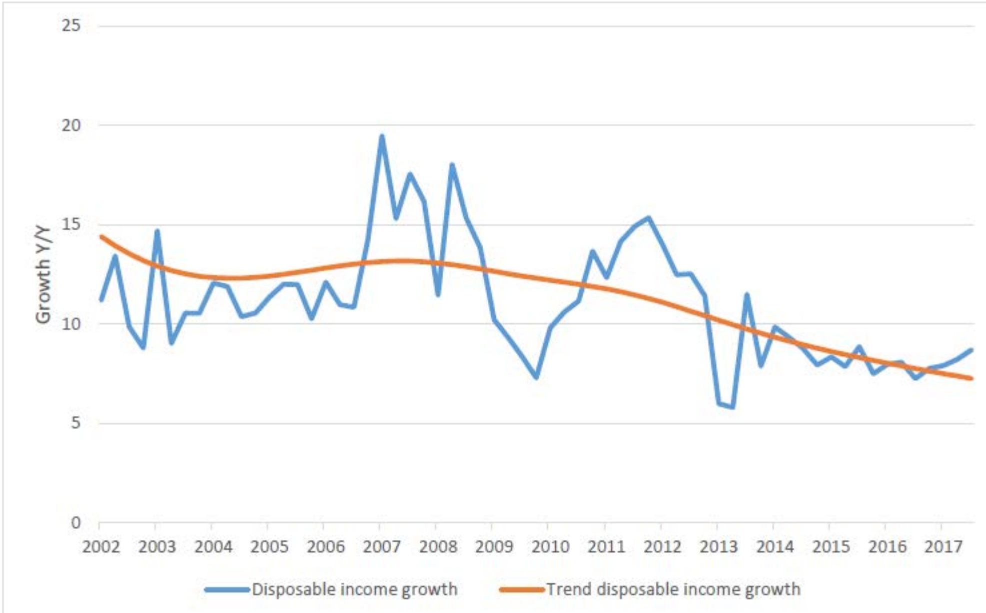


Figure 9: Disposable income growth vs. trend

Table 1: Estimates of China's Unemployment Rate

Reference	Data	1996	2000	2002	2007	2009
NBS	Based on urban residents registered as unemployed in unemployment centres	3%	3.1%	4%	4%	4.3%
Giles et al. (2005)	Based on China Urban Labour Survey and population census data	6.8%	10%	14%		
Knight and Xue (2006)	Based on adjusted administrative statistics (i.e., official rate), Urban Household Survey (1999) and population census data (1982, 1990, 1995, 2000)	8.5%	11.5%			
Liu (2012)	Based on Chinese Household Income Project Surveys (1988, 1995, 2002)			9.5%		
Wang and Sun (2014)	Based on household survey undertaken by Unirule Institute of Economics and the Horizon Research Inc. in 30 provincial capital cities (2007)				13.4%	
Feng et al. (2017)	Based on Urban Household Survey (1988-2009)	4.1%	7.8%	10.4%	8.1%	8.9%

Table 2: Keywords Used to Identify Articles Relevant to Labour Market

Category	Sub-category	Chinese	English translation
Negative labour market sentiment	Job loss	下岗	Layoff
	Unemployment	资遣 裁员 请辞 辞职 失业 失业保险	layoff layoff resign resignation unemployment unemployment insurance
	Wage reduction Dismissal	减薪 开除 解雇 革职 辞退 解聘 解聘 解除劳动合同	pay cut dismissed dismissal dismissed dismiss dismissed retired/resign dismiss the labour contract
	Getting fired	炒鱿鱼 被 炒 卷铺盖 丢饭碗	fried squid getting fired rolling up bed sheets lost rice bowl
	Bankruptcy	破产 公司破产 企业破产	bankruptcy company bankruptcy enterprise bankruptcy
Positive labour market sentiment	Job search	应征	application
	Employment Recruitment	求职 找工作	job search find a job

Continued on next page

Table 2 – continued from previous page

Category	Sub-category	Chinese	English translation
		雇用	employ
		招聘	recruitment
		招工	recruitment
		职缺	job vacancies
		岗位	job position
		招聘会	job fair
		再就业	re-employment
Labour market	Migrant workers	农民工 民工	migrant workers migrant workers
	Staff	职 工 员 工 职 员 上班族	staff employee staff office worker
	Job/positions	工 作 职 位 职 业 饭 碗 金饭碗	jobs position career rice bowl golden rice bowl

Table 3: Manual Classification of Articles in Training/Testing Subset

Number of articles representing positive labour market sentiment	187
Number of articles representing negative labour market sentiment	140
Number of articles relevant to the labour market	327
Number of articles irrelevant to the labour market	450
Total number of articles	777

Table 4: Performance of Support Vector Machine Classifier

Classifier	Total # of labelled articles	# of articles in training set	# of articles in testing set	Accuracy rate	Specificity rate	Sensitivity rate
Stage I	777	620	157	85%	89%	82%
Stage II	313	250	63	83%	94%	72%

Note: The discrepancy between the number of articles relevant to the labour market reported in Table 3 and the number of labelled articles reported for Stage II above reflects the removal of 14 articles that were related to Hong Kong, Macao or Taiwan (and not mainland China).

Table 5: Performance of Our Classification Methodology against Alternative Methods

Method	Classifier	Total # of labelled articles	# of articles in training set	# of articles in testing set	Overall Accuracy rate	(# of classified negative)/ (# of actual negative)	(# of classified positive)/ (# of actual positive)	(# of classified neutral)/ (# of actual neutral)
Method 1*	3-class classifier	777	621	156	73%	55%	57%	88%
Method 2*	Stage I binary classifier	777	621	156	85%	89%	82%	—
	Stage II 3-class classifier	293	234	59	52%	62%	48%	25%
Method 3	Stage I	777	620	157	85%	89%	82%	—
	Stage II	313	250	63	83%	94%	72%	—

*Note: The three-class classifier was designed to balance out our training set by using different weights for each class.

Table 6: Regional LMCIs' Relationship with Export Growth

Variables	Coastal LMCI	Inland LMCI	Overall LMCI
Export growth	0.00125**	0.00067	0.00195**
	(0.00056)	(0.00050)	(0.00085)
Coastal LMCI (-1)	0.70677***		
	(0.09087)		
Inland LMCI (-1)		0.7259***	
		(0.09233)	
Overall LMCI (-1)			0.58715***
			(0.10532)
Observations	54	54	54
Estimation Period	03Q2-16Q3	03Q2-16Q3	03Q2-16Q3
R-squared	0.58	0.56	0.47
Adjust R-squared	0.56	0.54	0.45

Notes: (1) The dependent variables are coastal LMCI, inland LMCI, and overall LMCI, respectively. (2) Standard errors are in parentheses. (3)The constant term is not shown. (4)***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table 7: Estimation Results for Various Wage Phillips Curve Specifications (1)

Variables	1	2	3	4	5	6
Disposable income growth (-1)	0.63***	0.6***	0.63***	0.63**	0.61***	0.46***
	(0.095)	(0.094)	(0.098)	(0.097)	(0.103)	(0.119)
Inflation expectations	0.12***	0.12**	0.13**	0.12**	0.03	0.04
	(0.046)	(0.045)	(0.049)	(0.047)	(0.068)	(0.062)
Urban demand-supply ratio (-1)			-0.7			
			(5.527)			
Official unemployment rate (-1)				-0.04		
				(3.184)		
Manufacturing employment PMI (-1)					0.54**	
					(0.267)	
Non-Manufacturing employment PMI (-1)						0.75**
						(0.318)
LMCI (-1)		5.05*				
		(2.578)				
Observations	56	56	56	56	48	40
Estimation Period	03Q2-17Q1	03Q2-17Q1	03Q2-17Q1	03Q2-17Q1	05Q2-17Q1	07Q2-17Q1
R-squared	0.55	0.58	0.55	0.55	0.62	0.68
Adjust R-squared	0.53	0.56	0.53	0.52	0.59	0.66

Notes: (1) The dependent variable is disposable income growth. (2) Standard errors are in parentheses. (3) The constant term is not shown. (4)***, **, and * indicate statistical significance at the 1%, 5% and 10% levels

Table 8: Estimation Results for Various Wage Phillips Curve Specifications (2)

Variables	1	2	3	4	5	6
De-trended disposable income growth (-1)	0.48***	0.4***	0.46***	0.31**	0.51***	0.47***
	(0.112)	(0.11)	(0.112)	(0.126)	(0.122)	(0.13)
Inflation expectations	0.1**	0.1**	0.11**	0.1**	0.06	0.07
	(0.043)	(0.04)	(0.045)	(0.041)	(0.067)	(0.063)
Urban demand-supply ratio (-1)			-3.36			
			(5.351)			
Official unemployment rate (-1)				-8.63**		
				(3.347)		
Manufacturing employment PMI (-1)					0.2	
					(0.252)	
Non-Manufacturing employment PMI (-1)						0.16
						(0.268)
LMCI (-1)		6.81***				
		(2.431)				
Observations	56	56	56	56	48	40
Estimation Period	03Q2-17Q1	03Q2-17Q1	03Q2-17Q1	03Q2-17Q1	05Q2-17Q1	07Q2-17Q1
R-squared	0.34	0.43	0.35	0.42	0.35	0.37
Adjust R-squared	0.32	0.39	0.31	0.38	0.31	0.32

Notes: (1) The dependent variable is de-trended disposable income growth. (2) Standard errors are in parentheses. (3) The constant term is not shown. (4)***, **, and * indicate statistical significance at the 1%, 5% and 10% levels,

Table 9: Wage Growth Forecasting Performance

RMSE Ratios: dynamic out-of-sample evaluation (2008Q2-2017Q1)

Model	T+1	T+2	T+3	T+4
Official unemployment rate	0.96	0.95	0.96	1.00
Urban demand-supply ratio	0.98	0.97	0.99	1.03
Manufacturing employment PMI	0.98	1.00	1.10	1.12
Non-manufacturing employment PMI	1.04	1.10	1.17	1.26**

Table 10: De-trended Wage Growth Forecasting Performance

RMSE Ratios: dynamic out-of-sample evaluation (2008Q2- 2017Q1)

Model	T+1	T+2	T+3	T+4
Official unemployment rate	0.98	0.96	0.95	0.97
Urban demand-supply ratio	0.86*	0.74**	0.72*	0.76
Manufacturing employment PMI	0.89	0.80*	0.79*	0.79**
Non-manufacturing employment PMI	0.87*	0.77**	0.75**	0.76**

Notes: (1) RMSE ratios are constructed by dividing the RMSE of the specification with the LMCI by the specification with the labour market indicator listed in the table. (2) ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table 11: Estimation Results for Various McCallum-type Monetary Policy Rules

Variables	1	2	3	4	5	6
De-trended TSF growth (-1)	0.82***	0.75***	0.92***	0.83***	0.84***	0.57***
	(0.065)	(0.066)	(0.059)	(0.065)	(0.075)	(0.085)
Deviation of real GDP from target (-1)	0.123	0.12	-0.05	0.06	-0.04	-0.06
	(0.125)	(0.118)	(0.114)	(0.140)	(0.203)	(0.158)
Deviations in inflation from target (-1)	0.46***	0.31**	0.32**	0.56***	0.39***	0.85***
	(0.134)	(0.138)	(0.119)	(0.167)	(0.142)	(0.161)
LMCI (-1)		-6.7***				
		(2.49)				
Urban demand-supply ratio (-1)			-21.31***			
			(4.853)			
Official unemployment rate (-1)				-3.59		
				(3.429)		
Manufacturing employment PMI (-1)					-0.26	
					(0.268)	
Non-Manufacturing employment PMI (-1)						0.38*
						(0.211)
Observations	53	53	53	53	49	41
Estimation Period	04Q2-17Q2	04Q2-17Q2	04Q2-17Q2	04Q2-17Q2	05Q2-17Q2	07Q2-17Q2
Adjust R-squared	0.79	0.82	0.85	0.79	0.78	0.79
Sum of squared residuals	153.3	133.16	109.35	149.88	140.18	75.02

Notes: (1) The dependent variable is de-trended total social financing growth. (2) Standard errors are in parentheses. (3) The constant term is not shown. (4)***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table 12: De-trended TSF Growth Forecasting Performance

RMSE Ratios: dynamic out-of-sample evaluation (2008Q2- 2017Q2)

Model	T+1	T+2	T+3	T+4
Official unemployment rate	0.82*	0.78*	0.77*	0.78*
Urban demand-supply ratio	1.12	1.14	1.14	1.11
Manufacturing employment PMI	0.85**	0.79**	0.79**	0.85**
Non-manufacturing employment PMI	0.97	1.01	1.06	1.18

Notes: (1) RMSE ratios are constructed by dividing the RMSE of the specification with the LMCI by the specification with the labour market indicator listed in the table. (2) ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Appendix A: List of Newspapers Covered in Database

Newspaper name	Province	Newspaper Name	Province
21st Century Business Herald	Guangdong	Sichuan Daily	Sichuan
Shanghai Securities News	Shanghai	Sichuan Economic Daily	Sichuan
China Business Times	Beijing	Dazhong Daily	Shandong
China Enterprises News	Beijing	Da Lian Daily	Liaoning
China PetroChemical news	Beijing	Tianjin Daily	Tianjin
China Taxation News	Beijing	Ningxia Daily	Ningxia
China Economic Times	Beijing	Guo Xi Daily	Guangxi
China Business	Beijing	Modern Life Daily	Guangxi
China Green Times	Beijing	Chengdu Business Daily	Sichuan
China Securities Journal	Beijing	Chengdu Daily	Sichuan
China Trade Journal	Beijing	Cheng Du Wan Bao	Sichuan
China High-Tech Industry Herald	Beijing	Baokan Wenzhai	Shanghai
Yunnan Daily	Yunnan	Wen Hui Bao	Shanghai
Ren Min Zheng Xie Bao	Beijing	New Express	Guandong
People's Daily Overseas Edition	Beijing	Modern Evening Times	Heilonggjiang
Evening Today	Tianjin	Xin Min Evening News	Shanghai
Jian Kang Shi Bao	Beijing	Shanghai Morning Post	Shanghai
Guangming Daily	Beijing	Chunchen Evening News	Yunnan
Lanzhou Daily	Gansu	Chutian Metropolis Daily	Hubei
Lanzhou Evening News	Gansu	Daily Update	Tianjin
Lanzhou Morning News	Gansu	Shantou Daily	Guangdong
Beijing Daily	Beijing	Shantou Tequ Wanbao	Guangdong
Beijing Morning Post	Beijing	Shantou DushiBao	Guangdong
Beijing Youth Daily	Beijing	Jiang Nan City News	Jiangxi
Ban Dao Morning News	Liaoning	Jiangxi Daily	Jiangxi
Hua Xi Du Shi Bao	Sichuan	The Mirror	Beijing
Nan Guo Zao Bao	Guangxi	Zheijiang Daily	Zheijiang
Nan Fang Daily	Guangdong	Hainan Daily	Hainan
Southern Metropolis Daily	Guangdong	Haikou Evening News	Hainan
Hefei Evening News	Anhui	China Light Industries Post	Beijing
Harbin Daily	Heilongjiang	Shenzhen Economic Daily	Guangdong

Newspaper name	Province
Shenzhen Evening News	Guangdong
Shenzhen Special Zone Daily	Guangdong
Hubei Daily	Hubei
Yanzhao Evening News	Hebei
Global Times	Beijing
Gan Su Nong Min Bao	Gansu
Gansu Daily	Gansu
Shen Huo Ri Bao	Shandong
Shijiazhuang Daily	Hebei
Fujian Daily	Fujian
Economic Information Daily	Beijing
Economic Daily	Beijing
Yangcheng Evening News	Guangdong
Xi An Daily	Shaanxi
Xi'an Evening News	Shaanxi
XiHai DuShi Bao	Qinghai
Jiefang Daily	Shanghai
Securities Times	Guangdong
Liaoning Daily	Liaoning
Liao Shen Evening News	Liaoning
Chongqing Economic Times	Chongqing
Chongqing Evening News	Chongqing
Qian Jiang Wan Bao	Zhejiang
Yinchuan Evening News	Ningxia
Changjiang Daily	Hubei
Qing Hai Daily	Qinghai
Qilu Evening News	Shandong

Appendix B: Variable and Data Description

Variable	Description/Source
Composite LMCI	The composite LMCI is constructed following the methodology described in Section 3. The index is normalized to a mean of 0. Data source: Wisers (see Section 2 for more details).
Headline CPI inflation	Constructed as the year-over-year growth rate in the headline CPI. Data source: National Bureau of Statistics of China / Haver Analytics.
Inflation expectations	Quarterly diffusion index based on survey responses on the direction of the CPI in the next quarter. An index of 50 or higher indicates that the price level in the next quarter is expected to increase (and the higher the index the higher the expectation of a rising price level in the next quarter). Data source: PBOC / Haver Analytics.
Urban labour demand-supply ratio	Ratio of demand for labour to supply of labour. Data source: Ministry of Human Resources and Social Security of China / Haver Analytics.
Official unemployment rate	Urban registered unemployment rate. Data source: Ministry of Human Resources and Social Security of China / Haver Analytics.

Employment sub-indices of the manufacturing and non-manufacturing PMIs	Monthly diffusion index based on survey responses on the direction of employment conditions in the current month. An index of 50 or higher indicates employment conditions are improving. Data source: National Bureau of Statistics of China / Haver Analytics.
Growth rate of per capita disposable income	Constructed as the year-over-year growth rate in urban per capita disposable income. Data source: National Bureau of Statistics of China / Haver Analytics.

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Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

Can media and text analytics provide insights into labour market conditions in China?[1]

Jeannine Bailliu, Xinfen Han, Mark Kruger,
Yu-Hsien Liu and Sri Thanabalasingam,
Bank of Canada

[1] This presentation was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

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International Department

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Labour statistics among China's worst

- The prize for the **dodgiest figures** goes to the labour market
  - Urban unemployment rate is "meaningless" Economist (2008)
  - Wage figures are also "lousy"

- Surveys suggest official rate **underestimates unemployment**
  - Knight and Xue (2007)
  - Wang and Sun (2014)

- Compared to other major countries, China's official unemployment rate shows **little sensitivity** to changes in output
  - Lam et al. (2015)

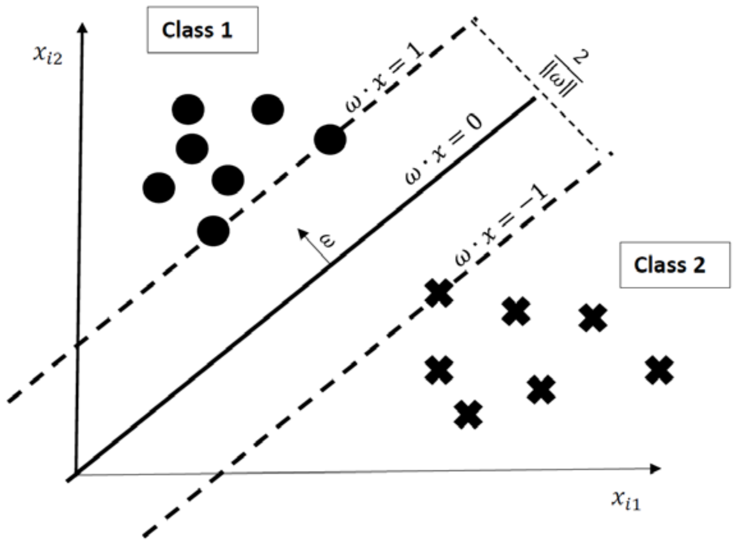
- Three relatively high frequency indicators capture formal employment, but not migrant workers
  - Migrant workers could make up 25% of urban employment
    - Wang and Wan (2014)

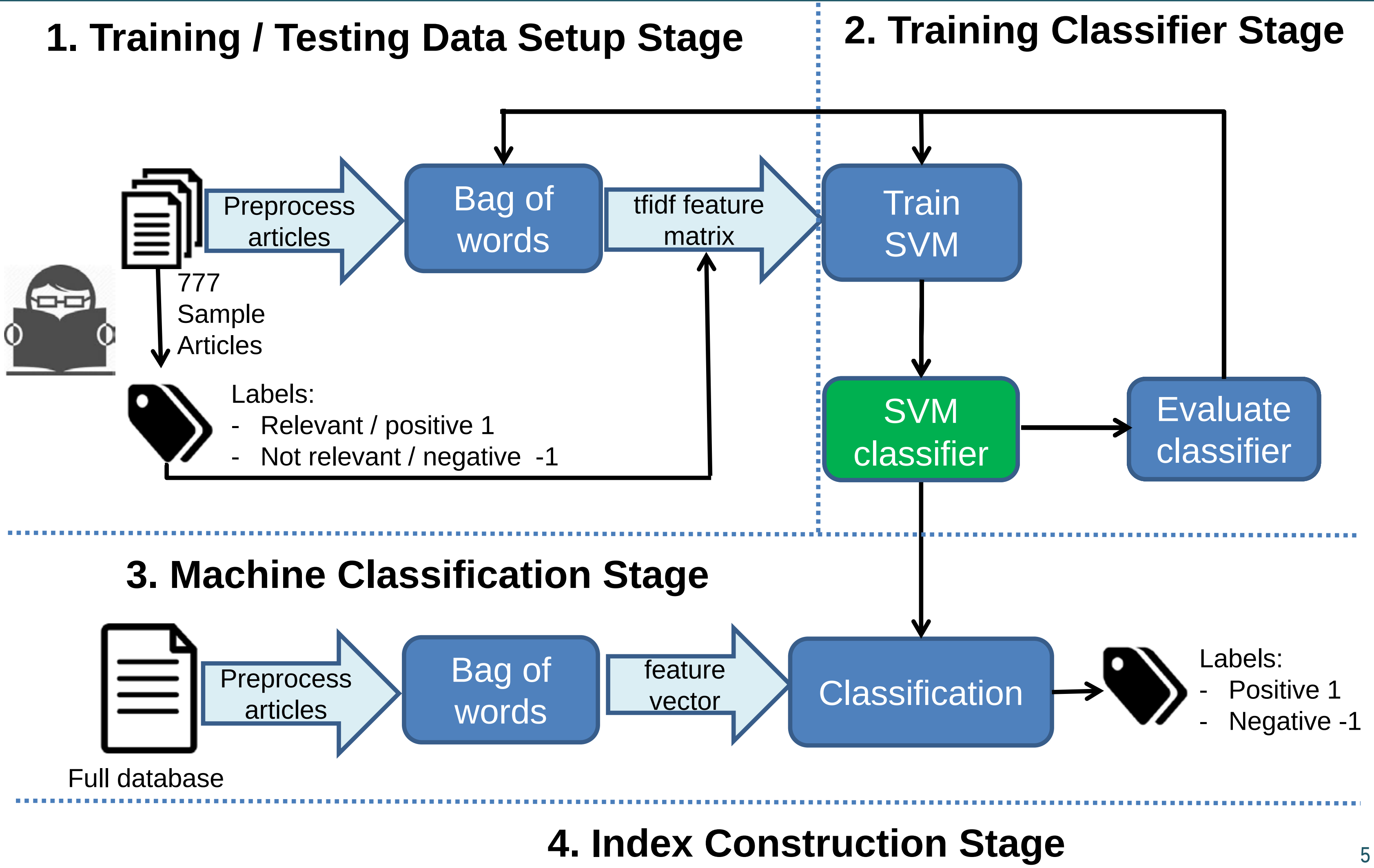
Our database

- **Chinese language** newspaper database
  - Wisers, a Hong Kong-based company
- We focus on **subset of 90** Chinese newspapers
  - Continuously published over **January 2003 to June 2017**
  - Broad geographic coverage
    - **26 out of 34 regions**
    - **77% population**
- Building the relevant article pool
  - 8 millions articles from predefined keywords search
  - downloaded all articles from randomly selected one day per month
    - **266,414 potentially relevant articles**

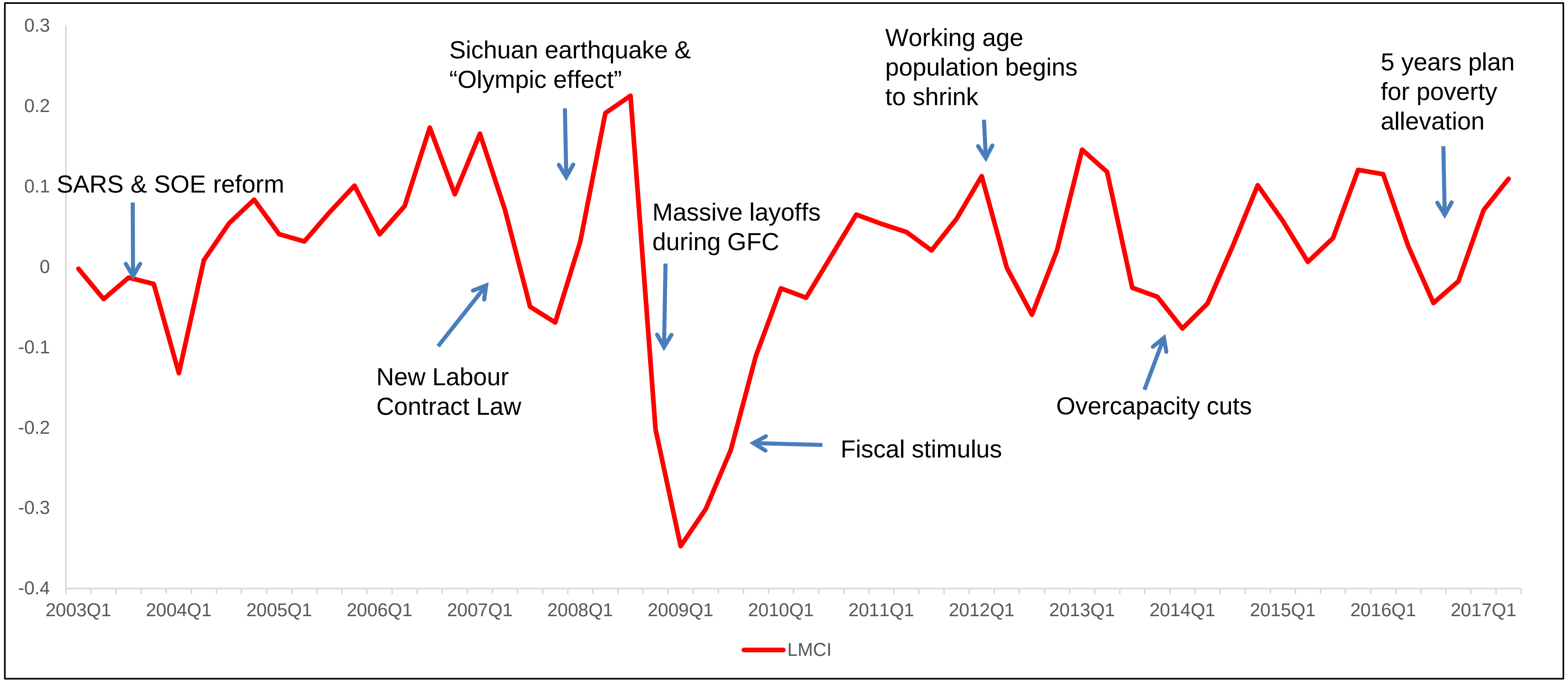
Text mining methodology

- Our approach is inspired by Tobback et al. (2016)
  - Use text mining to produce economic policy uncertainty index





Our Labour Market Conditions Index (LMCI)



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Text mining methodology

- **Why we use machine learning approach?**
  - Manual classification **costly**
    - 3 or 4 authors read and classify articles independently
    - Discuss disagreements until consensus reaches
  - Machine learning classification more **consistent**
- **Challenges parsing Chinese text**
  - In English, unique words are easy to identify since they are separated by spaces
  - Chinese text has no spaces between characters and a character, on its own, may not form a meaningful unit
  - Harbin LTP **natural language processing software**
- **Our methodology is generic** and can be applied to other classification problems

LMCI Validation

- Construct formal models to evaluate LMCI
  - **Wage** Phillips Curve
    - The co-movements between our LMCI and wage growth
  - **McCallum Rule** (1998) with "Chinese characteristics"
    - The PBOC responds in a counter-cyclical fashion to labour market conditions
- Construct two **regional sub-indices**
  - Our results show labour conditions in **coastal regions sensitive** to **export growth**, while in inland regions are not.

- Our study suggests that text analytics can be used to **extract useful labour market information** from Chinese media.

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Developments in the residential mortgage market in Germany - what can Google data tell us?[1]

Simon Oehler,
Deutsche Bundesbank

[1] This paper was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

Developments in the residential mortgage market in Germany – What can Google data tell us?

Session 5 – Big Data

Simon Oehler, Deutsche Bundesbank[1]

Abstract

This paper investigates the explanatory power of aggregate, publicly available Google Trends data for developments in the German residential mortgage market. For many consumption goods and services the internet serves as a means for households to acquire relevant information for example on prices, quality characteristics or legal and contractual conditions in advance of an actual purchase decision. Thus, households are also likely to rely largely on the internet (and in particular on search engines) in order to retrieve relevant information about potential providers of mortgage financing and the respective contractual conditions in the run-up to an actual loan agreement.

As households may subjectively choose different search terms in order to obtain (possibly the same) information on mortgage financing, the usefulness of several Google indicators, each representing the relative interest for a specific search term, is evaluated with respect to their predictive power for monthly changes in new mortgage business provided by banks to households in Germany. The performance of out-of-sample forecasts suggests that aggregate Google Trends data has the potential to serve as a valuable source of information for the prediction of mortgage market developments.[2]

Keywords: Forecasting, Internet search data, Google Trends, Google econometrics, residential mortgage markets, housing markets

JEL classification: C22, C52, C53

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[2] The paper represents the author's personal opinions and does not necessarily reflect the views of the Deutsche Bundesbank or its staff.

Contents

1. Introduction

Housing markets play an important role in most economies as a large share of overall economic activity is related to housing. Consequently, from a financial perspective, mortgage markets play an important role as mortgage debt often makes up for a large share of total outstanding aggregate debt in an economy. Thus, profound and timely analysis of mortgage market developments is of great importance for the whole economy and financial markets in general.

On a micro level, the housing market is of prime importance for many reasons. First, for many households dwelling accounts for a large share of their monthly expenditures, be they either for rental or mortgage rate payments. Second, for many households financing their property, mortgages make up the largest share of their total indebtedness. And third, the property at the same time often serves as a major part of a households' retirement provisions.

Therefore, and not least since the global financial crisis, analysts, policy makers and the wider public payed particular attention to mortgage market developments, resulting in an increased demand for detailed and timely information on this market segment.

One potential source of information on housing or mortgage markets in general is the internet. In most developed economies a large majority of households has access to the internet[3] which is used intensively for a vast amount of various economic activities. One of such is the acquisition of information in advance of purchase decisions. These can relate, for example, to consumption goods or (financial) services.

Most internet users worldwide rely on the Google search engine for information retrieval on the web. Accordingly, about 90% of all internet searches worldwide are currently processed by Google, with a similar share for Germany.[4] However, only few detailed official statistics exist on this topic. It is reasonable to assume that aggregate Google search data may contain useful signals on (changing) interests in certain topics, products, services etc. As these aggregate and anonymized data are published by Google Trends almost without any time lag, they could, in many cases, contain timely information exploitable e.g. for nowcasts or forecasts of demand for specific products & services.

In recent years, interest in internet search data has substantially increased and a number of research projects have made use of such data, in particular for forecasting exercises and the construction of novel indicators. For example, Choi and Varian (2009a,b) investigate the predictive power of Google data for nowcasting retail & automobile sales, home sales, travel activity and unemployment. At the Bank of England, McLaren and Shanbhogue (2011) have used internet search data for the analysis of labour and housing markets. Several papers have also investigated the potential of these data for the analysis of mortgage markets. Examples comprise Askitas and Zimmermann (2014) and Chauvet et al. (2016) who

[3] In Germany 87% of the overall population above the age of 10 years are internet users. For all individuals below the age of 45 years the share of internet users is almost 100%. See: https://www.destatis.de/EN/FactsFigures/SocietyState/IncomeConsumptionLivingConditions/UseInformationTechnologies/UseInformationTechnologies.html

[4] See: https://www.statista.com/statistics/216573/worldwide-market-share-of-search-engines/ and https://www.statista.com/statistics/445002/market-shares-leading-search-engines-germany/

seek to derive early indicators for mortgage delinquencies and default risk. Another example is Saxa (2014), who uses Google Trends data to forecast mortgage lending in the Czech Republic.
This paper contributes to the above mentioned literature as it evaluates the explanatory power of Google data for developments in the residential mortgage market in Germany, which, to my knowledge, has not been done so far. Moreover, this approach tries to strike a balance between pure data driven approaches (in the sense that the selection of potential predictors is solely based on the degree of correlation with a dependent variable of interest) and a "narrow" selection of search terms (i.e. selection of one or only very few search terms which are assumed to be thematically related to the object of interest). Thus, for this analysis, a set of search terms is selected from Google Trends, which is a priori restricted to the topic of mortgage lending. This approach significantly narrows down the number of potential predictors of actual mortgage business and is intended to help avoid finding possibly "spurious" correlations between the variable of interest and a very large set of Google Indicators. Consequently, this paper proposes a selection of specific search terms that could be of particular relevance for the construction of a mortgage market indicator for Germany. Further, and contrary to similar approaches, several "control" variables are included in the model specifications to account for other indicators that may have predictive power for mortgage market developments.
The remainder of the paper is structured as follows. In chapter 2 the Google data and some of their most important properties, including also potential drawbacks, are described. In chapter 3 model specifications and the variable selection procedure for the Google time series are explained. The respective results of in-sample as well as out-of-sample predictions are discussed in chapter 4. Chapter 5 concludes and provides an outlook on future work.

2. Data

The data on mortgage business are publicly available on the homepage of the Deutsche Bundesbank and comprise the volumes of new mortgages provided by banks to private households in Germany at a monthly frequency. Several breakdowns according to the respective agreed duration of a mortgage loan are available. In Germany mortgage contracts with durations longer than 5 years are largely prevailing. Nevertheless, as this project aims at evaluating German mortgage business as a whole, the aggregate over all agreed loan durations is taken into account. Thus, the respective interest rate, as far as considered, is a weighted average of interest rates recorded over all durations. As far as unemployment is considered as macroeconomic variable the respective time series contains the absolute number of unemployed persons according to the German law at a monthly frequency. The series is downloaded from the Bundesbank homepage.
All Google time series are downloaded from Google Trends' public website.[5] Each Google series obtained represents, in aggregate and anonymized form, the interest

[5] https://trends.google.de/trends/?geo=DE

of Google users in a specific search term over time.[6] More precisely, each series represents the number of queries for a specific search term relative to the overall number of all Google searches at a specific point in time, i.e. within a week or a month, and within a specific geographic region, i.e. at country or state level. Moreover, the data are provided as an index which means that the data is normalized to its maximum value equalling 100. This value corresponds to the highest relative "search intensity" over the sample period. As an example, the Google Index at period t for the German search term "Kredit" is computed as follows:

$$\boldsymbol{I(Kredit_t)} = \frac{\boldsymbol{R(Kredit_t)}}{\mathbf{max}\{\boldsymbol{R(Kredit_\tau)}\}} \times \mathbf{100} \text{ with } R(Kredit_t) = \frac{Kredit_t}{Google_t} \text{ and } \tau = 1, \ \dots, \ T$$

In practice this index is computed by using a random sample of all Google searches rather than actual Google searches. The actual sample size used for the computation of the index is not reported. It is important to mention, that the sampling mechanism could threat the stability of some of the Google series. Practically, if a series corresponding to a specific search term is downloaded at different times, the results often vary slightly. Even though not every time series in this project is checked accordingly, it seems that most of the time series used here are rather stable in this sense.[7] However, McLaren and Shanbhogue (2011) report that this issue may occur in particular with less popular search terms. One possible cure for this shortcoming is to download each series several times and simply compute averages over all observations.

Further, Google Trends allows for the use of search operators which make it possible to further refine search results according to specific needs. For example, entering the term "Kredit" without apostrophe's yields results for all searches containing this specific term including related extensions of the word, for example, "Hauskredit". On the contrary, adding apostrophes to a search term would only yield results for searches exactly matching a specific term, thus not including any related or but slightly different words. Additionally it is possible to also use the operators "+" and "-" in order to explicitly include or exclude specific expressions from a particular search query. Such modifications are important as the respective results often differ substantially.

Moreover, Google Trends does not consider spelling errors. Therefore, in order to take account of such issues the explicit mentioning of a misspelled search term is necessary. Thus, if a search term were known to be often misspelled in a particular way or context, an explicit mentioning as part of a query would be a feasible way to account for potential bias due to such an error. However, if there is no knowledge of this sort, such an approach can cause biases by its own. Consequently, as for the relevant search terms used in this paper, typos and respective probabilities of this sort are not known, they are not accounted for. On the contrary, Google often suggests users corrected search terms if misspellings are detected. Thus, "following"

[6] For further details on how Google Trends data are adjusted, see the following link: https://support.google.com/trends/answer/4365533?hl=en&ref_topic=6248052

[7] To test for this particular issue, series representing identical search terms were downloaded at different times. The computed respective correlations were around 95% or above.

such a suggestion on Google's website corrects the search term and redirects the user to the results for the presumably intended query.
Further, Google Trends also allows to only consider searches within a specific category as for example "Finance". This can be of particular relevance if search terms have ambiguous meanings. By restricting search results to a specific category, "noisy" searches which, in essence, are unrelated to the topic of interest, are excluded.[8] Even though, most of the search terms in this approach do not have particular ambiguous meanings, all time series extracted from Google trends are restricted to the category "Finance". This assures however, that noise from unrelated terms is unintentionally included.
As a result of these properties, the Google data used in this paper are selected according to specific considerations and restrictions. First, the selection of search terms is not solely data driven. Rather, the selection is a priori restricted to terms which are in a logical sense connected to mortgage financing topics, as far as this can be assured. Additionally, both, rather general terms related to the topic of mortgage financing as well as more specific variations of such topics are considered. For example "Kredit" is taken into account together with related "extensions" as "Kreditvergleich", "Wohnungsbaukredit" etc. This means, however, that overlaps in searches can exist. For example, a specific search for "Wohnungsbaukredit" should also be comprised in a search results for the term "Kredit". Nevertheless, this approach allows investigating, whether narrowly defined searches can outperform broadly defined, generic searches.
Overall, 37 times series are obtained from Google Trends. By definition, these terms only account for searches in German language. By selection, only searches for the German geography are considered, i.e. searches in German language conducted in other countries, in particular Switzerland or Austria, are not included in the sample. The data is of monthly frequency, the sample ranging from January 2004 until April 2018.
Graphical representations of selected, unadjusted time series are depicted in Graph 5 in the appendix below.

All time series, except from the interest rates, show seasonal patterns of different sort. The series for unemployment, however, is already seasonally adjusted when downloaded from the Bundesbank homepage.
The series for new mortgage business shows a strong yearly seasonal pattern in form of a sharp rise in mortgage volumes in the mid of the year. Therefore, July often is the month with the largest volume of new mortgage business throughout the year. Therefore, the series is seasonally adjusted using the X-11 decomposition method.
Also the Google time series show a particular seasonality. The most striking seasonal pattern, which is common to all Google series in the sample, is a sharp decline of the Google index in December with a subsequent strong rise in January. This pattern, however, does not seem to be a peculiarity of search terms related to mortgage topics as also several other studies using Google Trends data report similar observations. Thus, it is reasonable to assume that this seasonality is not originating from actual seasonal patterns in Google users' interest for mortgages but from other, and in particular "economically" unrelated, sources. For example calendar effects could be one possible explanation. As it was discussed above, the

[8] For example the search term "Jaguar" could be either intended to find information about the animal or a car manufacturer.

Google data is essentially an index constructed as the ratio of searches for a particular term over all searches conducted at a given time and region. Thus, the reported seasonal pattern for the months December and January could be related to the Christmas season, as around this time, people simply use Google more intensely in preparation for various Christmas related activities. The result would be an inflated denominator of the Google index in December. On the contrary, in January after the Christmas season this effect disappears again, resulting in the above mentioned rise of the indicators. A similar explanation, however related to the nominator of the ratio, would be that people towards the end of the year tend to look for other than mortgage related topics thus the Google index would decline even if the total number of searches were constant over time. To avoid potential biases due to this type of seasonality all Google time series are seasonally adjusted using the X-11 decomposition method.

In order to check for potential unit roots in the time series, augmented Dickey-Fuller tests were performed for all series. After log-transforming and first-differencing[9] each series, the Dickey-Fuller test statistics strongly rejected the Null-hypothesis for the presence of unit roots, thus implying covariance stationarity for all series.

3. Models

In order to assess the usefulness of Google data with respect to its explanatory power for cyclical variation in the growth rate of mortgage volumes, different single equation linear models are estimated and consequently benchmarked against each other in terms of out-of-sample forecast performance. The models estimated can essentially be divided into three groups. First, an autoregressive model is estimated by simply regressing current values of the dependent variable on lagged terms of its own. Thus, the resulting model is of the form:

$$\Delta \boldsymbol{mortgages_t} = \boldsymbol{\beta_m L^m} \Delta \boldsymbol{mortgages_t}$$

Second, this simple autoregressive model is augmented by current and lagged values of the series for the growth rate of the mortgage interest rate as well as the monthly growth rate of unemployment, as the latter is supposed to be an important indicator for households' willingness and ability to take up a loan for the financing of real estate.

$$\Delta \boldsymbol{mortgages_t} = \boldsymbol{\beta_m L^m} \Delta \boldsymbol{mortgages_t} + \boldsymbol{\gamma_m L^m} \Delta \boldsymbol{interest_t} + \boldsymbol{\theta_m L^m} \Delta \boldsymbol{unempl_t}$$

Third, the model including the control variables is augmented by a set of Google terms representing the (lagged) growth rate of households' interest in mortgages, chosen according to the below mentioned procedure.

[9] None of the series was integrated of an order higher than one.

$$\boldsymbol{\Delta mortgages_t = \beta_m L^m \Delta mortgages_t + \gamma_m L^m \Delta interest_t + \theta_m L^m \Delta unempl_t + \delta_m L^m \Delta Google_t}$$

For each of the above mentioned steps the model selection is performed with the help of a stepwise forward selection procedure in order to detect relevant regressors to be included in a model. The variables which are selected at a specific stage are kept in the model. Subsequently, additional potential regressors are added to the list of search regressors in the next stage and so forth. Thus at each stage, additional regressors potentially enter the model. The relatively large number of potential Google indicators results in a situation of a large number of potential models. Thus, for the Google indicators the procedure is twofold: First, the benchmark model, including the control variables, is estimated by adding a Google indicator (and its respective lags) one at a time to the list of search regressors in order to let the forward selection algorithm detect relevant lags. Those indicators, for which lags have been selected into the model, are kept aside and are further evaluated in the second stage. This procedure results in a reduced set of seven indicators. Subsequently, these preselected Google indicators are now used to find models for the forecasting exercise. For this purpose, the benchmark model including the controls is augmented by the preselected Google indicators which are allowed to be forward selected into the model one at a time. The resulting selected lags at a specific stage are then added to the model and additional indicators are again allowed to be forward selected. This procedure results in models including an increasing number of Google indicators as far as they prove to be stable and significant throughout the selection procedure.
This model selection and estimation procedure is performed on a subsample of the data ranging from January 2004 to December 2015 in order to treat the remaining part of the sample from January 2016 to April 2018 as "unseen" data, thus preserving it for out-of-sample forecast evaluation. Results are reported in section 4 as well as in the Appendix below.

4. Results

A summary of the estimation results is depicted in table 1 below. The benchmark model includes only lagged values of the dependent variable, i.e. actual volumes of mortgages provided to households each month. The results show, that the strongest autoregressive predictors are the first and third lag of the mortgage series as well as a more distant seventh lag. Overall this model captures around one third of the series' variation, where trend and seasonal components have already been accounted for.[10] In a second step additional regressors are allowed to enter the model, potentially containing useful information with respect to the growth in volumes of mortgages. Thus, the model is again stepwise forward selected, allowing for current and lagged values of the monthly change in interest rates for mortgages and the monthly changes in unemployment in Germany. The interest rate enters the model with a lag of two month and is, as expected, indicating a negative relationship between the growth in mortgage volumes and the respective changes

[10] Regressing the mortgage series on a linear trend variable and on a set of deterministic monthly dummy variables, 79% of the series' variance is explained in terms of R^2.

in interest rates. Contrary to this finding, (lagged) changes in unemployment do not enter the model.
The benchmark model, including the lagged interest rate, is then stepwise augmented by the Google regressors according to the procedure described above in Section 3. The model selection procedure ultimately choses the model which is labelled as "Google augmented III" incorporating lagged values of different search terms. These are "Baufinanzierung", "Hypothek" and "Kreditvergleich" and "Bauzins". The Google regressors which are included in the models, as reported below, thus have all proven to enter the benchmark model individually and in combination with other Google indicators and control variables.
Additionally to this, robustness tests are performed by either including or removing search terms from the models and by estimating the selected models on different sub-periods of the sample. The models reported here, prove to be robust to these tests.

Following the in-sample model selection and estimation procedure, the out-of-sample performance of the selected models is evaluated. The results of this exercise are summarized in table 2 below. Notably, the specification "Google augmented I" incorporates the search terms "Baufinanzierung" as well as "Kreditvergleich". For this model all Google terms show the expected positive signs.
As mentioned before, the models are estimated on a subsample of the data. The estimation period ranges from 2004M9 to 2015M12 including 136 observations. The remainder of the sample is kept aside for performing out-of-sample forecast evaluation of the models. Thus out-of-sample forecasts are produced for the period 2016M1 to 2018M4, i.e. 28 out-of-sample estimates are obtained. Subsequently, forecasts are compared to actual observations of this period and standard measures of forecast accuracy are calculated to evaluate the performance of the models. Results are depicted in table 2 in the appendix. With respect to the forecast evaluation criteria, the model including lags of all three search terms clearly outperforms the other models, in particular those not incorporating any Google information. However, the model "Google augmented I" containing additional "hard" information does not outperform the "pure" benchmark model without additional independent variables. Concretely, for the out-of-sample period reported above, the model "Google augmented II", including three Google search terms, outperforms the benchmark model by about 19 % and the benchmark model including additional "hard" economic data, even by 27 % in terms of the reported Root Mean Squared Error. An additional improvement in terms of forecast accuracy can be obtained by including the term "Bauzins" as reported in the model "Google augmented III". Further results for other models as well as other forecast evaluation measures are reported as well in table 1 and table 2 below. A graphical representation is depicted in Graph 1 in the appendix.
Thus far, dynamic forecasts have been computed, essentially assuming, that all forecasts had been performed in December 2015 (i.e. 2015M12) based on information which was available at this time. Consequently, in order to compute forecasts over the whole sample from 2016M1 to 2018M4 forecasted values are used to compute out-of-sample forecasts for more distant future periods.
Additionally, static forecasts are computed relating to the case as if from December 2015 on, each month a one-step-ahead out-of-sample forecast exercise would have been performed using all information available until a specific month, i.e. actual past values of growth in mortgage volume rather than forecasted values. The respective results for several models are presented in Graph 2 to 4 in the appendix below. The

main results are similar to the previous exercise. The improvement of the forecasts of the Google augmented model II over the forecasting period is about 17% relative to the benchmark model. The graphs of the forecasted series and further evaluation criteria are depicted as well in Graphs 2 to 4 below.

5. Conclusion

In this paper the usefulness of aggregate, publicly available Google Trends data as an indicator for developments on the residential mortgage market is evaluated. Google search data is considered a proxy for consumers' interest in certain topics for example in the course of planning activities in relation to large household purchases. For this purpose, a number of time series are downloaded from Google Trends, each representing the interest of Google users in specific topics over time.

First, a purely autoregressive model for the mortgage time series is estimated which is then augmented by distributed lags of the mortgage interest rates and unemployment as a macroeconomic indicator. Subsequently, Google data is included into the benchmark autoregressive distributed lag model. In this respect, a stepwise forward-selection procedure is applied in order to detect relevant Google predictors out of a large set of potentially useful regressors and to choose from an accordingly large set of potential models.

The results indicate that Google data has the potential to improve out-of-sample forecast accuracy for the monthly growth rate in mortgage volumes. Moreover, the search terms "Baufinanzierung", "Bauzins" "Hypothek" and "Kreditvergleich" seem to be particularly useful in terms of improving out-of-sample forecast accuracy. Further, checks revealed that the indicators are robust to different model specifications and different sample periods on which the models are estimated. On the contrary, other variables can be excluded for almost all model specifications. Thus, the number of potential relevant search terms is narrowed down to only a small subset of four indicators containing useful information, constituting another result of the analyses conducted so far.

However, to some degree, the results at this stage need further robustness checks. One exercise to be done is augmenting the benchmark model with survey data on the mortgage market and subsequently comparing such model specifications to Google augmented models. In this respect also further "hard" economic data needs to be evaluated as potential predictors. Relating to the problem of "model uncertainty" there is variety of econometric methods related to "shrinkage" and dimensionality reduction techniques which likely hold potential for this "data rich" setting too. Thus, for example, Ridge and Lasso regressions seem "natural" candidates to be applied here. Another check at this stage would be to test if the results obtained for the aggregate mortgage business series as dependent variable are valid for the mortgage series broken down according to the different agreed interest rate durations.

A great advantage of Google data in general is their coverage of a wide variety of topics which are of interest for the public. Along with the real time availability of data, this makes Google Trends an interesting tool for economics and social sciences in general.

However, some drawbacks remain most of which have already been described by the literature in this field. As Google data does not incorporate any survey design, e.g. the representativeness of the data may be an issue. However, a large share of the population in many countries uses the internet, of which again the largest share uses Google as the preferred search engine. Further Google is reported as an index, thus leaving open the question whether variance in the time series is attributed to changes in searches for a specific term (nominator) or overall search activity (denominator). Some of the drawbacks can potentially be cured by statistical methods; others need further investigation in order to clear out potential issues.

Overall, as this paper and the related literature shows, Google data incorporates useful information, for example in form of short term cyclicality, which can be exploited for nowcasting and forecasting. As Choi and Varian mention, this particularly works if consumers start planning purchases significantly in advance. Reasonably, this may specifically be the case for major household purchases, as mortgage lending is but one example. Thus, exploring the use and possibilities of Google data seems to be promising for the future, also in other fields of financial services. Given the flexibility and timely availability of this data source, it may serve researchers and analysts as a first insight into a specific topic of interest and beyond.

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Appendix

Table 1

Estimation Results

Dependent variable – new mortgage business, volumes, growth rates

	Benchmark	Incl. Controls	Google augmented I	Google augmented II	Google Augmented III
$\Delta mortgages_{t-1}$	-0.34***	-0.57***	-0.56***	-0.50***	-0.52***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
$\Delta mortgages_{t-2}$		-0.34***	-0.35***	-0.39***	-0.38***
		(0.07)	(0.07)	(0.07)	(0.07)
$\Delta mortgages_{t-3}$	0.29***				
	(0.08)				
$\Delta mortgages_{t-7}$	-0.18**	-0.21***	-0.20***	-0.27***	-0.27***
	(0.08)	(0.07)	(0.07)	(0.06)	(0.06)
$\Delta interest_{t-2}$		-1.11***	-1.02***	-0.99***	-1.02***
		(0.23)	(0.22)	(0.20)	(0.20)
$\Delta Baufinanzierung_{t-1}$			0.16***	0.16***	0.13***
			(0.05)	(0.04)	(0.04)
$\Delta Baufinanzierung_{t-3}$			0.12***	0.12***	0.11***
			(0.05)	(0.04)	(0.04)
$\Delta Hypothek_{t-1}$				-0.04**	-0.06***
				(0.02)	(0.02)
$\Delta Hypothek_{t-3}$				-0.08***	-0.09***
				(0.02)	(0.02)
$\Delta Kreditvergleich_{t-3}$			0.06***	0.08***	0.08***
			(0.03)	(0.03)	(0.03)
$\Delta Bauzins_{t-1}$					0.03***
					(0.01)
R^2	0.32	0.41	0.49	0.55	0.58
$Adj. R^2$	0.31	0.40	0.47	0.53	0.55
$DW\ stat$	2.09	1.91	1.96	1.99	2.03
$Sample\ Period$	2004M09 - 2015M12	2004M09 - 2015M12	2004M09 - 2015M12	2004M09 - 2015M12	2004M09 - 2015M12
$Num. Obs.$	136	136	136	136	136

Note: All time series are log-linearized and differenced.

Forecast Evaluation

Table 2

Sample: 2016M01 2018M04
Included observations: 28
Evaluation sample: 2016M01 2018M04
Number of forecasts: 7

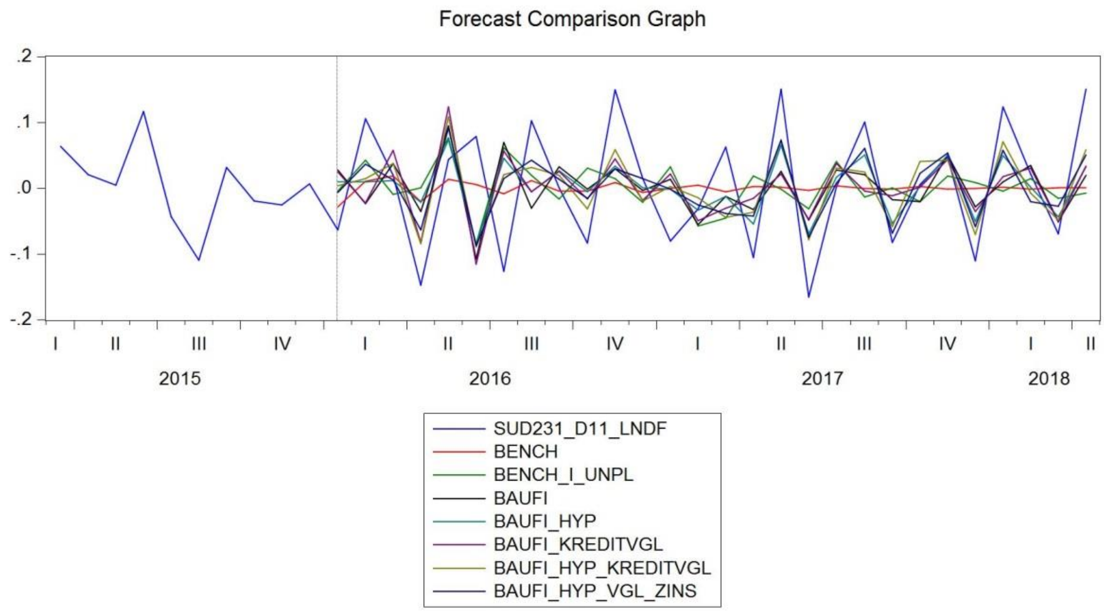
Combination tests
Null hypothesis: Forecast i includes all information contained in others

Equation	F-stat	F-prob
BENCH	7.933748	0.0001
BENCH_I_UNPL	5.851299	0.0010
BAUFI	10.54317	0.0000
BAUFI_HYP	6.456631	0.0006
BAUFI_KREDITVGL	10.02877	0.0000
BAUFI_HYP_KREDITVGL	4.755206	0.0033
BAUFI_HYP_VGL_ZINS	4.376260	0.0051

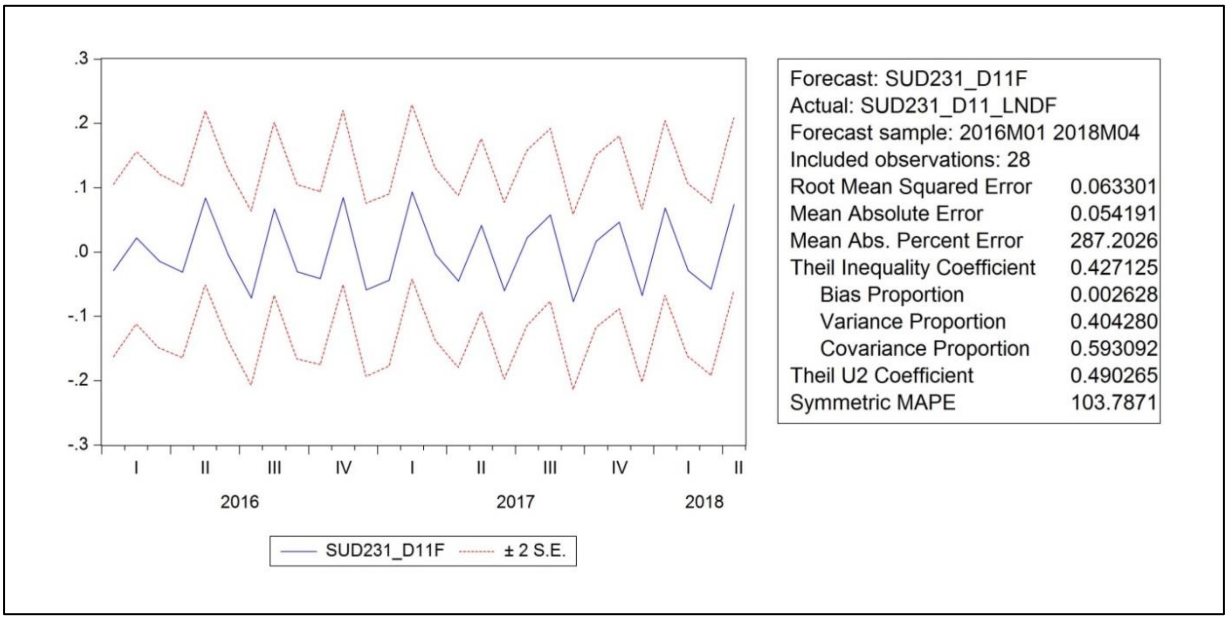
Evaluation statistics

Forecast	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
BENCH	0.090353	0.076160	112.5150	167.2447	0.874054	0.957484
BENCH_I_UNPL	0.102884	0.088681	282.8204	166.0138	0.803323	1.298619
BAUFI	0.095041	0.079783	306.7584	141.2235	0.698204	0.927898
BAUFI_HYP	0.079904	0.064154	222.1042	120.8835	0.590645	0.839572
BAUFI_KREDITVGL	0.093064	0.078871	290.7800	136.7531	0.656967	0.857488
BAUFI_HYP_KREDITVGL	0.072731	0.061808	252.6928	116.4031	0.498878	0.658610
BAUFI_HYP_VGL_ZINS	0.072015	0.058441	149.0011	102.9245	0.509604	0.726737

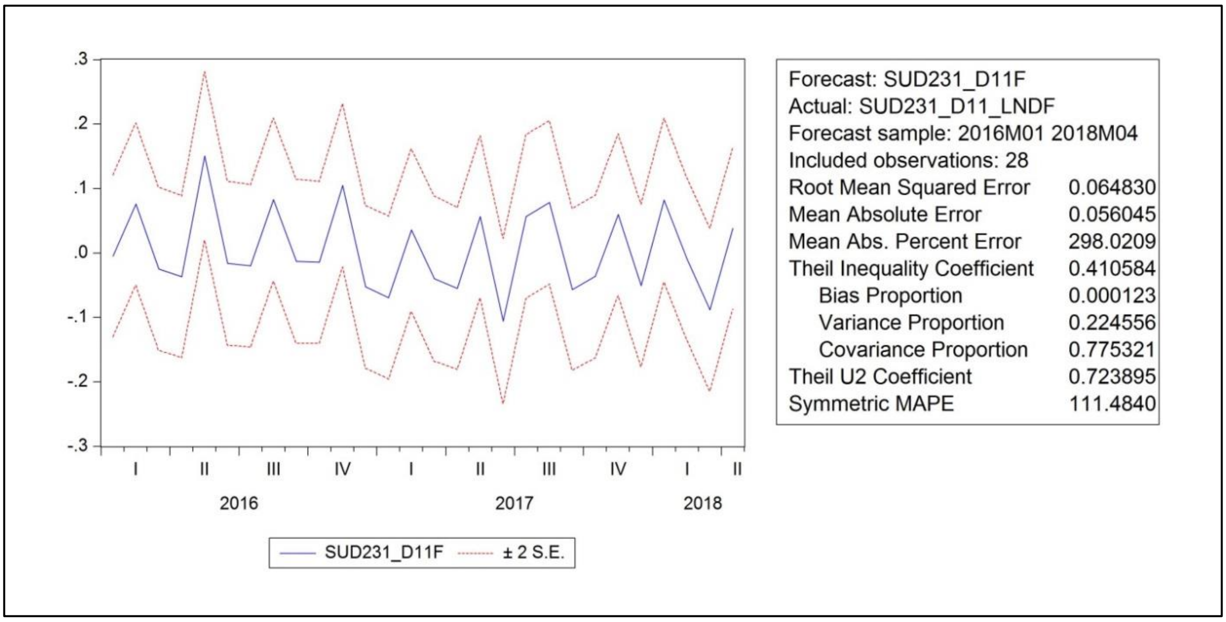
Graph 1 – dynamic out-of-sample forecasts



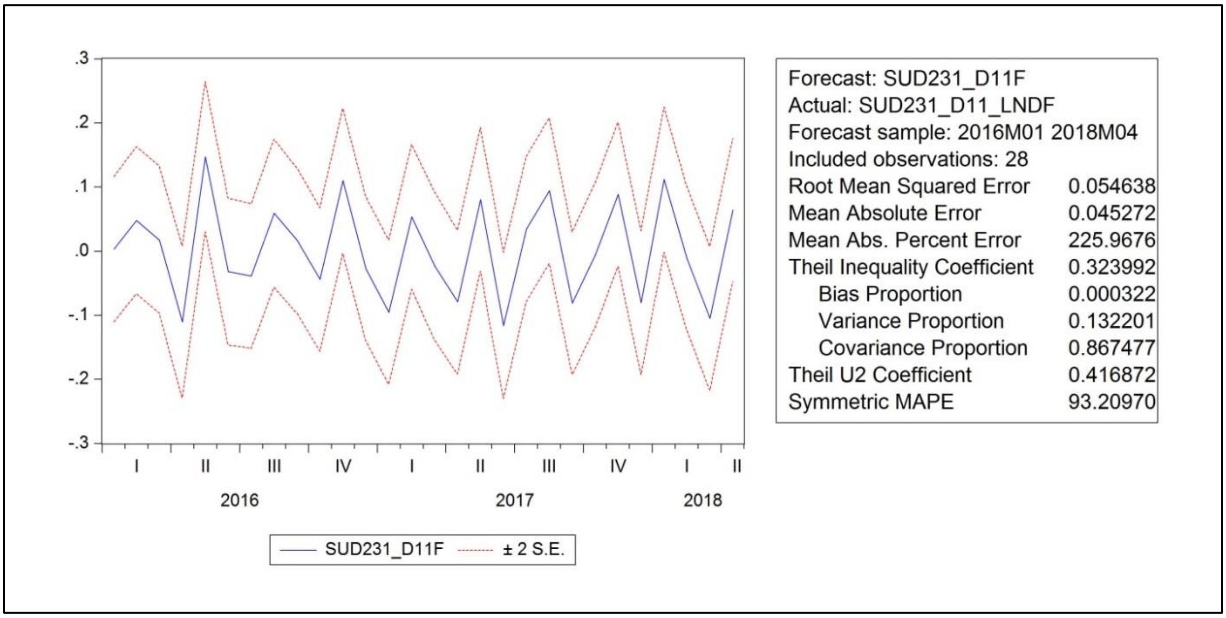
Graph 2 – Benchmark model – one step ahead (static) out-of-sample forecasts of monthly mortgage growth



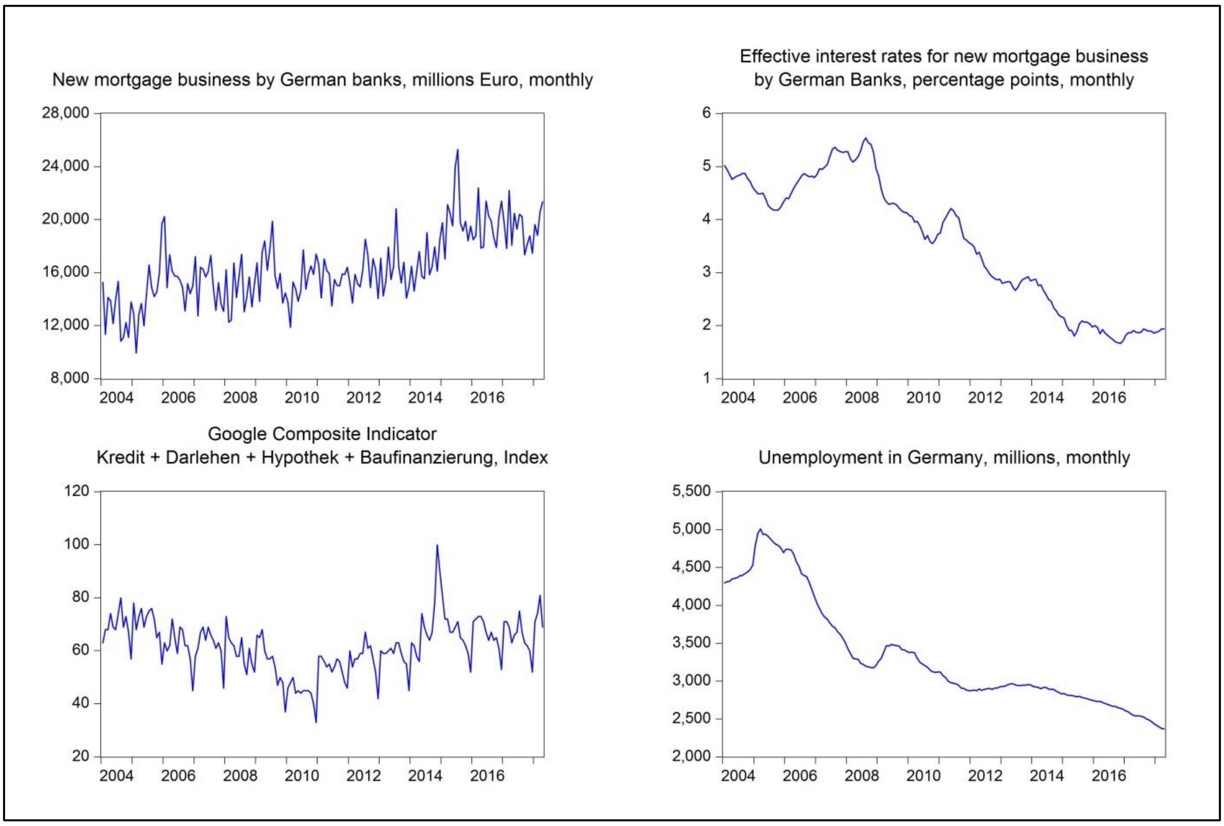
Graph 3 - Benchmark model with controls – one step ahead (static) out-of-sample forecasts of monthly mortgage growth



Graph 4 – Google Augmented II - one step ahead (static) out-of-sample forecasts of monthly mortgage growth



Graph 5 – graphical representation of selected time series, levels



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Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

Developments in the residential mortgage market in Germany - what can Google data tell us?[1]

Simon Oehler,
Deutsche Bundesbank

[1] This presentation was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

Developments in the residential mortgage market in Germany – What can Google data tell us?

9th IFC Conference , „Are post-crisis statistical initiatives completed?“, Session 5 – Big Data

Simon Oehler, Deutsche Bundesbank

Agenda

1. Motivation & Literature Review
2. Google Data
3. Econometric Approach
4. Results
5. Conclusion

1. Motivation & Literature Review

- **In recent years interest in internet search data has increased & research has started to investigate the potential of this new data source.**
- **Examples comprise:**
  - Choi, Varian (2011); Predicting the present with Google Trends
  - Schmidt, Vosen (2009); Forecasting Private Consumption, Survey-based Indicators vs. Google Trends
  - McLaren, Shanbhogue (2011); Using internet search data as economic indicators, BoE Quarterly Bulletin, Q2
  - Askitas, Zimmermann (2014); Detecting Mortgage Delinquencies with Google Trends
  - Chauvet, Gabriel, Lutz (2016); Mortgage default risk: New evidence from internet search queries
  - Saxa (2014); Forecasting Mortgages, CNB Working Paper

Why Google search data ?

“An individual's **interest in certain documents** (and not in others) is a **function of the individual's state** and so are search queries which are used to locate them. These queries are therefore utterances worth being investigated […]” - Askitas, Zimmermann (2014)

“We have found that [search] queries can be useful leading indicators for subsequent consumer purchases in situations where **consumers start planning purchases significantly in advance of their actual purchase decision**.” - Choi, Varian (2011), Predicting the Present with Google Trends

- Real estate & the financing thereof should meet this condition

Research question:

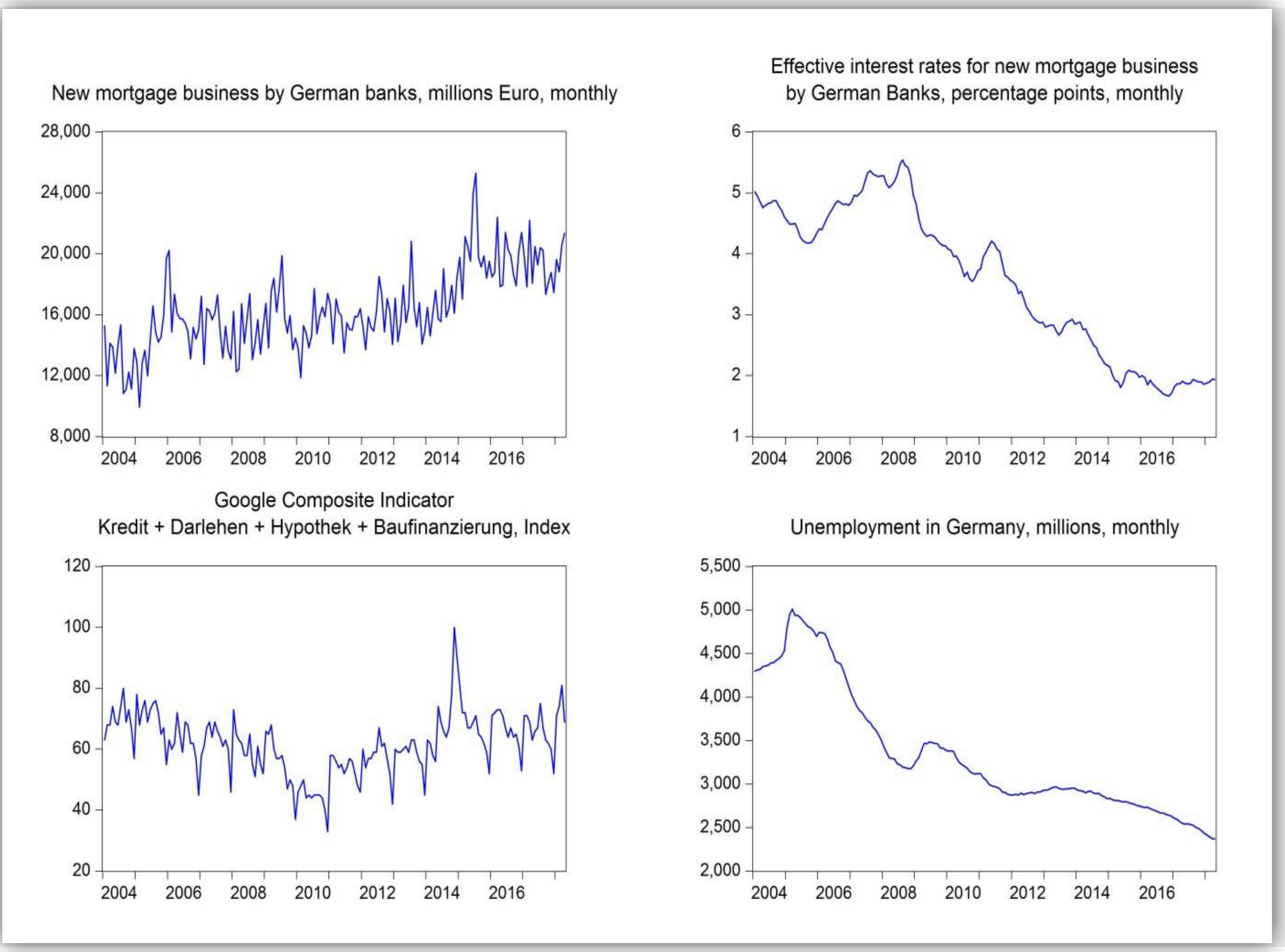
In how far can Google search data explain the variation in volumes of mortgage transactions at the federal level in Germany?

2. Google Data

- **37 Google series** are downloaded from https://trends.google.de/trends
- Selection is not solely "data driven". A priori **"economic/human reasoning"** involved as selection of time series is restricted to search terms relating to "mortgage" or "housing".
- Geography: Germany
- Language: German
- Frequency: Monthly
- Period: 2004 – April 2018
- Sampling: random sample of total searches is drawn by Google
- **Index:** no information about actual volumes or query shares

$$\boldsymbol{I(Kredit_t) = \frac{R(Kredit_t)}{\max\{R(Kredit_\tau)\}} \times 100} \quad \text{with } R(Kredit_t) = \frac{Kredit_t}{Google_t} \text{ and } \tau = 1, \ldots, T$$

2. Google Data



3. Econometric approach

− **All time series are log-transformed and first differenced.**

− **Seasonal adjustment:**

- **Response**: New mortgage business with seasonal patterns, particularly in July
- **Controls**:
  - Effective Interest rate: no seasonality
  - Unemployment: seasonally adjusted
- **Google**:
  - Almost all Google series with (strong) seasonal pattern around the end of the year: large drop in December and sharp rise in January of the subsequent year.

− **Modeling approach: Benchmark augmented by controls and Google data (stepwise forward selection procedure)**

- $\Delta mortgages_t = \beta_m L^m \Delta mortgages_t$
- $\Delta mortgages_t = \beta_m L^m \Delta mortgages_t + \gamma_m L^m \Delta interest_t + \theta_m L^m \Delta unempl_t$
- $\Delta mortgages_t = \beta_m L^m \Delta mortgages_t + \gamma_m L^m \Delta interest_t + \theta_m L^m \Delta unempl_t + \delta_m L^m \Delta Google_t$

4. Results
Out-of-sample forecasts

Forecast Evaluation
Date: 10/31/18 Time: 16:20
Sample: 2016M01 2018M04
Included observations: 28
Evaluation sample: 2016M01 2018M04
Number of forecasts: 7

Combination tests
Null hypothesis: Forecast i includes all information contained in others

Equation	F-stat	F-prob
BENCH	7.933748	0.0001
BENCH_I_UNPL	5.851299	0.0010
BAUFI	10.54317	0.0000
BAUFI_HYP	6.456631	0.0006
BAUFI_KREDITVGL	10.02877	0.0000
BAUFI_HYP_KREDIT	4.755206	0.0033
BAUFI_HYP_VGL_ZI	4.376260	0.0051

Evaluation statistics

Forecast	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
BENCH	0.090353	0.076160	112.5150	167.2447	0.874054	0.957484
BENCH_I_UNPL	0.102884	0.088681	282.8204	166.0138	0.803323	1.298619
BAUFI	0.095041	0.079783	306.7584	141.2235	0.698204	0.927898
BAUFI_HYP	0.079904	0.064154	222.1042	120.8835	0.590645	0.839572
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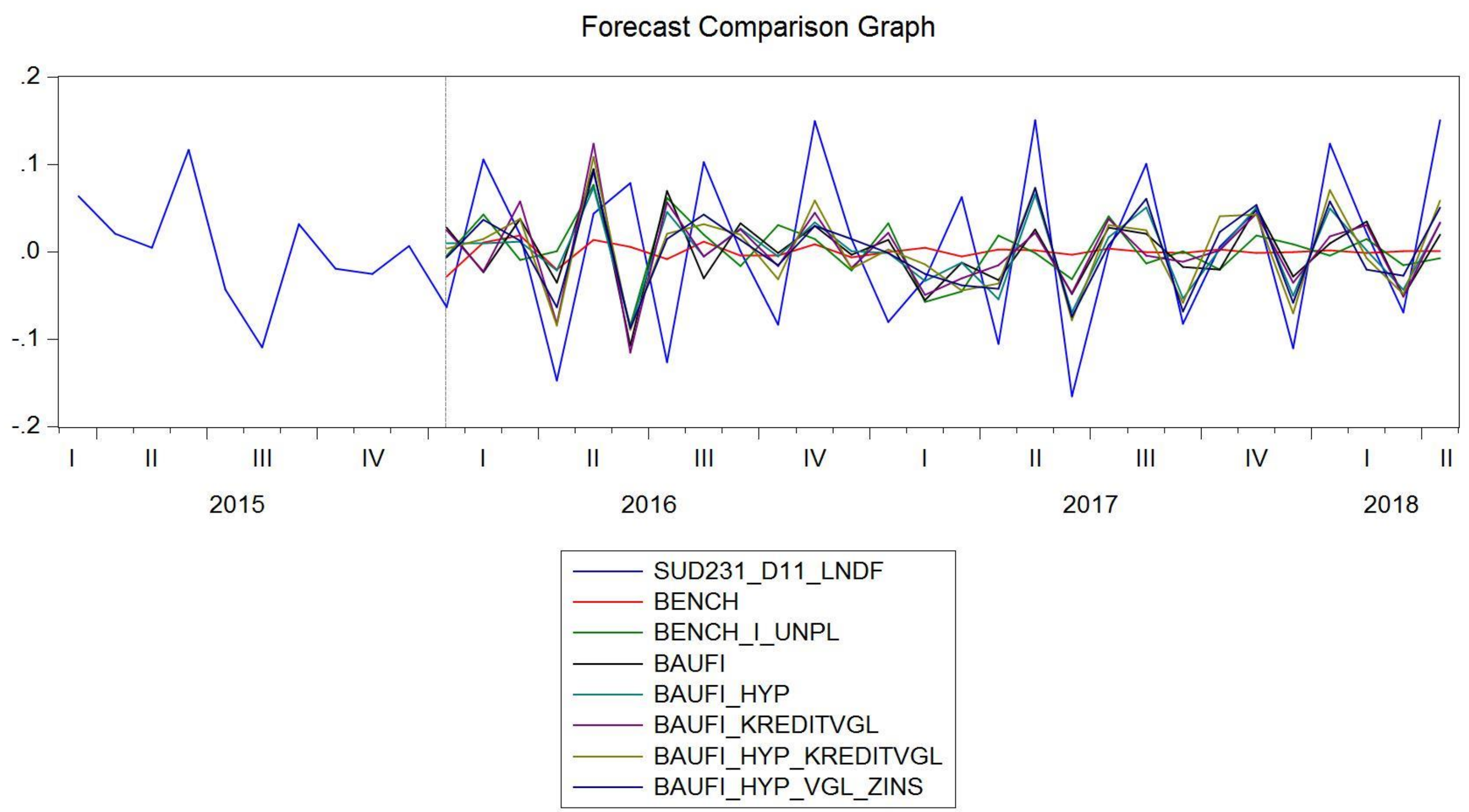
BAUFI_HYP_KREDIT	0.072731	0.061808	252.6928	116.4031	0.498878	0.658610
BAUFI_HYP_VGL_ZI	0.072015	0.058441	149.0011	102.9245	0.509604	0.726737

4. Results
Out-of-sample forecasts



5. Conclusion

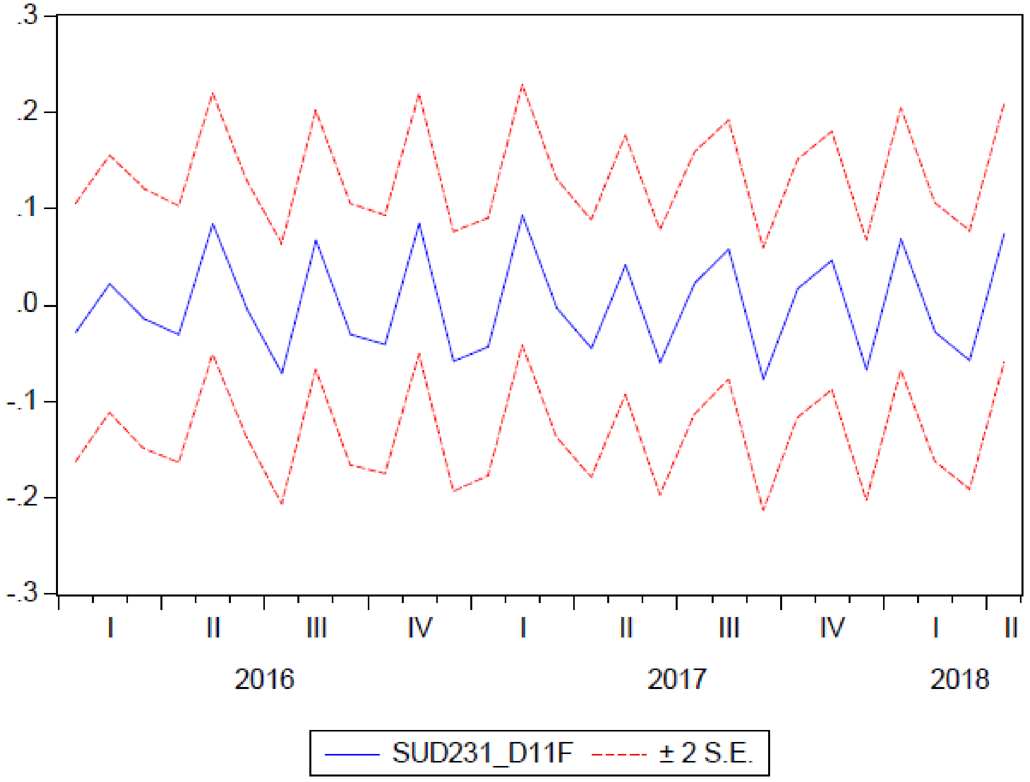
- **Results suggest that Google data contain (short term) cyclicality** which can be exploited for forecasting/nowcasting.
- In particular the search terms **„Baufinanzierung“, „Hypothek“, „Kreditvergleich“** and **„Bauzins“** proved to be significant and relevant indicators for the change in growth rates of mortgage business in Germany under the tested model specifications.
- Thus far, the models presented here control for mortgage market interest rates and unemployment as a macroeconomic indicator.
- Further robustness checks are needed. In particular:

  → Evaluate GoogleTrends relative to survey indicators
  → Further variable selection procedures to be applied

Thank you for your attention!

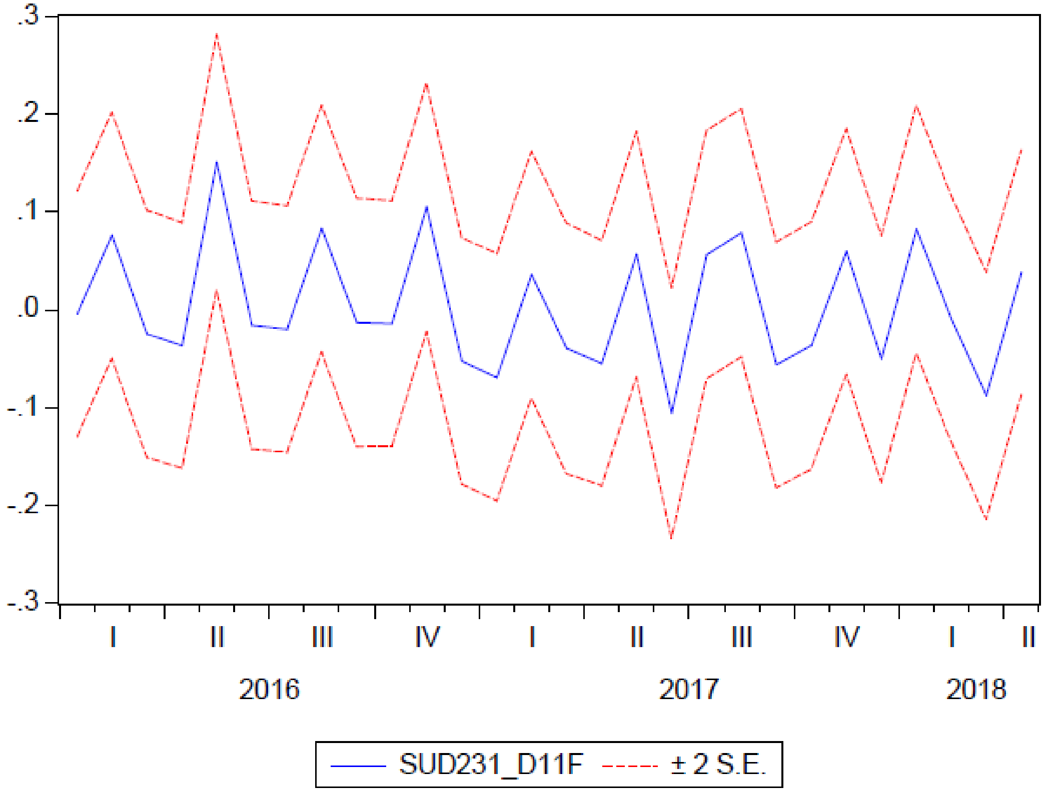
E-mail: simon.oehler@bundesbank.de

Backup I
Static Forecasts Benchmark



Forecast: SUD231_D11F	
Actual: SUD231_D11_LNDF	
Forecast sample: 2016M01 2018M04	
Included observations: 28	
Root Mean Squared Error	0.063301
Mean Absolute Error	0.054191
Mean Abs. Percent Error	287.2026
Theil Inequality Coefficient	0.427125
Bias Proportion	0.002628
Variance Proportion	0.404280
Covariance Proportion	0.593092
Theil U2 Coefficient	0.490265
Symmetric MAPE	103.7871

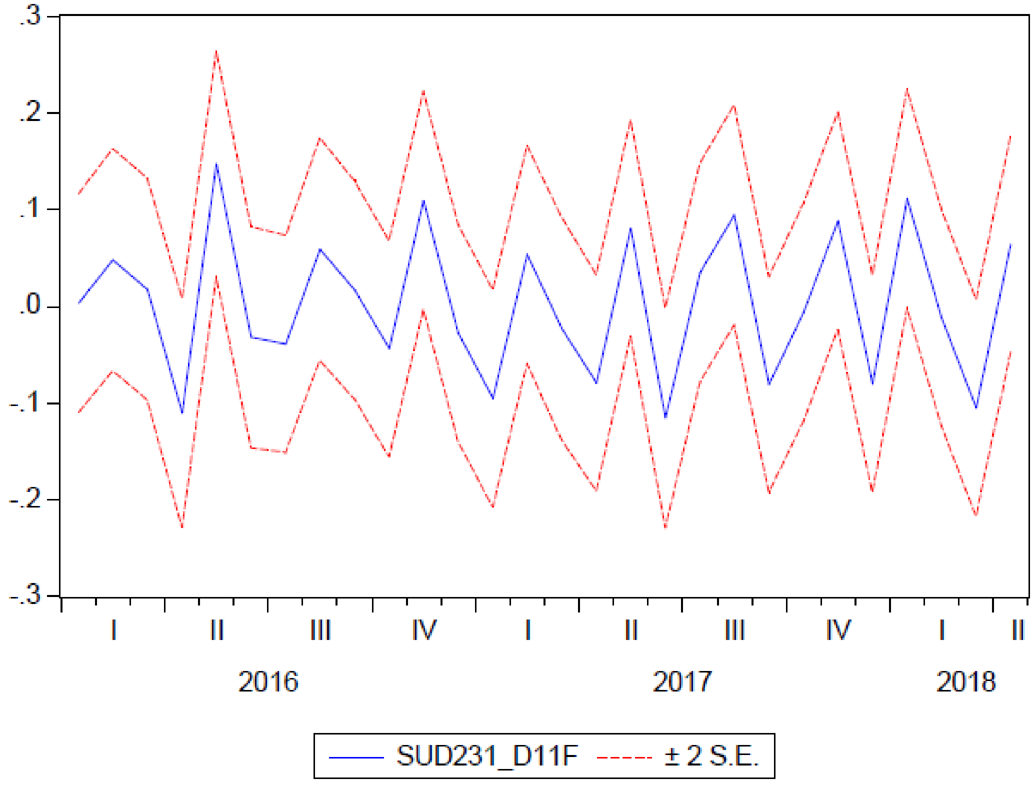
Backup II
Static Forecasts Benchmark with interest rate



Forecast: SUD231_D11F
Actual: SUD231_D11_LNDF
Forecast sample: 2016M01 2018M04
Included observations: 28

Root Mean Squared Error	0.064830
Mean Absolute Error	0.056045
Mean Abs. Percent Error	298.0209
Theil Inequality Coefficient	0.410584
Bias Proportion	0.000123
Variance Proportion	0.224556
Covariance Proportion	0.775321
Theil U2 Coefficient	0.723895
Symmetric MAPE	111.4840

Backup III
Static Forecast Google augmented II



Forecast: SUD231_D11F
Actual: SUD231_D11_LNDF
Forecast sample: 2016M01 2018M04
Included observations: 28

Root Mean Squared Error	0.054638
Mean Absolute Error	0.045272
Mean Abs. Percent Error	225.9676
Theil Inequality Coefficient	0.323992
Bias Proportion	0.000322
Variance Proportion	0.132201
Covariance Proportion	0.867477
Theil U2 Coefficient	0.416872
Symmetric MAPE	93.20970

Backup IV
Regression Output BAUFI_HYP_KREDITVGL

Dependent Variable: SUD231_D11_LNDF
Method: Least Squares
Date: 08/10/18 Time: 17:43
Sample (adjusted): 2004M09 2015M12
Included observations: 136 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
SUD231_D11_LNDF(-2)	-0.387154	0.067556	-5.730879	0.0000
SUD231_D11_LNDF(-1)	-0.503458	0.068513	-7.348352	0.0000
SUD231_D11_LNDF(-7)	-0.270081	0.063962	-4.222515	0.0000
SUD131_LNDF(-2)	-0.991662	0.204519	-4.848749	0.0000
GOOGLE_BAUFI_D11_LNDF(-3)	0.119307	0.044107	2.704970	0.0078
GOOGLE_HYP_D11_LNDF(-3)	-0.083612	0.020631	-4.052762	0.0001
GOOGLE_BAUFI_D11_LNDF(-1)	0.155329	0.043875	3.540303	0.0006
GOOGLE_KREDITVGL_D11_LNDF(-	0.086669	0.027745	3.123732	0.0022
GOOGLE_HYP_D11_LNDF(-1)	-0.042178	0.019847	-2.125220	0.0355

R-squared	0.558962	Mean dependent var	0.004244
Adjusted R-squared	0.531180	S.D. dependent var	0.080372
S.E. of regression	0.055031	Akaike info criterion	-2.897948
Sum squared resid	0.384611	Schwarz criterion	-2.705199
Log likelihood	206.0605	Hannan-Quinn criter.	-2.819619
Durbin-Watson stat	1.996244		

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Creating comprehensive data worlds using standardisation[1]

Stephan Müller,
Deutsche Bundesbank

[1] This paper was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

Creating comprehensive data worlds using standardisation[1]

Stephan Müller[2]

Keywords: Micro data, growing data worlds, data gaps, data integration, standardisation, harmonisation, SDMX, House of Microdata

Ever since the global financial crisis, the importance of micro data has been on the rise. The amount of data being collected is constantly growing and becoming increasingly varied. In a parallel development, statistical authorities are faced with a rising number of data providers. Against this backdrop, this short paper aims to illustrate ways of enhancing the usability of growing data worlds.

Growing data worlds

Since around 2008, the global financial crisis has led to a sharp shift in data needs and a surge in user groups. Many new statistical surveys were created to meet the huge demand for statistical information that emerged after the crisis. For example, the following questions had to be answered:

- How heavily affected are investors in Europe?
- Who holds which government bonds?
- What is the degree of risk concentration?
- How healthy are euro area banks?

Answering these questions increased the amount of available data enormously. Substantial technological progress meant that the data supply also expanded during this period. Examples of new technology include automatic recording of process data, social networks and search engines, as well as mobile phones, tablets and so on. And this went hand in hand with much larger computing power and new analysis techniques like machine learning. These developments led to an exploding data supply. And finally there was a paradigm shift from a macro to a micro perspective in terms of identifying certain heterogeneities. Facing with growing demand, growing supply and a shift from a macro to a micro perspective, it is therefore no exaggeration to say that the data universe is exploding. But can we really take advantage of all these newly available data?

[1] The paper is largely based on the book "Measuring the Data Universe" by Reinhold Stahl and Patricia Staab.

[2] Deutsche Bundesbank, Directorate General Statistics, stephan.mueller3@bundesbank.de

The data universe lacks order

The status quo is that, despite our exploding data universe, there are still yawning data gaps. So a pressing question now is: do we drill where the oil actually is or where it is easy to drill? The data universe still lacks order. For example, there is still nothing like a unique identifier – an actual barcode for information. There are, for instance, MFI code lists or the Legal Entity Identifier – but these are not really global or universal.

The lack of order is evident in the data universes of almost all companies and has given rise to countless initiatives since a large part of companies' data are stored in data silos. Examples of widespread initiatives are projects relating to data integration, business intelligence, data warehouses or big data. Additionally, chief information officers are being appointed to bring order into their companies' data world. But the results are often proprietary solutions in the respective industry branches or countries.

There is also much higher volatility in terms of evaluation requirements. One can say that the focus is no longer on the classical statistical production of pre-defined indicators. Instead data analysis is, more and more, being implemented on demand with a lot of information needing to be available at all times – especially since evidence-based policymaking is now central to the regulatory agenda. All in all, a new style of data collection with hundreds of dimensions has emerged, meaning that there are more data, several structures, little order, high complexity and only a few experts available to analyse the existing data. And while the data may look similar, they are in fact very heterogeneous. Also, progressing automation can only help to a certain degree. Automation itself is a useful tool for data processing, but does not really help in terms of understanding, analysing and handling data. Especially when it comes to recognising the relationships between various sets of data, the experts need to share their knowledge and to cooperate with each other.

Data integration

The current situation as described and the challenges involved raise the following question. What concrete measures can be taken to increase the usability of existing data? An important task is data integration. The process of data integration can be broken down into three steps. Each step can be technically supported and automated to a certain degree. Throughout the process, the degree of standardisation is increasing constantly and on an ongoing basis.

The process of data integration starts with heterogeneous data from various sources. The first step is logical centralisation, meaning that the data are stored physically or virtually in a common system. Common procedures can be used for administration, authorisation and access. This level of integration is what is meant when speaking of the data lake.

The second step is a uniform data modelling method with an order system, typically a uniform language using the same concepts and terms. An example is the use of SDMX as a standard designed to describe statistical data and metadata. Rule-based and automatable treatment of the data thus becomes possible. At this stage, one typically speaks of a data warehouse.

The third step is semantic harmonisation. Here, the same concepts, methods and code-lists are used to classify the data. This makes it possible to link the data, i.e. to actually integrate content. As a consequence, a common dictionary can be used. This part is definitely the most difficult. At the end, the integrated data are ready for linking and simplification.

As a simple metaphor for the three steps of data integration, imagine a high-rack warehouse. Step 1 is to simply store all items in the same storage location. Step 2 is to put all items on racks so that nothing is left on the floor. Step 3 is to label the racks using a uniform system.

However, those wishing to introduce data integration face a couple of challenges from the various stakeholders involved. Every stakeholder has his own agenda with his own requirements. For example, the existing IT standards for data integration in the IT industry are either branch-specific silo solutions or high-level formal frameworks. In addition, within most companies, silo thinking is more pronounced than interdisciplinary thinking. Data users are not interested in data integration and the production process in itself, they are only looking for a specific result. Challenges from outside are often associated with privacy and data protection issues as well as with a lack of direct incentives.

SDMX and the Bundesbank's central statistics infrastructure

To show how the Bundesbank deals with the topic of data integration, it is expedient to use the example of its statistical value chain. The Bundesbank receives data from its registered partners. The data are checked and aggregated in individual databases and IT systems for several primary statistics – in various data silos as it were. This represents the first step of data integration. Data from external organisations and commercial data sources are not modified.

The second step in data integration is to store macro and micro data in the Bundesbank's central statistics infrastructure. There, all data are stored in a common system and in SDMX format. The SDMX format allows all data to be edited using the same tools, and data sharing is also possible. As mentioned before, the most difficult part of data integration is step 3, namely semantic harmonisation. This would allow us to properly link all the available data, and the Bundesbank is currently working on making this possible.

At the end of the value chain are the different ways of using, disseminating and publishing the data. For example, there is an "access portal" for partners; this provides access to the available data not only to Bundesbank staff, but also to those of the Federal Ministry of Finance and the Federal Financial Supervisory Authority.

The use of SDMX as an organisational structure in the world of statistics has huge potential when it comes to data integration. The above-described statistical value chain leads to a certain data world. This world contains specific statistical data and metadata from different business areas. SDMX semantically translates the data into a uniform language. The SDMX keys can be considered as character strings that enable each time series of a dataset to be identified uniquely and read by a machine. After semantic translation, every time series of a dataset has a systematic designation and can be organised in a data warehouse and used on a platform-independent basis. Once the process of data integration is complete, all the data in the different data warehouses of the various organisations could potentially be accessed using a common software product via a technical interface. Even linking the data from the various data warehouses would then be possible.

A good example of standardisation in times of an exploding data universe is the Bundesbank's House of Microdata. It is based on SDMX and the central statistics infrastructure and constitutes a central microdatabase able to hold all microdata with high potential for analytical purposes. Direct access to the House of Microdata is only granted to internal Bundesbank users, on a need-to-know basis and in compliance with confidentiality regulations. External researchers are obliged to use the services of the Research Data and Service Centre. The House of Microdata – like the Research Data and Service Centre – is part of the Integrated Microdata-based Information and Analysis System (IMIDIAS) and enables bank-wide data integration and a common information model. For each dataset to be integrated, a potential analysis is conducted. Once a dataset is completely integrated, it can be connected along the corresponding dimensions, which have been coded using the same code lists. This is actually the third step of data integration, and the Bundesbank is currently doing its best to semantically harmonise its formally SDMX-classified microdata.

Outstanding issues in the context of standardisation

The analysis of the current situation may throw up to a couple of questions that might be relevant in the context of data standardisation and harmonisation in the future. At the moment, no globally consistent code lists are available yet. But is a truly global standard possible? Data standardisation and harmonisation are being promoted around the world but sometimes it seems everyone is tweaking the standard a little bit to meet their own needs. Meanwhile, truly universal and unique identifiers are urgently needed. Without them, we will always start over again. Another question might be whether the open source approach is appropriate for future efforts. In this context one could ask: why only share the data but not codes, knowledge, methods and programs? And do the global approach and the open source idea comply with confidentiality constraints and the legal framework? What good is a data warehouse if I am not allowed to share the data? Finally, are we investing enough time and effort into data literacy in order to sustainably increase the value of the existing data? Current discussions often only focus on technical aspects. But what about users' ability to really understand and master the data? An investment in data literacy would also improve trust in statistical statements.

Reference

Stahl, R. and Staab, P. (2018). Measuring the Data Universe. 1st ed. Springer International Publishing.

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Creating comprehensive data worlds using standardisation[1]

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Creating Comprehensive Data Worlds using Standardization

Stephan Müller, Deutsche Bundesbank

Are post-crisis statistical initiatives completed?
- The data universe is exploding -

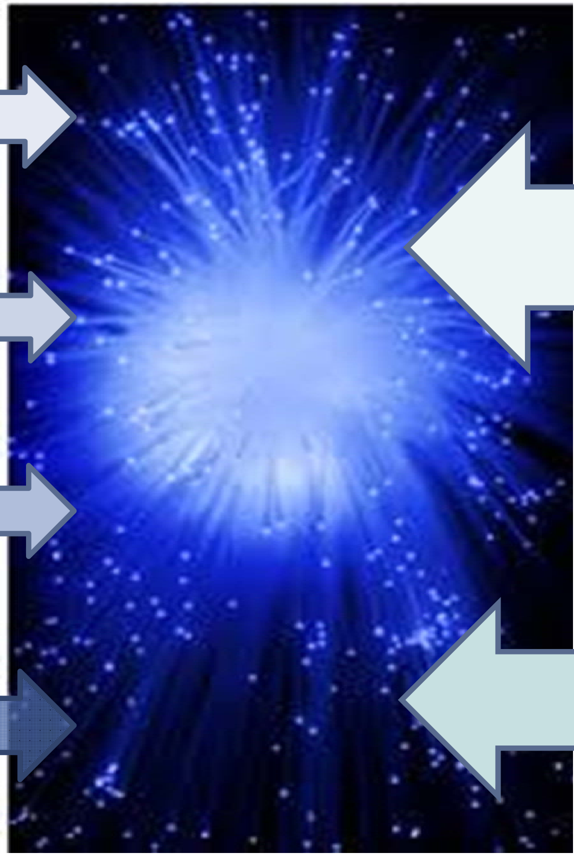
Demand for new statistical surveys

Banking crisis
How heavily affected are investors in Europe?

Sovereign debt crisis
Who holds which government bonds?

Banking union
What is the scope of risk concentration?

Low-interest-rate environment
How healthy are euro area banks?



Exploding data supply

Data amount is growing constantly and rapidly

- Automatic recording of process data (sensors, Internet of Things)
- Social networks and search engines
- Mobile phones and tablets

New technological developments

- More computing power: Big Data
- New analysis techniques: Machine Learning, AI

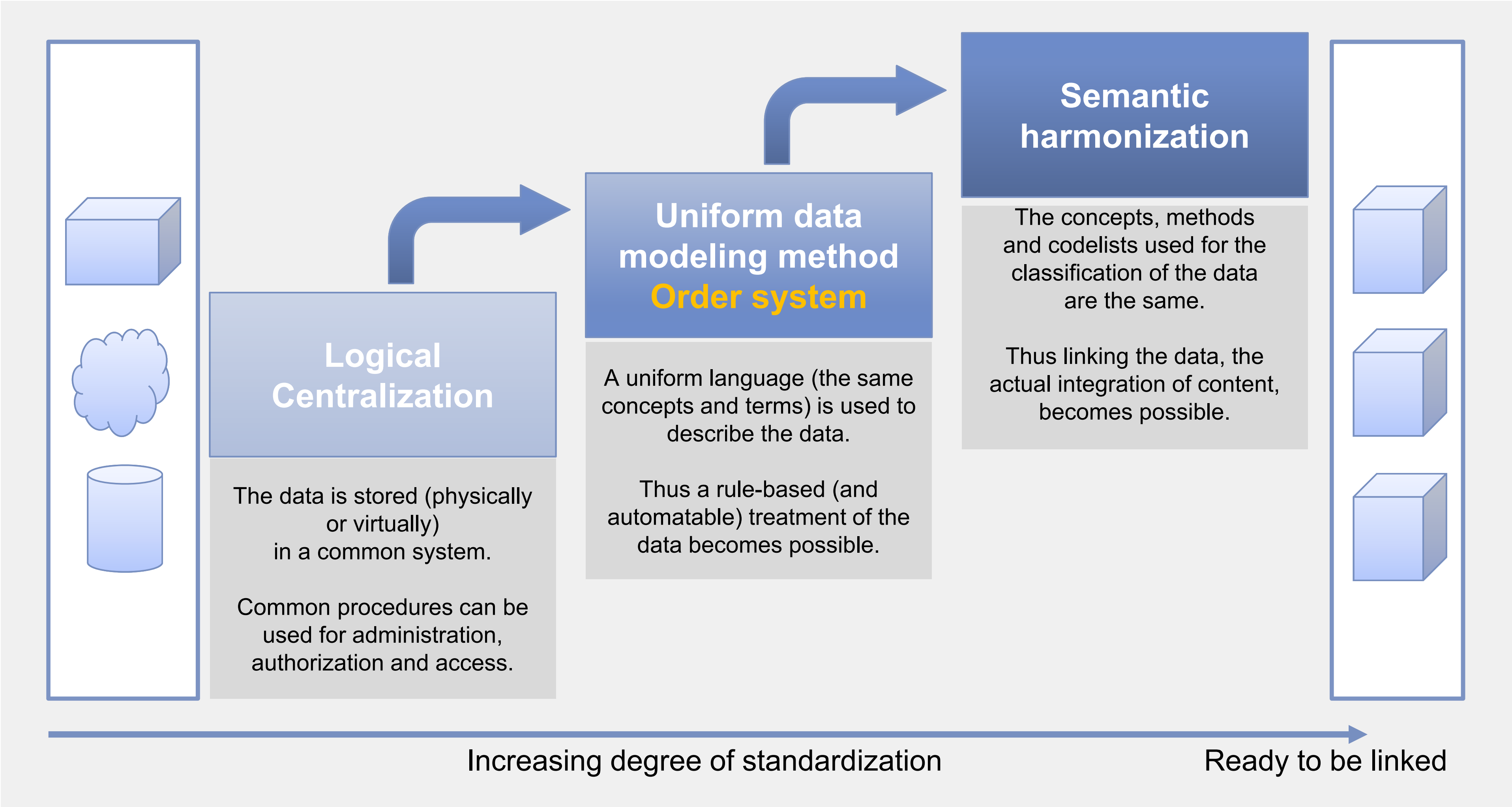
“Water, water, everywhere, but not a drop to drink.”

- **Yawning Data Gaps despite “Collectomania”**
  – Data is not collected where it's needed, but where it occurs. Still painful data gaps

- **The Data Universe lacks Orde**r
  – In IT: neither a system of order for data / information, nor a prominent standardization, nor a global identifier (“barcode for information”)
  – In companies: large part of the data stored in data silos; need for data integration / BI / DWH / Big Data projects / CIOs
  – In industry branches or countries: proprietary solutions

- **Using IT not Possible Without Content-Related Expertise**
  – No longer classical statistical production of prescribed indicators
  – Instead implementation of data analysis on demand
  – New style of data collections with hundreds of dimensions
  – Automation or lack of expertise could lead to comparing apples and oranges
  – Professional expertise crucial for evaluating and interpreting the results

The three steps of data integration



Challenges for those who want to introduce data integration

Challenges coming from…

…the IT industry and its customers

- Innovation speed of IT technology
- IT projects instead of business projects
- Existing IT standards for data integration

…within the company

- Individualistic mentality
- Silo thinking rather than interdisciplinary thinking

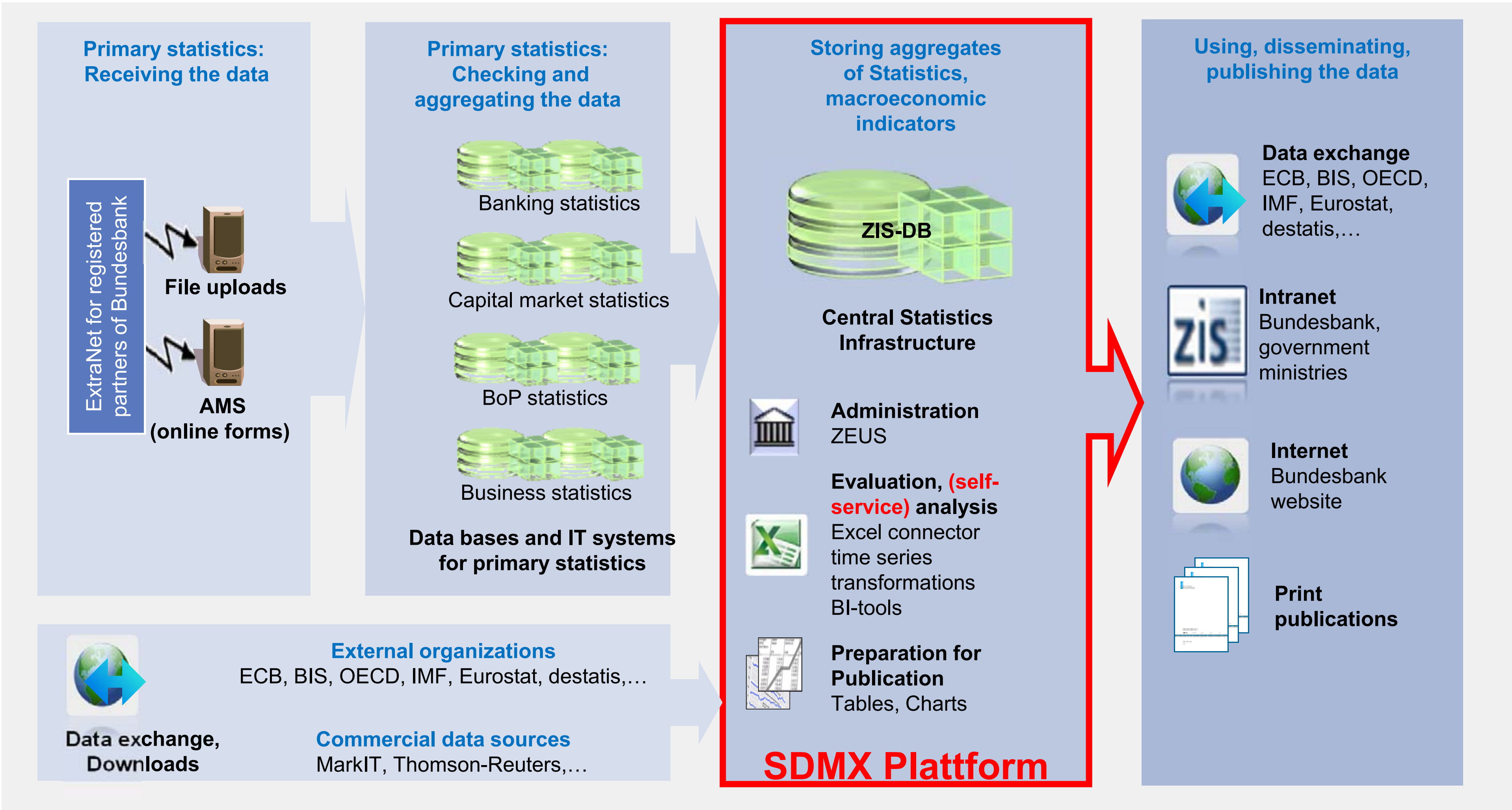
…data users (researchers, analysts)

- Researchers not interested in data integration and production process in itself but a specific result
- Gap between what analysts want and what even well-arranged data structures can offer

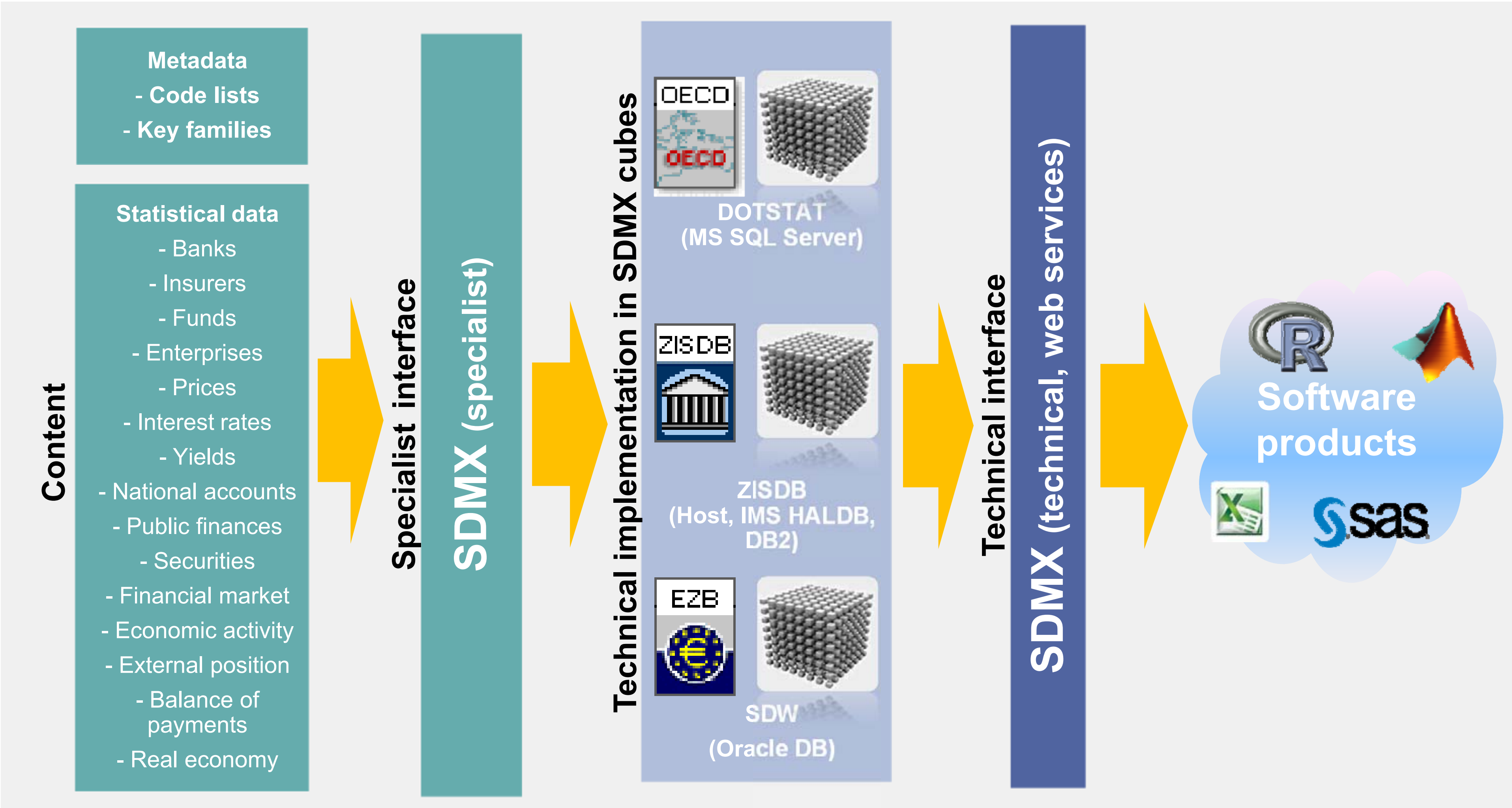
…outside

- Privacy and data protection
- Lack of direct incentives

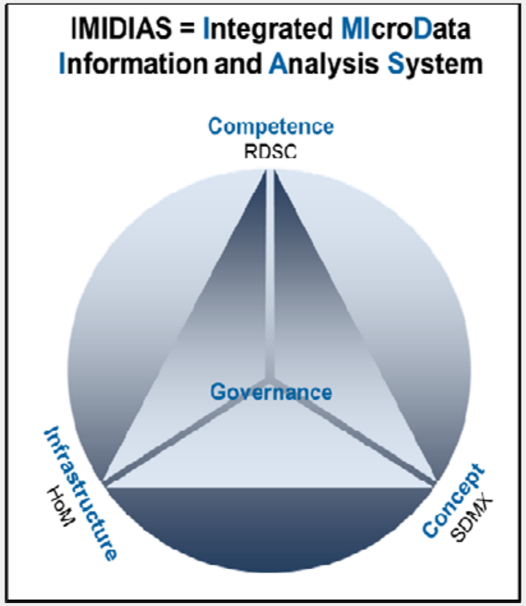
Directorate General Statistics
Value Chain



SDMX is used across domains and platforms
Decentralised data sinks on various technical platforms



SDMX and central statistics infrastructure
Basis for House of Microdata (HoM)



- In 2013, the Statistics Department was mandated to establish an **integrated interdepartmental information system for analytical and research purposes based on microdata** for various user groups (financial stability, research, monetary policy, supervision)
- This should be achieved by developing a Research Data and Service Centre (RDSC) and a **microdatabase (HoM, "House of Microdata")**
- This HoM is based on SDMX and the **Central Statistics Infrastructure**

− The SDMX model can be used without any problems for microdata.

− Data diversity requires standardization, SDMX provides a suitable framework

− Multidimensional approach, by using uniform code lists, offers an ideal means of linking and comparing data from different sources.

What is there to do?

- There are **no globally consistent code lists** so far
  - Is a **truly global standard** possible?
- Is the global approach and the open source idea in accordance with **confidentiality constraints and the legal framework**?
- **Open source** approach for future efforts?
- Do we invest enough time and effort in **Data Literacy?**

Ninth IFC Conference on “Are post-crisis statistical initiatives completed?”

Basel, 30-31 August 2018

Imputation for missing data through artificial intelligence[1]

Byeungchun Kwon,
Bank for International Settlements

[1] This paper was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

Imputation for missing data through artificial intelligence

Heuristic & Machine learning approach to impute missing values (Test case with macroeconomic time series from the BIS Data Bank)

Byeungchun Kwon[1]

Abstract

The paper presents the new paradigm of missing data imputation method, the heuristic and machine learning imputation (HMLI), and experimentally compares 6 popular imputation methods through the macroeconomic time series from BIS Data Bank. HMLI is one of non-linear regression models. The main difference is it is based on the genetic search and the support vector machine (SVM) algorithm. HMLI consists of two parts: the best dependent variables selection and the non-linear regression. To verify the robustness of HMLI, the paper measures RMSE between predicted missing values and actual values for HMLI and 6 popular imputation methods. I tested 3,070 times for macroeconomic time series. The result shows that HMLI RMSE is the lowest about 10 percent missing data rate and second lower RMSE about 40 and 70 percent missing data rates. In this paper, I test macroeconomic times series with single frequency only, it needs to test various time series types which are different frequencies, trend and seasonality patterns.

Keywords: Heuristic search, Machine learning, Artificial intelligence, Imputation

JEL classification: C61, C82

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Contents

1. Introduction

Time series data is widely used in various research fields and there are countless econometric functions and programs to analyse time series data. But most of mathematical analysis methodologies require complete time series data which means that all observations are filled with figures and it is not allow missing values. But missing observations are easily found in time series due to many reasons. Financial time series doesn't generate numbers on weekends and public holidays. In longitudinal studies, observations missing is usually happen. To put time series data in econometric functions, missing observations should be substituted reasonable figures.

In popular statistical tools like R and Stata, many imputation libraries exist based on various methodologies from simple interpolation to Kalman filter. In the Steffen et al., 2018, they compare 6 well known imputation methods in R for univariate time series.[2] To compare the imputation methods, it measured the root mean square error (RMSE) between actual values and predicted values. RMSE result shows that methods are so far apart statistically. It wonders these methods give us optimum imputation values about univariate time series. If we adopt the evolutionary process to impute missing values, Can we get more precise values?

This paper develops new imputation program based on the evolutionary process and machine learning algorithm, Heuristic and Machine Learning Imputation (HMLI). This is one of usual regression models so, it is composed of independent variable and dependent variables. But, HMLI does not know which dependent variables are the best set to impute missing values in independent variable. To find optimum dependent variables, HMLI introduces the genetic algorithm, one of heuristic search methods. This algorithm imitates natural evolutionary process so, we expect it can find one of best dependent variables sets through an iteration. Once this algorithm selects dependent variables, the model regresses dependent variables to an independent variable and predicts missing values. Regression method of HMLI is the support vector machine (SVM). SVM is one of the most efficient machine learning algorithm, which is mostly used for pattern recognition since its introduction in 1990s.

To verify HMLI model robustness, the paper measures RMSE between predict missing values and actual values from HMLI and 6 traditional imputation methods about 3,070 macroeconomic time series. All of the data are monthly frequency and retrieved from BIS Data Bank. It shows that RMSE from HMLI is lowest about 10 percent missing data rate and second lower RMSE about 40 and 70 percent missing data rates.

[2] Imputation methods

aggregate	Replacing NA with the overall mean
structTS	Filling NA through seasonal Kalman filter
locf	Last observation carried Forward; replacing NA with most recent non-NA value
approx	Replacing NA with linear interpolation
irmi	Iterative Robust Model-Based Imputation; filling NA through autoregressive imputation
interp	Linear interpolation for non-seasonal series. If seasonal series, a robust STL decomposition proceeded

This paper is structured as follows: section 2 explains HMLI model structure; section 3 shows the model computing process; section 4 shows experiment; and finally, section 5 includes key concluding remarks.

2. HMLI structure

As general regression model, HMLI structure is also composed of dependent variables and independent variable. The independent variable is the time series which has missing observations. HMLI model has two differences with the traditional regression model; dependent variable selection and regression line fitting.

In the traditional regression model, researchers normally select dependent variables to explain the model itself statistically and predict an independent variable correctly. But it is difficult to find best dependent variables for various reasons. If computer algorithms find optimum combination of dependent variables and predict independent variable with low error rate, it could be a perfect solution for imputation.

This paper applies the heuristic search (genetic algorithm) to select dependent variables. Heuristic search is a rule of thumb technique to find a solution more quickly when traditional approach is limited. For examples, total number of combinations to choose 6 time series from 10,000 time series is about 13×10^{20}. It is too big to compute all combinations within limited time. In this case, heuristic search could be a solution to approximate the exact solution.

In the model, genetic algorithm is implemented as heuristic search algorithm. Genetic algorithm imitates the natural selection process of Charles Darwin about natural evolution such as inheritance, mutation and crossover. A set of dependent variables is same as one chromosome and single dependent variable in the chromosome is a gene. Bad prediction means the dependent variables set can be regarded as recessive and will be disappeared in next iteration.

For the regression line fitting, HMLI model implements the support vector machine (SVM) which is one of the most efficient machine learning algorithm, which is mostly used for pattern recognition since its introduction in 1990s[3]. Once SVM calculates optimum parameters in the model, it predicts missing observations using actual dependent variables.

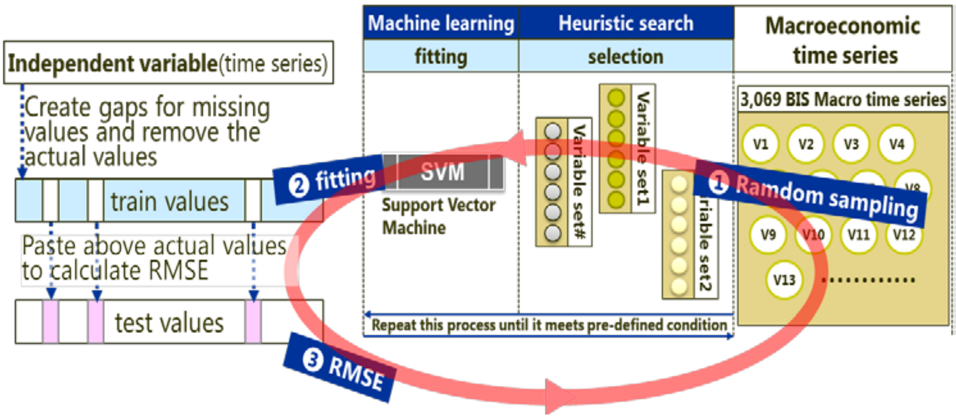
This heuristic search and machine learning combination repeats dependent variables selection, regression line fitting, missing observation prediction and performance review through the root mean square error (RMSE) between actual and prediction values. Termination condition of the repetition can be either RMSE satisfaction or iteration number.

[3] Boon Giin Lee, Teak Wei Chong, Boon Leng Lee, Hee Joon Park, Yoon Nyun Kim, Beomjoon Kim, "Wearable Mobile-Based Emotional Response-Monitoring System for Drivers", Human-Machine Systems IEEE Transactions on, vol. 47, no. 5, pp. 636-649, 2017.

1

Box: HMLI structure flow chart

As HMLI iterates this step 100 times, RMSE generally gets smaller and converged on certain number. It is heavily depending on initial values about which times series are selected to dependent variables, number of gaps and positions.



3. HMLI computing process

HMLI computing process consists of 9 steps. By iterating these steps, HMLI implements an evolutionary process. This iteration programming consumes computing resources heavily.

3.1 Steps for time series data pre-processing

STEP 1 (Data pre-process): If time series value range is wide, SVM objective function might be not working properly and calculation performance of normalization values is much faster[4]. Normalization is needed both independent and dependent variables. Once normalization is done, it starts to add gaps in independent variable. This added gaps replace actual values in time series and it will use as testing values. To decide which dates become gaps in time series, the model uses the exponential distribution and λ is a missing rate.

STEP 2 (Train and test data separation): In the step 1, the actual values, which are replaced with gaps, will be used to test values. Once HMLI model generates prediction values, RMSE between test and predicted values is a factor about performance of dependent variables. Except testing values in dependent variables, the other values is used as a train data.

STEP 3 (Sampling dependent variables): It is a random sampling process to pick a certain number of dependent variables from total variables. In this paper, it

[4] Ioffe, Sergey; Christian Szegedy (2015). "Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift"

randomly picks 6 time series for dependent variables from 3,069 macroeconomic time series and repeat it 10 times to create 10 sets of dependent variables.

3.2 Steps for evolutionary process

STEP 4 (Regression): Through the train data, SVM calculates best fitting curve. By putting test data into this fitting curve, SVM generates predicted values.

STEP 5 (RMSE calculation): It calculate RMSE between prediction values from SVM fitting curve and actual values replaced with gaps on STEP 1. Low RMSE means that dependent variables are good to predict gaps.

STEP 6 (Selection process): About 10 sets of dependent variables, this step calculates RMSE and ranks the sets. Based on this rank, it removes 5 lower ranked sets.

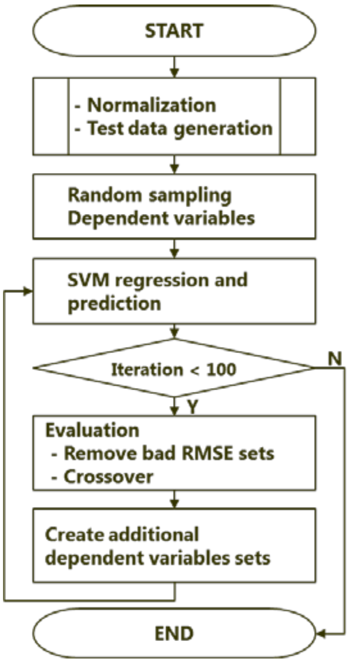
STEP 7 (Dependent variables crossover): Extract unique variables from top 5 ranked sets and generate 2 new dependent variables sets. If it cannot generate new dependent variables set, skip this process.

STEP 8 (Additional dependent variables sampling): For next iteration, 10 dependent variables sets are required. Including top 5 ranked sets and 2 crossover sets, create additional sets until it becomes 10 sets.

STEP 9 (Repetition): It repeats n times from step 4 to step 8. In this paper, Number n sets up 100. Normally, an iteration ends when it satisfies a certain condition. For example, if RMSE is less than a certain number, it stops the iteration. But this paper uses an iteration number as a termination condition because it reaches convergence level within 100 iterations.

2

Box: HMLI process diagram



4. Experiment

To verify HMLI model usability, this paper compares HMLI with six popular imputation methods. Experiment data is macroeconomic time series from BIS Data Bank. As a result, HMLI model shows very low RMSE and it is one of best imputation models.

4.1 Data and methods

4.1.1 Experimental data set

Experiment data is 3,070 macroeconomic time series from BIS Data Bank. It retrieves 26,193 monthly time series from the BIS Data Bank. To remove similar and complete time series, it extracts 3,070 time series which means that correlation coefficient is less than 0.97 between each other.

From 3,070 time series, it chooses a time series for independent variable and 3,069 time series are dependent variables set. Therefore, number of experiments is 3,070. Time period of 3,070 time series is from January 2010 to December 2017. Because it is monthly frequency, each time series has 96 observations.

4.1.2 Missing data rate

3,070 macroeconomic time series are complete data so, it doesn't have gap in the time series. To test traditional imputation methods and HMLI, it replaces actual values to gaps in an independent variable. Replaced actual values is used to calculate RMSE with predicted values for gaps through SVM.

Gaps are generated based on the exponential distribution and λ is missing data rate. So, bigger λ creates more gaps. In this experiment, it use three missing data rates; 0.1, 0.4 and 0.7. Average number of gaps 96 observations is 9.13 gaps for 0.1 missing rate, 31.52 gaps for 0.4 missing rate and 48.74 gaps for 0.7 missing rate.

Because the exponential distribution randomly pick gaps, it repeats 3 times for each missing rates. Therefore one independent variable is tested 9 times for each imputation methods.

4.1.3 Traditional imputation methods

In statistical packages, many imputation libraries exist and it can classify two types. So some libraries don't support both data types.

- Univariate time series imputation; single time series
- Multivariate time series imputation; panel data

There are many time series data analysis libraries in R. And this paper uses six imputation methods which are na.aggregate, na.locf, na.StructTS, na.approx methods of zoo library and na.interp method of forecast library and ar.irmi of VIM and customized function of Steffen, et al., 2015.

4.2 Experiment design and platform

About six traditional imputation methods, it executes 9 imputations, which are 3 different missing rate and 3 different random seed, for one variable. Total number of experiments is 165,780 which consists of

- 6 imputation methods × 3,070 variables × 3 missing rates ×3 random seeds

In case of HMLI method, it iterates 100 times for evolutionary process per one independent variable and each iteration has 10 different dependent variables sets. Total number of experiment is 27,630,000 which consists of

- 3,070 independent variables ×10 dependent variables sets ×100 iterations ×3 missing rates ×3 random seeds

The paper uses the open source R script developed by Steffen, et al., 2015 for traditional imputation methods experiment. And HMLI model is developed by parallel Python script. Both scripts are executed on Intel i7 CPU (8 cores) and it took 9 hours to finish the experiment.

4.3 Result

HMLI evolutionary process performance

While HMLI model repeats an evolutionary process, it expects mean square error (MSE) between actual and predicted values get smaller. In figure 1 MSE plot of the iterations for a time series used in this paper shows MSE decrease.

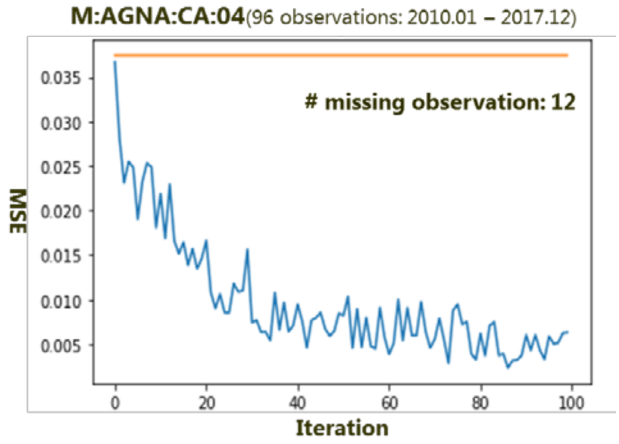


Figure 1: MSE plot for a macroeconomic time series

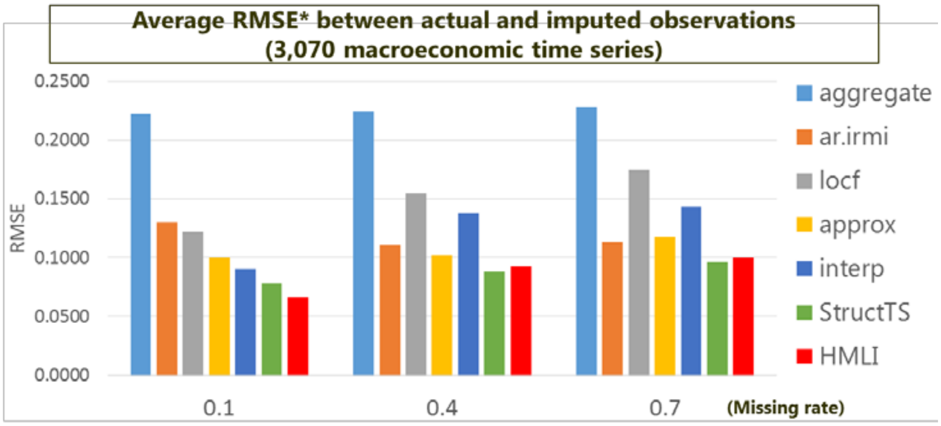
In figure 2 MSE plot of the iterations for 3,070 time series used in this paper shows average MSE of the time series also decrease as the iteration goes by which means the evolutionary process works well in HMLI.

Figure 2: Average MSE plot for 3,070 macroeconomic time series

Comparison of traditional methods

To measure HMLI performance, this paper compares RMSE between HMLI and 6 traditional imputation methods result about 3,070 time series, 3 different missing rates and 3 random seeds. About 6 traditional imputation methods, this paper uses forecast and zoo libraries in R because these libraries are popular to pre-process and analysis time series data.

In figure 3 average RMSE imputation results for macroeconomic time series shows that HMLI and StructTS are the best overall results.



Missing rate	aggregate	ar.irmi	locf	approx	interp	StructTS	HMLI
0.1	0.2221	0.1301	0.1218	0.0998	0.0901	0.0781	**0.0658**
0.4	0.2247	0.1107	0.1552	0.1020	0.1384	**0.0880**	**0.0924**
0.7	0.2280	0.1130	0.1749	0.1175	0.1432	**0.0961**	**0.1001**

Figure 3: Average MSE plot for macroeconomic time series and 3 missing rates

5. Conclusions

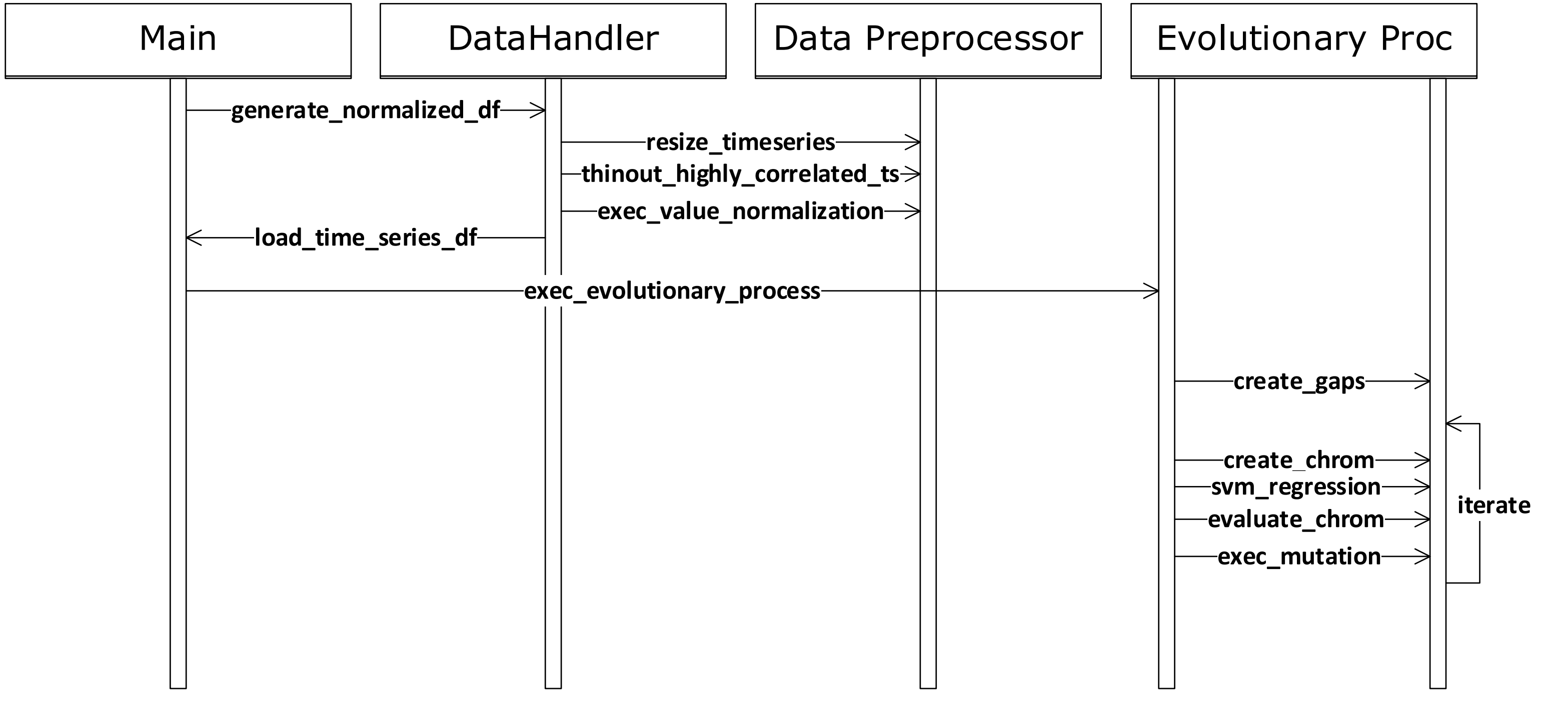
This paper describes HMLI model and compares traditional methods. HMLI result shows it is a competitive solution about missing observation imputations. In this paper, it skipped a model calibration procedure and machine learning methods comparison. It expects that the model performance can be improved through missed procedures.

The one thing we have to know is that HMLI model is very complicated and use much computing power than traditional methods because of the evolutionary process. If the other methods are able to find a reasonable solution, HMLI is not compatible any longer.

HMLI model design can have a wide application in many fields of econometric modelling like time series forecasting, macroeconomic time series now-casting or low frequency to high frequency series benchmarking. But HMLI model design cannot be a solution for the research areas require explanation or causality. Selected dependent variables through heuristic algorithms are random variables and not related to independent variable at all.

HMLI model is implemented by Python language and it is open script on the website. Also the experiment result is published. The data used in the paper cannot be share because of access permissions. But any time series data can be tested on HMLI model.

Annex 1 – HMLI model[5] sequence diagram



[5] Source code: https://github.com/byeungchun/HeuristicImputation

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Ioffe, Sergey, "Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift", Christian Szegedy, 2015

Boon Giin Lee, Teak Wei Chong, Boon Leng Lee, Hee Joon Park, Yoon Nyun Kim, Beomjoon Kim, "Wearable Mobile-Based Emotional Response-Monitoring System for Drivers", Human-Machine Systems IEEE Transactions on, vol. 47, no. 5, pp. 636-649, 2017

Moritz, S., Sardá, A., Bartz-Beielstein, T., Zaefferer, M., Stork, J., "Comparison of different Methods for Univariate Time Series Imputation in R", CoRR, abs/1510.03924., 2015

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BANK FOR INTERNATIONAL SETTLEMENTS

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BANK FOR INTERNATIONAL SETTLEMENTS

Imputation for missing observation through Artificial Intelligence

A Heuristic & Machine Learning approach

(Test case with macroeconomic time series from the BIS Data Bank)

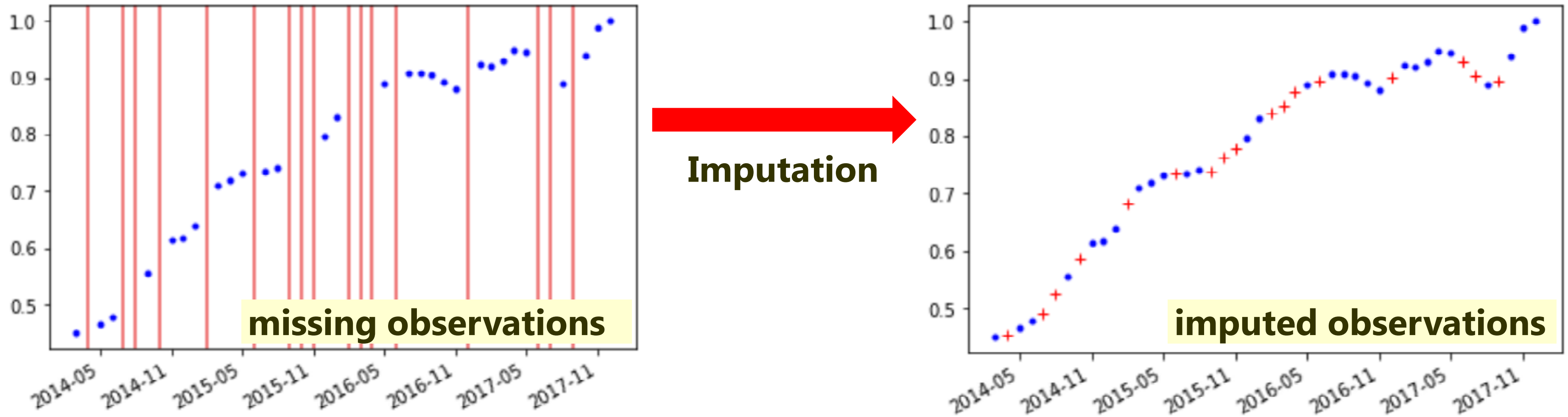
Byeungchun Kwon

Bank for International Settlements

Disclaimer: The views expressed in the presentation are those of the author and do not necessarily reflect those of the Bank for International Settlements

Missing observation imputation in univariate time series

- To impute missing observations in univariate time series, statisticians mainly use Interpolation, Moving Average, LOCF (Last Observation Carried Forward), Seasonal Decomposition, Kalman Smoothing and etc.

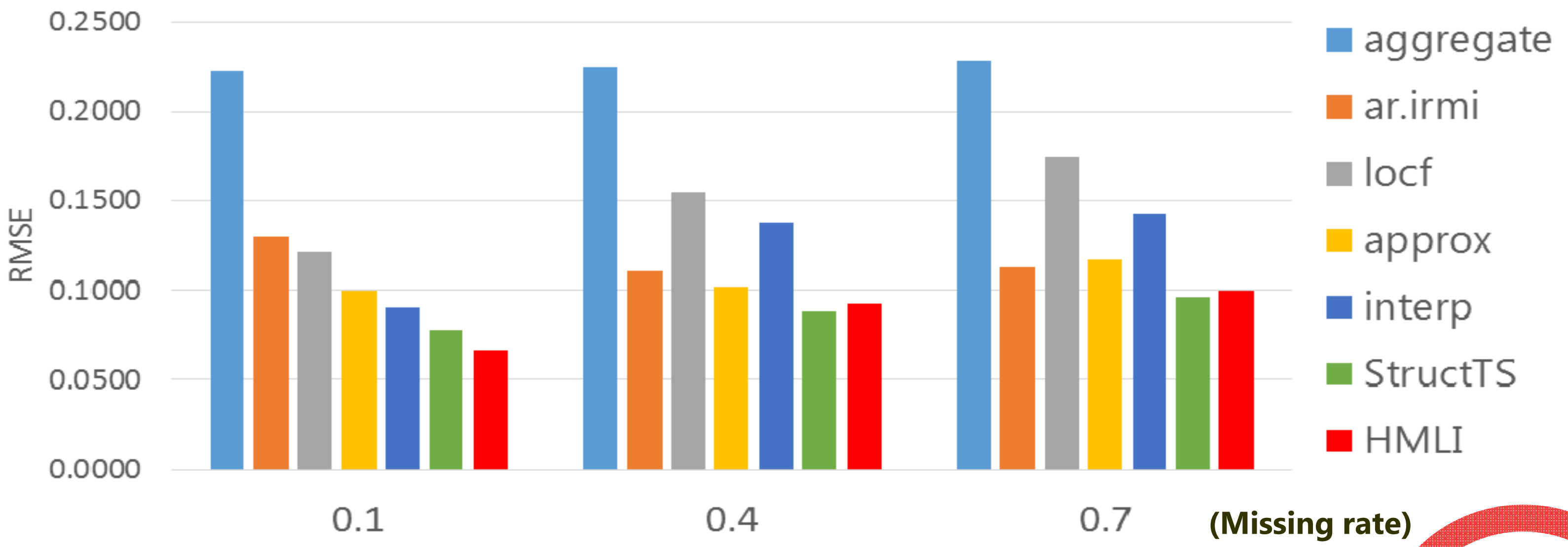


- How precise are the results? Is this the best method?

→ Let’s build an Artificial Intelligence model and let’s compete with traditional models

Average RMSE* between actual and imputed observations (3,070 macroeconomic time series)

* **RMSE**: Root-Mean-Square Error



Missing rate	aggregate	ar.irmi	locf	approx	interp	StructTS	HMLI
0.1	0.2221	0.1301	0.1218	0.0998	0.0901	0.0781	**0.0658**
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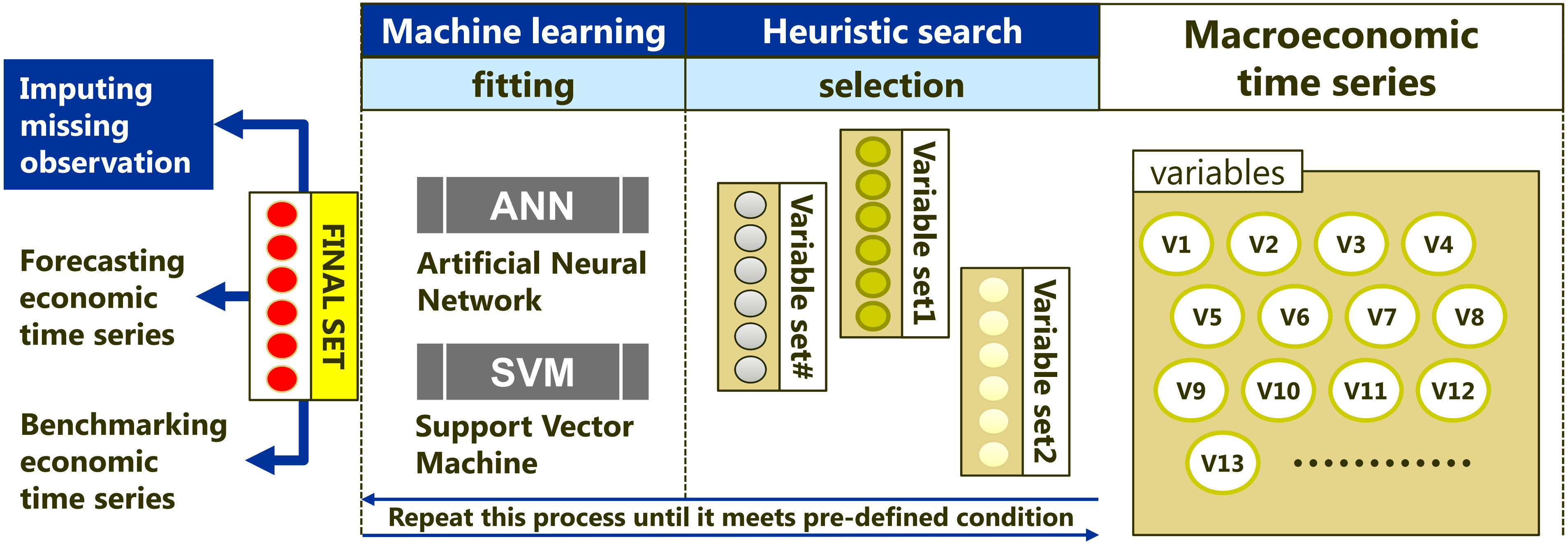
**** Comparison of different Methods for Univariate Time Series Imputation in R, Steffen Mortiz, Oct 2015***

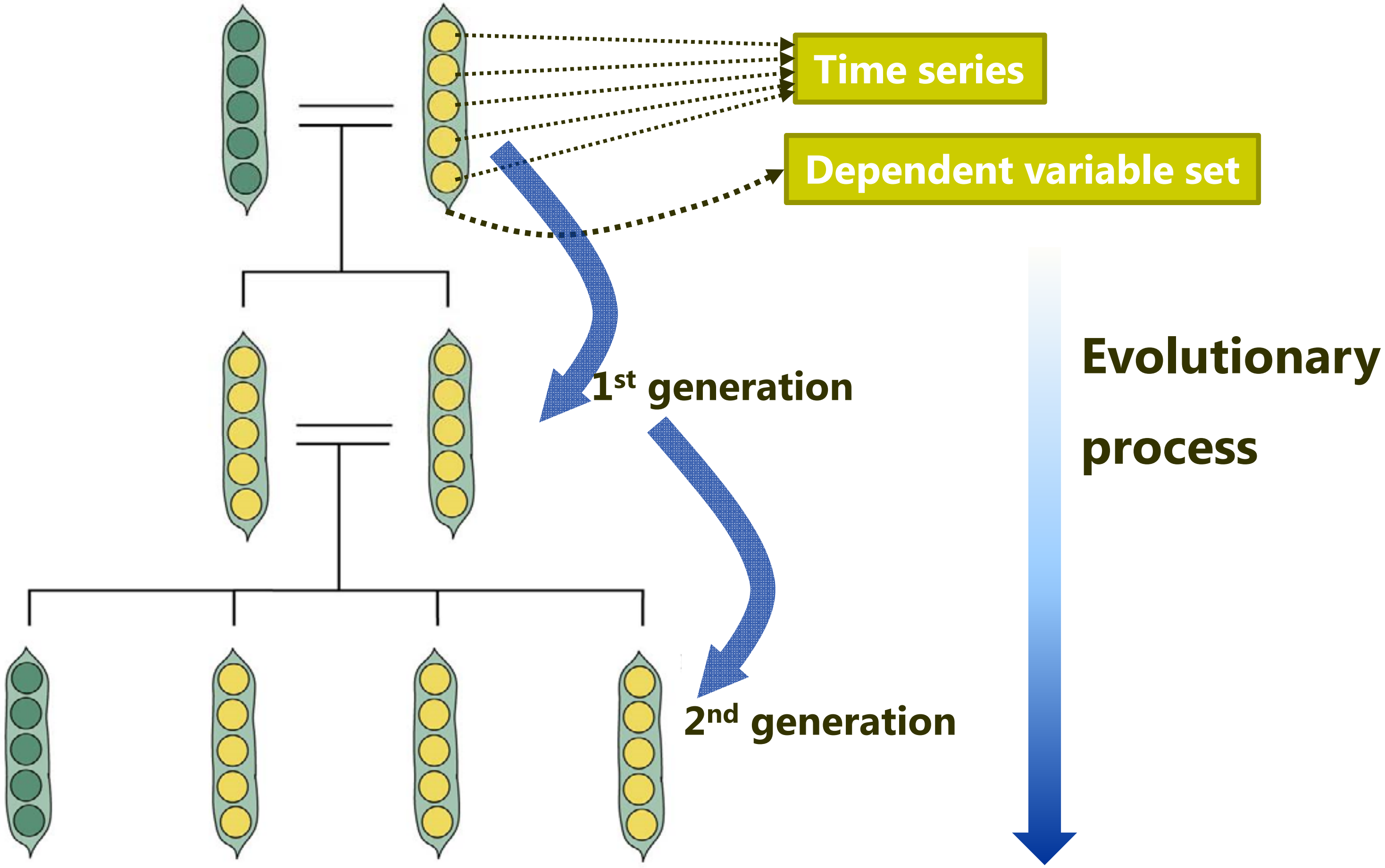
- aggregate: replacing NA with the overall mean
- structTS: filling NA through seasonal Kalman filter
- locf(Last observation carried Forward): replacing NA with most recent non-NA value
- approx: replacing NA with linear interpolation
- irmi(Iterative Robust Model-Based Imputation): filling NA through autoregressive imputation
- interp: linear interpolation for non-seasonal series. If seasonal series, a robust STL decomposition proceeded

HMLI (Heuristic & Machine Learning Imputation) structure

- HMLI is a nonlinear regression model
- Heuristic method selects dependent variables without manual intervention
- Machine Learning method estimates parameters in the model

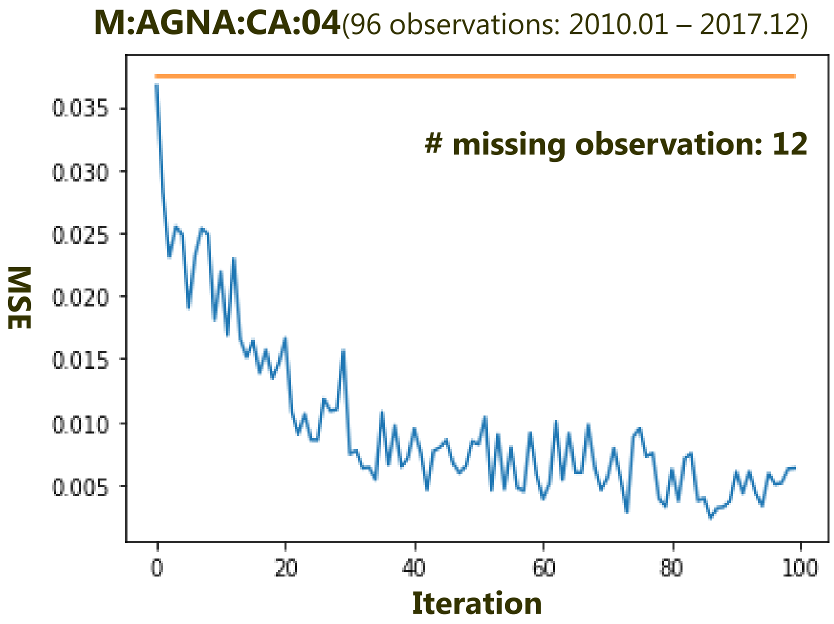


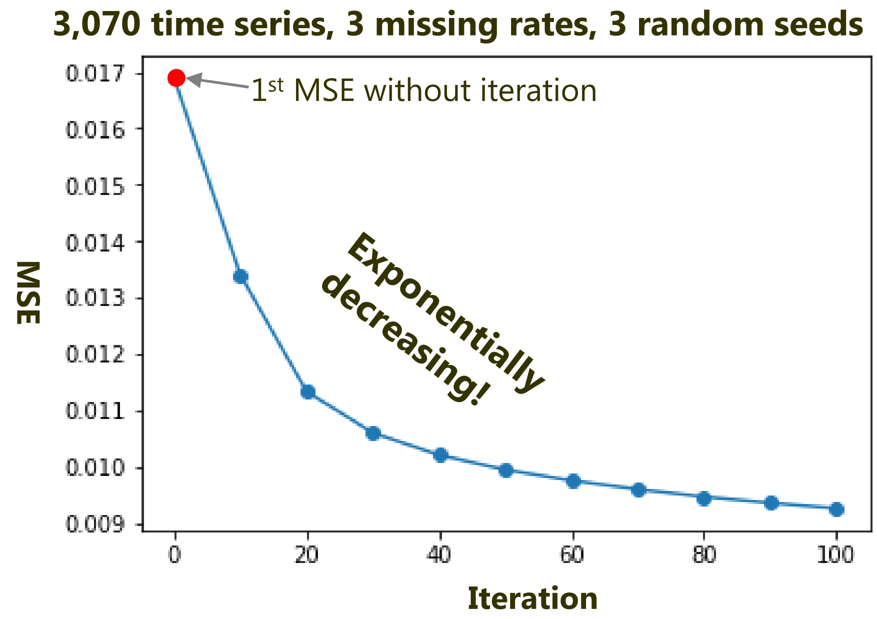
HMLI process – Idea from Mendelian Genetics



Adaptation in Natural and Artificial Systems, Holland, 1975
Natural Computing Algorithm, Barbazon et al., 2015

Mean square error (MSE) by iteration





Average MSE for 27,630 experiments

iteration	0	10	20	30	40	50	60	70	80	90	100
MSE	0.0169	0.0134	0.0113	0.0106	0.0102	0.0099	0.0097	0.0096	0.0095	0.0094	0.0093

HMLI process

Pre-processing: create gaps in a complete time series

(Number of gaps are decided by the exponential distribution and λ is missing rate)

Jan-17	Feb-17	Mar-17	Apr-17	May-17	Jun-17	Jul-17	Aug-17	Sep-17	Oct-17	Nov-17	Dec-17
0.011885	0.017447	0.019291	0.011446	0.004332	0	0.007348	0.007055	0.011885	0.004332	0.007055	0.017447

Jan-17	Feb-17	Mar-17	Apr-17	May-17	Jun-17	Jul-17	Aug-17	Sep-17	Oct-17	Nov-17	Dec-17
NA	NA	0.019291	0.011446	NA	0	0.007348	NA	0.011885	0.004332	0.007055	0.017447

STEP1: remove gaps from the time series

Mar-17	Apr-17	Jun-17	Jul-17	Sep-17	Oct-17	Nov-17	Dec-17
0.019291	0.011446	0	0.007348	0.011885	0.004332	0.007055	0.017447

STEP2: (sampling) pick 6 time series from 3,070 for dependent variables and repeat this process 10 times

Dependent variable candidates

V1 V2 V3 V4 V5 V6 V7 V8 ••• V3070

Set #1 V1 V5 V33 V114 V555 V1116

Set #2 V100 V455 V1333 V3114 V3555 V4116

••••••

Set #10 V1 V5 V33 V114 V555 V1116

STEP3: SVM regression and predict gaps(missing observations)

	RMSE	ranking
SET #1	0.004	1
SET #2	0.019	10
⋮		
SET #10	0.010	5

STEP4: calculate RMSE* between the actual and predict observations

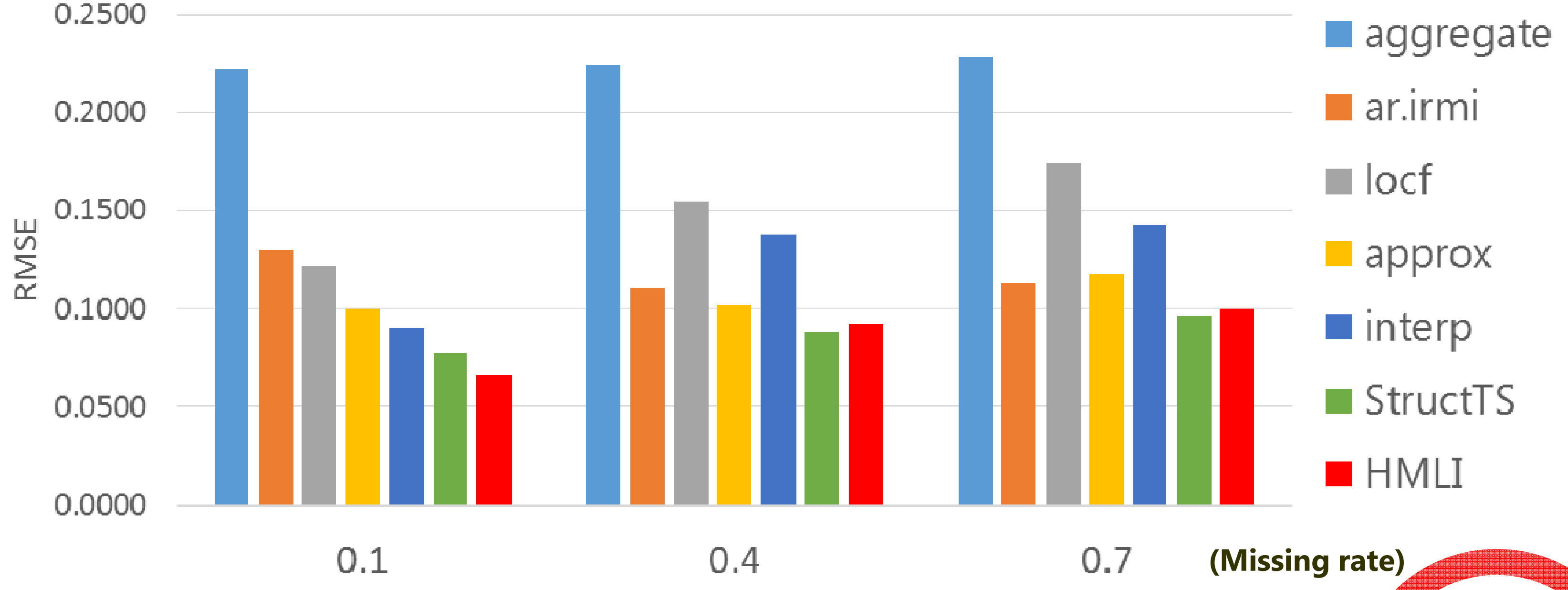
STEP5: remove 5 lower ranked sets

STEP6: generate 2 new sets through top 5 sets

STEP7: redo STEP2, but repeat 3 times to generate 3 sets

STEP8: iterate 100 times from STEP3 to STEP7

Average RMSE* between actual and imputed observations (3,070 macroeconomic time series)



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Findings

- HMLI is one of the best solutions to impute missing observation from macroeconomic time series
- Heuristic & machine learning combination is effective in a complex space

Follow-up tasks

- Parameter calibration – number of dependent series, iteration, cutoff rate and etc.
- Test various time series data sets: different frequencies and pattern (trend, seasonality)
- Apply other machine learning functions like CNN(Convolutional Neural Networks)

Additional info

- HMLI is a Python script program and it is free. Please find the script on https://github.com/byeungchun/HeuristicImputation
- Also, experimental results are shared on this site

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A machine learning approach to outlier detection and imputation of missing data[1]

Nicola Benatti,

European Central Bank

[1] This paper was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

A machine learning approach to outlier detection and imputation of missing data

Nicola Benatti

In the era of ready-to-go analysis of high-dimensional datasets, data quality is essential for economists to guarantee robust results. Traditional techniques for outlier detection tend to exclude the tails of distributions and ignore the data generation processes of specific datasets. At the same time, multiple imputation of missing values is traditionally an iterative process based on linear estimations, implying the use of simplified data generation models. In this paper I propose the use of common machine learning algorithms (i.e. boosted trees, cross validation and cluster analysis) to determine the data generation models of a firm-level dataset in order to detect outliers and impute missing values.

Keywords: machine learning, outlier detection, imputation, firm data

JEL classification: C81, C55, C53, D22

Contents

Introduction

In a world made of data, different outlier detection techniques have been applied to different types of data. From the most standard techniques such as the deletion of observations in the tails of the distributions, to more tailor made variable-specific threshold-setting methods, data analysts always find difficulties in identifying a general framework for outlier detection which can be easily applied to a whole dataset without compromising its integrity. Such analysis tended to become even more difficult in the recent years with the increase in availability of very large datasets. These contain large numbers of variables for which it becomes tedious to set variable-specific thresholds while their distributions are linked to each other by construction.

An outlier is generally considered as an observation which is significantly distant from the other considered observations. Since in a dataset variables are often partially related with each other, we can consider an outlier a data entry which is lying far from the others on a n-dimensional space, where n is the number of variables in the dataset.

It is important to clarify that an outlier is not necessarily a mistake. A simple example could be a sport champion who excels in her discipline. She is an outlier and she is definitely not a mistake. All we can do then, is to rank observations by their likelihood of being anomalies and start analysing, knowing both which are their expected values and how the reported values have been generated. If necessary we have to look for information which is not contained in our dataset in order to confirm or reject an observation.

The literature tends to distinguish between three dimensions according to which to define an observation as outlying.

The first one is the distribution of a specific variable under observation. In economics literature in particular, data cleaning processes often consist in dropping the lowest and highest percentiles of each considered variable, leading in this way to the deletion of a fixed percentage of information, part of which may not only be correct, but also might have major economic meaning.

A less drastic approach is the one of eliminating observations which exceed a certain number of standard deviations from the mean, assuming in this way that the data is following a symmetric distribution. Since this is often not the case, the mean can also be substituted by the median to account for the skewness of the distribution.

Single variable distribution-based techniques are quite simple to implement but will only allow spotting extremely high or extremely low observations, excluding the potential outliers within the distribution.

For this reason distance based techniques started being applied to large datasets, such as k-nearest neighbourhood which clusters observations into groups and flags as outlying observations which lay the furthest away from any recognised group. These techniques can be completely data driven (unsupervised machine learning) but, by themselves, do not exploit the fact that having available the whole dataset we want to find outliers in, this machine learning algorithm can be implemented instead in a supervised fashion and provide information on the data generating model behind it.

There is then another way of detecting outliers which I am going to present in this paper. The idea of this technique is, like in cluster analysis, to look at joint distributions but, additionally, to exploit the information available in a supervised way and estimate the data generation model of a specific variable. The model will then provide the data analyst with a set of suggested features (i.e. which features are driving the determination process of a specific variable), their importance, the fitted values for the estimated variables (i.e. to be used for data imputation) and ranks the observations by their likelihood of being mistakes. Once the data analyst has these pieces of information, she can use them to prioritise the analysis of potential errors.

This framework combines the supervised and unsupervised frameworks under a probabilistic model and reduces assumptions on the data structure to its minimum allowing also for the estimation of the expected values which can be furthermore used to impute missing observations.

Construction of the dataset and data description

In order to show an application of the technique described in this paper, I use the iBACH dataset of non-financial corporations' balance sheet data. The dataset has been collected on a stable form since December 2017 by the Working Group Bank for the Accounts of Companies Harmonized (WG BACH), under the mandate of the European Committee of Central Balance Sheet Data Offices (ECCBSO).

The Working Group BACH is active since 1987 in the collection and analysis of aggregated balance sheet data of non-financial corporations and its members are the Central Balance Sheet Data Offices of European countries. While the collection, the analysis and the dissemination of these data has always been carried on at an aggregate or meso level (i.e. information has always been aggregated by country, industry, year, size class and quartile), in June 2017 the working group BACH received the mandate to create a task-force for the collection of individual company data (iBACH) that can be shared among researchers of the participating institutions.

Since February 2018 this dataset was disseminated by the European Central Bank (ECB), which functions as a hub for the data collection, to its internal users and to the WG BACH representative members who are in charge of disseminating and promoting the dataset in their countries. The iBACH dataset contains yearly balance sheet, financial and demographic variables of non-financial corporations. It currently covers six EU countries (Belgium, Spain, France, Italy, Portugal and Slovakia).

It has to be mentioned that this type of data surely helps my analysis since, by construction, data generation models (i.e. joint distributions) of several balance-sheet variables are the same (or very similar) across countries and years; which means that accounting rules generally hold.

It is also important to mention that, both before and after reaching the ECB, the quality of these data is checked extensively by applying a set of accounting validation rules which highlight a first set of reported mistakes. The data is then corrected and resubmitted to the ECB iteratively until the number of spotted accounting mistakes is minimised.

The dataset contains the following 66 variables:

Demographics:	**Income statement:**
Address	Operating revenue
Address 2	Financial expenses
Firm's status of activity	Net turnover
City	Financial income
Consolidation code	Extraordinary income
Country	Costs of goods sold
Identification number	Labour costs
Legal form	Depreciation and amortization
Name	Interests on financial debt
Legal form in the national codification	Tax on profit
Number of employees	EBIT, net operating profit
Number of months for the account exercise	EBITDA
Localisation information	Profit and loss
Sector of activity (NACE code)	Profit and loss before taxation
Year	Cash flow
Year of incorportation	Value added
Year of liquidation of the firm	
Zipcode	
Liabilities:	**Assets:**
Shareholders funds	Total assets
Capital, reserves, earnings and other equity instruments	Total current assets
Total liabilities	Total fixed assets
Short-term debt	Intangible fixed assets
Other current liabilities	Tangible fixed assets
Total current liabilities	Financial fixed assets
Long-term debt	Total inventories
Total non-current liabilities	Trade receivables
Short-term debt owed to credit institutions	Other receivables
Long-term debt owed to credit institutions	Other current receivables
Trade credit	Deferred assets
Payments received on account of orders, current	Deferred current assets
Deferred liabilities, current	Other financial assets, current
Deferred liabilities, non current	Cash and bank
Provisions	
Investment accounts:	
Acquisition less sales and disposals of intangible assets	
Acquisition less sales and disposals of tangible fixed assets	
Acquisition less sales and disposals of financial fixed assets	

The panel structure of the dataset is as follow:

Number of firms reporting

	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
BE		204,825	218,707	233,180	250,392	264,474	284,327	297,899	326,480	344,480	362,762	377,386	382,669	349,034
ES							450,538	447,540	459,076	450,146	443,527	583,081	560,570	324,701
FR	184,812	192,206	198,107	208,534	225,408	233,267	233,865	244,843	260,670	260,565	250,048	253,758	257,950	261,051
IT	492,472	517,464	540,517	560,140	582,993	600,656	613,021	624,235	634,278	629,865	627,317	621,722	618,177	464,353
PT	16,920	17,547	15,176	342,588	357,480	367,237	366,806	365,821	373,230	373,500	378,731	382,779	390,730	392,030
SK												99,389	99,584	97,869

In spite of the data quality checks mentioned above, several data quality issues remain, both in terms of non-plausible values reported and values which are not reported at all.

For these reasons I follow the most recent literature on data science techniques for estimation in order to determine at first the data-generation model and its features for each numeric variable reported, later the expected value of each observation in the dataset and finally which observations have are most likely to be errors.

Given the high computational power needed to run the algorithms described in the next chapter, the original dataset was filtered to select a random sample of 10% of the overall observations. This subsample consists of 2,345,338 observations on which the proposed model is trained and subsequently tested.

Since not all countries report demographic variables and not all these would add information but rather slow down the process, I removed part of the demographic columns from the analysis. On the other hand, I define the set of variables that have to be considered as categorical (e.g. sector, country and legal form).

Last but not least, in order to train and test the models that I am estimating for each variable, I create a training sample picking up randomly 2/3 of the observations. The remaining 1/3 of observations is kept as testing sample. In this way I will be able to calibrate the algorithm on 2/3 of the data and test the results on the remaining 1/3.

Empirical strategy

While in the pages above I describe the general principles that I apply in my methodology, it is now time to go more in details on the various steps of the detection process.

In the paragraphs below I will first briefly described how I use well-known algorithms in a combination and with a scope not yet covered by the literature. I will first outline the XGBoost algorithm by T Chen, C Guestrin (2016) used to determine the data-generation model, producing the sets of features and their importance for each estimated variable and the fitted values of the observations. I will then use the GridSearch algorithm to select the models' hyper-parameters that minimize my objective function. Following I propose using the DBSCAN algorithm (density based clustering algorithm) for flagging outlying observations. Last but not least I introduce the concept of feature additive ranking (FAR) to determine the reported cells which are most likely to be reported wrongly.

Extreme Gradient Boosting

In order to estimate the data-generating model, the importance of its features and to predict the response variable y_i given the set of explanatory variables $\boldsymbol{x} = \{x_1, \dots, x_n\}$, I use the Extreme Gradient Boosting (XGBoost) technique developed by Chen and Guestrin.

The objective of the algorithm is, given the training data, to find the best parameters to minimize the expected value of an objective function $F(\theta)$ which is composed by a training loss $L(\theta)$ and a regularization part $\Omega(\theta)$:

$$F(\theta) = L(\theta) + \Omega(\theta)$$

Xgboost is based on tree-ensembles technique. The concept behind it is that y_i is classified into different leaves of a tree given the values of $\boldsymbol{x}_i$. These trees are weak learners and normally have a very few splits. Since a single tree would not be strong enough to properly estimate y_i, the prediction of different trees are summed up together into a tree ensemble model.

The authors of XGBoost developed it as an additive learning algorithm which means that one tree is added at every iteration of the algorithm, the principle being that each new tree predicts the residuals of errors of the (sum of) the previous trees:

$$\begin{aligned}
\hat{y}_i^{(0)} &= 0 \\
\hat{y}_i^{(1)} &= f_1(x_i) = \hat{y}_i^{(0)} + f_1(x_i) \\
\hat{y}_i^{(2)} &= f_1(x_i) + f_2(x_i) = \hat{y}_i^{(1)} + f_2(x_i) \\
&\dots \\
\hat{y}_i^{(t)} &= \sum_{k=1}^{t} f_k(x_i) = \hat{y}_i^{(t-1)} + f_t(x_i)
\end{aligned}$$

At this stage, the algorithm adds the best tree available at each iteration, but in order to improve the performance, the authors of XGBoost added a regularization term which penalises complexity.

Moreover, Chen and Guestrin prune trees so that a tree will not be added to the model if the gain is smaller than gamma, preventing overfitting.

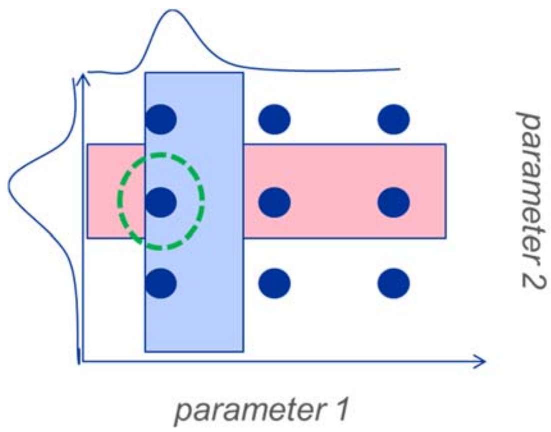
Last but not least, once the algorithm has successfully run on the data, it provides the contribution (importance) of independent variables on the determination of the dependent variable, which turns out being extremely useful for the user to understand the data generating model.

Xgboost is available as a ready-to-run Python package (xgboost) which includes a wide set of hyper-parameters including the type of model that one wants to specify (classification, linear, logit, poisson), the subsample on which to train the model, the number of estimators, the maximum depth of a tree and many others.

More information regarding the methodology and the package can be found on the Xgboost website (http://xgboost.readthedocs.io/en/latest/tutorials/model.html).

Hyperparameter optimisation

One of the usual criticisms to machine learning techniques is that the researcher biases the algorithm by imputing his personal judgment when choosing its hyperparameters. Recent literature investigates the possibility of setting the hyperparameters of a machine learning algorithm by testing on the data which one is the optimal set of hyperparameters for the model.



Gridsearch, the algorithm available within the python scikit-learn python package, exhaustively searches through a subset of specified hyperparameters. The algorithm trains the machine learning algorithm with each set of possible combination (Cartesian product) of hyperparameters and evaluates the performance on the testing set by picking the tuple that goes in the estimation model with the highest explanatory power.

The hyperparameters of XGBoost estimated by the Gridserach algorithm here are:

- Max_depth: maximum depth of a tree, increase this value will make the model more complex / likely to be overfitting.
- Eta: step size shrinkage used in update to prevents overfitting. After each boosting step, we can directly get the weights of new features and eta actually shrinks the feature weights to make the boosting process more conservative.

- Subsample: subsample ratio of the training instance. Setting it to 0.5 means that XGBoost randomly collected half of the data instances to grow trees and this will prevent overfitting.
- N_estimators: Number of boosted trees to fit.

Two main issues need to be raised here. The first is that XGBoost presents a much wider set of hyperparameters which I set as default due to the fact it would be too computationally intense to specify them all. The second issue is that Gridsearch is looking for the best solution among the combinations of parameters in the portfolio I chose based on common practice but it is not sure that the minimisation process yields a global minimum. A better but more computational demanding approach would be to use a random search algorithm or a Bayesan search algorithm, increasing however significantly the time to run the process.

The medians of the parameters chosen by Gridsearch for all variables estimated are the following:

max_depth=5,

learning_rate=0.1,

subsample=0.7,

n_estimators=1500

Flagging outlying observations

In the two paragraphs above I described two processes relatively easy to find in the literature, even in combination with each other. What instead was not widely investigated yet is how by using XGBoost and Gridsearch algorithms a data analyst can detect outliers.

Having estimated the data generating model behind each y_i of our set, I estimate the fitted values for each observation and compute the estimation residuals.

At this stage I apply a specific cluster analysis algorithm called Density-based spatial clustering of applications with noise (DBSCAN by Ester, Kriegel, Sander and Xu 1996) on the vectors of residuals and relative residuals (i.e. the residuals as percentage of the reported value) of each model and flag as outlier the observations which are the most distant from their nearby neighbours.

This award-winning algorithm has the great advantage of isolating on the set of absolute and relative residuals those in a low density area. Compared to KNN techniques, in particular, it allows not to set the number of clusters to find and to flag as outliers the datapoints that lay in low-density areas , while the parameters to be specified are the physical distance ε (which is variable-specific), and minPts which is the desired minimum cluster size which I set to 3.

Feature-additive ranking

While the technique above is widely used to spot outliers in distributions, I now apply it to the residuals of a regression problem. In this way I will be able to spot observations which do not fit into my data generation model. However, what might happen is that a value spotted as outlier is not an actual reporting error while one of its determining features is instead reported erroneously (i.e. one of the independent variables that feed the model). In other words, when spotting an outlying observation, we cannot assume that it is an actual mistake until we check if any of the other variables that generate it are wrongly reported or not.

For example, if the identity A=B+C+D identified by the XGBoost algorithm is not respected, it could be because of a mistake in reporting any of the variables among A, B, C or D.

In order improve the ranking of potential errors in the data, I introduce the feature-additive ranking technique (FAR) which sums up the contribution of any variable by unit of observation (in my case entity-year) each time (in each model) this is flagged as an outlier.

$$FAW_{v,j,y} = \sum_{k=0}^{n} f_{j,y,k} * i_{v,j,y,k} * w_k$$

where:

v=variable

j=firm

y=year

k=outlier model

FAW=feature additive weight

f=outlier flag

i=importance

w=model weight

Using the FAW score, I then rank the information per unit of observation by the highest sum of FAW scores, highlighting the cell (variable-firm-year) supposed to be the most important in determining an outlying observation. This technique allows data analysts to prioritise their investigation on the "most-likely-to-be wrong" variable, cutting drastically investigation times.

Results

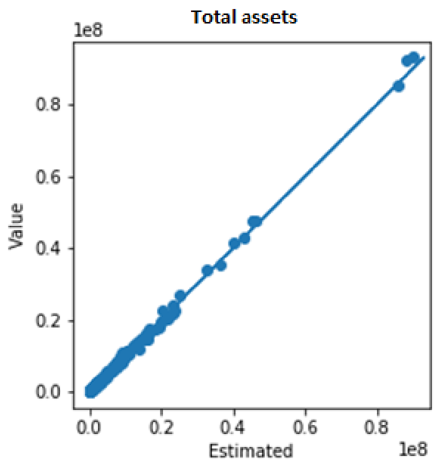
Having such a large dataset of balance sheet data and such computationally expensive algorithms, the procedures to flag outliers for each single variable runs on a standard laptop for more than a week before providing the final calibrated models.

For each variable analysed we now know the importance of each other variable (feature) in its determination and we store the calibrated data generation model to be used for further estimations of fitted values.

The overall performance of XGboost is extremely high and the median R-squared when fitting the calibrated models on the test dataset has a median of 0.8757. Given such a high performance, the system can be used for data imputation when missing values are reported.

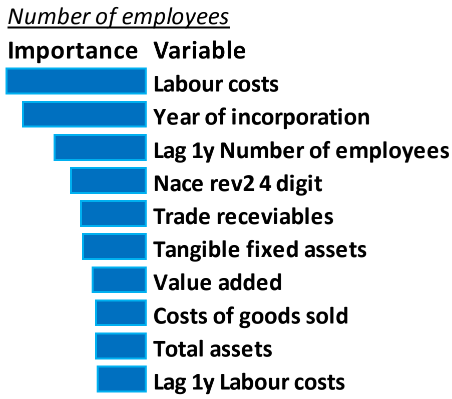
For example, the importances of the first eleven variables estimating total assets of firms rank as follows:

When looking at the results of the estimation of total assets on the test sample, which, just to remind the reader is not the dataset on which the algorithm was calibrated, the algorithm predicts perfectly each reported value and the observations all lay on the bisector:

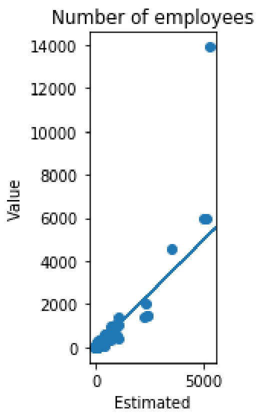


In the case of total assets, the variable is usually extensively checked by a set of validation rules before the data arrives at the ECB which make sure no observation is indeed reported erroneously.

When estimating of the number of employees, instead, the ten most important variables are the following:



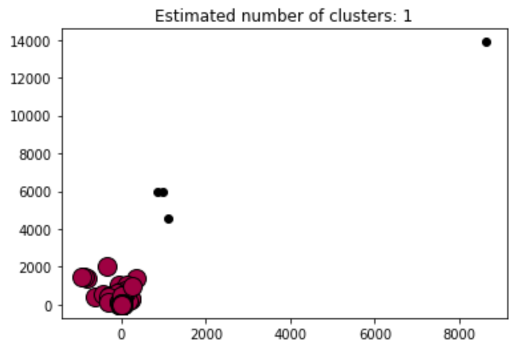
In this case it is easy to spot that certain actual values are far from the bisector line, given that the number of employees is not a balance sheet variable and does not have validation rules run a-priori on the data.



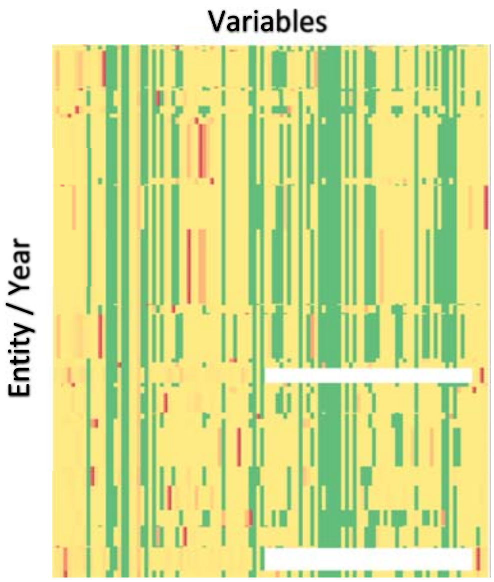
At this stage, the residuals of each variable estimation model are taken separately and analysed using the DBSCAN algorithm in order to flag anomalies in how the dataset fits the model.

In the figure below the black dots represent observations which both in absolute and relative terms lay distant from the value suggested by the data generation model. The red dots instead, represent observations whose residuals from the model are similar with each other and, given the accuracy of XGboost in prediction, are very close to zero.

Number of employees flagged observations



As explained by the methodology above, we do not stop at here. In fact, it could be that the number of employees reported by the firm x is flagged as an outlier but when looking at the time series of the entity, the number reported seems to be perfectly plausible. In fact, it could still be that while the number of employees seems plausible, the labour costs reported by the firm dropped drastically compared to the previous years. For this reason, we check if either of the variables is significantly important in the contribution to the estimation of any other outlying observation by using the FAR technique described above. Once the FAW scores are created, they are inserted in a heat-map which eases the work of the data analyst.



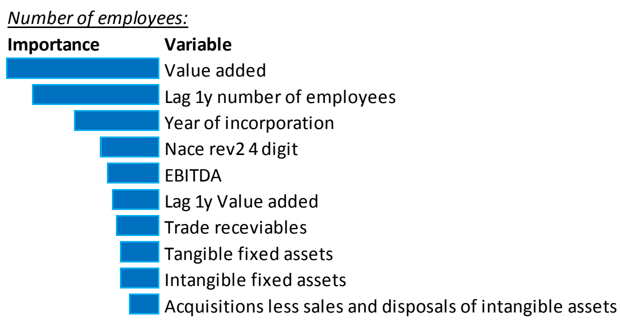
In this way the person analysing the data can not only focus on the outlying variables but also on the subcomponents that are most likely to affect that specific observation.

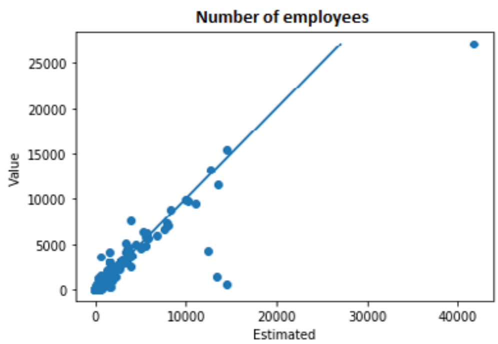
A great value added of this methodology, moreover, is that once the XGBoost algorithm is trained, the estimated model for each variable can be stored and does not need to be re-calibrated every time new data comes in. When new data comes into the system, it can then be evaluated in few seconds by using the rules established in the past.

This characteristic will boost the performance of those investigating these data.

A further empirical application: employment missing data imputation

In order to provide some more taste of what this procedure is capable of, I tested the XGboost model to be used for data imputation of the "number of employees" variable. The "number of employees" is a variable which is often not available in non-financial corporations' datasets because it is not part of the information which has to be reported in a balance-sheet. As we could see above, using the procedures proposed in this paper we can easily and very well estimate this information when the variable "Labour Costs" is available. However it can be that the whole information on employment (both number of employees and labour costs) is missing. We want then to test the estimation of the number of employees without using the information on labour costs. The results that we get are the following:





Although the estimation is not as precise as the estimation proposed when including the Labour cost variable, XGBoost seems to be an extremely adaptive method for estimating missing values, also when some main components are missing. In fact, this methodology improves further the performance of the methodologies previously used based on LASSO algorithm (Novello 2017).

Two general applications of this technique could be, as shown, the imputation missing values (or confirmed mistakes that were removed) but also the creation of a synthetic anonymised datasets for research purposes.

Conclusions

This paper presents an application of a combination of supervised and unsupervised machine learning with a final feature-additive ranking technique in order to spot mistakes in outlying datapoints. The model provides the data analysts with guidance on which variables to prioritise when controlling an outlying observation and which is their expected value given the data generation model identified by the algorithm. Moreover, the methodology described seems to be useful also for additional steps of data quality improvement such as data imputation.

This technique also provides guidance for the construction of new data quality checks that could prevent the submissions of mistakes.

Further improvements to this process are already in the pipeline. In particular, the increase in the sample size as soon as the full deployment of the big-data environment will be finalised at the ECB. Moreover, the comparison of the results obtained with those obtained by using neural networks and multi-target regressions which from the recent literature seem to be even more powerful estimation tools.

Last but not least, the part of the tool which is now based on cluster analysis could become a usupervised classification problem if we could get from the data owners confirmation on whether a spotted potential mistake is actually an error or not. If we could have that information available the problem we are analysing would fundamentally change and we could develop an algorithm which would learn how to classify mistakes instead of outliers.

Annex

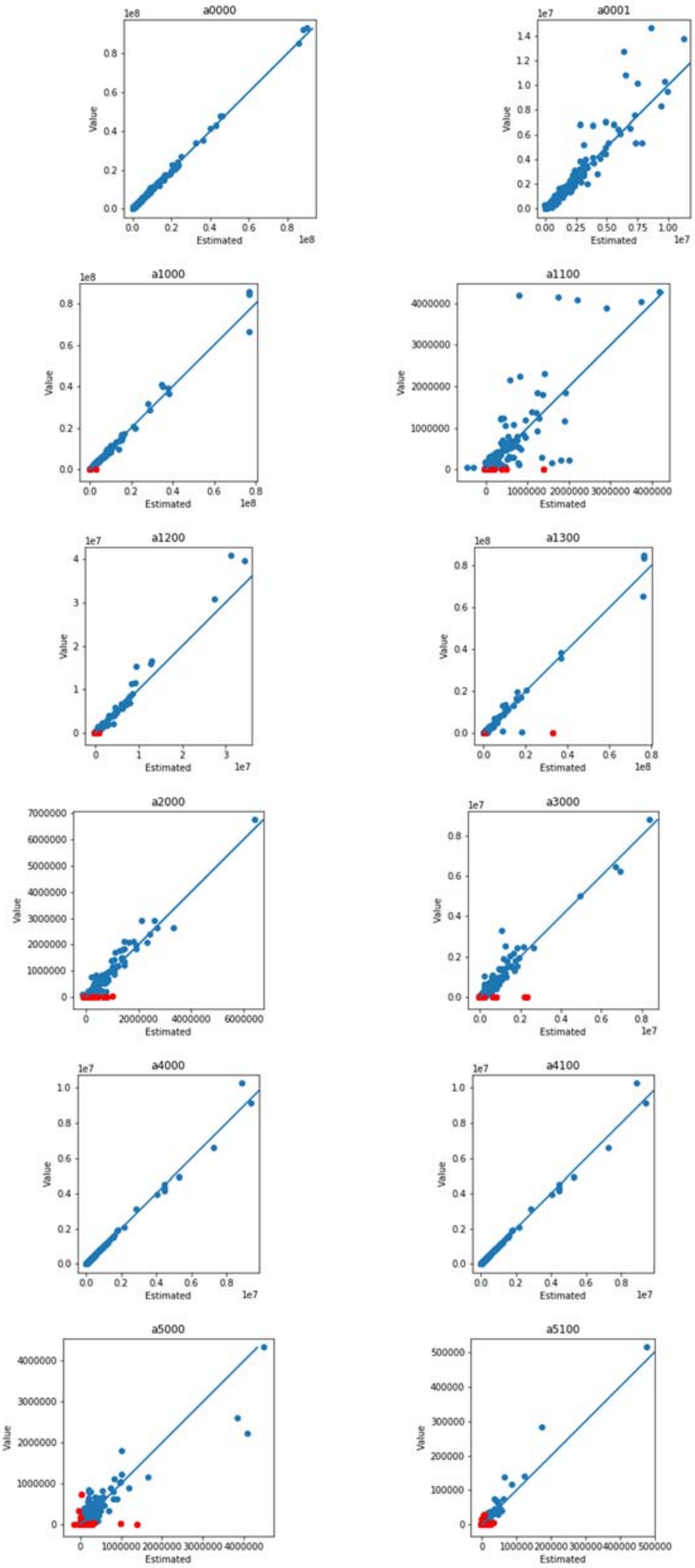
I – Description of variables

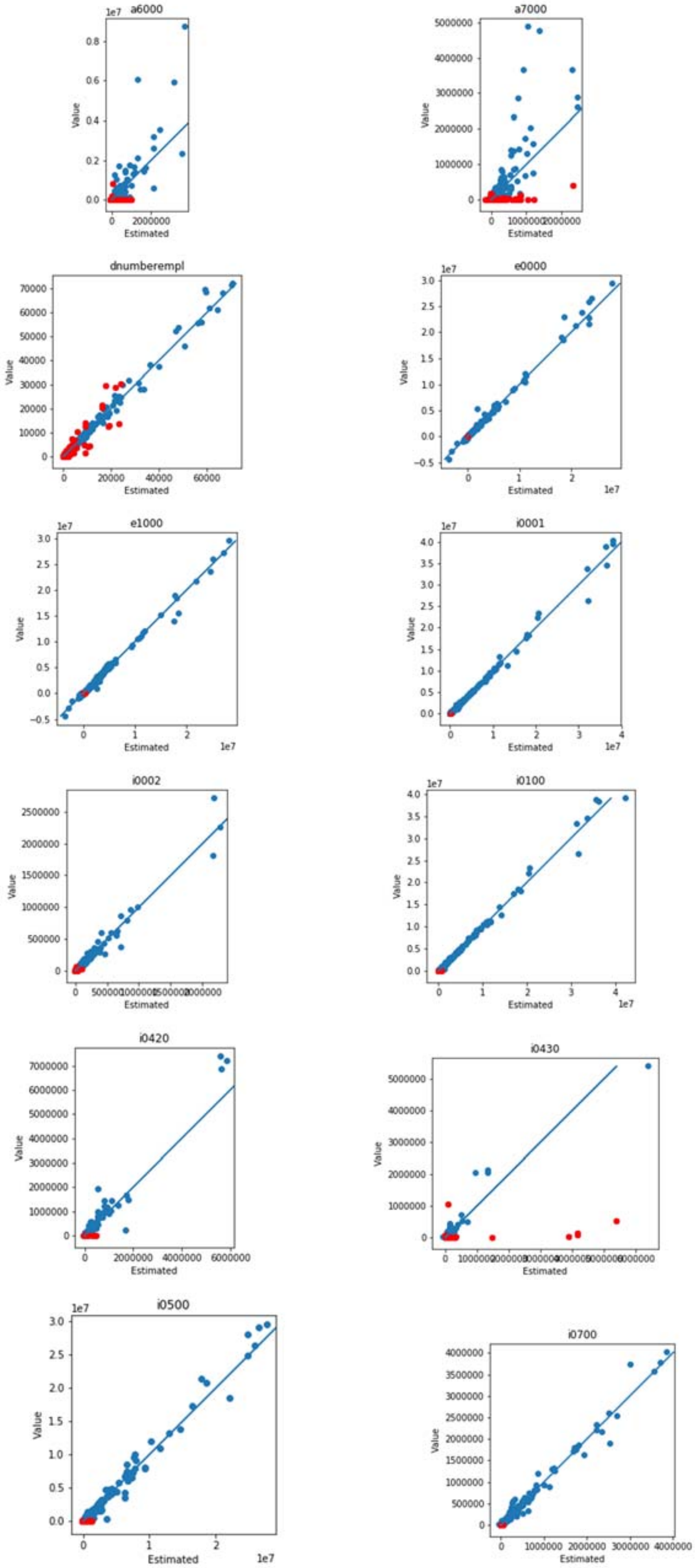
Variable:	Description:
A0000	Total assets
A0001	Total current assets
A1000	Total fixed assets
A1100	Intangible fixed assets
A1200	Tangible fixed assets
A1300	Financial fixed assets
A2000	Total inventories
A3000	Trade receivables
A4000	Other receivables
A4100	Other current receivables
A5000	Deferred assets
A5100	Deferred current assets
A6000	Other financial assets, current
A7000	Cash and bank
DADDRESS1	Address
DADDRESS2	Address 2
DCEASE	Firm's status of activity
DCITY	City
DCONSO	Consolidation code
DCOUNTRY	Country
DID	Identification number
DLEGAL	Legal form
DNAME	Name
DNLEGAL	Legal form in the national codification
DNUMBEREMPL	Number of employees
DNUMBERMTH	Number of months for the account exercise
DREGIO	Localisation information
DSECTOR	Sector of activity (NACE code)
DYEAR	Year
DYINCORP	Year of incorportation
DYLIQUID	Year of liquidation of the firm
DZIPCODE	Zipcode
E0000	Shareholders funds
E1000	Capital, reserves, earnings and other equity instruments
I0001	Operating revenue
I0002	Financial expenses
I0100	Net turnover
I0420	Financial income
I0430	Extraordinary income
I0500	Costs of goods sold

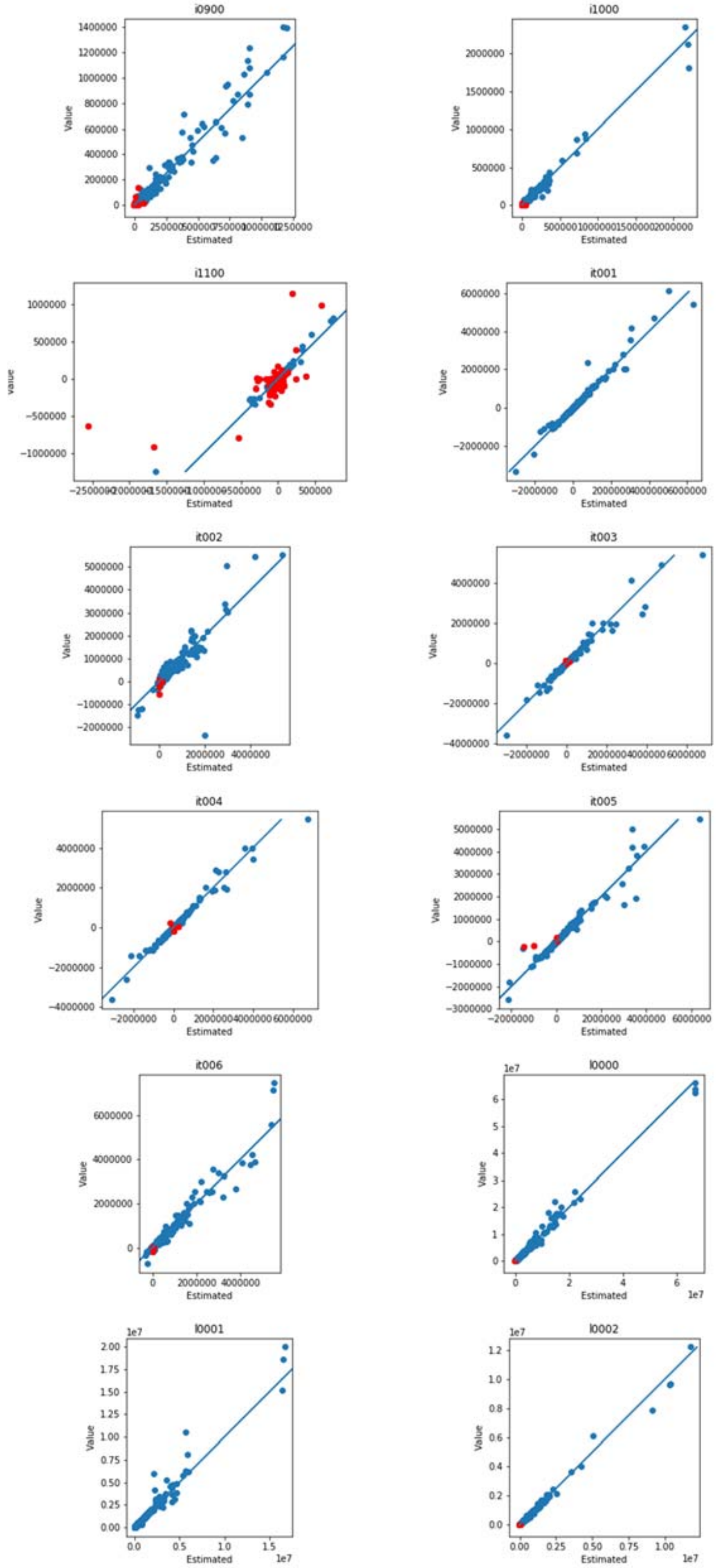
I0700	Labour costs
I0900	Depreciation and amortization
I1000	Interests on financial debt
I1100	Tax on profit
IT001	EBIT, net operating profit
IT002	EBITDA
IT003	Profit and loss
IT004	Profit and loss before taxation
IT005	Cash flow
IT006	Value added
L0000	Total liabilities
L0001	Short-term debt
L0002	Other current liabilities
L0003	Total current liabilities
L0004	Long-term debt
L0006	Total non-current liabilities
L2100	Short-term debt owed to credit institutions
L2200	Long-term debt owed to credit institutions
L4000	Trade credit
L5000	Payments received on account of orders, current
L6100	Deferred liabilities, current
L6200	Deferred liabilities, non current
LP000	Provisions
N1000	Acquisition less sales and disposals of intangible assets
N2000	Acquisition less sales and disposals of tangible fixed assets
N3000	Acquisition less sales and disposals of financial fixed assets

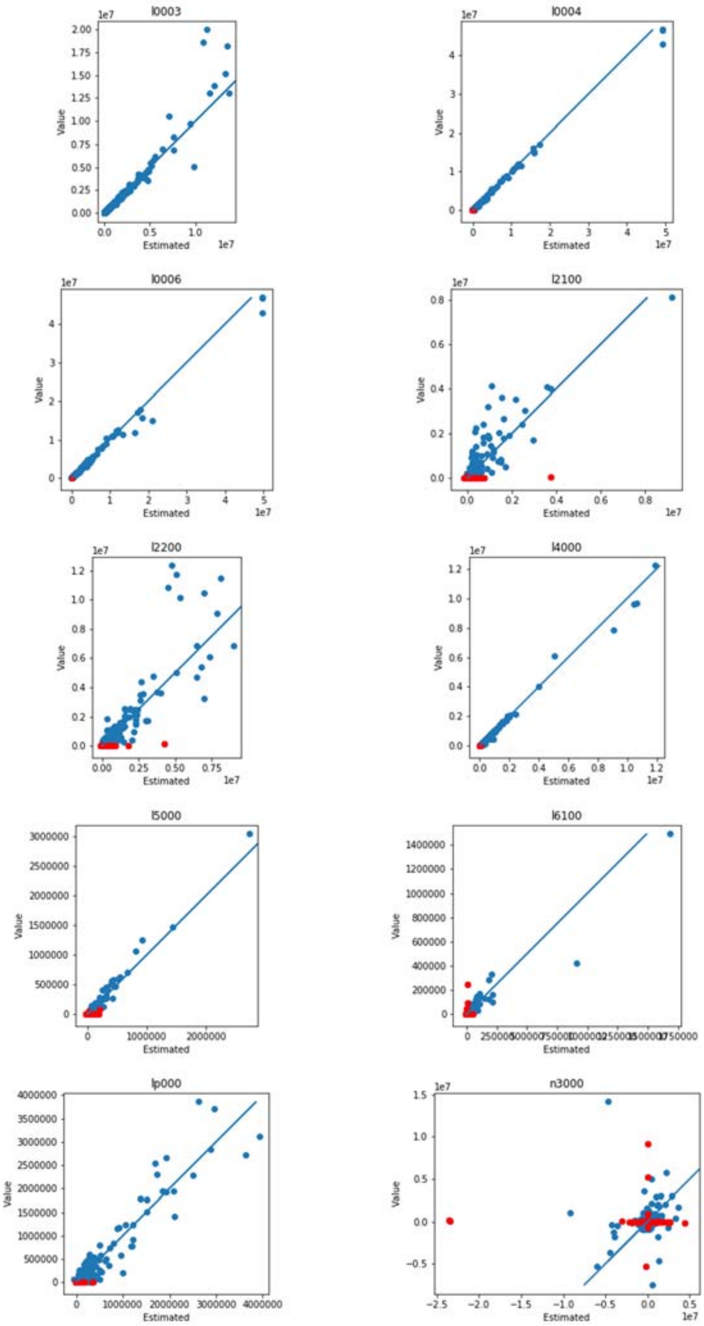
II- Results of the estimation.

The blue line is the bisector.




a6000
a7000
dnumberempl
e0000
e1000
i0001
i0002
i0100
i0420
i0430
i0500
i0700
Value
Estimated


i0900
i1000
i1100
it001
it002
it003
it004
it005
it006
l0000
l0001
l0002
Value
Estimated


l0003
l0004
l0006
l2100
l2200
l4000
l5000
l6100
lp000
n3000
Value
Estimated
1e7

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BANK FOR INTERNATIONAL SETTLEMENTS

Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

A machine learning approach to outlier detection and imputation of missing data[1]

Nicola Benatti,
European Central Bank

[1] This presentation was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

EUROPEAN CENTRAL BANK

EUROSYSTEM

Nicola Benatti
European Central Bank

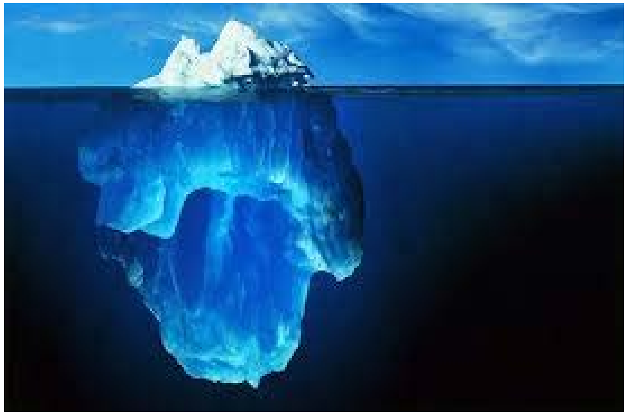
A machine learning approach to outlier detection and imputation of missing data

9th IFC Conference 30-31 Aug 2018, Basel

Overview

What is an outlier?

- An outlier is an observation which is significantly distant from the other considered observations.



- Often outliers are identified by assuming the true distribution of each variable separately to be a known one.

- Alternatively, distributional methods are used but they do not suggest the true values of the Observation.

- It is very important that outliers are not automatically considered as errors since extreme cases can still be justified.

- The aim of this analysis is to rank observations that need to be assessed by their likelihood of being errors.

The iBACH dataset

- Balance sheet and profit and loss data of firms collected by the European Committee of Central Balance Sheet Data Offices (ECCBSO) within its WG on Bank for the Accounts of Companies Harmonized (BACH).
- Aggregate database available since several years but firm level data (iBACH) available to participating countries since February 2018.
- 66 numeric variables taken into consideration in the analysis I carry out

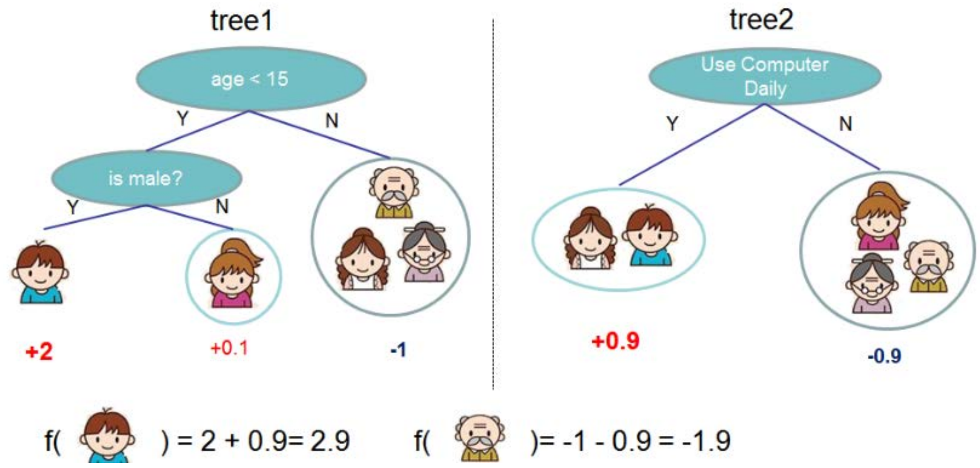
Number of entities

	dyear													
dcountry	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
BE		204,825	218,707	233,180	250,392	264,474	284,327	297,899	326,480	344,480	362,762	377,386	382,669	349,034
ES							450,538	447,540	459,076	450,146	443,527	583,081	560,570	324,701
FR	184,812	192,206	198,107	208,534	225,408	233,267	233,865	244,843	260,670	260,565	250,048	253,758	257,950	261,051
IT	492,472	517,464	540,517	560,140	582,993	600,656	613,021	624,235	634,278	629,865	627,317	621,722	618,177	464,353
PT	16,920	17,547	15,176	342,588	357,480	367,237	366,806	365,821	373,230	373,500	378,731	382,779	390,730	392,030
SK												99,389	99,584	97,869

Sum of n_entities broken down by dyear vs. dcountry. Color shows sum of n_entities. The marks are labeled by sum of n_entities.

Estimation: XGBoost, Gridsearch

- The estimation technique used is extreme gradient boosting (Chen 2016, in the python package xgboost)



- The hyperparameters are set using a Gridsearch algorithm (M. Claesen, B. De Moor 2015, in the python package Gridsearch) which iterates over a tuple of values and choses the optimal set for the following hyperparameters of xgboost: max depth, eta, subsample, number of estimators

Detection: Distance measures and importance averaging

- **<u>Outlier flagging methods using estimation residuals:</u>**
  - K-nearest neighbour on absolute and relative distance from true value
  - Distribution based on both absolute and relative distance from true value

- **<u>Importance averaging:</u>**
  - While causality is confirmed, it might not be clear where the error comes from

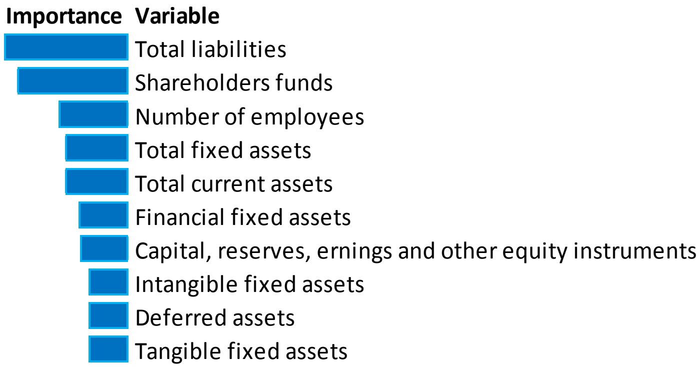
A=B-(C*D) is false

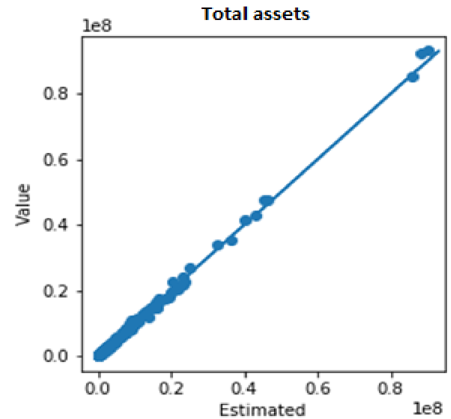
Which variable among A, B, C and D is wrong?

  - For each firm/year I sum the contribution of each variable to the model of detected outliers and create a ranking of “most-likely-to be wrong”.

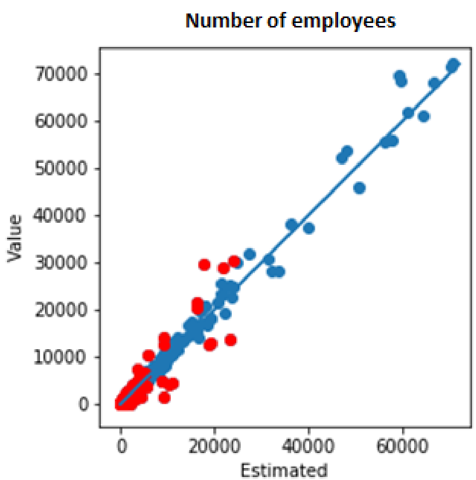
Results

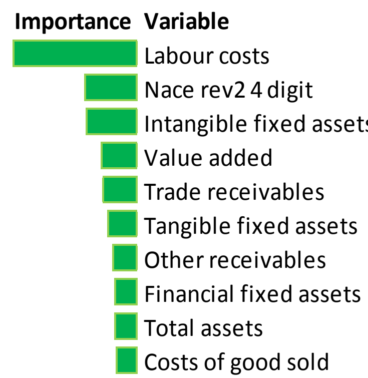
The algorithm allows to accurately estimate all variables analysed.





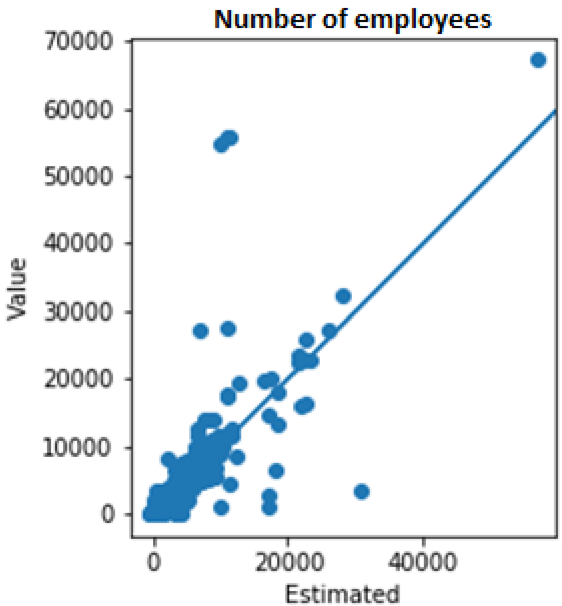
The outliers detected re sent to the NCBs to be investigated, ranked by likelihood of being errors.

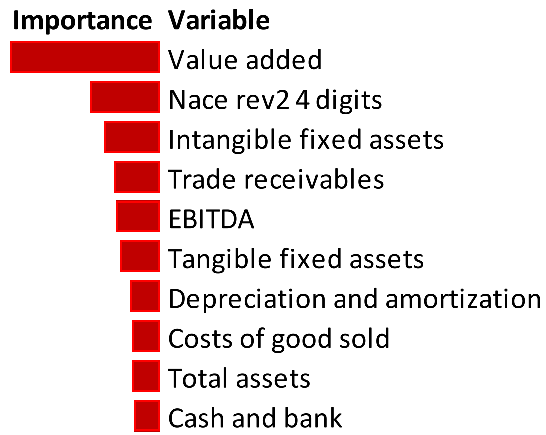




Imputation

The same methodology can be used to estimate the missing values in the dataset. As an exercise, when estimating employment, forcing out the labour costs variable, the estimation still over-performs the methodology used previously internally.





Conclusions

- This paper presents an application of a combination of supervised and unsupervised machine learning with a final feature-additive ranking technique in order to spot mistakes in outlying datapoints.
- The methodology described seems to be useful also for additional steps of data quality improvement such as data imputation.
- This technique also provides guidance for the construction of new data quality checks that could prevent the submissions of mistakes.

Further improvements:

- The increase in the sample size.
- The inclusion of lagged variables would allow for using long-term-short-term memory frameworks.
- The comparison of the results with neural networks and multi-target regressions.
- Inclusion of the confirmation on whether a spotted potential mistake is actually an error or not to transform the distance measure into a classification problem.

Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

A robust machine learning approach for credit risk analysis of large loan level datasets using deep learning and extreme gradient boosting[1]

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Evaggelos Stavroulakis and Aristotelis Klamargias,
Bank of Greece

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[1] This paper was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

A robust machine learning approach for credit risk analysis of large loan level datasets using deep learning and extreme gradient boosting

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Abstract

In the aftermath of global financial crisis of 2007–2008, central banks have put forward data statistics initiatives in order to boost their supervisory and monetary policy functions which will lead to central banks possessing big databases increasing the need for robust data mining processes and financial statistical modelling to support more informed decision making. Conventional econometric methods fail to capture efficiently the information contained in the full spectrum of the datasets. To address these challenges, in this work we investigate the analysis of a corporate credit loans big dataset using cutting edge machine learning techniques and deep learning neural networks.

The novelty of our approach lies in the combination of a data mining algorithms that aim to reduce dimensionality in the data and increase accuracy in predicting the future behaviour of corporate loans, to facilitate a more effective micro and macro supervision of credit risk in the Greek banking system. Our analysis is based on a large dataset of loan level data, spanning a 10 year period of the Greek economy with the purpose of performing obligor credit quality classification and quantification of Probability of Default under a through the cycle setup.

We perform extensive comparisons of the classification and forecasting accuracy of the proposed methods, using a 3-years' period out-of-time sample. Our experimental results are benchmarked against other traditional methods, like logistic regression and discriminant analysis methods, yielding significantly superior performance. In the final stage of our analysis, a robust through the cycle financial credit rating is developed which can offer a proactive monitoring mechanism of the credit risk dynamics in a financial system. Finally the methodological framework introduced can support a more in depth analysis of database initiatives like ECB AnaCredit.

Keywords: Credit Risk, Neural Networks, Deep Learning, Extreme Gradient Boosting.

JEL classification: G24, C38, C45, C55

Contents

1. Introduction

In the aftermath of global financial crisis of 2007–2008, central banks have put forward data statistics initiatives in order to boost their supervisory and monetary policy functions. In the coming years central banks will possess big databases increasing the need for robust data mining processes and financial statistical modelling to support more informed decision making. Under this era, central banks should simultaneously enrich their statistical techniques in order to accommodate the increase availability of data, and to exploit all possible dimensions of information collected. Big financial datasets usually pose significant statistical challenges because they are characterized by increased noise, heavy-tailed distributions, nonlinear patterns and temporal dependencies. Conventional econometric methods fail to capture efficiently the information contained in the full spectrum of the datasets. To address these challenges, in this work we focus on the analysis of a corporate credit loans big dataset using cutting edge machine learning techniques, like Extreme Gradient Boosting (XGBoost) and deep learning neural networks (MXNET).

The novelty of our approach lies in the combination of a data mining algorithms that aim to reduce dimensionality in the data and increase accuracy in predicting the future behaviour of corporate loans, to facilitate a more effective micro and macro supervision of credit risk profile in the Greek banking system. Our analysis is based on a large dataset of loan level data, spanning in a 12 year period of the Greek economy. Data are collected by Bank of Greece for statistical and banking supervision activities. The dataset is comprised of more than 200k records of corporate and SME loans of the Greek banking system, with information related to the one-year-ahead delinquency behaviour. Features collected for analysis include companies' historical data of properly selected set of financial ratios, along with historical data of macro variables relevant to the Greek economy. To ameliorate the issue of high dimensionality in the data we used an advanced machine learning algorithm, called Boruta, to perform the variable importance selection in a multivariate holistic approach. Extreme gradient Boosting and Deep neural networks are used for performing obligor credit quality classification and quantification of Probability of Default under a through the cycle setup.

We perform extensive comparisons of the classification and forecasting accuracy of the proposed methods, using a 3-years' period out-of-time sample. Our experimental results are benchmarked against other traditional methods, like logistic regression, and discriminant analysis methods, yielding significantly superior performance. Furthermore, it is also found that the performance of deep neural-network models depend on the choice of activation function, the number and structure of the hidden layers, and the inclusion of dropout and batch normalization layers signalling increase flexibility in addressing complex datasets and potential increased classification capabilities. In the final stage of our analysis, a robust through the cycle financial credit rating scale is developed which can accommodate the efficient benchmarking of A-IRB models and offer a proactive mechanism of the credit risk dynamics in a financial system. In addition, it can support top down stress testing exercises offering a more risk sensitive and accurate forecasting framework.

In all the methodological framework introduced can support a more in depth analysis of database initiatives like ECB AnaCredit[1].

2. Literature Review

In the domain of credit risk modelling, more accurate and robust systems to drive expert decisions have been employed in recent years, exploring new statistical techniques especially from the field of machine and deep learning. In the last decades, a plethora of approaches has been developed to address the problem of modelling the credit quality of a company, using both quantitative and qualitative information.

Several studies have explored the utility of probit models (Mizen and Tsoukas, 2012) and linear regression models (Avery, et al., 2004). These models however, suffer from their clear inability to capture non-linear dynamics, which are prevalent in financial ratio data (Petr and Gurný, 2013). Another class of statistical models used for credit rating is hazard rate models. These models extend the time horizon of a rating system, by looking at the probability of default during the life cycle of the examined loan or portfolio (Chava and Jarrow, 2004 & Shumway, 2001).

A Bayesian inference-based analogous to support vector machines (SVMs) (Vapnik, 1998), namely Gaussian processes, has been considered by Huang (2011). A drawback of this approach is its high computational complexity, which is cubic to the number of available data points, combined with the assumption of normally distributed data. Yeh et al. (2012) applied Random Forests (Breiman, 2001) in credit corporate rating determination, Zhao et al, (2015) employed feed forward neural networks in the same domain whereas Petropoulos et al (2016) made use of Student's-t hidden Markov models

Addo et al. (2018) focus on credit risk scoring where they examine the impact of the choice of different machine learning and deep learning models in the identification of defaults of enterprises. They also study the stability of these models relative to a choice of subset of variables selected by the models. More specifically, they build binary classifiers based on machine and deep learning models on real data in predicting loan default probability. The top features from these models are selected and then used for testing the stability of binary classifiers by comparing their performance on separate data. They observe that the tree-based models are more stable than the models based on multilayer artificial neural networks.

Khandani et al. (2010) apply machine learning techniques (generalized classification and regression trees (CART)-like algorithm (Breiman et al., 1984)) to construct nonlinear nonparametric forecasting models of consumer credit risk. They combine customer transactions and credit bureau data from January 2005 to April 2009 for a sample of a major commercial bank's customers; thus, they are able to

[1] https://www.ecb.europa.eu/stats/money/aggregates/anacredit/shared/pdf/explanatorynoteanacreditregulation.en.pdf

construct out-of-sample forecasts that significantly improve the classification rates of credit-card-holder delinquencies and defaults.

Butaru et al. (2016) use account-level credit card data from six major commercial banks from January 2009 to December 2013; they combine consumer tradeline, credit bureau, and macroeconomic variables to predict delinquency, employing C4.5 decision trees, logistic regression and random forests. They find substantial heterogeneity in risk factors, sensitivities, and predictability of delinquency across banks, implying that no single model applies to all six institutions. The results suggest the need for a more customized approached to the supervision and regulation of financial institutions, in which capital ratios, loss reserves, and other parameters are specified individually for each institution according to its credit risk model exposures and forecasts.

Galindo and Tamayo (2000) test CART decision-tree models on mortgage-loan data to detect defaults. They also compare their results to the Neural Networks (ANN), the k-nearest neighbor (KNN) and probit models, showing that CART decision-tree models provide the best estimation. Huang et al. (2004) provides a survey of corporate credit rating models showing that Artificial Intelligence (AI) methods achieve better performance than traditional statistical methods. The article introduces a relatively new machine learning technique, support vector machines (SVM), to the problem in attempt to provide a model with better explanatory power. They used backpropagation neural network (BNN) as a benchmark and obtained prediction accuracy around 80% for both BNN and SVM methods for the United States and Taiwan markets.

Motivated from all the aforementioned research endeavours we revisit the issue of credit risk modelling following a different venue. We explore two state of the art techniques namely Extreme Gradient Boosting (XGBoost) and deep learning neural networks in order to obtain at first maximum information gain from a loan level large size data source and secondly to create a useful, from a regulatory scope, credit rating grade system measuring credit risk in supervised banks portfolios.

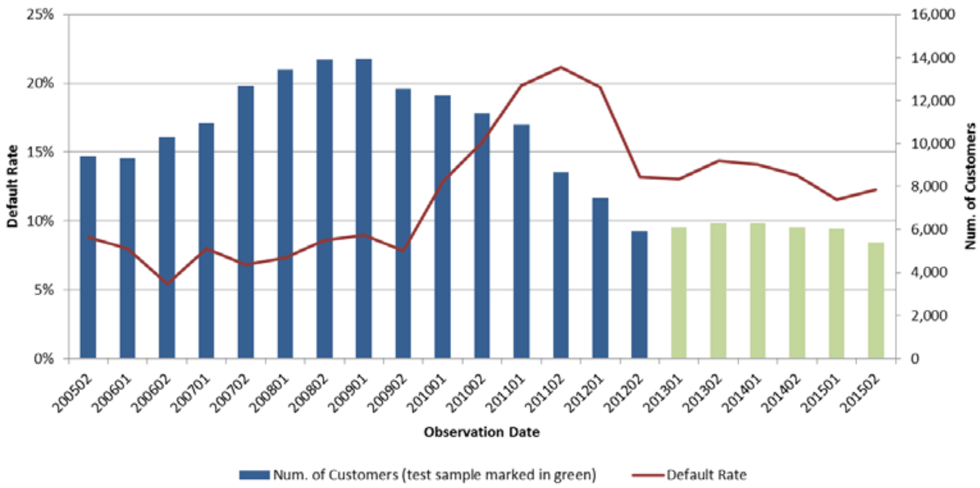
3. Data collection processing and variable selection

We have collected loan level information on Corporate and SME loans of the Greek banking system, from the supervisory database of the Central Bank of Greece. The data collection procedure excludes special cases of obligors from the financial sector, including banks, insurance, leasing, and factoring companies, due to the very unique nature of their business models, which deviate quite a lot from the business models of commercial companies.

The adopted definition of a default event in this dataset is in line with the rules of the Credit Risk Regulation (CRR). Specifically, a loan is flagged as delinquent if it is either 90 days past due or it gets rated as delinquent based on each bank's internal rating rules. At each observation snapshot, all performing loans are considered. At the end of the 12-month observation period, each obligor is categorized as either good (i.e., performing) or bad (i.e., non-performing). At the end the dependent variable in our dataset is a binary indicator, with the value of one flagging a default event (i.e., the obligor is categorized as bad at the end of the 12-month observation period).

The dataset covers the 2005-2015 period; a 10 years' period with semi-annual information (i.e. semi-annual snapshots). The selected time period, seems to approximate a full economic cycle, in terms of the default rate evolution. Figure 1, shows the number of customers included in each snapshot and the corresponding default rate. The overall dataset includes approximately 200.000 unique customers, resulting in even more records on a facility level, as one customer may have more than one facility in one or more than one banks with different risk characteristics (for example the average facility number in the credit risk supervisory database reaches 120.000 records per quarter). It is clear that the default rates have elevated in the most recent period, i.e. from the second half of 2010 and onwards, compared to the older observations, i.e. up to 2010. Specifically, the default rates follow an increasing trend in the 2010-2011 periods, where they peak at 21.2% in the second half of third quarter of 2011. Thereafter, they follow a decreasing trend. The default rates seem to have flattened out since 2013, remaining stable at around 12%-13%.

Figure 1: Greek banking system business portfolio metric evolution



In order to perform the modelling and prediction methodology, our approach incorporates the companies' 5 year lagged historical data of properly selected set of financial ratios along with 10 quarters lagged historical macro variables relevant to the Greek economy (both shown analytically in the Appendix). This is based on the assumption that financial ratios carry all the information necessary to describe and predict the internal state of a company, providing adequate insights on how profitable an examined company is, what the trends are.

The combined dataset of lagged financial ratios and macro variables along with some data transformations, led to a set of 354 predictor variables (distinct time-series) as potential candidates for our modelling procedures. Fitting a machine learning model to such a huge number of independent variables (relative to the size of the dataset) is doomed to suffer from the so-called curse of dimensionality problem, whereby the fitted classifier may seem to yield very good performance in the training dataset, but it turns out to generalize very poorly, yielding a catastrophically low performance outcome in the test data. Thus, to ensure a good performance outcome for our model, we need to implement a robust independent variable (feature) selection stage, so as to limit the number of used features to the absolutely necessary. Besides, apart from increasing the generalization capabilities of the fitted models, such a reduction is also important for increasing the computational efficiency of the explored machine learning algorithms.

We employ the Boruta algorithm to independently assign importance to the available features. The Boruta algorithm is based on a postulated Random Forest model. Based on the inferences of this Random Forest, features are removed from the training set, and model training is performed anew. Boruta infers the importance of each independent variable (feature) in the obtained predictive outcomes by creating shadow features. Specifically, the algorithm performs the following steps: First, it adds randomness to the given dataset by creating shuffled copies of all features (shadow features). Then, it fits a Random Forest on the extended dataset and evaluates the importance of each feature. In every iteration, it checks whether a real feature has a higher importance than the best of its shadow features, and constantly removes features which are deemed unimportant. The comparison is done based on Z score. The algorithm stops when all features are classified as important or are rejected as noise. In our study, we employ the Boruta Package, provided by the R programming language, to implement variable selection. In this way, all features relevant to both dependent variables are selected based on error minimization for the fitted Random Forest models, in each iterative step of the algorithm. From the Boruta variable selection process 65 variables out of 354 candidates were selected for the moment development alleviating dimensionality issues. The so-obtained dataset was split into three parts:

- An in-sample train dataset, comprising data pertaining to the 70% of the examined companies, obtained over the observation period 2005-2012, which was used for model development.
- An in-sample test dataset, comprising the data pertaining to the rest 30% of the companies for the period 2005-2012 which was employed for assessing the parameter calibration.
- An out-of-time dataset that comprises all the data pertaining to the observation period of year 2013-2015 (marked in green in Figure 1) which was employed for validation purpose and testing the generalization capacity of all candidate models.

4. Model Development

Given the extended number of employed predictors and the large scale dataset employed we resort to a methodology from the general domain of Machine Learning techniques called Extreme Gradient Boosting (henceforth XGBoost) and a Deep Learning Technique used to train, and deploy deep neural networks (MXNET). The supervisory motivation for employing such types of methodologies rests on the availability of large scale supervisory data, which are expected to further augment in the near future (e.g. ECB's AnaCredit project), upon which the capability of pattern detection by traditional statistical methodologies is limited due to multicollinearity, dimensionality and convergence issues.

The XGBoost is a boosting tree algorithm that is an enhancement over tree bagging methodologies, such as Random Forests (Breiman 2000), which have gained significant ground and are frequently used in many machine learning applications across various fields of the academic community. The basic philosophy of bagging is based on combining three concepts: i) Creation of multiple datasets; ii) building of multiple trees and iii) bootstrap aggregation or bagging. It adopts a divide-and-conquer approach to capture non-linearities in the data and perform pattern recognition. Its core principle is that a group of "weak learners" combined, can form a "strong predictor" model.

For example in the case of Random Forests the algorithm is based on the random generation of a number of classification trees which is the so called Forest. Tree generation is randomly performed in an iterative mode so in each iteration, a random subsample of the included features is selected from the dataset by means of bootstrap. Then, a tree is generated from using the CART algorithm which contains a relatively limited number of features. After constructing the random trees, prediction is performed using Bagging. Each input is entered through each decision tree in the forest and produces a forecast. Then, all predictions of each tree are aggregated either as a (weighted) average or majority vote, depending whether the underlying problem is a regression or a classification, respectively.

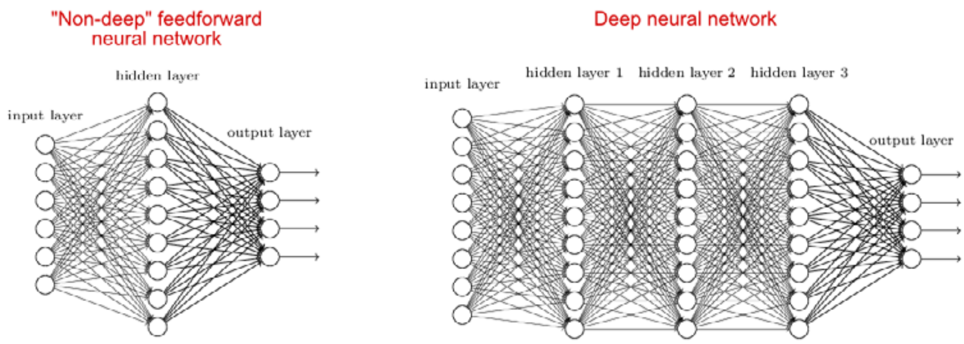
Gradient Boosting trees model is proposed by Friedman (1999) and has the advantage of reducing both variance and bias. It reduces variance because multiple models are used (bagging), whereas it additionally reduces bias in training the subsequent model by telling him what errors the previous models made (boosting). In gradient boosting each subsequent model is trained using the residuals (the difference between the predicted and true values) of previous models. XGBoost (Extreme Gradient Boosting) is an advanced implementation of gradient boosting algorithm, offering increased efficiency, accuracy and scalability over simple bagging algorithms. It supports fitting various kinds of objective functions, including regression, classification and ranking. XGBoost offers increased flexibility, since optimization is performed on an extended set of hyperparameters, while it fully supports online training.

We developed XGBoost in the context of our study by utilizing the XGBoost R package. We performed an extensive cross-validation procedure to select a series of entailed hyper parameters, including the maximum depth of trees generated, the minimum leaf nodes size to perform a split, and the size of sub-sampling for building the classification trees and the variables considered in each split. The objective function used for the current problem was logistic due to the binary nature of the dependent variable while the area under the curve (AUROC) metric was used for model selection in the context of cross-validation. The AUROC of a classifier is equivalent to the probability that the classifier will rank a randomly chosen positive instance higher than a randomly chosen negative instance. In practice, the value of AUROC varies between 0.5 and 1, with a value above 0.8 denoting a very good performance of the algorithm. To reduce overfitting tendencies, we tuned the γ hyper parameter, which controls model complexity by imposing the requirements that node splits should yield a minimum reduction in the loss function, as well as the α and λ hyper parameters, which perform regularization of model weights similar to shrinkage techniques such as LASSO.

Besides Extreme Gradient Boosting we implement also a Deep Neural Network (henceforth DNN) to address the issue of corporate default forecast. Deep learning has been an active field of research in the recent years, as it has achieved significant breakthroughs in the fields of computer vision and language understanding. In particular they have been extremely successful in as diverse time-series modelling tasks as machine translation (Cho et al., 2014, Tu et al., 2016.), machine summarization (See et al., 2017) and recommendation engines (Quadrana et al., 2017). However, their application in the field of finance is rather limited. Specifically, our paper constitutes one of the first works presented in the literature that considers application of deep learning to address this challenging financial modelling task.

Deep Neural Networks differ from Shallow Neural Networks (one layer) on the multiple internal layers employed between the input values and the predicted result (Figure 2). Constructing a DNN without nonlinear activation functions is impossible, as without these the deep architecture collapses to an equivalent shallow one. Typical choices are logistic sigmoid, hyperbolic tangent and rectified linear unit (ReLU). The logistic sigmoid and hyperbolic tangent activation functions are closely related; both belong to the sigmoid family. A disadvantage of the sigmoid activation function is that it must be kept small due to their tendency to saturate with large positive or negative values. To alleviate this problem, practitioners have derived piecewise linear units like the popular ReLU, which are now the standard choice in deep learning research ReLU, (Vinod & Hinton, 2010).

Figure 2: Shallow and Deep Neural Networks



On a different perspective, since DNNs comprise a huge number of trainable parameters, it is key that appropriate techniques be employed to prevent them from overfitting. Indeed, it is now widely understood that one of the main reasons behind the explosive success and popularity of DNNs consists in the availability of simple, effective, and efficient regularization techniques, developed in the last few years. Dropout has been the first, and, expectably enough, the most popular regularization technique for DNNs (Srivastava et al., 2014). In essence, it consists in randomly dropping different units of the network on each iteration of the training algorithm. This way, only the parameters related to a subset of the network units are trained on each iteration. This ameliorates the associated network overfitting tendency, and it does so in a way that ensures that all network parameters are effectively trained.

Inspired from these merits, we employ Dropout DNNs with ReLU activations to train and deploy feed forward deep neural networks. More precisely we employ the Apache MXNET toolbox of R[2]. We postulated deep networks that are up to five hidden layers deep and comprise various numbers of neurons. Model selection using cross-validation was performed by maximizing the AUROC metric.

We benchmark the abovementioned techniques versus traditional statistical techniques employed in Probability of Default modelling, such as Logistic regression (Logit) and Linear Discriminant Analysis (LDA). Logistic regression is an approach broadly employed for building corporate rating systems and retail scorecards, due to its parsimonious structure. It was first used by Ohlson (1980) to predict corporate bankruptcy based on publicly available financial data. Logistic regression models determine the relative importance of each independent variable in the classification outcome using the fitting dataset. In order to account for non-linearities, and to relax the normality assumption, a sigmoid likelihood function is typically used (Kamstra et al. 2001).

Linear discriminant analysis (LDA) is a method to find a linear combination of features that characterizes or separates two or more classes of objects or events. The main assumptions are that the modelled independent variables are normally distributed and that the groups of modelled objects (e.g. good and bad obligors) exhibit homoscedasticity. LDA is broadly used for credit scoring. For instance, the popular Z-Score algorithm proposed by Altman (1968) is based on LDA to build a rating system for predicting corporate bankruptcies. The normality and homoscedasticity assumptions are hardly ever the case in real-world scenarios, thus, being the main drawbacks of this approach. As such, this method cannot effectively capture nonlinear relationships among the modelled variables, which is crucial for the performance of a credit rating system. We implemented this approach in R using the MASS R package. Before estimating both the logit and the LDA model we dropped collinear variables based on correlation cut-off threshold of 50%.

5. Model Evaluation

Classification accuracy, as measured by the discriminatory power of a rating system, is the main criterion to assess the efficacy of each method and to select the most robust one, in terms of discriminatory power and performance misinterpretation. We tested a series of metrics that are broadly used for quantitatively estimating the discriminatory power of each scoring model, such as the Area Under the ROC curve metric, as well as the Kolmogorov Smirnov (KS) statistic as performance measures.

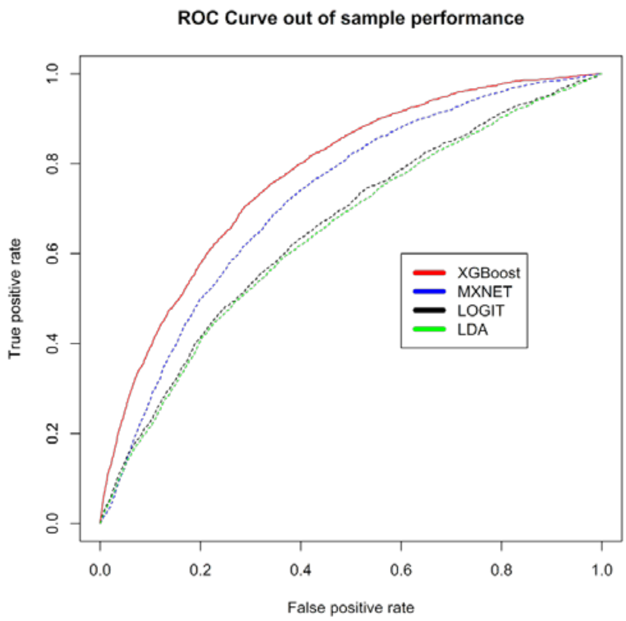
[2] https://mxnet.incubator.apache.org/api/r/index.htm

Classification Accuracy Model Comparison		Table 1
	KS	AUROC
Logit	24%	66%
LDA	23%	65%
XGBoost	42%	78%
MXNET	35%	72%

Classification Accuracy Metrics: Kolmogorov - Smirnov (KS), Area Under ROC curve (AUROC).

Further, we present in Figure 3 the ROC curveS corresponding to the methodologies analysed. This curve is created by plotting the true positive rate against the false positive rate at various threshold settings. As such, they illustrate the obtained trade-offs between sensitivity and specificity, as any increase in sensitivity will be accompanied by a decrease in specificity. The closer the curve follows the left-hand border and then the top border of the ROC space, the more accurate the modelling approach. The corresponding ROC curve of extreme gradient boosting (XGBoost) is higher over all the considered competitors supporting the high degree of efficacy and generalization capacity of the proposed employed machine learning system.

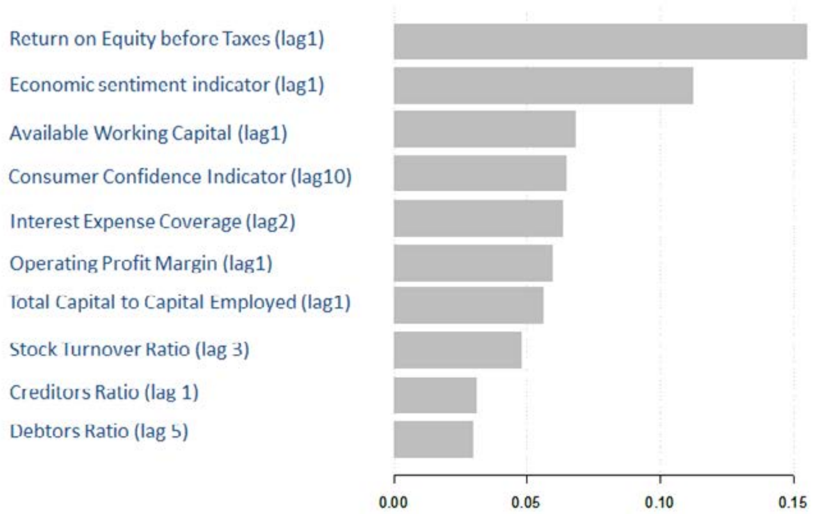
Figure 3: ROC curve for forecasting a default event on 1 year horizon



From Table 1 and Figure 3 we deduce that the XGBoost and MXNET algorithms provide better classification accuracy compared to traditional classification methods such as Logistic Regression and Linear Discriminant analysis. As a robustness check other widely employed classification techniques were employed namely the CART algorithm, Random Forests and One Layer Neural Networks (Shallow) but their performance did not surpass the XGBoost and MXNET which is logical if you consider that the first two are subcases of XGBoost whereas Shallow Neural Network are subcases of MXNET algorithm.

Boosting and Bagging algorithms, even though they are computation intensive, have the relative advantage that they are not "black boxes" regarding the factors affecting the final result, since they provide a module for calculating variable importance measures through reshuffling. In other words after predicting with the benchmark model the reshuffling technique predicts hundreds of times for each variable in the model while randomizing that variable. If the variable being randomized hurts the model's benchmark score, then it is an important variable. If, on the other hand, nothing changes, then it is a useless variable. We run the variable importance algorithm and we show in Figure 4 the ranked list of first ten more important variables

Figure 4: XGBoost variable importance plot. The x-axis describes the percentage contribution of the predictor in the "real" model.



It appears that the most important financial ratio predictor for the default probability of a company is Return on Equity followed by the availability of working capital and Interest Expense Coverage. In essence the company return, the availability of financial resources and the prudent leverage policy may assure the viability of a business. In addition the economic climate, seem to play an additional important role in business viability since the Economic sentiment indicator and the Consumer confidence indicator are rendered important in the model whereas other widely employed factors such as GDP growth seem not to be predominant. What is important is that XGBoost includes both macro variables and financial ratios capturing both the systemic and idiosyncratic behaviour in obligor's credit quality, thus both discriminatory and calibration test exhibit stability and steady performance.

6. Rating System Calibration

An essential aspect of each classification system lies in the creation of a way to represent the classification results to a rating system which can be employed for supervisory purposes in the course central banking operations. For this purpose, we apply a credit rating system calibration process. Calibration of a credit rating system is a mapping process under which each score value is matched to rating grade, which is then associated with a probability of default. To perform the calibration of our systems, the development sample population of each scoring model was split into groups. Specifically, 50 groups (i.e. ranges of scores) were created of equal size, each one including 2% of the total population. Each group is associated with the default rate observed in the development sample.

When necessary, ranges of scores were grouped together, in order to ensure monotonicity of the obtained default rates, maximum intra-rate homogeneity of the observed default rates, and maximum inter-range heterogeneity. In order to overcome overfitting issues and create a reasonable system, each grade included at least 4% of the development population. Grouping optimization was performed based on the Information Value metric.

The following graphs visualize the calibration performed for each rating system. In specific, the first graph present the default rate associated to each of the 50 groups initially created, while the second graph show the default associated to the final selected grades.

Figure 5: Estimated Default Rate of the Initial Grouping (50 Groups)

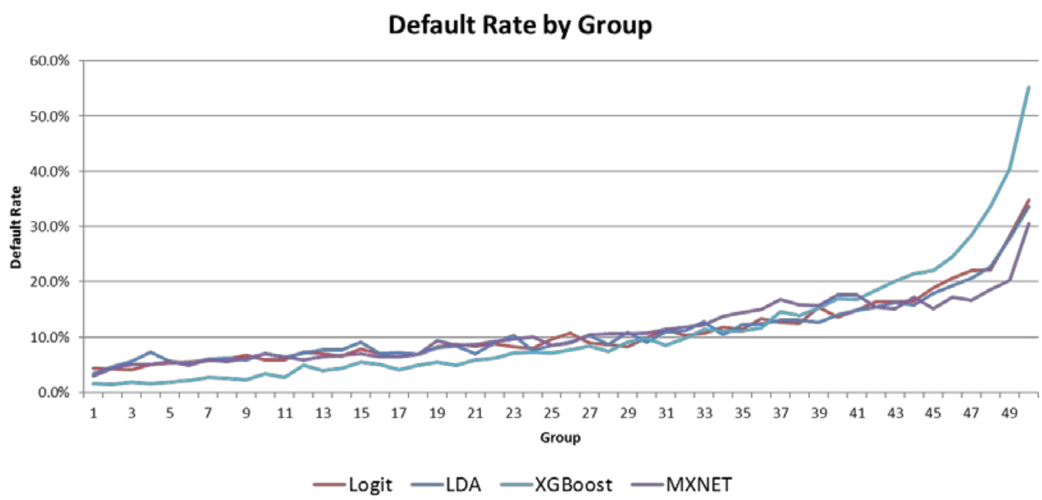
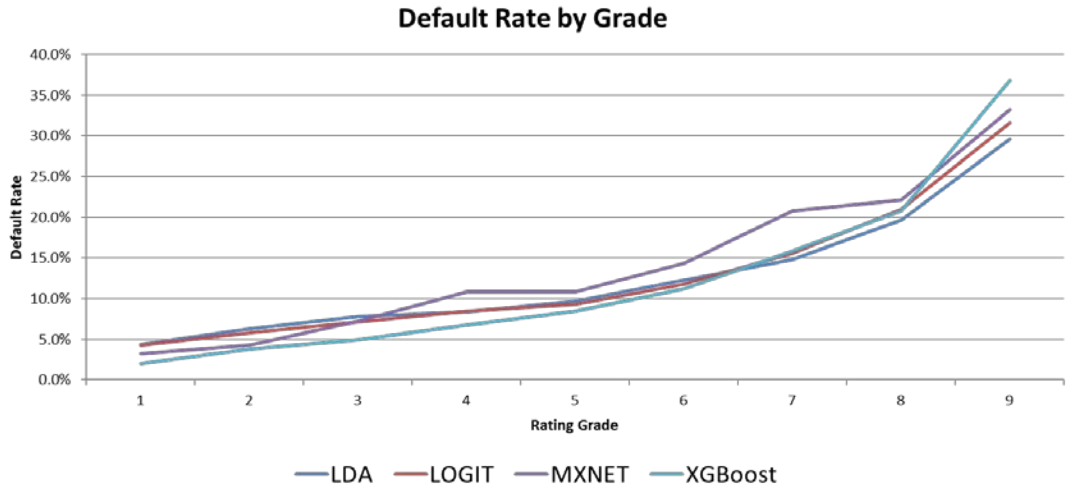


Figure 6: Estimated Default Rate of the Final Selected Grades (9 Grades)



Based on the Figures 5 and 6 it is clear that the XGBoost model is able to produce a more granular calibration. This means that the XGBoost calibration can assign lower default rates to the low grades, and vice versa higher default rates to higher grades, compared to the other models. In order to assess the calibration of the rating systems developed, the binomial test, the normal, the sum of square error, and the brier score validation metrics are utilized. The estimated probability of default was also compared with the out-of-sample observed default rate. The validation methodologies that are typically being applied in the industry include the most, if not all, of the metrics included in our analysis. Additional tests, such as the Bayesian error rate, Chi-square (or Hosmer-Lemeshow) test, that could also have been used, were omitted mainly due to the fact that they produce similar results and conclusions.

Performance Metrics — Table 2

Credit Rating System

	SSE	BRIER
Logit	4.3%	11.3%
LDA	4.8%	11.4%
XGBoost	0.2%	10.1%
MXNET	0.6%	11.0%

Rating System Calibration Metrics: Sum of Square Error (SSE), Brier's score (BRIER).

In the Appendix (Tables 4-7) are shown the calibration results for each evaluated model, i.e. the estimated probability of default per rating grade (based on the default rate on the development sample) and the observed default rate in the out-of-time period. We deduce that Binomial and Normal tests fail for the rating systems developed based on the LDA and Logit models. The estimated PDs are lower than the observed default rates for almost all grades. On the other hand, the MXNET and XGBoost rating systems perform better as the estimated PDs are not statistically different to the observed default rates.

Estimated and Actual default frequency metrics			Table 3
	Estimated Probability of Default	Observed Default Rate (Out of sample)	Observed Default Rate (In sample)
Logit	8.20%	13.10%	11.00%
LDA	7.80%		
XGBoost	13.50%		
MXNET	15.00%		

Estimated Probability of Default vs observed Default Rate in out-of-sample and in-sample population

Based on Table 3 it is clear that the rating system developed based on the XGBoost model, is more accurate in terms of PD quantification, compared to the other candidate models due to the more granular calibration achieved by XGBoost. Analytically, XGBoost has marginally overestimated the observed default rate in the validation sample whereas MXNET overestimated the default rate which is good from regulatory perspective. On the other hand, LDA and Logit based systems significantly underestimated the observed default rate.

Deep neural networks provide promising results even though they do not outperform the XGBoost algorithm. The fact is that this methodology provides the opportunity of creating a large combination of different structures based on the number of layers, the selection of activation functions, the number of perceptrons and normalization layers which can be inserted in the optimization process. In the appendix (Figure 7) some illustrative alternative employed structures is shown. Therefore the potentials for Deep Neural Networks algorithms (such as MXNET) in pattern detection in the era of "big data" in which the central banking system is entering are enormous, given that the flexibility of structures is much greater than Boosting and Bagging mechanistic algorithms.

7. Conclusion

In order to tackle the issue of pattern detection in large loan level datasets for extracting information regarding credit risk and exposure credit quality, we employ a combination of data mining algorithms that aim to reduce dimensionality in the data and increase accuracy in predicting the future behaviour of corporate loans. Our analysis is based on a large dataset of loan level data, spanning in a 10 year period of the Greek economy with the purpose of performing obligor credit quality classification and quantification of Probability of Default under a through the cycle setup.

We perform extensive comparisons of the classification and forecasting accuracy of the proposed methods, using a 3-years' period out-of-time sample and we deduce that the Extreme Gradient Boosting technique along with Deep Neural Networks provide better performance in terms of classification accuracy and credit rating system calibration compared to widely employed techniques in credit risk modelling such as Logistic Regression and Linear Discriminant Analysis. In addition the inclusion of both macro variables and financial ratios captures both the systemic and idiosyncratic behaviour in obligor's credit quality, thus both discriminatory and calibration test exhibit stability and steady performance.

Our findings provide significant oversight for regulatory purposes given that in the coming years, central banks will possess big databases increasing the need for robust data mining processes and financial statistical modelling to support more informed decision making. For example the proposed approaches could find fruitful ground on the European Central Bank's AnaCredit initiative for the collection of loan level data. "Big Data" as referred often entail dimensionality issues, increased noise and other significant statistical challenges which cannot be addressed from traditional statistical techniques.

Regarding the final model selection XGBoost seems to be the methodology marginally outperforming Deep Neural Networks (MXNET) but the latter methodology provides the opportunity of increased flexibility over boosting techniques through a large combination of different structures which may optimize the bias variance trade-off. As a prospect of future research it may be explored whether alternative Deep Neural Network structures, such as recurrent DNN or convolutional networks, may increase the classification accuracy or whether potential forecast combinations among machine and deep learning techniques may further allow boosting of the results.

Appendix

Financial Ratios Employed

- Working Capital
- Employed Capital (Assets minus Current Liabilities)
- Return on Equity before Taxes
- Return on Equity before Interest and Taxes
- Profit before taxes to Employed capital
- Gross Margin to Sales
- Operating Margin to Sales and other income
- Earnings before Interest and Taxes to Sales and other income
- Sales and other income to Employed Capital
- Sales and other income to Equity
- Equity and Long Term Loans to Net Fixed Assets
- Debt to Equity
- Interest Expense Coverage
- Equity to Employed Capital
- Working Capital to Short Term obligations
- Immediate Cash Ratio
- Debtors Ratio
- Creditors Ratio
- Stock turnover Ratio

Macro Variables Employed

- Gross Domestic Product yearly growth
- Investment yearly growth
- Export yearly growth
- Consumption yearly growth
- Economic sentiment indicator
- Consumer Confidence Indicator
- Unemployment Rate
- Inflation
- Stock Market Returns
- Stock Market Volatility
- Deposit Rates
- Loan Rates
- 10 year Government bond spread
- 5 year Government bond spread
- 1 year Government bond spread

Binomial and Normal Validation Tests

Validation Testing - Logistic Regression model				Table 4
Rating Grade	Estimated Probability of Default	Observed Default Rate (Out of sample)	Binomial Test	Normal Test
1	4.21%	6.46%	0.00%	0.00%
2	5.77%	8.83%	0.00%	0.00%
3	7.10%	10.84%	0.00%	0.00%
4	8.38%	13.97%	0.00%	0.00%
5	9.32%	17.46%	0.00%	0.00%
6	11.77%	21.46%	0.00%	0.00%
7	15.53%	23.45%	0.00%	0.00%
8	20.95%	29.64%	0.00%	0.00%
9	31.57%	40.00%	5.07%	4.86%

Binomial and Normal tests examine the null hypothesis that the actual default rate of a credit rating grade is not greater than the forecasted probability of default

Validation Testing - Linear Discriminant Analysis				Table 5
Rating Grade	Estimated Probability of Default	Observed Default Rate (Out of sample)	Binomial Test	Normal Test
1	4.36%	7.37%	0.00%	0.00%
2	6.25%	9.90%	0.00%	0.00%
3	7.76%	12.28%	0.00%	0.00%
4	8.38%	13.80%	0.00%	0.00%
5	9.63%	21.68%	0.00%	0.00%
6	12.19%	20.89%	0.00%	0.00%
7	14.75%	26.01%	0.00%	0.00%
8	19.64%	27.58%	0.00%	0.00%
9	29.65%	30.19%	51.73%	52.55%

Binomial and Normal tests examine the null hypothesis that the actual default rate of a credit rating grade is not greater than the forecasted probability of default

Validation Testing - Extreme Gradient Boosting (XGBoost)				Table 6
Rating Grade	Estimated Probability of Default	Observed Default Rate (Out of sample)	Binomial Test	Normal Test
1	1.99%	1.52%	95.15%	94.66%
2	3.78%	2.34%	99.96%	99.92%
3	4.89%	3.88%	96.81%	96.45%
4	6.72%	5.39%	98.28%	98.03%
5	8.41%	6.96%	98.75%	98.58%
6	11.18%	9.75%	99.07%	98.97%
7	15.86%	15.09%	86.36%	86.33%
8	20.82%	22.57%	1.64%	1.57%
9	36.81%	38.43%	5.95%	5.92%

Binomial and Normal tests examine the null hypothesis that the actual default rate of a credit rating grade is not greater than the forecasted probability of default

Validation Testing - MXNET				Table 7
Rating Grade	Estimated Probability of Default	Observed Default Rate (Out of sample)	Binomial Test	Normal Test
1	3.2%	0.9%	99.4%	98.5%
2	4.2%	3.5%	80.9%	81.1%
3	7.2%	2.6%	100.0%	100.0%
4	10.8%	6.4%	100.0%	100.0%
5	10.8%	15.6%	32.0%	32.1%
6	14.3%	23.1%	8.2%	8.1%
7	20.8%	28.9%	61.5%	61.9%
8	22.1%	30.2%	90.5%	90.5%
9	33.2%	32.9%	56.6%	56.8%

Binomial and Normal tests examine the null hypothesis that the actual default rate of a credit rating grade is not greater than the forecasted probability of default

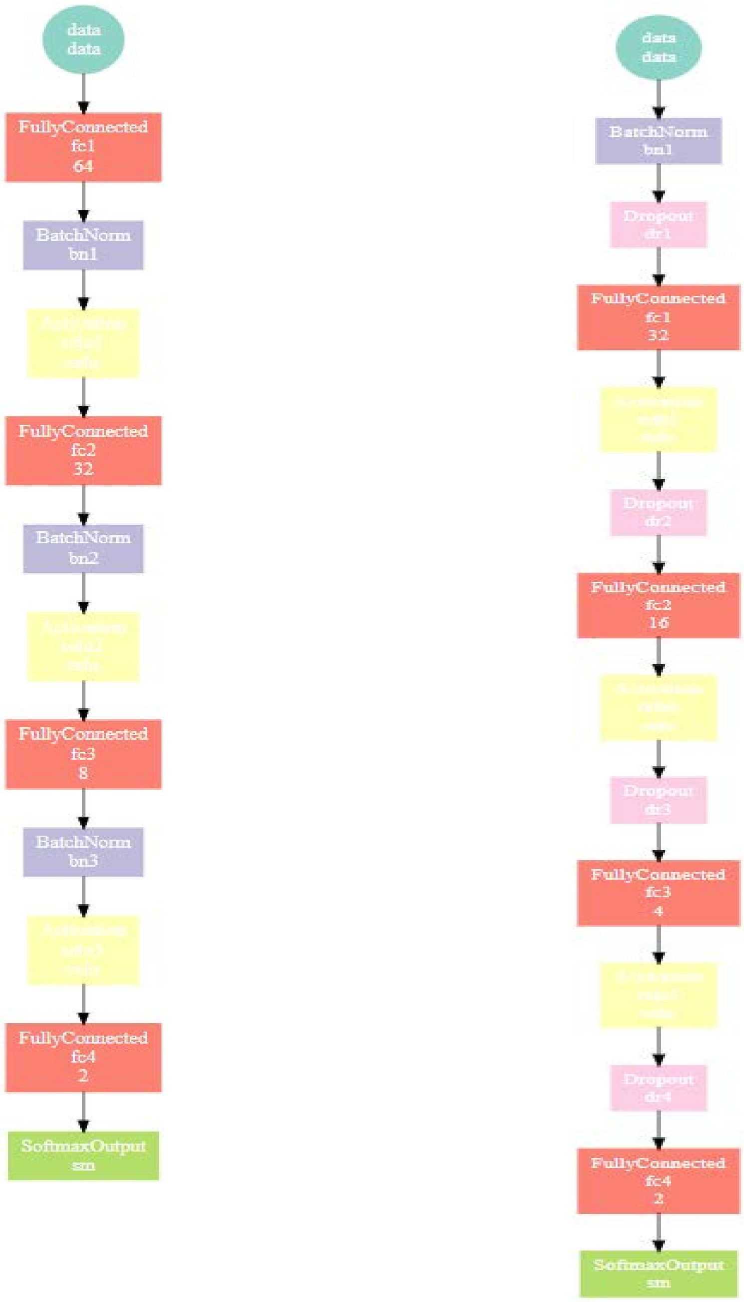


Figure 7: Illustrative structure of some Deep Neural Network structures employed in the optimization process

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BANK FOR INTERNATIONAL SETTLEMENTS

Ninth IFC Conference on “Are post-crisis statistical initiatives completed?”

Basel, 30-31 August 2018

A robust machine learning approach for credit risk analysis of large loan level datasets using deep learning and extreme gradient boosting[1]

Anastasios Petropoulos, Vasilis Siakoulis,
Evaggelos Stavroulakis and Aristotelis Klamargias,
Bank of Greece

[1] This presentation was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

A robust machine learning approach for credit risk analysis of large loan level datasets using deep learning and extreme gradient boosting

9th biennial IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

BANK OF GREECE
Anastasios Petropoulos
Vasilis Siakoulis
Evangelos Stavroulakis
Aristotelis Klamargias

The views expressed in this paper are those of the authors and not necessarily those of Bank of Greece

Credit Risk Analysis Tool

In a nutshell

Novel Rating System for Greek banks business portfolios

Proactive monitoring

Economic assessment

Modeling technique

- Extreme Gradient Boosting
- Deep Neural Networks

Main Drivers

- Company Financial Ratios
- Macroeconomic factors

Implementation

- Corporate and SME loans of the Greek banking system, from the supervisory database of the Central Bank of Greece

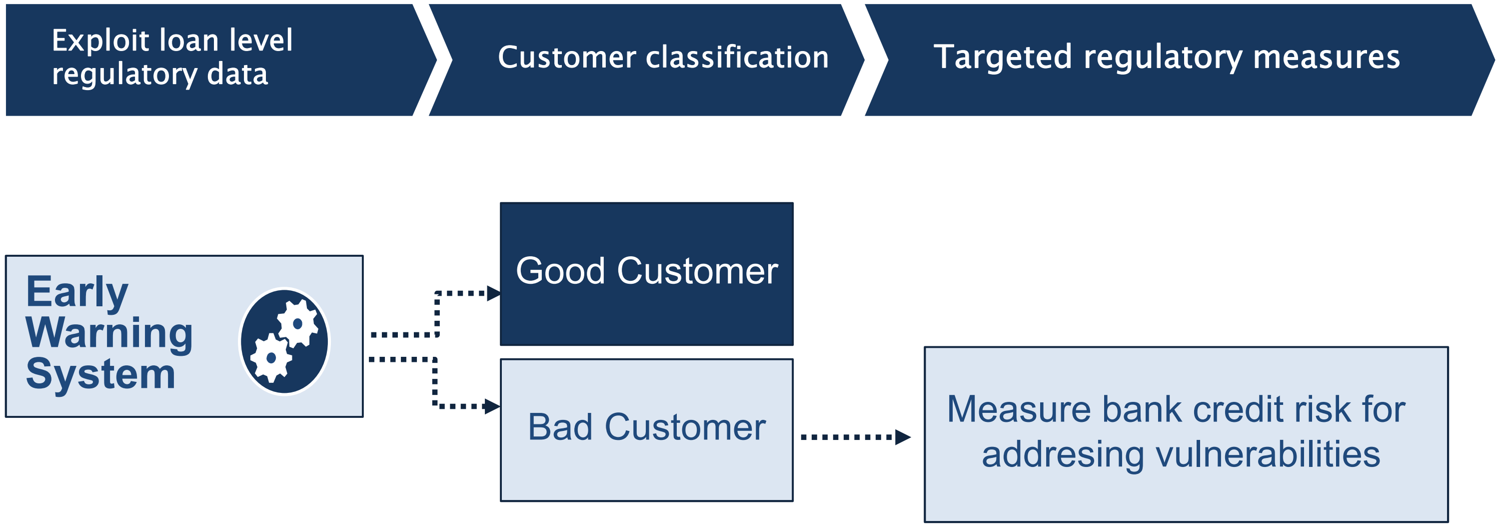
Credit Risk Analysis

Machine and Deep learning techniques

- "Learn" without being explicitly programmed
- Unveiling new determinants and unexpected forms of dependencies among variables.
- Tackling non linear relationships.

- Use of ML and Deep Learning are favored by the technological advances and the availability of financial sector data.
- Supervisory authorities should keep up with the current developments.

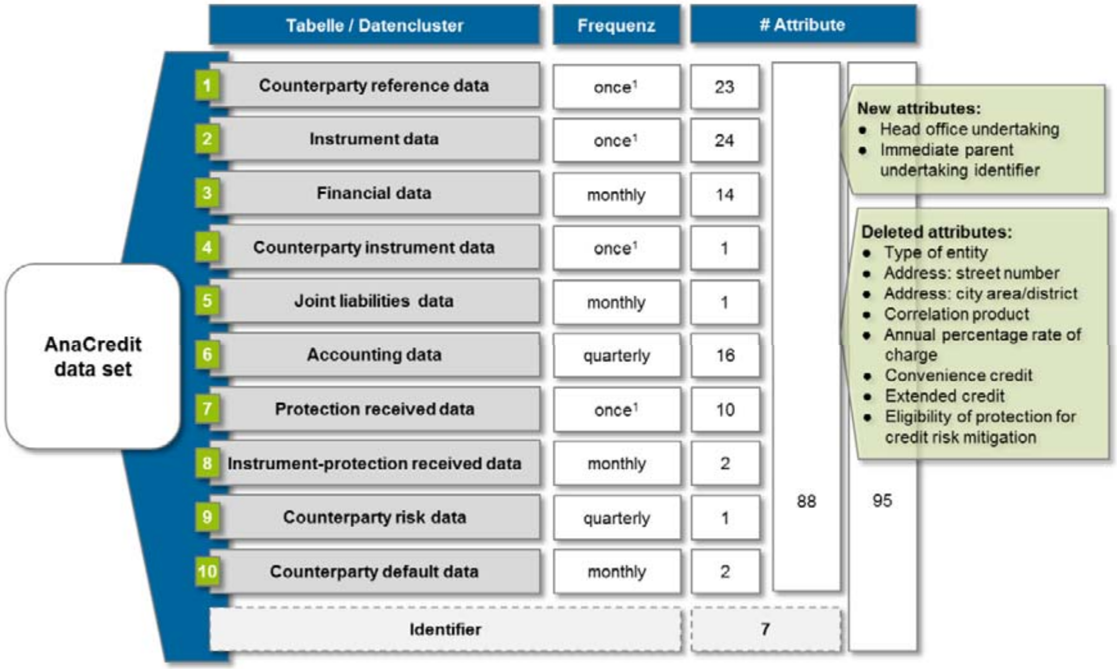
Credit Risk Analysis
Bank of Greece – Regulatory Purpose



Credit Risk Analysis – Big Data

Anacredit project European Central bank

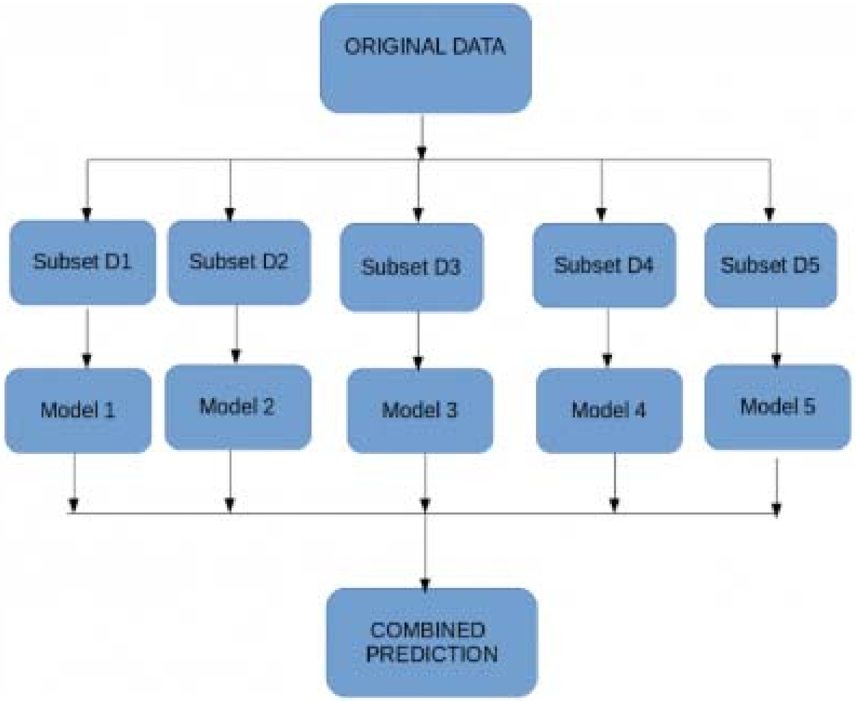
Reporting threshold 25.000 euro



Source: ECB regulation on the collection of granular credit and credit risk data as of May 18th, 2016

- AnaCredit will be a new dataset with detailed information on individual bank loans in the euro area.
- The project was initiated in 2011 and data collection is scheduled to start in September 2018.

Credit Risk Analysis
Bagging – Different models vote for the result

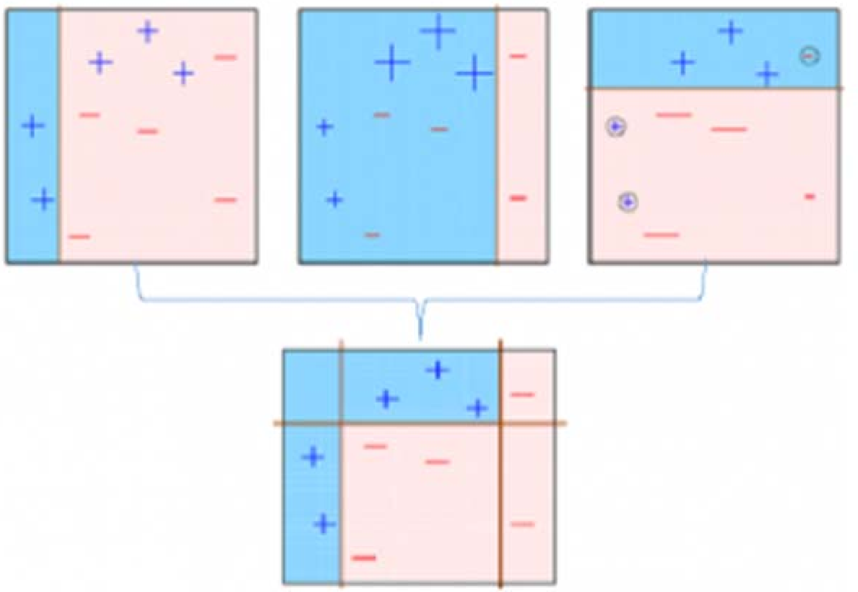


source: Analytics Vidhya

- Multiple subsets are created from the original dataset, selecting observations with replacement and a base model (weak model) is created on each of these subsets.
- The models run in parallel and are independent of each other.
- The final predictions are determined by combining the predictions from all the models.
- Random Forests are common employed bagging techniques.

Credit Risk Analysis

Boosting – Each model learns from the errors of the previous

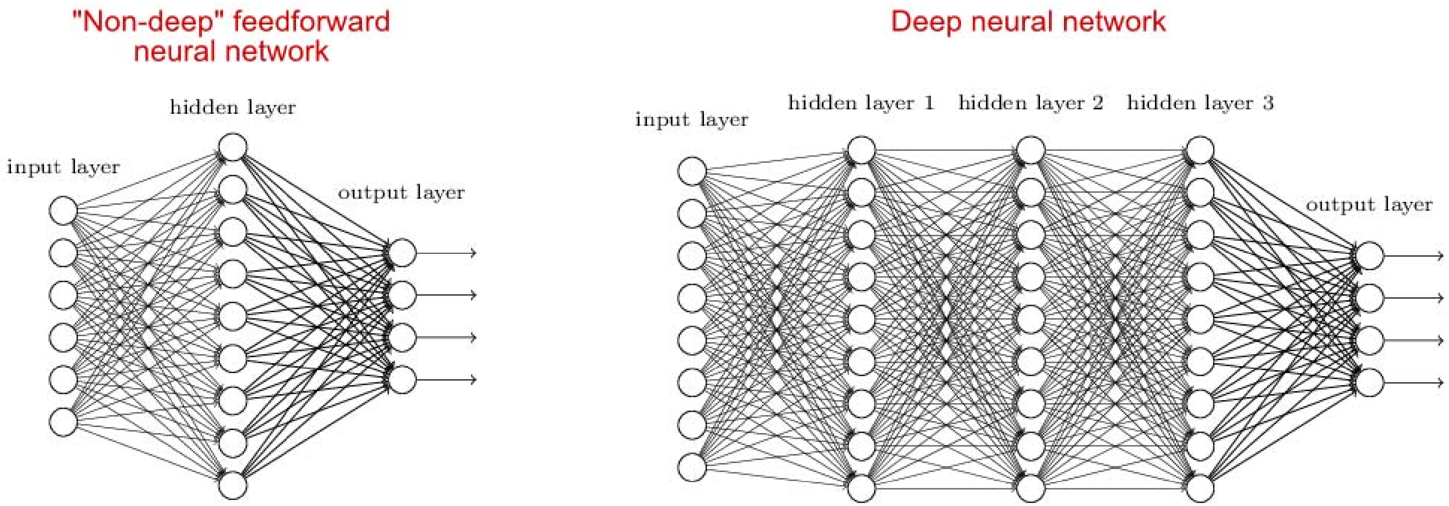


source: Analytics Vidhya

- A base model is created based on a subset of the original dataset which is used to make predictions on the whole dataset.
- Errors are calculated and observations which are incorrectly predicted, are given higher weights (large plus signs).
- Another model is created which tries to correct the errors from the previous model.
- Similarly, multiple models are created, each correcting the errors of the previous model.
- The final model (strong learner) is the weighted mean of all the models (weak learners).

Credit Risk Analysis

Deep Neural Networks-Unlimited potential for Architectures

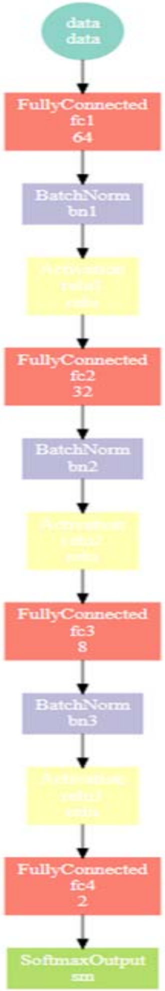


Deep neural network is simply a feedforward network with many hidden layers. It has the following advantages compared to one layer networks (“shallow”)

- A deep network needs less neurons than a shallow one
- A shallow network is more difficult to train with our current algorithms (e.g. it has more nasty local minima, or the convergence rate is slower)

Credit Risk Analysis

Deep Neural Networks-Unlimited potential for Architectures

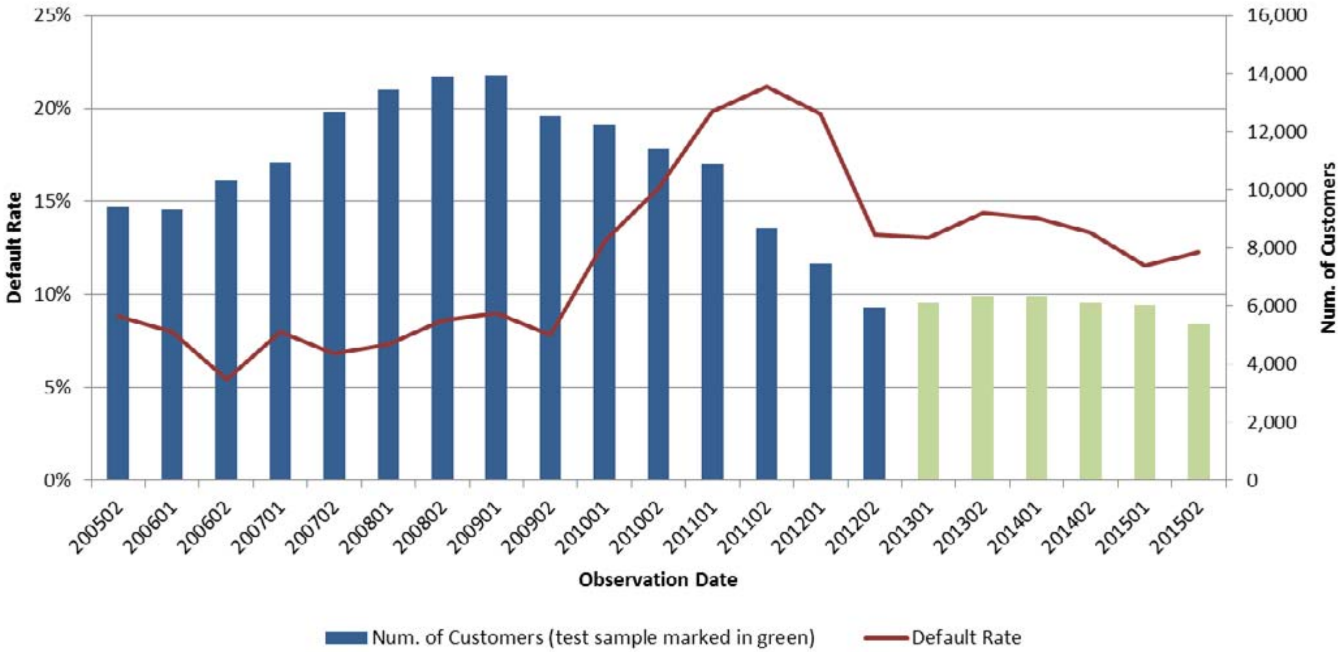


This methodology provides the opportunity of creating a large combination of different structures based on

- Number of layers,
- Selection of activation function
- Number of perceptrons
- Normalization layers
- Dropout adjustments

Which can be employed in the optimization process

Credit Risk Analysis
Problem at hand



- We have collected loan level information on Corporate and SME loans of the Greek banking system, from the supervisory database of the Central Bank of Greece.
- A loan is flagged as delinquent if it is either 90 days past due or it gets rated as delinquent based on each bank's internal rating rules.
- The forecast horizon for a default event is 1 year whereas the variables employed include macro data and company specific financial ratios.

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EUROSYSTEM

Credit Risk Analysis

Many Predictor Candidates - Curse of dimensionality

Boruta (aka Leshy): Slavik deity dueling in forests. 1906 illustration

- We employ **Boruta algorithm** for tackling the dimensionality issue. This is sequential Random Forest based algorithm which removes non relevant variables decreasing the dimensionality space.

BANK OF GREECE
EUROSYSTEM

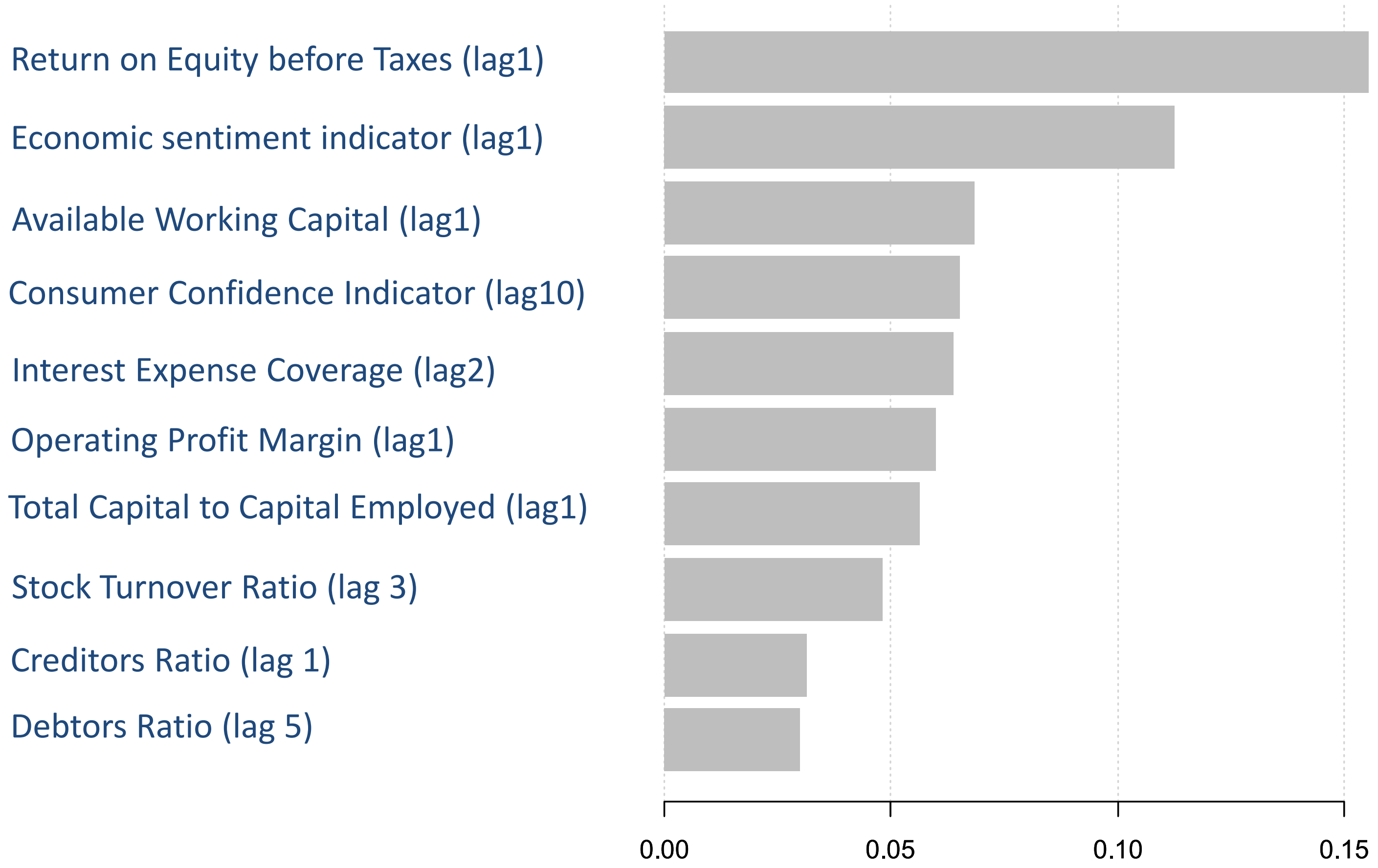
Credit Risk Analysis

Many Predictor Candidates - Curse of dimensionality

Boruta Algorithm – steps:

- First, it adds randomness to the given dataset by creating shuffled copies of all features (shadow features).
- Then, it fits a Random Forest model (bagging model) on the extended dataset and evaluates the importance of each feature based on Z score.
- In every iteration, it checks whether a real feature has a higher importance than the best of its shadow features, and constantly removes features which are deemed unimportant

Extreme Gradient Boosting
Variable Importance



Extreme Gradient Boosting

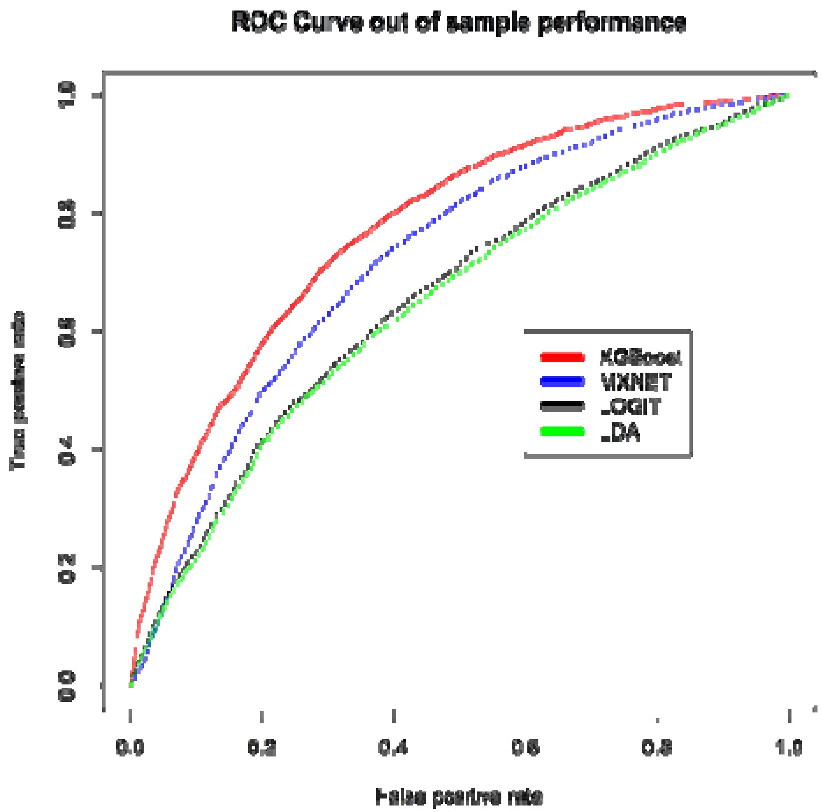
Classification Accuracy

Classification Accuracy Model Comparison	KS	AUROC
Logit	24%	66%
LDA	23%	65%
XGBoost	42%	78%
MXNET	35%	72%

Table 1

Classification Accuracy Metrics: Kolmogorov - Smirnov (KS), Area Under ROC curve (AUROC).

XGBoost and **MXNET** algorithms provide better classification accuracy compared to traditional classification methods such as Logistic Regression and Linear Discriminant analysis.



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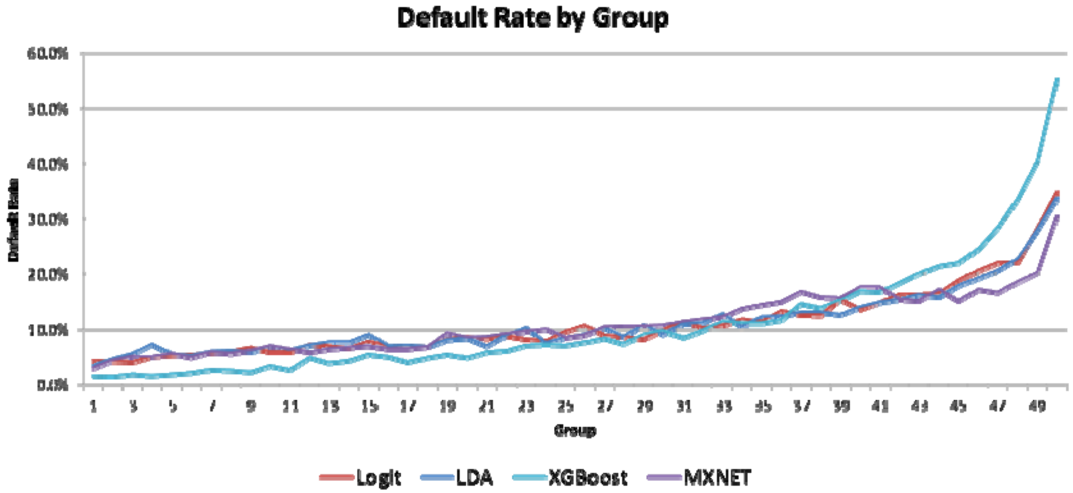
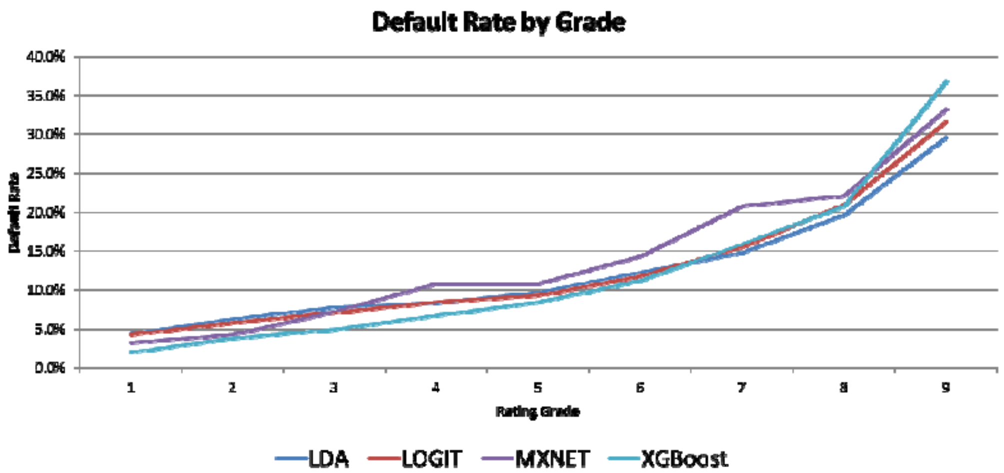
Credit Risk Analysis

Calibrating a Rating system



Initial credit rating segmentation in 50 grades



Final credit rating segmentation in 9 grades

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Deep Neural Networks

Rating System Performance

Performance Metrics Credit Rating System		Table 2
	SSE	BRIER
Logit	4.3%	11.3%
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Rating System Calibration Metrics: Sum of Square Error (SSE), Brier's score (BRIER).

Estimated and Actual default frequency metrics			Table 3
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LDA	7.80%		
XGBoost	13.50%		
MXNET	15.00%		

Estimated Probability of Default vs observed Default Rate in out-of-sample and in-sample population

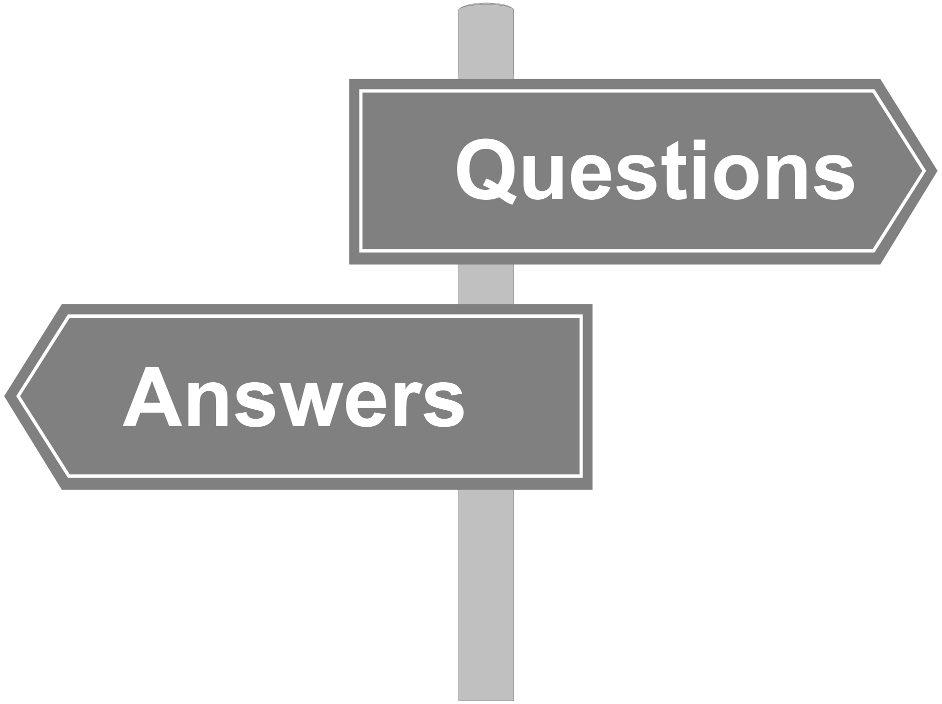
- Based on SSE and Brier score the MXNET and XGBOOST rating systems perform better than Logistic Regression and Linear Discriminant analysis.
- The estimated PDs for MXNET and XGBOOST are closer to the observed default rates.

Credit Risk Analysis
Our Contribution

- ✓ Extensive exploration of advanced statistical techniques
- ✓ An automated algorithm for tackling dimensionality issues
- ✓ Application to a regulatory large size dataset
- ✓ Robust validation and Performance Measures
- ✓ Large potential for application in large datasets (Anacredit)

Credit Risk Analysis

Q&A



Thank you!

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BANK FOR INTERNATIONAL SETTLEMENTS

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Measuring stakeholders' expectation on central bank's policy rate[1]

Alvin Andhika Zulen and Okiriza Wibisono,
Bank of Indonesia

[1] This paper was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

Measuring Stakeholders' Expectation on Central Bank's Policy Rate

Alvin Andhika Zulen[1] and Okiriza Wibisono[2]

Abstract

In recent decades, the role of market expectation on central bank's policy rate has been increasingly acknowledged in monetary policy formulation. In this research, we develop a machine learning-based technique for identifying the expectation of stakeholders on Bank Indonesia's policy rate. The expectations are extracted from news, starting from 14 days before the monthly Board of Governor's meeting. We achieve an F1-score of 76.8% from out-of-sample evaluation on classification result. The resulting monthly expectation index has 78.6% correlation with the index generated from Bloomberg's monthly survey.

Keywords: policy rate expectation; text mining; machine learning; big data

JEL classification: C02, E52, E58

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Contents

1. Background

Expectations on future economic conditions are among the factors that greatly influence the economic actors in making decision. If consumers expect higher inflation in the future, then they increase their consumption expenditures in the present.

One of the indicators that central banks consider in formulating monetary policy is markets' expectation on policy rates. Quoting (Fischer, 2017), "... those times when financial markets and the central bank have different expectations about what a central bank decision will be. Such situations lead to surprises and often to market volatility. " The main objective in measuring expectations on central bank's policy rate is to avoid market volatility that occurs when market participants have different expectations from the monetary policy taken by central bank. Unexpected movement of Fed Fund Rate is proven in affecting yields of Treasury Bills (Kuttner, 2000) and stock prices (Bernanke & Kuttner, 2004) significantly. If central bank will take a monetary policy that is different from market expectations, a communication strategy is needed so that the volatility in financial markets can be minimized (Fischer, 2017). In addition to avoid volatility, the measurement of policy rate expectations can be an input for projection of macroeconomic indicators, such as inflation and GDP, as implemented by the Monetary Policy Committee (MPC) of the Bank of England (Joyce & Meldrum, 2008).

Because the variable is unobservable, the measurement of expectation on economic indicators, including policy rates, is a nontrivial task. There are two main methods for measuring expectations, i.e. market-based method and survey-based method.

In market-based method, expectations are estimated based on the movement of the price of certain instruments in financial markets. For example, in U.S. financial markets, there is Fed Funds Futures instrument that serves for hedging against changes in The Fed's monetary policy. The price of this instrument is linked directly with the average of overnight Fed Funds Rate. If the average is decreased then the price of Fed Funds Futures will go up, and vice versa. Thus, expectation on policy rate can be estimated from Fed Funds Futures prices, and changes in expectation are estimated from the instrument's price movement.

For countries with no interest rate hedging instruments similar to Fed Funds Futures, the measurement of expectation is based on the price of the instrument that moves along with the policy rate, e.g. Treasury Bills, unsecured interbank loan, Forward Rate Agreement (FRA), and Overnight Index Swap (OIS) (Joyce et al., 2008). Nevertheless, measurement with those instruments is more difficult because of additional factors that contribute to pricing, such as credit risk, liquidity risk, and term premium. It is necessary to apply specific calculations and assumptions to exclude these factors in order to obtain an accurate expectation on policy rates.

Survey-based method offers a simpler alternative to measure policy rate expectation. In this method, the survey institution (which can be the central bank itself) asks respondents directly about their expectation on policy rate in the future. This method is also in accordance with recommendation in Manski (2004) that the expectation level can't be inferred only from the observed choice or action (revealed preference analysis). An expectation measure should be supported by numbers that are explicitly expressed by the respondents.

In Indonesia, Bloomberg conducts a monthly survey of expectations on Bank Indonesia's policy rate (BI 7-day Reverse Repo Rate, formerly BI Rate), i.e. the Economist Estimates Survey. Respondents of the survey are mostly from banking and securities company. Approximately, two weeks before the monthly Board of Governor's Meeting, Bloomberg asked 20-30 respondents about their estimation of Bank Indonesia's policy rate that will be set in the meeting.

This research aims to develop a new measure of stakeholders' expectation on Bank Indonesia's policy rate, as a complement to the Bloomberg survey. From methodological perspective, we show how to utilize textual data to develop the new measure, by employing machine learning-based technique. Based on our observations, a fair amount of expectations on policy rate are quoted in news articles, as seen in Figure 1. Expectations quoted in the news tend to have more varied sources. In addition to market participants, governments, authorities (e.g. Financial Services Authority (OJK), Deposit Insurance Corporation (LPS), Indonesia Stock Exchange (BEI)), and real sector entrepreneurs often express their expectations on Bank Indonesia's policy rate. Hence, it has potential to be used as data source for measuring the expectations.

The paper is organized as follows. In section 2, we provide literature reviews on measuring policy rate expectation and text mining for economic news. In section 3, we discuss the data and methodology. In section 4, we provide a summary of the results and evaluation of the model. In section 5, we conclude the paper and offer some thoughts for future works

Example of Expectation on Bank Indonesia's Policy Rate in News Articles — Figure 1

The central bank of Indonesia (Bank Indonesia, BI) is expected to keep its benchmark interest rate (BI rate) at 7.50 percent at Thursday's Board of Governors' Meeting (14/08) as inflation has eased to 4.53 percent (year on year) in July while the country's current account deficit may nearly double in the second quarter of 2014 to four percent of gross domestic product (GDP) from 2.06 percent of GDP in the previous quarter.

Expectation of unchanged policy rate

Although we continue to believe there is no urgency to increase interest rates, we believe the Bank is likely to hike pre-emptively and prioritize stability over growth. **Therefore, we now expect BI to raise the 7-day reverse repo rate by 25 bps to 4.50% on May 17**. More hikes are likely to follow, but the pace of tightening will remain sluggish under the new Governor.

Expectation of policy rate hike

Bank Indonesia is expected to cut the rate further, following Monday's announcement by the Central Statistics Agency (BPS) showing slowing inflation in February, says Eric Alexander Sugandi, an economist at Standard Chartered Bank in Jakarta.

Expectation of policy rate cut

2. Literature Review

2.1 Survey-Based & Market-Based Method for Measuring Expectation on Policy Rate

Questions on policy rate expectations have been included in various economic and financial surveys. For example, Christensen & Kwan (2014) used the monthly Blue Chip Financial Forecast survey and Survey of Primary Dealers to evaluate whether expectations of market participants are aligned with expectations of the Federal Open Market Committee (FOMC) expectations or not. At Bank Indonesia, the results of Bloomberg survey as described in the previous section are utilized to provide information on policy rate expectation in the Board of Governors Meeting.

Survey-based method has a major advantage over market-based method, i.e. simpler for analysis. Several studies (Christensen & Kwan, 2014; Joyce & Meldrum, 2008; Friedman, 1979) used average or median values to aggregate policy rate expectations of all respondents. For comparison, a research with market-based method (de los Rios & Reid, 2008) used three instrument prices for estimating the probability of Bank of Canada's policy rate changes.

In addition to simpler analysis, we can also calculate the distribution of respondents' expectations with survey-based method. If there are 30 respondents, for example, we can calculate the percentage of respondents who expect a policy rate cut and the percentage of respondents who expect a policy rate hike. In market-based method, the distribution of these expectations can't be provided (Christensen & Kwan, 2014).

However, survey-based method also has several disadvantages compared to market-based method. Market-based method captures the real expectation in the market, i.e. the price of the instrument will move along with market expectation because they are "risking" their money in the instrument (money on the line). Given its subjective nature, in survey-based method, it's possible that the respondents didn't respond according to their actual expectation. Another disadvantage is that the survey-based method is not practical to be done in high frequency (e.g. daily), whereas with market-based method, expectation can be calculated on a daily basis or even from hour-to-hour, if the referred instruments are widely traded.

2.2 Text Mining on Economic News

Text data have been widely used for research in economics and finance. Sahminan (2008) identified keywords that reflect a tight, neutral, or loose monetary policy inclination in the press release statement of Bank Indonesia over the period from January 2004 to December 2007. The econometric analysis shows that monetary policy statements that contain loose or neutral policy inclination tend to lower interbank interest rates, while monetary policy statements with tight policy inclination tend to have no impact on interbank interest rates (asymmetric effect). Rosa & Verga (2007) applied similar method to analyze the impact of European Central Bank (ECB) press releases.

In those studies, the identification of keywords in the press release texts is done manually. Researchers read the press releases one by one and record the keywords that appear in the press releases. Nowadays, text mining algorithms are growing rapidly along with the adoption of big data and machine learning. These algorithms can automatically "read" and "extract" relevant information from the text, such as the person's name, the organization's name, and the keywords. Compared to the manual way, text mining allows us to make use of much larger text data than press releases, including news and social media.

Bollen et al. (2011) proved that the mood expressed by Twitter users can be analyzed to improve the stock market prediction. Moods are identified using keywords, e.g. "I feel ..." and "I'm ...", and then categorized into different types of mood by using OpinionFinder and Google-Profile of Mood States (GPOMS). Similar to Bollen et al. (2011), O'Connor et al. (2010) created a public sentiment index from positive and negative word occurrences in economic related tweets. This index correlated with the Gallup's Economic Confidence Index at 73.1% and with the Index of Consumer Sentiment (ICS) from the Reuters/University at 63.5%.

In addition to social media data, news data are also widely used to analyze economic conditions. Baker et al. (2016) developed an Economic Policy Uncertainty (EPU) index by using news articles from 10 leading U.S. newspapers. The EPU index reflects the frequency of articles that contain the following trio of terms: economic (''economic'' or ''economy''); policy (''Congress,'' ''deficit,'' ''Federal Reserve,'' ''legislation,'' ''regulation,'' or ''White House), and uncertainty (''uncertain'' or ''uncertainty''). The EPU indexes have also been constructed for 11 other countries with list of keywords that are tailored to the language and economy.

In terms of monetary policy, Nardelli et al. (2017) developed the Hawkish-Dovish (HD) index that measures media's perception of ECB communications. The HD index is computed by using two methods: semantic orientation (SO) and support vector machine (SVM). The HD index based on SO method is computed by counting the co-occurrences of strings with a fixed set or pre-determined words/expressions that are normally associated with "hawkish" and "dovish" concepts to determine the tone of the document. For the SVM method, instead of using predefined set of keywords, the algorithm automatically looks for patterns in text documents to select the words with the highest discriminative power and determines the tone of a document based on them. Similar Hawkish-Dovish research has also been done earlier by Lucca & Trebbi (2009) for the FOMC statements.

Those two studies measured media's perception after each press conference following monetary policy meetings. As far as our observation, there is no research utilizing news data to measure policy rate expectation before the monetary policy meetings.

3. Methodology

3.1 Data

3.1.1 News Articles

The news data used in this research obtained from Bank Indonesia's Cyber Library. Cyber Library is an internal repository of news articles related to economic and financial topics. The news articles data are available on a daily basis since 1999, thus covering the whole period since Bank Indonesia set the policy rate (BI Rate) in July 2005. The data used in this research are from January 2006 to February 2018.

3.1.2 Policy Rate Expectation Survey

In order to measure the accuracy of policy rate expectation obtained from the news, a benchmark indicator is required for comparison. In this research, we use Economist Estimates Survey from Bloomberg, as described in the first chapter. Survey results are available starting from two weeks before the monthly Board of Governor's meeting, although data from several respondents are often only available close to the date of the meeting. Each respondent gives their estimation on Bank Indonesia's policy rate which they think will be set in the meeting. An example of the survey result is shown in Figure 2.

Example of Bloomberg's Economist Estimates Survey — Figure 2

3.2 Machine Learning Model

In order to extract the policy rate expectation from news articles automatically, we build a text mining model by using machine learning-based technique. This section will describe the steps taken in developing the model.

3.2.1 Data Filtering

News articles collected from Bank Indonesia's Cyber Library are not entirely relevant for measuring policy rate expectations. First of all, the news articles are filtered in following steps:

1. Publication Date Filtering

   From all the news articles available in Cyber Library, we only used news articles that are published within 14 to 1 days prior to each monthly Board of Governor's meeting.

2. Sentences Spliiting

   News articles are splitted into sentences to simplify the extraction of policy rate expectation. Text splitting is done automatically by using Natural Language Toolkit (NLTK) in Python.

3. Keywords Filtering

Sentences from the previous step are filtered again, leaving only sentences that contain keywords related to Bank Indonesia's policy rate, e.g. "BI Rate", "BI 7-days reverse repo rate", and "Bank Indonesia's policy rate".

Thus, the result from these stages is a collection of sentences containing keywords related to Bank Indonesia's policy rate and published on D-14 to D-1 prior to each monthly Board of Governor's meeting. In total, there are 5,700 news articles (2% of overall news in Cyber Library) and 16,000 sentences (0.2% of overall sentences in Cyber Library) that meet the specified criteria.

3.2.2 Annotation

Text mining that make uses of machine learning techniques require annotated datasets for training the algorithms. Annotation is the process of attaching additional information into a collection of texts. Annotation is needed to "teach" the text mining algorithm how to extract the information from the texts, so that the process can be done automatically in the future.

In this research, annotation is done on sentence-level, as the smallest data unit. We added a categorical information about policy rate expectation to each sentence, with 4 (four) possible values as follows:

1. 0: sentence with no expectation information;
2. 1: expecting no change in policy rate;
3. 2: expecting policy rate hike;
4. 3: expecting policy rate cut.

This categorical information will be used as target class in machine learning algorithms.

Each sentence is annotated by two annotators to minimize human error and subjectivity. If a sentence is annotated differently by both annotators, the sentence will be annotated by the third annotator. We also provide an annotation guidance so that the annotations can be given consistently by each annotator.

In total, we collected 4,445 sentences that have been annotated, out of 16,000 sentences generated in previous steps. Table 1 shows the proportion of sentences for each policy rate expectation category.

Annotated Sentences

Table 1

Policy Rate Expectation Category	Number of Annotated Sentences	Percentage (%)
Policy Rate Hike	355	8%
Policy Rate Cut	660	15%
Policy Rate Unchanged	490	11%
No-Expectation	2,940	66%

3.2.3 Pre-processing

After annotating the sentences, one more step is required in order to start training the classification model using machine learning algorithms. Each sentence must be transformed into numerical vector, because machine learning algorithms can only process numerical data.

Each sentence is transformed into numerical vector that contains following information:

1. bag-of-keywords (n-grams): number of keywords' occurrences in the sentence;
2. number of words in the sentence;
3. number of characters in the sentences;
4. numbers and percentages quoted in the sentence;
5. word embedding vector.

All transformations are done by using Pandas and Scikit-learn libraries in Python.

3.2.4 Model Construction

Sentences that have been annotated and transformed into numerical matrix (1 line = 1 sentence) are used as input for machine learning algorithms. Machine learning algorithms will learn the patterns in input data to construct classification model with target function to classify the category of policy rate expectation.

$$\hat{f}(sentence\_vector) \in \{rate\ hike, rate\ cut, rate\ unchanged, no\ expectation\}$$

The data are splitted into 2 datasets: training dataset and test dataset. Training dataset is used to build the classification model. Test dataset is used in model evaluation to provide unbiased evaluation on the model. We split the data using approximately 80:20 ratio (training dataset: 3,645 sentences; test dataset: 800 sentences).

We use 5 (five) machine learning algorithms in this research to find the best classification model for solving the task, i.e.:

1. Logistic regression: modeled the linear relationship between independent variables and the expectation category as dependent variable;
2. Naïve bayes: modeled the probability of expectation category based on Bayes' theorem with the independence assumptions between predictors;
3. Decision tree: modeled the decision tree that predict expectation category (represented in the leaves) based on a set of decision rules (represented in the branches);
4. Random forest: combined the predictions of multiple decision trees with bootstrapping aggregation;
5. XGBoost: an implementation of gradient boosted tree by DMLC (http://dmlc.ml/).

3.3 Index Calculation

3.3.1 Expectation Index from News

The best classification model that has been constructed in previous step is then applied to classify the policy rate expectation category on all 16,000 sentences in the dataset. From the classification results, we calculate the monthly policy rate expectation index in following steps:

1. Each sentence with policy rate expectation is given a score: +1 for expecting policy rate hike; -1 for expecting policy rate cut; 0 for expecting no change in policy rate. Sentences with no information on policy rate expectation ware excluded from index calculation.
2. Each news article is given a score: the mean score of sentences (as calculated in 1st step) in the article.
3. The expectation index from news for month t is defined as the mean score of articles (as calculated in 2nd step) that are published in that month.

$$Expectation\ Index\ News_t = \frac{1}{|C_a|}\sum_a score(a) = \frac{1}{|C_a|}\sum_{s_a}\left(\frac{1}{|C_{s_a}|}score(s_a)\right)$$

$|C_a|$ = number of articles in month t

$score(a)$ = score of article a

$|C_{s_a}|$ = number of sentences in article a with policy rate expectation

$score(s_a)$ = score of sentence s in article a

The monthly expectation index has following characteristics:

- Range of index: [-1,+1].
- The index will be close to +1 if there are more news with expectation of policy rate hike.

  The index will be close to 0 if there are more news with expectation of unchanged policy rate.

  The index will be close to -1 if there are more news with expectation of policy rate cut.
- Positive index means more news with expectations of policy rate hike compared to policy rate cut.

  Negative index means more news with expectations of policy rate cut compared to policy rate hike.
- If $index_{t1} > index_{t2}$ then the proportion of news with expectation of policy rate hike is greater in t_1 than in t_2.

  If $index_{t1} < index_{t2}$ then the proportion of news with expectation of policy rate cut is greater in t_1 than in t_2.

3.3.2 Expectation Index from Bloomberg Survey

As described earlier in section 1, in the Economist Estimates Survey, Bloomberg asked respondents about their estimation on Bank Indonesia's policy rate that will be set in the next Board of Governors' meeting. These estimation numbers need to be converted so that they are comparable with the expectation index. The conversion is done as follows:

$$score(x)_t = \begin{cases} +1 : if\ prediction(x)_t > BI\ Rate_{t-1} \\ 0 : if\ prediction(x)_t = BI\ Rate_{t-1} \\ -1 : if\ prediction(x)_t < BI\ Rate_{t-1} \end{cases}$$

$score(x)_t$ = score of respondent x in month t

$prediction(x)_t$ = policy rate prediction respondent x in month t

$BI\ Rate_{t-1}$ = Bank Indonesia's policy rate in month $t-1$

The expectation index from Bloomberg survey for month t is defined as the mean score of all respondents in the month.

$$Expectation\ Index\ Bloomberg_t = \frac{1}{|C_x|}\sum_x score(x)$$

$|C_x|$ = number of respondents in month t

4. Result & Analysis

4.1 Classification Model Evaluation

Classification models that have been trained in the previous steps need to be evaluated in order to measure their accuracy in predicting the target class (i.e. policy rate expectation). We use F1-score as metric for evaluation, in order to get a balanced classification model with the optimal balance of recall and precision.

The result of out-of-sample evaluation for each machine learning model are given in Table 2. We can see that the logistic regression model has the best F1-score (76.8%), compared to other machine learning models. The model also has the best recall score. Hence, the logistic regression model becomes our choice for measuring policy rate expectations in the following sections.

Classification Model Evaluation

Table 2

Classification Model	Accuracy	Recall	Precision	F1
Logistic regression	83.4%	**83.2%**	71.2%	**76.8%**
Naïve bayes	80.6%	83.2%	64.5%	72.7%
Decision tree	73.0%	65.7%	53.4%	58.9%
Random forest	78.0%	72.6%	63.3%	67.6%
XGBoost	**84.1%**	75.9%	**75.6%**	75.7%

Note: Blue-shaded cells denote the best result for each evaluation metric

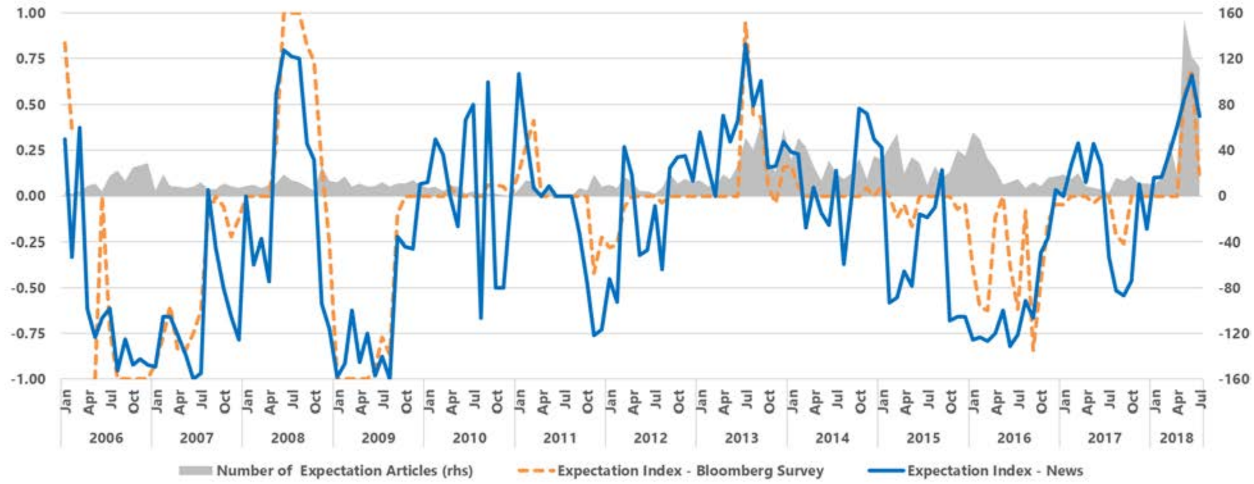
4.2 Result Evaluation

For result evaluation, we calculate the correlation between policy rate expectation index generated from news and from Bloomberg survey. Graphs of both indices from January 2006 to July 2018 are presented in Figure 3. We can see that both indices are moving in the same direction generally, with a correlation of 78.6%. The correlation value indicates that the policy rate expectation index from news is potential to be used as a new measure of policy rate expectation.

The policy rate expectation index from news tends to be more volatile, e.g. in the second half of 2010. This is likely due to there are some periods (months) where number of sentences containing policy rate expectation in Cyber Library is very low. From 146 months of data (January 2006 to February 2018), there are 56 months where the number of sentences containing policy rate expectation are less than 10.

Plot of Policy Rate Expectation Index

Figure 3



For some periods, the expectation index from news can "predict" the direction of policy rate more precisely than the expectation index from Bloomberg survey, as presented in Table 3. Overall, compared to the actual change in policy rate, the expectation index from news has a correlation of 76.6%, the expectation index from Bloomberg survey has a correlation of 84.5%.

Comparison between Expectation Index from News and from Bloomberg Survey

Table 3

Period	Event	Expectation Index from News	Expectation Index from Bloomberg Survey
January 2007	Policy rate cut	-0.93	-0.92
March 2007	Policy rate cut	-0.66	-0.60
May 2007	Policy rate cut	-0.87	-0.84
June 2007	Policy rate cut	-1.00	-0.75
July 2007	Policy rate cut	-0.97	-0.63
December 2007	Policy rate cut	-0.79	-0.13
May 2008	Policy rate hike	0.56	0.28
December 2008	Policy rate cut	-0.72	-0.26
June 2009	Policy rate cut	-0.98	-0.95
July 2009	Policy rate cut	-0.88	-0.77
August 2009	Policy rate cut	-1.00	-0.87
February 2011	Policy rate hike	0.34	0.27
October 2011	Policy rate cut	-0.47	0.00
November 2011	Policy rate cut	-0.76	-0.42
February 2012	Policy rate cut	-0.58	-0.27
June 2013	Policy rate hike	0.41	0.00
September 2013	Policy rate hike	0.63	0.44
November 2013	Policy rate hike	0.16	-0.04
February 2015	Policy rate cut	-0.58	0.00

Comparison between Expectation Index from News and from Bloomberg Survey

Table 4

Period	Event	Expectation Index from News	Expectation Index from Bloomberg Survey
January 2016	Policy rate cut	-0.79	-0.39
February 2016	Policy rate cut	-0.77	-0.61
March 2016	Policy rate cut	-0.79	-0.63
June 2016	Policy rate cut	-0.82	-0.38
August 2017	Policy rate cut	-0.52	-0.21
September 2017	Policy rate cut	-0.54	-0.26

5. Conclusion & Future Work

5.1 Conclusion

In this research, we develop a new measure of stakeholders' expectation on Bank Indonesia's policy rate. From methodological perspective, we show how to utilize news articles data to develop the new measure, by employing machine learning-based technique. The expectations are extracted from news, starting from 14 days before the monthly Board of Governor's meeting. The machine learning model is trained by using sentences that have been annotated manually.

From out-of-sample evaluation, we achieve an F1-score of 76.8% on classification accuracy by using logistic regression model. The resulting monthly expectation index has 78.6% correlation with the expectation index generated from Bloomberg's monthly survey.

5.2 Future Work

There are several improvements in the methodology that can be applied for future works.

- Opinion Holder Identification

Currently, the calculation of the expectation index of each month use the average score of the articles. This makes the index is not entirely comparable to expectation measure obtained from Bloomberg survey (news articles vs. survey respondents). We need to identify the opinion holder for each sentence that contains policy rate expectation. Once identified, opinion holders whose expectations are quoted in several articles are counted only once in index calculation.

Another benefit of opinion holder identification is for grouping expectations based on institutional group of the opinion holder, e.g. government, authorities, banking, capital market, industry, academics, and research institutes. Thus, we can further examine which institutional groups expect policy rate hike, cut, or unchanged.

- Data Source Addition

The number of news articles used in this research is not big enough, i.e. 5,700 news articles in 146 months, or about 40 news articles per month. The addition of new data sources can be done with web crawling on online news websites. In addition, we also consider to use news in English language, although additional works are needed to develop a text mining model for English language.

- Classification Model Improvement

Nowadays, artificial neural network (especially deep learning) is state-of-the-art technique for text classification, including opinion extraction task (Irsoy and Cardie, 2014). The currently used classification model, i.e. logistic regression, can be replaced with a neural network model to improve the accuracy. However, it is necessary to annotate more sentences, given the neural network model requires a large amount of training data.

- Expectation vs. Wish vs. Suggestion

Currently, annotated sentences also include phrases of wishes, hopes, and suggestions on the policy rate. We need to separate sentences that contain expectation (or prediction) with sentences that contain wish (or suggestion), so that the index only contains information related to expectations. Rule-based method (using keywords e.g. "expects" vs. "wishes") or machine learning method could be used for the task.

- Expectation Period Identification

Sometimes, sentences that contains policy rate expectations are not referring to the next Board of Governors' meeting, but rather several months or even a year later (e.g. "He predicts BI Rate to be hiked only one more time this year, at the end of 2014."). Such sentences need special handling, i.e. by classifying it as expectation of unchanged policy rate for the next meeting, and as expectation of policy rate hike for meeting at the end of 2014.

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Measuring stakeholders' expectation on central bank's policy rate[1]

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Bank of Indonesia

[1] This presentation was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

BANK INDONESIA
BANK SENTRAL REPUBLIK INDONESIA

Measuring Stakeholders' Expectation on Central Bank's Policy Rate

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OUTLINE

BANK INDONESIA
BANK SENTRAL REPUBLIK INDONESIA

- BACKGROUND
- LITERATURE REVIEW
- METHODOLOGY
- RESULT & ANALYSIS
- CONCLUSION & FUTURE WORKS

#1 BACKGROUND

BANK INDONESIA
BANK SENTRAL REPUBLIK INDONESIA

*… those times when **financial markets and the central bank have different expectations about what a central bank decision will be**. Such situations lead to surprises and often to **market volatility**.*

(Stanley Fischer, 2017)

Bloomberg
Economist Estimates Survey

- **Respondents : ± 20 – 30 economists**
- **Timeframe : Starting from weeks before the monthly Board of Governor's Meeting**
- **Question : Estimation of Bank Indonesia's policy rate that will be set in the meeting**

Develop a new measure of stakeholders' expectation on Bank Indonesia's policy rate, as a complement to Bloomberg survey.

Utilize textual data to develop the new measure, by employing machine learning-based technique.

BANK INDONESIA
BANK SENTRAL REPUBLIK INDONESIA

#1 BACKGROUND

Expectation of unchanged policy rate

The central bank of Indonesia (Bank Indonesia, BI) is expected to keep its benchmark interest rate (BI rate) at 7.50 percent at Thursday's Board of Governors' Meeting (14/08) as inflation has eased to 4.53 percent (year on year) in July while the country's current account deficit may nearly double in the second quarter of 2014 to 4% of GDP from 2.06% of GDP in the previous quarter.

Expectation of policy rate hike

Although we continue to believe there is no urgency to increase interest rates, we believe the Bank is likely to hike pre-emptively and prioritize stability over growth. **Therefore, we now expect BI to raise the 7-day reverse repo rate by 25 bps to 4.50% on May 17.** More hikes are likely to follow, but the pace of tightening will remain sluggish under the new Governor.

Expectation of policy rate cut

Bank Indonesia is expected to cut the rate further, following Monday's announcement by the Central Statistics Agency (BPS) showing slowing inflation in February, says Eric Alexander Sugandi, an economist at Standard Chartered Bank in Jakarta.

#2 LITERATURE REVIEW

BANK INDONESIA
BANK SENTRAL REPUBLIK INDONESIA

Measuring Expectation on Policy Rate

1 Market Based Method

Based on the movement of the price of certain instruments in financial markets, e.g.:

- Fed Funds Futures
- T-Bills
- Forward Rate Agreement (FRA)
- Overnight Index Swap (OIS)

2 Survey Based Method

Asks respondents about their expectation on policy rate in the future, e.g.:

- Blue Chip Financial Forecast Survey
- Primary Dealers Survey
- Bloomberg Economist Estimate Survey

Text Mining on Economic News

- Economic Policy Uncertainty (EPU) Index
- Measuring Public's Consumer Confidence
- Predicting Stock Market from Social Media
- Measuring Perception on Central Banks' Communication

#3 METHODOLOGY

1 Data Collection

- Daily news articles from **Bank Indonesia's Cyber Library.**
- Data period: **January 2006 – February 2018.**
- **Data Filtering** to filter out news that are not relevant for measuring policy rate expectations.
  - **News articles** : **Published within 14 days prior to monthly Board of Governor's meeting**.
  - **Sentences** : **Contained keywords related to Bank Indonesia's policy rate**, e.g. "BI Rate", "BI 7-days reverse repo rate", and "Bank Indonesia's policy rate".
- Survey result from **Bloomberg Economist Estimates Survey**, as the benchmark indicator.

2 Data Annotation

- **Annotation** to 4,445 sentences, by adding a **categorical information about policy rate expectation**.

Policy Rate Expectation Category	Annotated Sentences	Percentage (%)
0 - No-Expectation	2,940	66%
1 - Policy Rate Unchanged	490	11%
2 - Policy Rate Hike	355	8%
3 - Policy Rate Cut	660	15%

#3 METHODOLOGY

BANK INDONESIA
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3 Data Preprocessing

- **Transformation of sentences into numerical vectors**, with following information:

Bag-of-words (n-grams)	Number of words	Numbers and percetages quoted
Number of characters	Word embedding vector	

4 Model Construction

- **Using 5 machine learning algorithms** to find the best classification model for solving the task.

1. Logistic Regression	2. Naïve Bayes	3. Decision Tree
4. Random Forest	5. XGBoost	

- Dataset : Splitting **training-testing datasets with 80:20 ratio..**

5 Index Calculation

- **Expectation Index from News**

$$score(s_a) = \begin{cases} +1 : expecting\ policy\ rate\ hike \\ 0 : expecting\ no\ change\ in\ policy\ rate \\ -1 : expecting\ policy\ rate\ cut \end{cases}$$

$$Expectation\ Index\ News_t = \frac{1}{|C_a|} \sum_{s_a} \left(\frac{1}{|C_{s_a}|} score(s_a) \right)$$

- **Expectation Index from Bloomberg**

$$score(x)_t = \begin{cases} +1 : if\ prediction(x)_t > BI\ Rate_{t-1} \\ 0 : if\ prediction(x)_t = BI\ Rate_{t-1} \\ -1 : if\ prediction(x)_t < BI\ Rate_{t-1} \end{cases}$$

$$Expectation\ Index\ Bloomberg_t = \frac{1}{|C_x|} \sum_x score(x)$$

#4 RESULT & ANALYSIS

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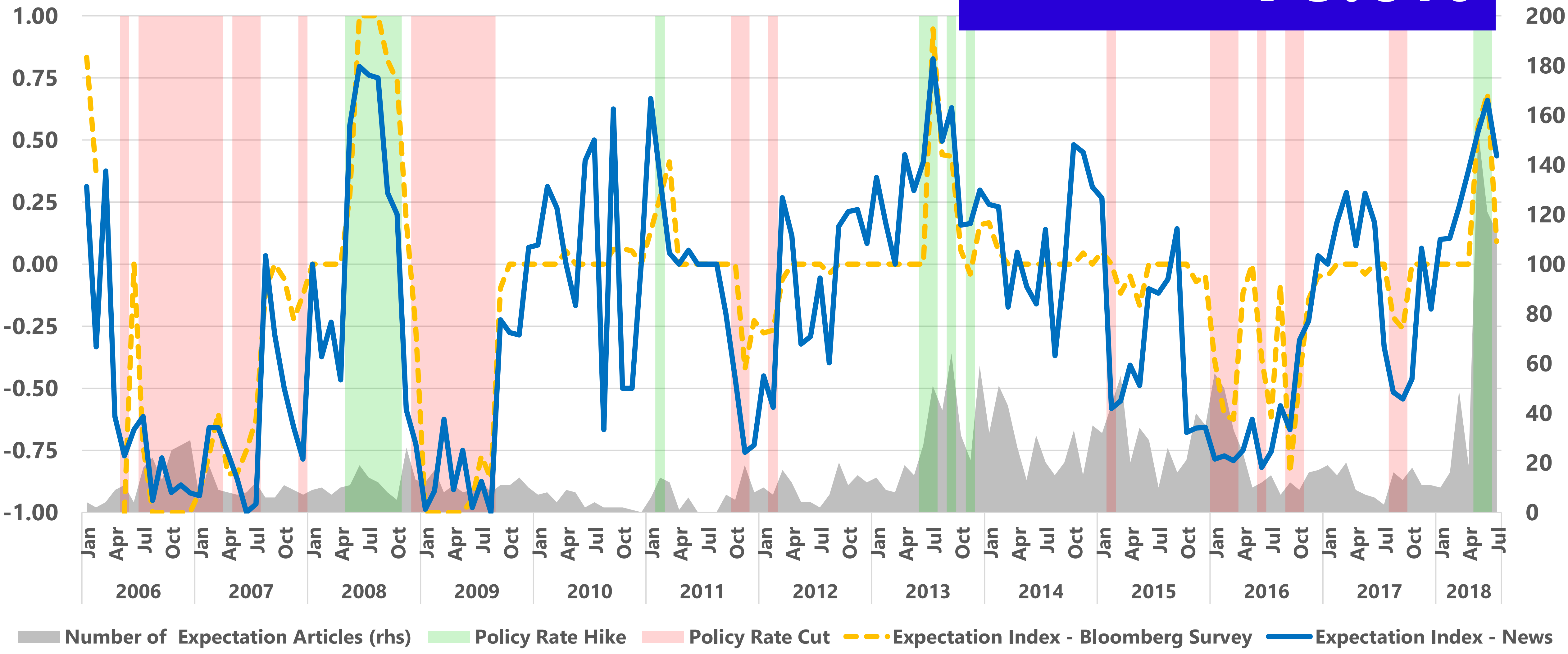
Classification Model	Accuracy	Recall	Precision	F1
Logistic Regression	83.4%	**83.2%**	71.2%	**76.8%**
Naïve Bayes	80.6%	83.2%	64.5%	72.7%
Decision Tree	73.0%	65.7%	53.4%	58.9%
Random Forest	78.0%	72.6%	63.3%	67.6%
XGBoost	**84.1%**	75.9%	**75.6%**	75.7%

#4 RESULT & ANALYSIS

Correlation = 78.6%



#5 CONCLUSION & FUTURE WORKS

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*We develop **a new measure of stakeholders' expectation on Bank Indonesia's policy rate**. The correlation value indicates that the policy rate expectation index from news is **potential to be used as a new measure of policy rate expectation**.*

*From methodological perspective, we show how to **utilize news articles data to develop the new measure, by employing machine learning-based technique**.*

Future Works		
	1	Opinion holder identification
	2	Data source addition (including English news)
	3	Classification model improvement (e.g. using deep learning)
	4	Expectation vs. Wish vs. Suggestion
	5	Expectation period identification

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Thank You

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Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

Two is company, three's a crowd: automated pairing and matching of two-sided reporting in EMIR derivatives' data[1]

Sébastien Pérez-Duarte and Grzegorz Skrzypczynski,
European Central Bank

[1] This paper was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

Two is company, three's a crowd

Automated pairing and matching of two-sided reporting in EMIR derivatives' data

Sébastien Pérez-Duarte, Grzegorz Skrzypczynski

Abstract

The European Market Infrastructure Regulation (EMIR), which was the European response to the G20 commitment to reform OTC derivatives markets, mandates EU counterparties to report extensive details of their derivative transactions to trade repositories. One of the features of EMIR is the double-sided reporting obligation, which means that details of a trade between two EU entities will be reported separately by each of the counterparties. According to the regulation, the two counterparties have to agree on a unique trade identifier and on the characteristics of the trade itself (so-called common data) before submitting the report. However, after 4 years of EMIR reporting the regulators are still faced with a significant number (up to 55%) of trades that cannot be reconciled.

The existence of both paired and non-paired trades in the EMIR dataset offers an outstanding opportunity to analyse patterns of regulatory misreporting. This paper studies the set of paired trades to understand the pitfalls of double-sided reporting and proposes different measures to assess the level of consistency between two sides of the same trade. It discusses also ways to choose automatically one set of data, if two counterparties provide conflicting information on the trade. Those insights are further used to design an algorithm to pair the trades in the set of non-paired transactions, i.e. transactions that could not be paired using the unique trade identifier.

The proper detection of these misreporting errors allows supervisory authorities to better address the issue with reporting counterparties, provides statisticians with correct aggregates without double counting the same transactions, and ensures that policy makers have a more accurate view of the distribution of risks.

Keywords: pairing, matching, derivatives, two-sided reporting

JEL classification: C18

Table of contents

1. Introduction

In response to the financial crisis of 2008, the G20 leaders committed in 2009 in Pittsburgh to implement a set of reforms that would strengthen the international financial regulatory system. One of the objectives set by G20 was improving over-the-counter derivatives market and one of the measures to achieve this was reporting of the OTC derivatives contracts to trade repositories.[1] In Europe, this obligation was imposed by the Regulation (EU) 648/2012 of the European Parliament and of the Council of 4 July 2012 on OTC derivatives, central counterparties and trade repositories, or European Market Infrastructure Regulation (EMIR).[2]

EMIR provided European authorities with access to information on both over-the-counter (OTC) and exchange-traded (ETD) derivative contracts of unprecedented granularity and size. The ECB receives detailed information about over 30 million open contracts of euro-area entities every day.[3] This rich dataset offers unique opportunities, but presents also significant challenges due to its size and complexity.

One of the particular challenges, which the researchers working with the data have to face, is the issue of double-sided reporting. According to the EMIR regulation, both counterparties to the contract have to report the trade to the trade repository (assuming that they are both located in the EU). This means that both legs of the trade are reported as separate observations, which has to be taken into account in the process of data analysis. While this brings considerable benefits in terms of data quality management, as the regulators can compare the information provided by two counterparties, it leads also to certain issues in data aggregation and analysis.

As envisaged by EMIR regulatory and implementing technical standards, the counterparties are obliged to mutually agree on a unique trade identifier before reporting the trade. This requirement, however, turned out to be very difficult to comply with by the reporting agents, in particular in the first years of reporting.[4] Since then there have been significant improvement in the legal framework, as well as in the industry's ability to exchange the trade identifier before the reporting deadline. Additionally, the trade repositories, together with ESMA, have put a lot of effort into implementing the reconciliation process, where information is exchanged on a daily basis between the TRs, in order to assess the completeness and consistency of reporting, and ensure the pairing of the two legs of the transactions. As reported by ESMA, "*average pairing rates in November 2017 rose to 87%, from 55% in November 2016*".[5] However, in the set of all outstanding trades, which includes both new and old trades, the number of non-paired observations is much

[1] For more information on post-crisis reforms of derivative markets see ECB (2016)

[2] See: https://www.esma.europa.eu/regulation/post-trading

[3] Apart from the report on outstanding contracts ("trade state" report), the authorities receive also daily updates on the new transactions, valuation updates and other lifecycle events ("trade activity" report).

[4] See Maxwell (2104)

[5] See ESMA (2017), p. 40

higher, reaching around half of the reported dataset. This poses significant challenges to researchers using the data and hinders its meaningful aggregation.

The goal of this paper is to provide insights into the nature of the non-paired trades and to attempt to apply an automated procedure to find the corresponding legs in the non-paired sample. For this purpose, we draw on the method applied by Agostoni, et al. (2018) to the dataset collected under the ECB Money Market Statistical Regulation (MMSR), with some modification to account for differences between the two reporting frameworks and operational challenges related to the size of the EMIR dataset.

The paper is organized as follows. Chapter 2 briefly outlines the method used. Chapter 3 describes the choice of grouping variables and other parameters of the matching procedure. Chapter 4 presents the outcome of the quantitative analysis of the unpaired EMIR sub-sample, while Chapter 5 concludes.

2. Method

For the purpose of analysis we have adopted a modified method from Agostoni, et al. (2018). Similarly to MMSR dataset EMIR reports consist of counterparty-specific variables, noted Y_i,[6] and trade-specific variables, noted X_i.[7] The counterparties are obliged to agree on the values of trade-specific variables before reporting the trade. While this cannot be safely assumed in the cases when counterparties failed to agree on the trade ID, we can still expect that the characteristics of the trade reported by the two counterparties will not differ significantly.

It is not expected that Y_i will be consistent between two legs of the same trade. However some variables of Y_i may contain information that the reporting entity provides on its counterparty,[8] thus they could be cross-compared with the information included in the other leg. The identifiers of the counterparties are a good example of such relationship: for a paired trade *id_of_the_reporting_counterparty*$_{t1}$ should be equal to *id_of_the_other_counterparty*$_{t2}$, and vice versa. We denote $\tilde{Y}_i$ as a vector formed by switching corresponding variables of Y_i.

In terms of data type, we can distinguish the following types of variables:

- categorical (discrete) variables
- dates

[6] Those include, identifiers of counterparties to the trade and other agents involved in the transactions, sector of the reporting counterparty, and information on valuation and collateral

[7] Those include information on the contract, like asset class, product and underlying ID, information on notional, various timestamps related to the transaction, details on clearing, and asset-class specific variables.

[8] The contract value is one exception to this rule. It is included in the counterparty-specific variables, as, by construction, two counterparties observe the contract value with opposite sign. Additionally, there may arise differences due to different valuation methodologies, time of valuation, etc. For the purpose of our pairing exercise, however, the absolute value of this variable proves to be useful, and was treated in a similar way to trade-specific variables.

- timestamps
- numerical variables

2.1 Clustering and grouping of trades

We denote X^g and Y^g a subset of X and Y, respectively. Those will be called "grouping variables" below.

Definition: two legs u and v are **clustered** if the variables match in the following way: $X_u^g = X_v^g$ and $Y_u^g = Y_v^g$. The clustering relationship is symmetric, reflexive and transitive, and allows partitioning the set of all trades into disjoint clusters.

Definition: two legs u and v are **grouped**, if the variables match in the following way: $X_u^g = X_v^g$ and $Y_u^g = \tilde{Y}_v^g$. The grouping relation is symmetric.

If two legs u and v are grouped, then all trades of the cluster of u are grouped with all trades of the cluster of v. The grouping relation splits the dataset into sub-groups, from which potential paired trades can be drawn. To illustrate with an example: if Y^g consists of ID's of reporting and other counterparty, and X^g contains only asset class, then each trade in asset class Z, reported by the entity A, with counterparty B, will be grouped with every trade in asset class Z, reported by the entity B, with counterparty A.

2.2 Matching distance

We denote X^m a subset of X, further described as the set of "matching variables". X^g and X^m do not contain the same variables.[9]

For the purpose of determining the optimal candidates for paired trades in the grouped dataset, we calculate a matching distance between each pair of trades in a group:

$$d_m(u,v) = \sum_{x \in X^m} w_x \, f_{T(x)}(u,v,\tau_x)$$

where:

- w_x is the weight associated to variable x, indicating the importance of the variable in the decision to pair two trades
- $f_{T(x)}(u,v,\tau_x)$ is a distance function between the values of the variable x between legs u and v, taking parameter τ_x
- $T(x)$ is the type of variable x (categorical, date, timestamp, or numerical)

For simplicity we have considered the discrete distance function depending on the type of the underlying variables. The distance functions' representations are taken in this paper to be binary, but other choices are possible; the selection is summarized in Table 1.

[9] By definition, for all trades in the group $X_u^g = X_m^g$. Thus, using any variable from X^g in the matching process does not bring any additional benefit.

Distance functions	Table 1
Data type	$f_{T(x)}(u, v, \tau_x)$
Categorical	If $x_u = x_v$ then $f_{T(x)}(u, v, \tau_x) = 0$ else $f_{T(x)}(u, v, \tau_x) = 1$
Date	If the absolute distance between x_u and x_v is less or equal to τ_x days then $f_{T(x)}(u, v, \tau_x) = 0$ else $f_{T(x)}(u, v, \tau_x) = 1$
Timestamp	If the absolute distance between x_u and x_v is less or equal to τ_x seconds then $f_{T(x)}(u, v, \tau_x) = 0$ else $f_{T(x)}(u, v, \tau_x) = 1$
Numerical	If the relative difference[10] between x_u and x_v is less or equal τ_x% then $f_{T(x)}(u, v, \tau_x) = 0$ else $f_{T(x)}(u, v, \tau_x) = 1$
All variables	If x_u is NULL and x_v is NULL then $f_{T(x)}(u, v, \tau_x) = 0$ If x_u is NULL and x_v is not NULL, or vice versa then $f_{T(x)}(u, v, \tau_x) = 0.5$

The methodology could be further extended to allow for continuous output of the distance function for continuous variables, introduce string metrics to better measure the distance between categorical variables, account for correlation between variables, or take into account common misreporting patterns (e.g. reversing the legs of interest rate derivatives). We leave these considerations for future work.

2.3 Classification of trades

The calculation of the matching distance between grouped trades allows us to classify the trades along the conditions described in the table below. For this purpose we define the *best match* of a trade as the trade from its group, to which it has the lowest matching distance (if this condition is satisfied by multiple trades, then *best match* is not determined).

Trade classification	Table 2
Trade classification	Definition
Perfect match	The trade has a best match, and the relation is reciprocal. Additionally, the matching distance is equal to 0, i.e. the trades are identical within the bounds of the matching conditions.
Imperfect match	The trade has a best match, and the relation is reciprocal. The matching distance is higher than 0, which may indicate misreporting of some characteristics of the trade.
No match	There exists no trade, with which the trade has a grouping relation.
Perfect matching group	There exist multiple trades, with distance 0 to each other. The trades can be considered perfect matches, but it is not possible to determine the exact legs of the particular trades.
Ambiguous	All other cases – the grouped trades could not be unambiguously matched.

[10] The relative difference is $\mathrm{rd}(x, y) = 2\frac{|x-y|}{|x|+|y|}$ if both $x \neq 0$ and $y \neq 0$, 0 otherwise.

3. Determination of the grouping and matching variables

One of the differences between the EMIR and MMSR datasets is the fact that a significant sub-sample of the EMIR trades can be unambiguously paired by using the trade identifier reported by the counterparties. This UTI-paired sub-sample can be used to determine the optimal parameters of our matching procedure, in particular X^g, w_x, and p_x. For this purpose we have grouped together trades by their counterparties' identifiers and trade identifier, and calculated a variety of statistics on a variable-by-variable basis to check the consistency of data reported in two distinct legs. This allows selecting the variables that offer the highest degree of similarity between the two legs as grouping variables, other variables as matching variables, and the observed patterns between the matching variables as elements in the selection of the thresholds.

All calculations in this paper were carried out on data received from five trade repositories[11] for the reference date of 5 July 2018, with a total of 32,780,000 trade state reports.

3.1 Grouping variables

The identifiers of both counterparties were by construction included in the set of grouping variables, as it allows restricting the size of the groups to the level, which facilitates calculating matching distance between all members of the group. This approach has some limitations, as it does not allow addressing the potential issue of ID misreporting. [12] This phenomenon will be further explored in follow-up work.

We have considered variables with following characteristics as potential candidates for grouping variables set X^g:

- the variables that are very well-populated, i.e. less than 10% of paired trades have missing information in both legs of the trade,
- the variables that exhibit high matching of the non-empty values, i.e. the information provided in the two legs is equal for more than 98% observations.

Figure 1 shows the distributions of two abovementioned metrics across different variables. The green rectangle in bottom right of the chart represents the criteria for the grouping variables.

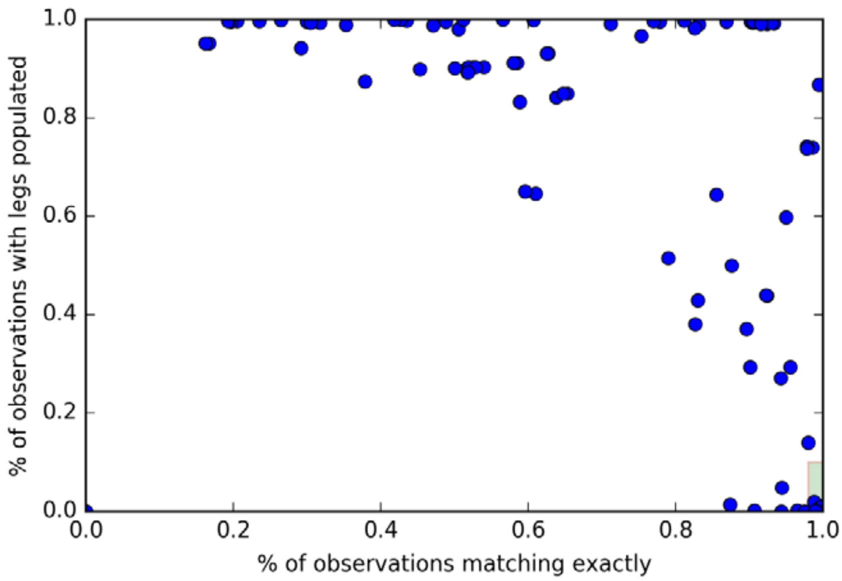
[11] DTCC Derivatives Repository Ltd. (DDRL), Krajowy Depozyt Papierów Wartosciowych S.A. (KDPW), Regis-TR S.A., UnaVista Ltd, and ICE Trade Vault Europe Ltd.

[12] The problem of ID misreporting if further discussed in chapter 4.

Determination of grouping variables

Scatterplot between share reported and share matching exactly

Figure 1



Source: EMIR data, UTI-paired sample, ECB calculations. The green rectangle in bottom right of the chart represents the criteria for the grouping variables.

Based on this analysis, combined with expert knowledge, the following variables were chosen as grouping variables:

- ID of the reporting counterparty (LEI)
- ID of the other counterparty (LEI)
- Asset class (interest rate, currency, equity, commodity, credit)
- Contract type (swap, option, forward, etc.)
- Clearing status (cleared, not cleared)
- Execution date (extracted from the execution timestamp)

3.2 Matching distance weights

The weights introduced in section 2.2 serve the purpose of assigning more importance to variables that signal a higher probability of two legs being the correct match. The weight can be derived from the likelihood that a noisy observation is in fact equal to the target.

We describe the case of a categorical variable X; we observe only $\hat{X}$, a perturbed version of X. We assume that with a probability p the variable is not perturbed, and when the variable is perturbed it is given randomly one of the values of the variable, with assignment proportional to the existing distribution of values. The probability p is the **fidelity** of the variable (the higher the fidelity, the more we can trust the match) and the share of the category is the inverse of the specificity (the higher the **specificity**, the lower the chance that a match is random).

We have a known value of x and want to determine the probability that when we observe the perturbed value $\hat{X}$ the underlying true value of X is k. This corresponds to $P(X = k|\hat{X} = k)$. We note q_k the share of category k of the variable X. Then $P(X = k|\hat{X} = k) = p + (1-p)q_k$. Similarly, $P(X = k|\hat{X} \neq k) = (1-p)q_k$. We bound by below the first probability by p and bound by above the second one by $(1-p)q$, where q is the share of the most common category of the variable X. Then the contribution of variable X in the match can be estimated in a worst-case way by

$$P(X = \hat{X}|\hat{X}) = p\left(\frac{1-p}{p}q\right)^{\mathbb{1}_{\hat{X}\neq X}}$$

The product of several such variables is the probability of the good match, and the contribution of each variable to the opposite of the log-likelihood is thus the term in the matching distance in section 2.2, and we can thus set

$$w_x = \log\left(\frac{p_x}{q_x(1-p_x)}\right).$$

The higher the specificity $1/q_x$ and the higher the fidelity p_x, the higher the weight (as long as $p_x \geq 1/2$, which we assume in what follows).

3.3 Parameters of distance function

The threshold parameters τ_x of the distance function where chosen on the basis of percentiles of (absolute and relative) differences between values of the legs of the trades in the paired sample. The parameters were selected so that $f_{T(x)}(u, v, \tau_x)$ accepts 98% observations in the paired sample.

3.4 Verification of matching parameters

The selected grouping variables, weights, and parameters were verified by running the procedure on the UTI-paired sample, shown in Table 3. Due to the complexity of the measures and the size of the data, the calculations were carried out on a random representative 1% sample of trades.

Classification of trades in the UTI-paired sub-sample — Table 3

Classification	Number of trades	Percentage
Perfect match	91,861	48.74%
Imperfect match	53,505	28.39%
Perfect matching group	24,484	12.99%
Ambiguous	10,431	5.53%
No match	8,191	4.35%
Total	188,472	100.00%

Source: ECB calculations, based on data received from trade repositories (1% sample of trades).

The results obtained confirm the robustness of the method. For 77% trades the procedure was able to find the matching leg. For another 13% the procedure determined the existence of the perfect matching group, although the trades were too similar to distinguish the individual trades.

4. Analysis of the non-UTI-paired trades

The procedure applied above was applied to the non-UTI-paired sub-sample with the following results:

Classification of trades in the non-UTI-paired sub-sample

Table 4

Classification	Number of trades	Percentage
Perfect match	70,175	0.48%
Imperfect match	421,613	2.88%
Perfect matching group	11,233	0.08%
Ambiguous	700,686	4.78%
No match	13,459,158	91.79%
Total	14,662,865	100,00%

Source: ECB calculations, based on data received from trade repositories[13]

As shown in Table 4, the results of the pairing exercise in the non-UTI-paired sample indicate that most of the trades cannot be paired. 92% of the trades are not in a grouping relationship with any other trades (those trades are further defined as the **unpaired sample)**. Put differently, it means that counterparty A reports a trade with counterparty B, but there is no corresponding trade reported by counterparty B with counterparty A within the same group [same asset class and contract type; same clearing status and execution date]. Potential reasons are discussed and quantified in the following sections.

4.1 Trades with entities from non-EU jurisdictions

EMIR applies to entities resident in the EU, thus the trades concluded with counterparties outside the EU are expected to appear only once in the dataset. In order to assess the extent of this phenomenon we have used the GLEIF dataset,[14] combined with information reported within EMIR, to identify the trades that were carried out with counterparties from other jurisdictions. As shown in Figure 2 the share of those trades in the unpaired sample amounts to over 35%, with significant contribution of trades with US (18.5%)[15] and Swiss (6%) counterparties.[16]

[13] Around 140,000 of the trades (1% of the non-UTI-paired sample), forming one particularly large grouping set, could not be classified by the procedure due to the size of the set. The inclusion of those trades, however, would not materially change the results.

[14] GLEIF is Global Legal Entity Identifier Foundation, which is responsible i.a. for managing reference database of LEI codes. The LEI is an ISO standard for identification of legal entities. For more details visit https://www.gleif.org

[15] All the percentages refer to the share in the unpaired sample.

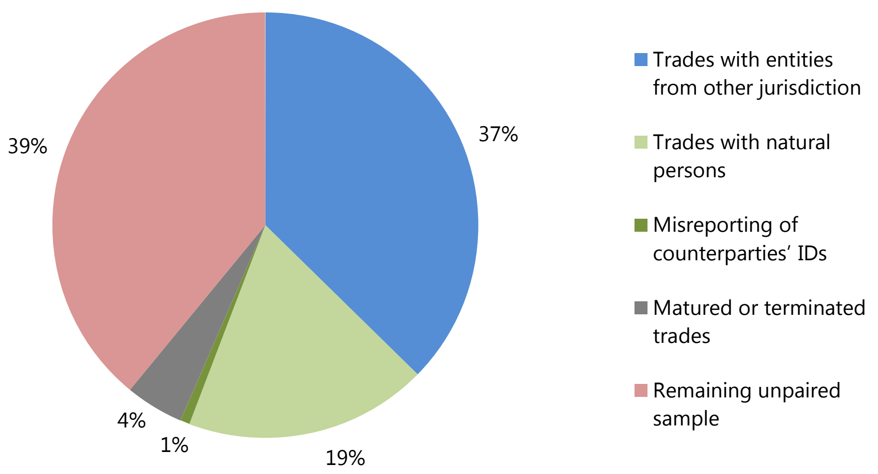
[16] We have also identified a non-negligible amount of trades (around 9%), where information about the country of the other counterparty is missing. Those trades are kept in the unpaired sample.

4.2 Trades with natural persons

The EMIR regulation does not impose the reporting obligation on natural persons, hence for trades carried out by private individuals we will see only the leg reported by the counterparty of the trade. To identify such trades we used the type of the identifier, assuming that the counterparties identified by the "client code", instead of LEI are not legal entities.[17] As shown in Figure 2, this filtering allows us to restrict the size of the unexplained unpaired sample by a further 18%.

Breakdown of the unpaired sample

Figure 2



Source: EMIR data, ECB calculations. Full sample. Non-exclusive categories removed from the sample in the order shown in the chart, e.g. the Trades with natural persons does not include any Trade with entities from other jurisdictions, although the latter can include Trades with natural persons.

4.3 Misreporting of counterparties' IDs

In case the reporting entity misreports its ID or the ID of its counterparty, then the two legs of the trade will have different counterparty pairs, and they will not be grouped together for the matching procedure. To assess the degree to which the dataset could be affected by that issue, we checked whether the IDs reported in the unpaired sample could be found in the GLEIF reference database. As shown in Figure 2, the extent to which this effect could explain the unpaired sample seems to be limited.

Another type of ID misreporting can occur, when the reporting entity submits a valid LEI code as the ID of the other entity, but this is not the LEI with which the other counterparty identifies itself. This could happen, for instance, when the reporting entity reports the ID of the parent company of its counterparty. To assess this phenomenon, we carried out a separate exercise, in which we replaced the IDs of the entities with the LEIs of their ultimate parents from the GLEIF relationship

[17] While this approach follows EMIR guidelines on reporting, it cannot be excluded that some counterparties incorrectly assign a client code to a legal entity, which should be identified by LEI. This is, however, outside the scope of this paper.

database,[18] and then re-run the grouping procedure. The result was the reduction of the unpaired sample by less than 0.5% observations. Thus, it was concluded that information from GLEIF relationship database is not useful in improving the outcome of the pairing exercise.[19]

4.4 Matured or terminated trades

If a trade is terminated early or compressed away, the entity is expected to send this information to the trade repository, which should remove the trade from the trade state report. Furthermore, the trade repository should remove all the trades that reached their maturity date. If any of these obligations is not met, we may see in the trade state report trades that do not exist anymore. To assess this we:

- checked the remaining unpaired sample for existence of trades, for which the maturity date or termination date lies in the past,
- cross-checked the trades with information reported on trade activity reports from the preceding two months. If there was any indication that the trade has been terminated or compressed, we flagged it as an expired trade.

By following the above steps, we have identified further 4% of the trades, which could be deducted from the unpaired sample.

4.5 Understanding the unpaired sample

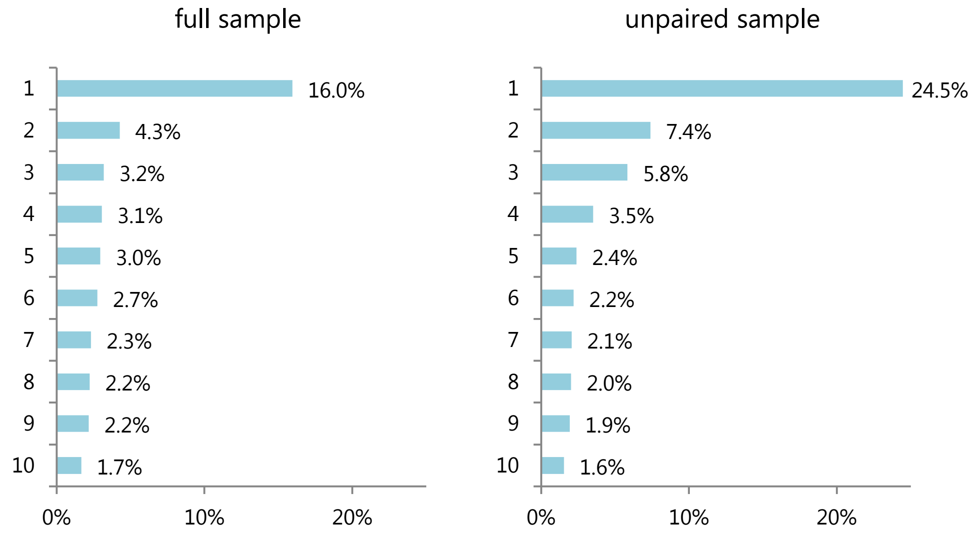
After taking the steps described above, we are left with around 5 million trades, constituting 40% of the original unpaired sample. The remaining observations may constitute a case of underreporting (i.e. one of the counterparties failed to meet its reporting obligation), or may be an incorrect reports. Figure 3 presents some descriptive statistics of the set of remaining trades.

[18] See https://www.gleif.org/en/lei-data/access-and-use-lei-data/level-2-data-who-owns-whom

[19] It may be possible that the identification issue lies in the entity managing the fund rather than the fund itself. Other sources of data, also covering other relation types (e.g. fund–management company) could be more successful in improving the pairing outcomes. We leave these considerations for future work.

Share of largest reporters in the unpaired and the full sample

Figure 3



Source: EMIR data, ECB calculations.

In particular the trades in the unpaired sample seem to be significantly more concentrated that in the full sample of trades. This may hint at the existence of systematic issues in reporting by some large reporters of EMIR data.

We investigated further the explanatory factors behind the possibility of pairing with a simple logistic regression (Table 4) on a randomly selected 1% sample. All coefficients are significant at the 1% level and t-statistics are not displayed. Among the most salient results, and other things being equal, cleared trades, intragroup trades, and trades within the euro area are more likely to be paired, while trades that have no contract value reported (as in Abad et al. (2016)) and trades executed before 2018 or close to the reporting date are less likely to be paired. With regards to other breakdowns, like asset class or contract type, the trades with the lower pairing are those that are classified as “Other”.

Logit regression

Odds ratios, probability of being paired — Table 4

Variable	Odds ratio	Variable	Odds ratio
Asset class		Location of other counterparty	
Commodity	1	Euro area	1
Credit	0.547	Other EU	0.405
Currency	0.508	RoW	0.00676
Equity	0.619	Nature of reporting party	
Interest rate	0.745	CCP	1
Other	0.324	Financial	1.378
Missing	1.371	Non-financial	4.740
Contract type		Other	2.600
Contracts for difference	1	Missing	5.220
Forwards	1.906	Execution date	
Forward rate agreements	1.919	<= 2013	0.247
Futures	0.879	2014-2017	0.403
Option	1.197	2017	0.645
Other	0.420	2018 Q1	1.178
Swap	1.770	2018 Apr-May	1.197
Swaption	1.899	2018 Jun	1
Missing	0.173	2018 Jul	0.599
Clearing Status		> Aug 2018	0.608
No	1	Contract value missing	
Yes	1.720	No	1
Missing	0.439	Yes	0.590
Intra group		Notional amount (log)	1.036
No	1		
Yes	4.228		
Missing	0.669		
Observations	295,721		

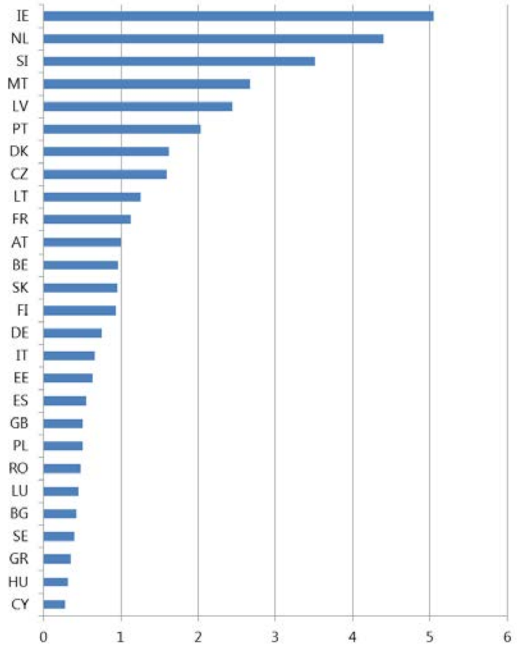
Source: ECB calculations, based on data received from trade repositories for 5 July 2018. 1% sample.

While it is clear that non-EU trades will not be double-reported in the context of EMIR, it is reasonably surprising that within the EU, the pairing success varies substantially by country. This could imply that counterparties from those countries fail to meet the reporting obligation more often, or that there exist some particular difficulties in agreeing on the content of the report by entities from those countries. Another reason could be, however, misreporting or overreporting of the reporting counterparties, and further case-by-case analysis would be needed to fully understand underlying reasons for country disparities.

Pairing success by country of the other counterparty

Figure 4

European Union countries



Source: EMIR data, ECB calculations.

5. Conclusions

The paper applies an automated pairing procedure to the EMIR dataset on derivatives, by grouping the similar trades together, and then classifying them according to the matching distance between each member of the group. Although the robustness of the procedure is successfully verified on the UTI paired sub-sample of the EMIR dataset, and contrary to the similar work on the MMSR dataset, the procedure fails to produce significant improvements for understanding the unpaired dataset. The paper further analyses the set of trades that could not be successfully paired.

In terms of data aggregation, the paper indicates that there is no single optimal approach to the treatment of the non-paired sample. While a limited set of the observations represents trades that could indeed be paired, the rest of the unpaired sample has to be treated with caution. While some of the trades can be considered unpairable (trades with counterparties outside the EU, or with natural persons), the others may be the effect of underreporting, or may be incorrectly reported transactions, which should be then removed from the dataset.

The paper finally offers also some insights regarding further improvement of the quality of data reported under EMIR. We have observed clear patterns between some characteristics of the trades and the probability of being paired. Furthermore, the concentration of entities in the unpaired sample is higher than in the full EMIR dataset. This suggests that focusing on the few most important contract types and/or entities may bring significant benefits in terms of data quality. These results may be of benefit to national competent authorities, supporting their efforts in improving the quality of EMIR reporting.

The follow-up work may include further refinement of the pairing procedure, and incorporating the time dimension into the analysis. A particularly interesting area of interest could be addressing the issue of potential counterparties' ID misreporting. To this end, alternative reference datasets could be added to understand the links between entities, or the pairing procedure could be applied to the dataset without grouping the trades by the counterparties (to allow matching of the trades with non-identical counterparty pairs. Those paths will be explored in future research.

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Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

Ninth IFC Conference on "Are post-crisis statistical initiatives completed?"

Basel, 30-31 August 2018

Two is company, three's a crowd: automated pairing and matching of two-sided reporting in EMIR derivatives' data[1]

Sébastien Pérez-Duarte and Grzegorz Skrzypczynski,
European Central Bank

[1] This presentation was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

EUROPEAN CENTRAL BANK

EUROSYSTEM

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Sébastien Pérez-Duarte

DG-Statistics, European Central Bank

Two is company, three's a crowd:

Automated pairing and matching of two-sided reporting in EMIR derivatives' data

IFC conference

Are post-crisis statistical initiatives completed?

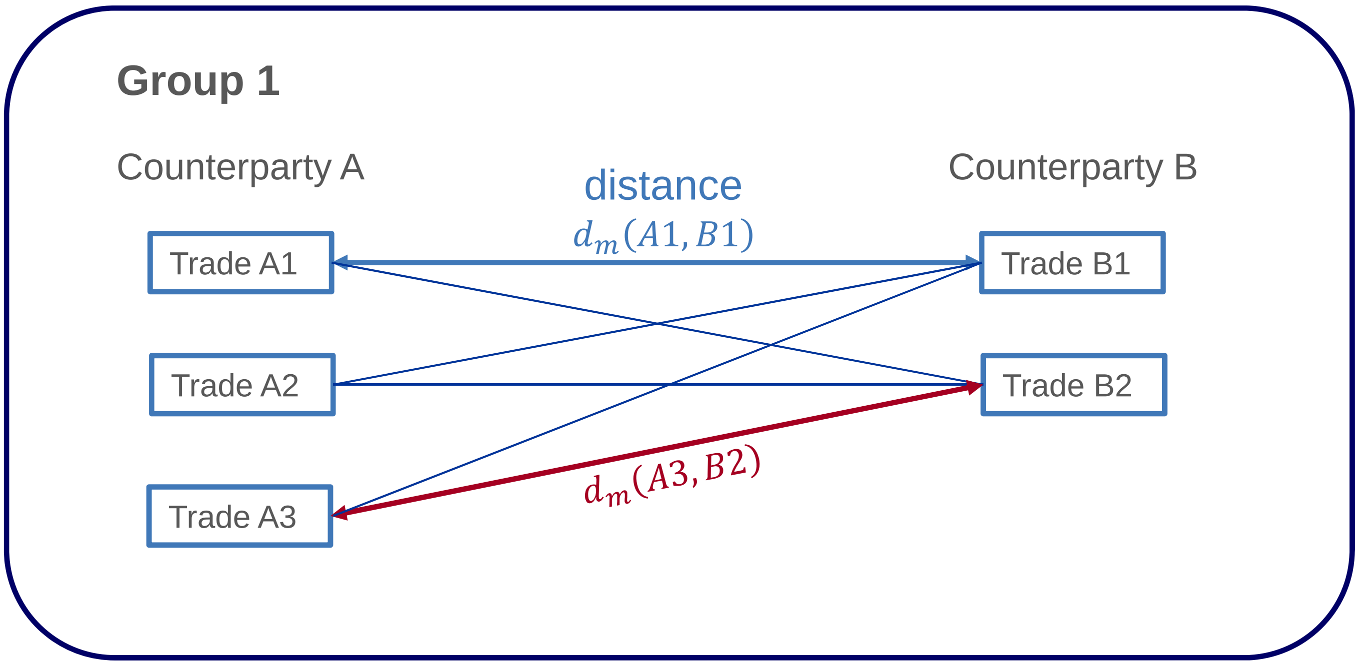
30-31 August 2018, Basel

Motivation: double-sided reporting in EMIR

- EU counterparties report **derivative transactions** to trade repositories
- Separately by both counterparties (**double-sided reporting**)
  - Improves data quality monitoring
  - ⓘ Risk of double-counting when analysing and aggregating the data
- **UTI (Unique Transaction Identifier)** to link trades, agreed between counterparties
  - Challenges in implementation (not unique, different UTIs for the same trade)
  - Work on improving pairing and matching (inter-TR reconciliation process)
  - Global initiatives to harmonise UTI between jurisdictions
  - ESMA estimates pairing rate at 87% = but newly reported trades only

Method

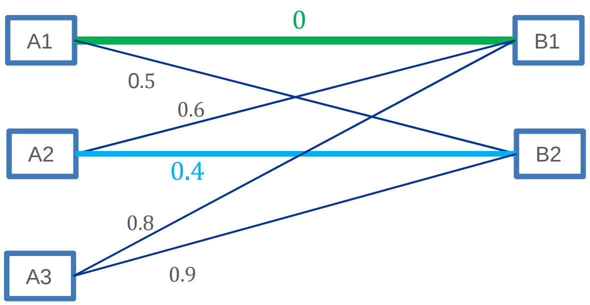
- The trades are split into groups with same values of the **grouping** variables
- The procedure calculates the **matching distance** between each member trade of the group



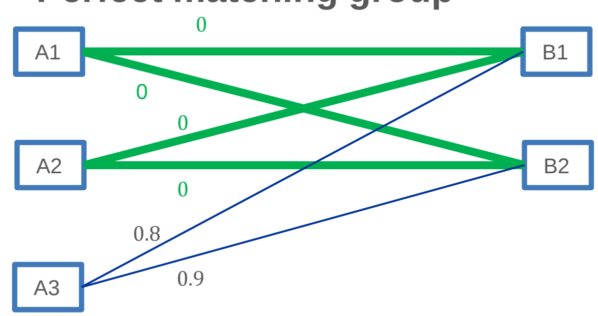
Classification of trades

- Depending on outcome, exclusive categories

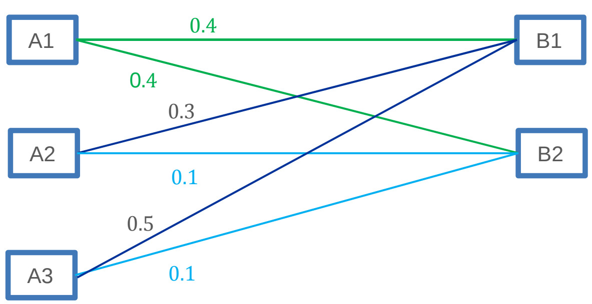
Perfect match / imperfect match



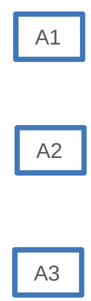
Perfect matching group



Ambiguous



No match



Implementation

- Sample paired with UTI was used to calibrate the parameters
- **Grouping variables**:
  - Counterparties' IDs
  - Asset class
  - Contract type
  - Clearing status
  - Execution date
- **Matching distance weights**: function of fidelity (how good) and specificity (how revealing) of the variable
- **Thresholds of the distance function**: to accept 98% of the observations in the paired sample

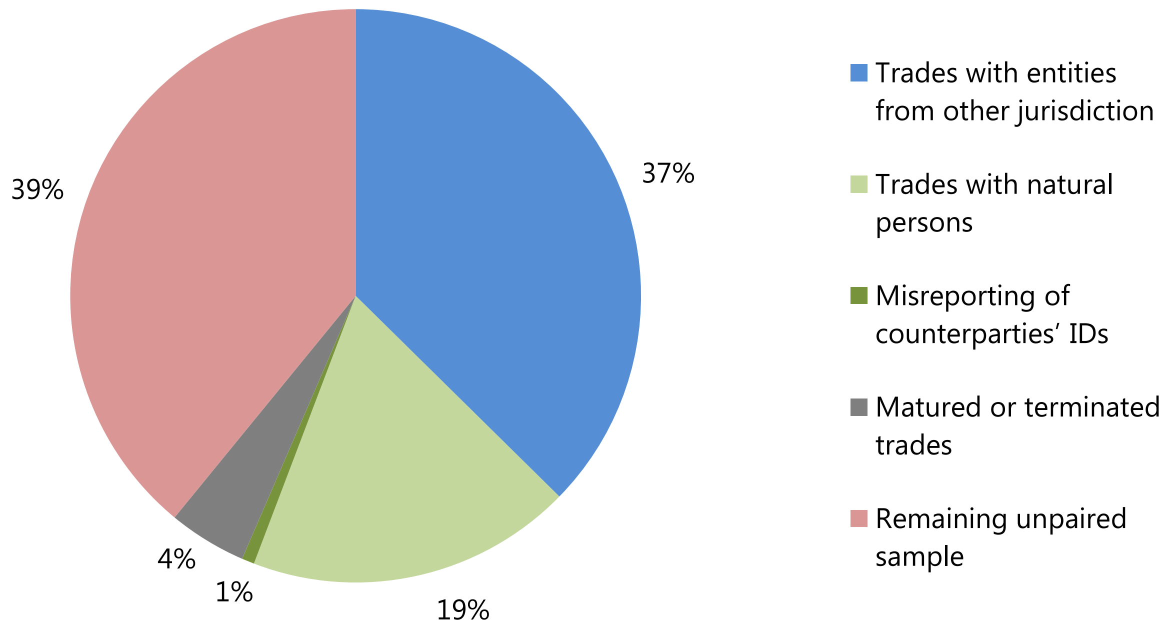
Implementation

- Our procedure has limited impact in the non-paired sample
- Most of these trades don’t have any counterpart in their group
  ➔ other reporting issues are at stake

	Paired sub-sample	Non-paired sub-sample
Perfect match	48.74%	0.48%
Imperfect match	28.39%	2.88%
Perfect matching group	12.99%	0.08%
Ambiguous	5.53%	4.78%
No match	4.35%	91.79%

Some things we will never be able to pair

Breakdown of the unpaired sample



- Remaining 40% of the unpaired sample:
  - may be a result of underreporting
  - may constitute invalid reports

What can't we pair?

Logit regression - Odds ratios, probability of being paired

Variable	Odds ratio		Variable	Odds ratio
Asset class			**Location of other counterparty**	
Commodity	1		Euro area	1
Credit	0.547		Other EU	0.405
Currency	0.508		RoW	0.00676
Equity	0.619		**Nature of reporting party**	
Interest rate	0.745		CCP	1
Other	0.324		Financial	1.378
Missing	1.371		Non-financial	4.740
Contract type			Other	2.600
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Forwards	1.906		**Execution date**	
Forward rate agreements	1.919		<= 2013	0.247
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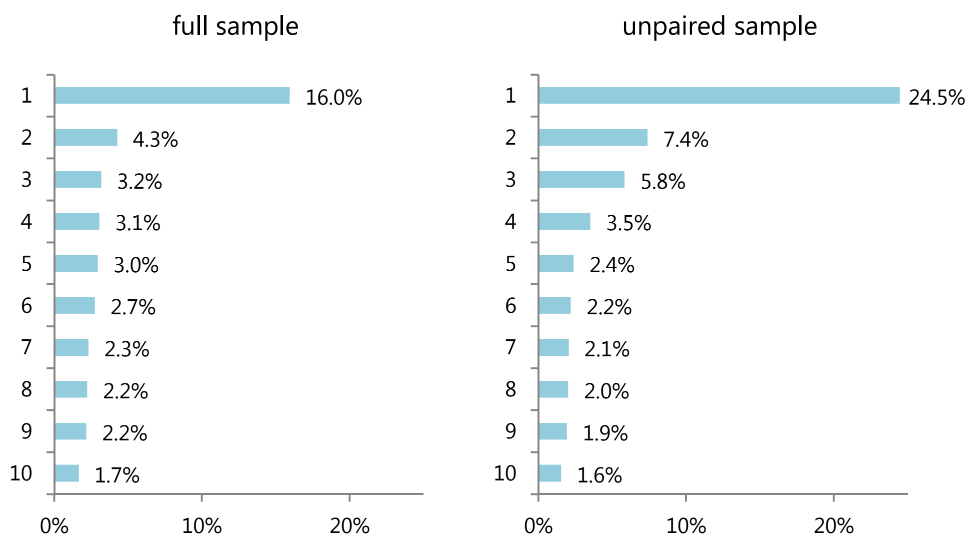
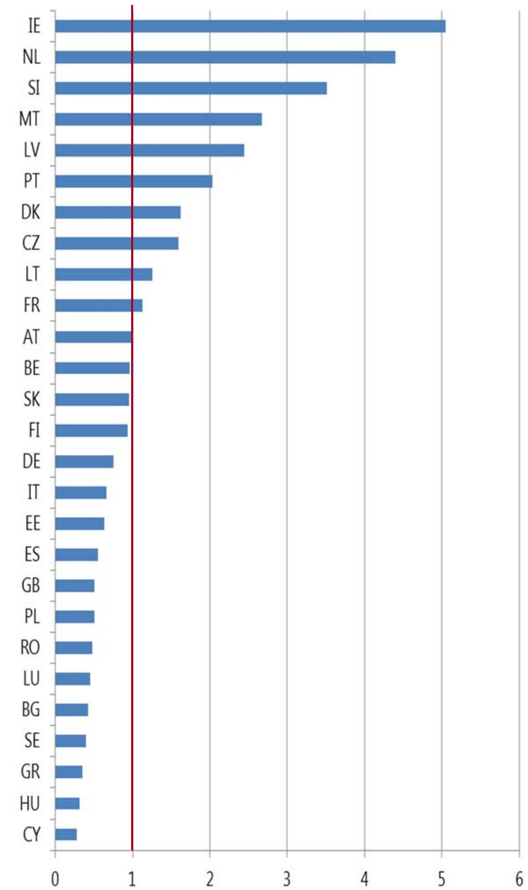
Intra group			Notional amount (log)	1.036
No	1			
Yes	4.228			
Missing	0.669			

What can't we pair?

Share of largest reporters in the unpaired and the full sample



Pairing success by country of the other counterparty *(odds ratio)*



Conclusions

- Caution is recommended when **making assumptions** about the unpaired sample **to compute aggregates**
- A **significant share of the non-paired sample is difficult to interpret,** and cannot be easily reconciled
- There exist some **clear patterns** between some characteristics of the contracts and **probability of being paired**
- The unpaired sample exhibits **higher concentration** with regards to reporting entities
- A **focused data quality management** process may bring **significant benefits with limited effort**

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Evaluation of the transmission of the monetary policy interest rate to the market interest rates considering agents expectations [1]

Deicy Cristiano-Botia, Eliana Gonzalez-Molano
and Carlos Huertas-Campos,
Bank of the Republic, Colombia

[1] This paper was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

Evaluation of the transmission of the monetary policy interest rate to the market interest rates considering agents expectations

Deicy Cristiano-Botia, Eliana Gonzalez-Molano, Carlos Huertas-Campos[1]

Abstract

Alternative economic models are used to determine whether policy interest rate expectations and unanticipated changes in the reference interest rate affect saving and credit interest rates. We found empirical evidence that policy surprises have predict power to set passive and active interest rates. Similarly, results show that to fix their interest rate financial entities take into account their expectations about policy rate. On the other hand, we found evidence of changes in deposits rates in advance of the announcement of the monetary authority and no significant change on the day of the announcement and the day after the change.

Keywords: Expectations, Monetary Policy, Interest Rates and Transmission Mechanism.

JEL classification: D84, E43, E52, E58

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Contents

1. Introduction

A way to evaluate the degree of transmission of changes in the monetary policy interest rate to market interest rates is to measure it after the decision of the Central Bank. I.e., calculating how much has changed a specific interest rate once the Board of Directos make a policy announcement. This methodology does not consider the effects of the expectations of agents on the transmission. For example, the market can anticipate and partially incorporate the changes in the policy rate to the rates of interest of the economy, and therefore, the transmission would be underestimated. This is important, since in theory, both not anticipated and anticipated changes in the policy rate by financial institutions have effects on the setting of market interest rates.

In this context, this document analyzes the transmission of changes in the monetary policy interest rate on the 90-day deposit rate and the interest rates for credits for both ordinary and preferential loans, considering the expectations of agents on future monetary policy decisions. These expectations are based on the information available each period and the agents forecast ability.

Empirical analysis comprises three exercises. Firstly, we evaluate the effect that has the unanticipated component of changes in the policy rate to market rates (Vargas et al (2012)). This component is defined as the forecasting error that agents make to project changes in the policy rate using all available information. Second, we present a model under the conditional expectations hypothesis, in which, a medium-term interest rate is defined as the average of the expected short term rates for all periods until maturity. Finally, an analysis of the behavior of short-term interest rates is made considering daily data and taking into account the time intervals defined in Roley and Sellon (1995). To this end, we evaluate the prospective or anticipated effect and the immediate effect of the changes in the policy rate decomposing the estimation in three time periods: a day previous to the announcement, the day of the announcement and the day Post-announcement.

This document consists of four sections and the first is this introduction. Section two contains a review of literature and section three explains the econometric models and present estimation results and the final section concludes.

2. Literature review

According to Loayza and Schmidt-Hebbel (2002) monetary policy rules that use central banks evaluate its efficiency and optimality mainly through four channels of transmission of monetary policy: the interest rate channel, the channel of asset prices, the exchange rate channel and credit channel. These channels affect the macroeconomic variables in different speed and intensity.

Alternatively, the literature identifies the expectations channel, which considers the intertemporal effects associated with the projections of the stance of the Monetary Authority and the present and future behavior of the main variables of the economy. In this way, the beliefs of agents on the shocks and the expected behavior of the main macroeconomic variables affect the effectiveness of the transmission. Similarly, effectiveness also depends on the credibility of the Central Bank and the agents reaction to future policy announcements. To the extent that the credibility of the Central Bank and other institutions is high, the expectations channel has a greater role given that the formation of expectations will be in line with the economic policy measures.

In theory, long-term rates can be defined as the average of the expected interest rates of short term until the maturity plus a risk premium. Therefore, it is important to know the expectations of agents on future changes in the policty rate. Faced with this situation, Ellingsen & Söderström (2001) argue that monetary policy actions respond to new and private information, as well as changes in the preferences of the central bank in terms of the stabilization of the output and inflation. Thus, a forecast of the policy rate must include all these variables.

One of the first analysis of the response of interest rates before the FED reference rate changes was made by Cook and Hahn (1989), who analyzed the daily relationship between the policy rate and the treasure bonds rates with maturities from 3 months up to 20 years. The authors analyzed for the 70's the movement of the interest rates of the Treasury bonds in the days close to the FED announcement (two days prior to each ad, the day of the announcement and the two days following the ads). They found that the market requires at least one day after the announcement of the FED to consider that the change is carried out. During this period the response of short-term rates was strong, moderate for the mid-term and weak for the long term (being significant for all maturities). Likewise, to analyze the relevance of the theory of expectations, the authors found a strong influence of the expectations on the movements in the daily market rates at the different maturities.

Roley and Sellon (1995) studied the response of the long-term rates taking into account the tendency of the market to anticipate monetary policy actions. They found that these forecasts influence the transmission of changes in the policy rates to long-term interest rates. As the authors says, financial institutions have incentives to match the profitability of its portfolio to different maturities. Therefore, they include and adjust their expectations on long-term interest rates, considering the expected future changes in the short-term rates. As an approach of future long-term interest rates, the authors build an average rate from rates of short-term futures. They warn that the response in the long term rates can be inverse to that described by the monetary traditional view, since it depends not only on the expectations of policy rate, but also in the expected persistence of this. In this regard, Roley and Sellon make one caveat to mention that the magnitude of the expected response may vary depending on the perception that agents have on the phase of the economic cycle in which the economy is currently. Thus, surprising policy announcements (which do not correspond to the perceived phase of the economic cycle) will generate a greater response in rates since agents should adjust their investments for short or long term depending on the expected persistence.

Kuttner (2001) estimated for United States (between June 1989 and February 2000) a uniform and inferior interest rates response with respect to that found by Cook and Hahn, using the same methodology but with information from the federal funds futures market of the United States (as proposed by Roley and Sellon (1995)). The author suggests that the difference is in comparing changes in rates expected and unexpected in the period posterior to the monetary policy announcement. They found that the response of interest rates to anticiated policy action is low, while that of unanticipated changes is high and significant.

The relationship between monetary policy and long-term interest rates is widely documented, however, responses differ across countries. Skinner and Zettelmeyer (1995) conducted an analysis for Germany, France, United Kingdom and United States on the response of long-term rates to policy actions using the unanticipated component of monetary policy. It was found that for the United States long term rates are adjusted in 41.2% of the unanticipated shock, for the United Kingdom this setting is 27.9%, while there is a lower setting for Germany and France (10.1% and 8.7%, respectively).

On the other hand, authors like Thornton (2009) and Vargas et al (2012) analyzed the disconnection of the mechanism using market-based measures and structural factors such as fiscal policy. Thornton (2009) estimated again the response of interest rates reviewing Kuttner method, as it suggests that the changes in the federal funds rates respond to both monetary policy news, and others news of the market or the environment in general.

To correct the problem of bias some authors suggest the use of high-frequency data, others suggest the structural identification through simultaneous equations using constraints in the matrix of variances and covariances[2] . However, Thornton applied a model that conceptualizes more

[2] See Gürkaynak, Sack, and Swanson (2007); and Craine and Martin (2008).

accurately changes in the market interest rate by including in the Kuttner method two parameters: one that considers the bias to shocks generated by news of the environment and another that estimates the bias to unexpected changes in the policy rate. Separately estimated the effect for all days of the sample, and not only for the days prior or subsequent to the policy announcement, including a dichotomous variable to identify the days when monetary events occur. Their results indicate that traditional specification overestimates the effect of monetary policy, and that there is no transmission at rates exceeding 3 years of maturity, with the exception of 20 years, which is significant but with negative effect.

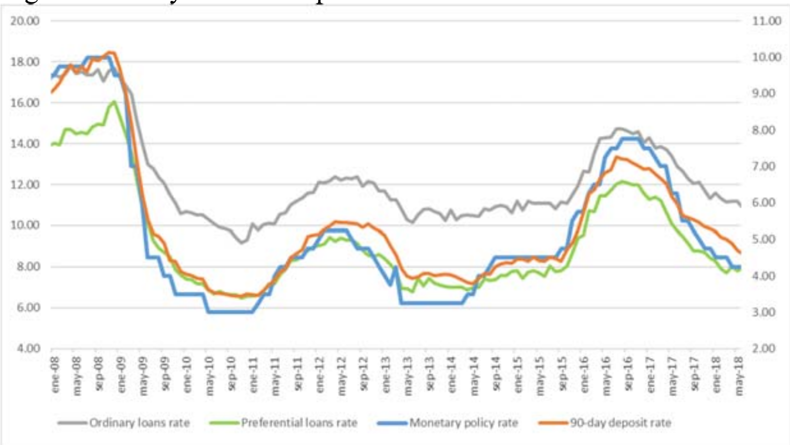
The literature also suggests that structural factors and the prevailing macroeconomic conditions may explain the transmission of the policy interest rate to market interest rates. Vargas et al (2012) analyzed the relationship between the credibility of the Central Bank and the transmission mechanism of monetary policy in Colombia for the period 2002-2011. In particular they analyze whether under a regime of monetary policy credibility, a change in the policy interest rate has less chance of being understood as a transitional move and more likely to be incorporated in government long-term bonds and, in general, in the interest rate of the financial market as being considered as a persistent long term monetary policy signal.

The authors apply the methodology of local projections proposed by Jorda (2005) in order to estimate the Impulse-response function (FIR) of the rate of interest on public bonds (TES) to an unexpected monetary shock. They later estimate a similar model to build the FIR of the market interest rate for loans and deposits given the shock in the monetary component as not anticipated by the agents. The results show, that after the reforms presented at the beginning of the decade of 2000, the response is more persistent for both the bonds and the market rates. They considered that structural improvements of policy that provide reliability to the economy, in particular the fiscal, has a positive effect on monetary policy, allowing to wide the maturity of bonds and as a result generate a deepening in that market. Therefore, they conclude that the strength of the monetary transmission mechanism is the result of structural factors as a sound fiscal policy and greater depth of fixed-rate public debt market.

3. Estimation of the impact of unanticipated shocks in the policy rate on market interest rates

This section discusses three types of models that explain the behavior of interest rates (passive and active) in response to unanticipated shocks in the policy interest rate for the period between October 2008 and May 2018; Figure 1 shows the dynamics of the deposit, the commercial credit interest rates and the policy rate. The market rates move with the policiy rate, but not at the same pace and magnitude. In the first model we estimate the response of a monetary surprise on the market intrest rates. In the second, a passive interest rate to a horizon of p periods forward (where p is a short period for an interest rate) is expressed as the average of the expected short-term (policy rate) for each period until maturity p. In the latest model we analyze daily 90-day deposit rate to determine if the effect of monetary policy decisions is made before, the day of the announcement, or immediately after the announcement.

Figure 1. Policy rate and deposit and credit market interest rates



Source: Financial Superintendency, Banco de la República.

3.1 The effect of unanticipated monetary policy shocks on the market interest rates

The change in the market interest rate (Δi_t) is explained by the unanticipated change in the policy rate (Ψ_t).

$\Delta i_t = \alpha_0 + \alpha_1 \Psi_t + \epsilon_t$ (Eq. 1)

Where i_t could be either the monthly 90-day deposit rate or the commercial loans rate for ordinary and preferential credits for the period from may,2002 to may,2018. (Ψ_t) is defined using two alternatives. In the first one, a regression model for the policy rate is estimated as a function of a set of variables available for all economic agents when the Board of Directors make policy decisions. We follow the work of Vargas et al, (2012), in which, they asume monetary authority does not necessarily follows a standard Taylor rule, but apart from the output gap and inflation deviation from target may include expectations. Thus, we include other variables that may add some information and signals of future behaviour of the policy actions. So, with variables describe in equation 2, we obtained a one-step ahead forecast for the policy rate and we define the unanticipated monetary policy shock as the forecasting error obtained from this equation.

$$i_t^p = f\left(Y,\ \bar{\pi}, \pi^{USA},\ \Delta s, ICI,\ CCI\right)_{t-p} + \Psi_t \qquad \text{(Eq 2.)}$$

$$\Psi_t = i_t^p - i_{t/t-1}^p$$

Where Y : Output gap, $\bar{\pi}$: Inflation deviation from target, π^{USA}: USA Inflation, Δs : Nominal devaluation, ICI: installed capacity index, CCI: consumer confidence index.

The second alternative (Equation 3), considers as a measure of the unanticipated monetary policy shocks the forecasting errors of the expectations of the policy rate made by the agents through the monthly expectations survey[3].

$\Psi'_t = TI_t - E_{t-1}(TI_t)$ (Eq. 3)

The estimation results for the 90-day deposit interest are shown in Table 1.

Table 1. Estimation of effect of unanticipated monetary policy shock

90-day Deposit rate		
Coeficient	1	2
Shock	0.44	0.49
	(0.11)	(0.17)
constant	-0.005	-0.003
	(0.00)	(0.00)
Adjusted R^2	0.28	0.11

* Significant at 10%, ** significant at 5%, *** significant at 1%
1: monetary shock estimated as the forecasting error from equation 2
2: monetary shock estimated as the forecasting error from expectation survey

The coeficient associated to the monetary shock with both measures of the shock is positive, significant and close each other and may be interpreted as the change in the 90-day deposit rate due to an unanticipated change in the policy rate.

The estimation results for the credit rates are shown in Table 2.

Table 2. Estimation of the effect of unanticipated monetary policy shock on the commercial credit interest rates

Commercial credit rates

Ordinary loans			**Preferential loans**		
	1	2		1	2
Shock	0.43	0.58	Shock	0.56	0.7
	(0.11)	(0.22)		(0.11)	(0.22)
constant	-0.003	-0.004	constant	-0.005	-0.003
	(0.00)	(0.00)		(0.00)	(0.00)
Adjusted R^2	0.11	0.06	Adjusted R^2	0.17	0.08

* Significant at 10%, ** significant at 5%, *** significant at 1%
1: monetary shock estimated as the forecasting error from equation 2
2: monetary shock estimated as the forecasting error from expectation survey

[3] The monthly expectations survey is applied to financial analysts and some institutions of economic research. It asks expectations about future inflation, Exchange rate, output and the policy rate for different horizons.

The results indicate that the monetary policy shock, obtained with both methodologies is significant in explaining the changes in both commercial credits rates. However, for preferential loans, the transmission is higher than for ordinary loans and there is a non negligible difference in the estimates of the two definitions of the shock.

Using Equation 1 and the local proyections methodology proposed by Jordà (2005), we estimate the impulse-response function of a monetary shock on the market interest rates. The FIR for the 90-day deposit rate is shown in Figure 2 for both definitions of the shocks. The effect is larger and longer for the shock estimated from the model than from the survey of expectations. For expectations definition of the monetary shock, the effect is bigger one month after the shock (84%) and last up to 10 months. For the shock obtained from the model the peak of the effect of the monetary shock is also one month after the shock is observed, but the effect is smaller (55%) and last longer, up to 15 months.

Figure 2. FIR of a monetary policy shock on the 90-deposit interest rate

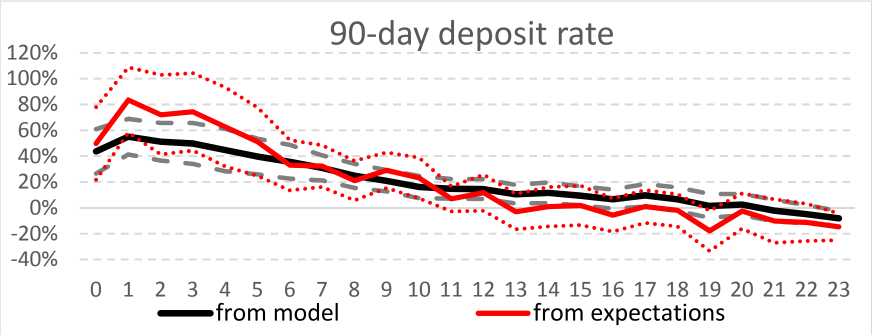
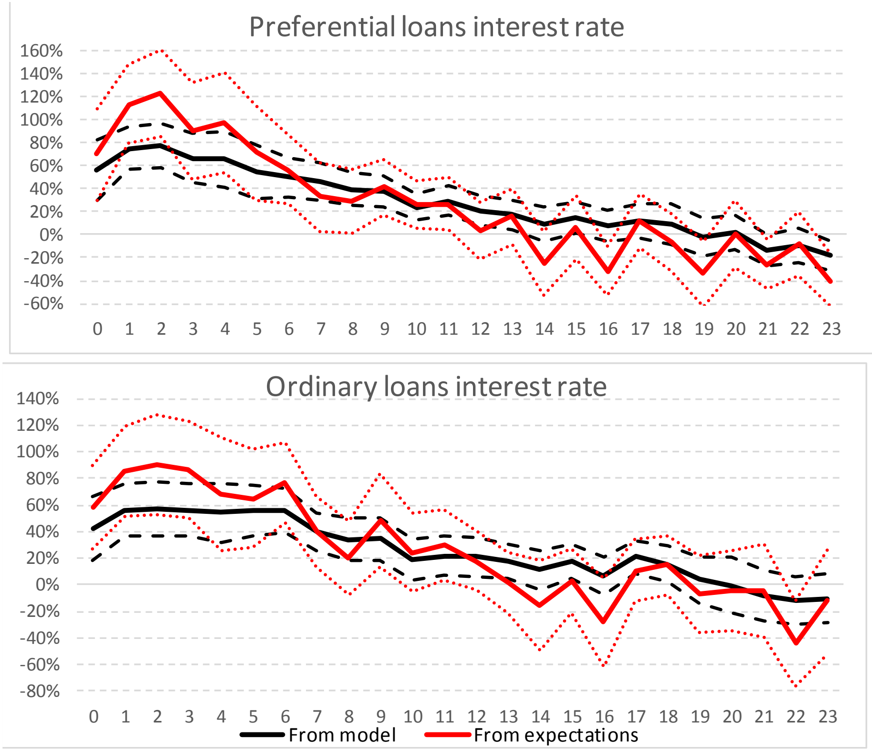


Figure 3. FIR of a monetary policy shock on commercial credit interest rates



For credit rates, we observed that the effect is higher for the preferential than for the ordinary loans rate. The duration of the effect is shorter than the observed for the deposit rate, about 8 to 10 months. The reaction of credit rates is bigger for the shock defined from expectations than from the model. The preferential rate overreact to the unanticipated change in the policy rate with the former definition of the shock and the peak of the effect is two months after the shock occurs. For the ordinary rate the reaction is less than proportional to the shock but also the peak is two months after the shock occurs. With the later defintion of the shock, the effect last longer, like 12 to 13 months, and the magnitud of the responses are inferior to those of the shock measured with expectations. Again, the effect is bigger for the preferential rate than for the ordinary rate.

3.2 unanticipated monetary shocks estimated as the average of short-run expectations

In theory, market interest rates can be defined as the average of the short run interest rates up to maturity. In this exercise, we use the policy rate as a proxy of the short-run interest rate and the 90-day deposit rate as the market rate. It is not possible to do this exercise for the commercial credit rates since the maturiry is at least a year and there is not expectations for the policy rate available for further horizons than eleven months ahead. Thus, the 90-day deposit rate in monrth t, is defined as the average of the policty rate in month t, and the expectations for the next two months (i_t^{mp}), $E_t[i_{t+1}^{mp}]$ y $E_t[i_{t+2}^{mp}]$.

$$i_t^{90-day} = \frac{1}{3}\left(i_t^{mp} + E_t[i_{t+1}^{mp}] + E_t[i_{t+2}^{mp}]\right) \qquad \textit{(Eq. 4)}$$

Thus, the change in the 90-day deposit rate is represented by:

$$\Delta i_t^{90-day} = \frac{1}{3}\left(i_t^{mp} - E_{t-1}[i_t^{mp}]\right) + \frac{1}{3}\left(E_t[i_{t+1}^{mp}] - E_{t-1}[i_t^{mp}]\right) + \frac{1}{3}\left(E_t[i_{t+2}^{mp}] - i_{t-1}^{mp}\right) \qquad \text{(Eq. 5)}$$

then, by adding an error term, the model may be rewritten as:

$$\Delta i_t^{90-day} = \alpha_1\left(i_t^{mp} - E_{t-1}[i_t^{mp}]\right) + \alpha_2\left(E_t[i_{t+1}^{mp}] - E_{t-1}[i_{t+1}^{mp}]\right) + \alpha_3 E_t[i_{t+2}^{mp} - i_{t-1}^{mp}] + \epsilon_t \text{ (Eq. 6)}$$

Where we define the following terms:

$$unanticipated\ monetary\ policy\ surprise = i_t^{mp} - E_{t-1}[i_t^{mp}]$$
$$expectations\ revision = E_t[i_{t+1}^{mp}] - E_{t-1}[i_{t+1}^{mp}]$$
$$expectations\ of\ the\ monetary\ policy\ rat\ in\ the\ whole\ period = E_t[i_{t+2}^{mp} - i_{t-1}^{mp}]$$

The last term is the total change of the monetary policy rate in the whole period up to maturity of the 90-day deposit rate, which is the average of the changes in the policy rate of each month.

$$E_t[\Delta i_{t+2}^{mp} + \Delta i_{t+1}^{mp} + \Delta i_t^{mp}] \qquad \text{(Eq. 7)}$$

then,

$$\Delta i_t^{90-day} = \alpha_1\ unanticipated\ monetary\ shock + \alpha_2 expectations\ revision + \alpha_3 expectation\ of\ total\ change\ in\ the\ policy\ rate + \epsilon_t$$

In order to estimate the Equation 6 we use the expectations for the policy rate from the monthly expectation survey. Results are shown in Table 3.

Table 3. Estimation of Equation 6

	Coeficient	Estimate	std error
Monetary policy surprise	α_1	0.188	0.089
expectation revision	α_2	0.124	0.121
expectation of total change in the polity rate	α_3	0.465	0.095

* Significant at 10%, ** significaant at 5%, *** significant at 1%

Both (α_1) and (α_3) coeficients are significant and thus, the monetary policy shocks and the expectations on the total change of the policy rate up to maturity are important to set martket 90-day deposit rate. On the other hand, it seems that the revisions of agents expectations (α_2) has not effect on setting the market rate.

In general the estimated model validates the theorical model, since the hyphotesis of equal weights of the three components, equal to (1/3) is not rejected, although the parameter of the expectations revision is not significant.

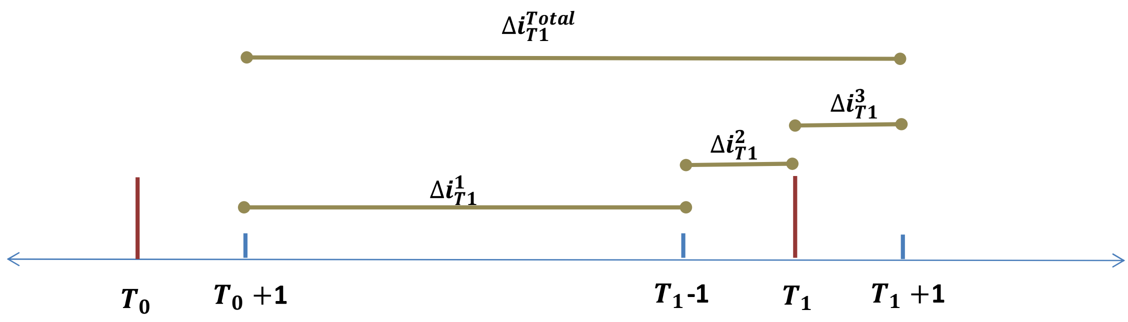
In summary, the changes in the 90-day deposit rate are mainly explained by the expectations of the agents about the changes in the policy rate as well as the monetary policy surprises, while the revisions of the expectations agents make about the policy rate on the different horizons up to maturity (90 days) seems not to be relevant to set this passive interest rate.

3.3 estimation of the effect of the changes in the policy rate through time.

Another alternative to check the transmission of the changes in the monetary policy rate to the market rates that involve expectations of the agents about the policy rate is the methodology proposed by Roley y Sellon (1995). They propose to analyse the effect in different moments during a month. Thus, estimate the anticipated effect, the effect that ocurs the day of the policy announcement and the day after the announcement. So, if for example the Board of Directors made two announcements about changes in the policy rate at the end of month T_0 and at the end of month T_1, then the three mentioned effects could be measure in the following way:

1. The anticipated effect $\left(\Delta i_{T_1}^1 = i_{T_1-1} - i_{T_0+1}\right)$ is the change in the market rate between the day after the later announcement (T_0+1) and the day before the actual announcement (T_1-1). Thus, this effect catches the revisions of the expectations of future actions of the monetary authority due to either a monetary policy surprise at time T_0 or for a change in the fundamentals, incorporating new information about the state of the economy, and then market interest rates are adjusted days before the actual announcement of the monetary authority.
2. The effect that ocurs the day of the announcement $\left(\Delta i_{T_1}^2 = i_{T_1} - i_{T_1-1}\right)$ is the change in the market rate between the day before the announcement (T_1-1) and the day of the announcement (T_1).
3. The inmmediate effect $\left(\Delta i_{T_1}^3 = i_{T_1+1} - i_{T_1}\right)$ is the change in the market rate between the day of the announcement (T_1) and the day after that (T_1+1).
4. Thus, the total effect $\left(\Delta i_{T_1}^{Total} = i_{T_1+1} - i_{T_0+1}\right)$ is the total change of the market rate between (T_0+1) y (T_1+1), which is the sum of the three former effects.

Figure 4. Decomposition of the effect of a policy rate change in the market rate



With this definitions we can estimate the effect of a change in the policy rate on the market rate on the three periods of time and the aggregate response using the following model:

$$\Delta i_T^j = \phi_0 + \phi_1 \Delta i_T^{mp} + \nu_T \quad con \ j = 1{,}2{,}3{,}4$$

The results of this exercise for the 90-day deposit rate are shown in Table 4.

Table 4. The effect of a change in the policy rate on the 90-day deposit rate

	Before MP decision	Day of the MP decision	Day after MP decision	Total change
ϕ_1	0.440***	-0,081	0.265*	0.624***
	(0,1476)	(0,1472)	(0,1363)	(0,1090)
ϕ_0	0.0015***	-0.0015***	-0,0001	-0,0001
	(0,0004)	(0,0004)	(0,0004)	(0,0003)

* Significant at 10%, ** significant at 5%, *** significant at 1%

The estimation results suggest that the martket adjust interest rates with anticipation to the Board of Directors announcement and in second place, the day after the announcement. Changes that ocurr the day of the announcement are not significant in the setting of the market rates. As a result, summing up all the three effects, the complete response is around 62% of the change in the policy rate. In summary, the anticipated effect is the most important in setting the 90-day deposit rate by the financial institutions.

4. Conclusions

In this document we evaluate three methodologies to estimate the effect of expectations about the monetary policy rate and the unanticipated changes in the policy rate on the market deposit and credit interest rates. The results show that in first place, the monetary policy surprises have an important effect on setting the market rates for both deposits and credits finding a bigger effect on credit than in deposit rates.

In the particular case of the 90-day deposit rate, the factor that seems to mainly explain the dynamic of the market rate are the expectations of the policy rate and in second place the presence of unanticipated changes in the policy rate.

Finally, the third exercise, suggest that the 90-day deposit rate changes with anticipation to the changes in the policy rate as the agents expectations take into account that a change in the policy rate would take place in the future. On the other hand, changes after the announcement of monetary policy are not significant. These results validate the importance of expectations on the policy rate when setting market interest rates.

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Evaluation of the transmission of the monetary policy interest rate to the market interest rates considering agents expectations [1]

Deicy Cristiano-Botia, Eliana Gonzalez-Molano and Carlos Huertas-Campos,
Bank of the Republic, Colombia

[1] This presentation was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

Transmission of the policy rate to market interest rates considering agentes expectations

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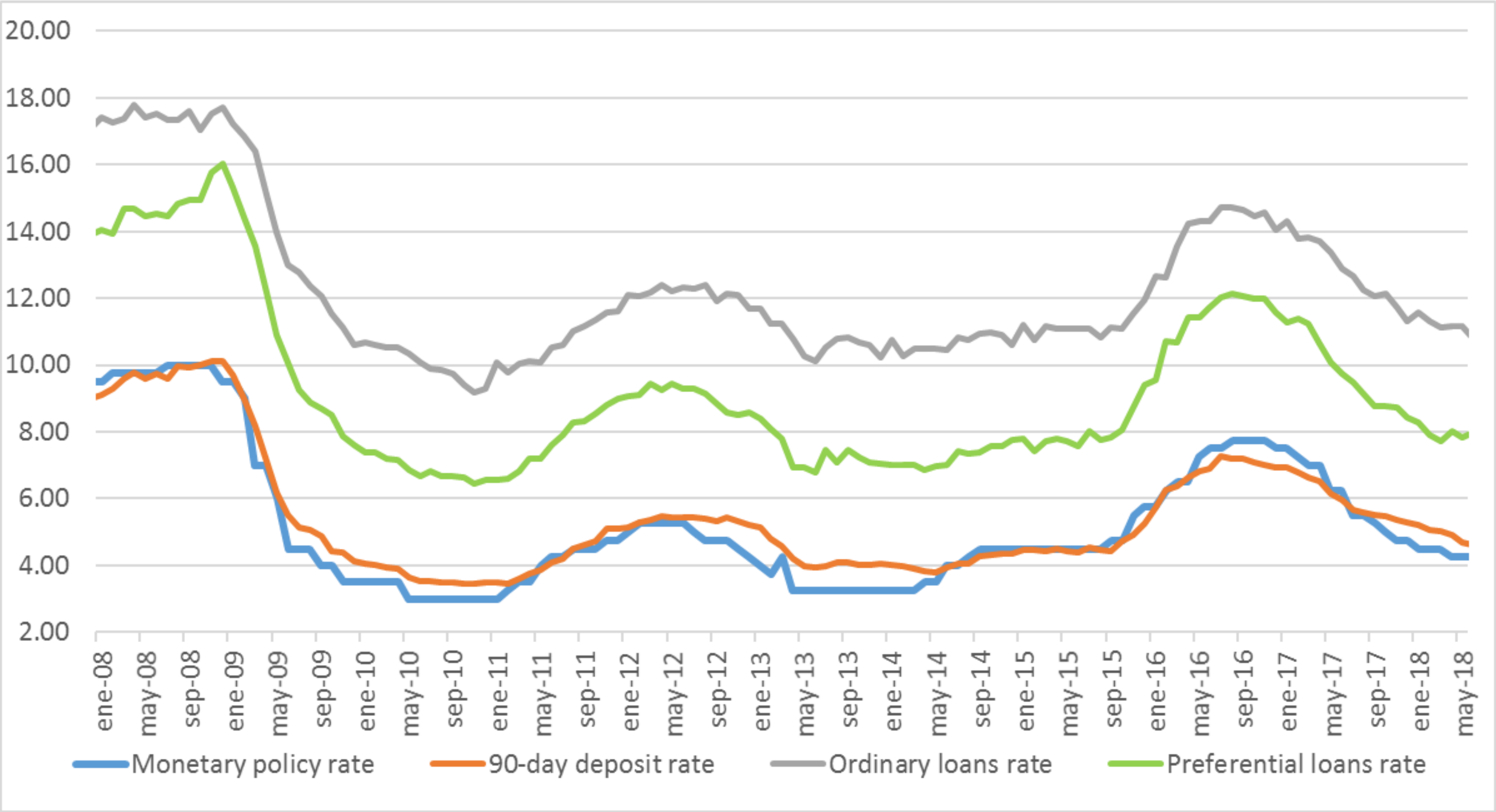
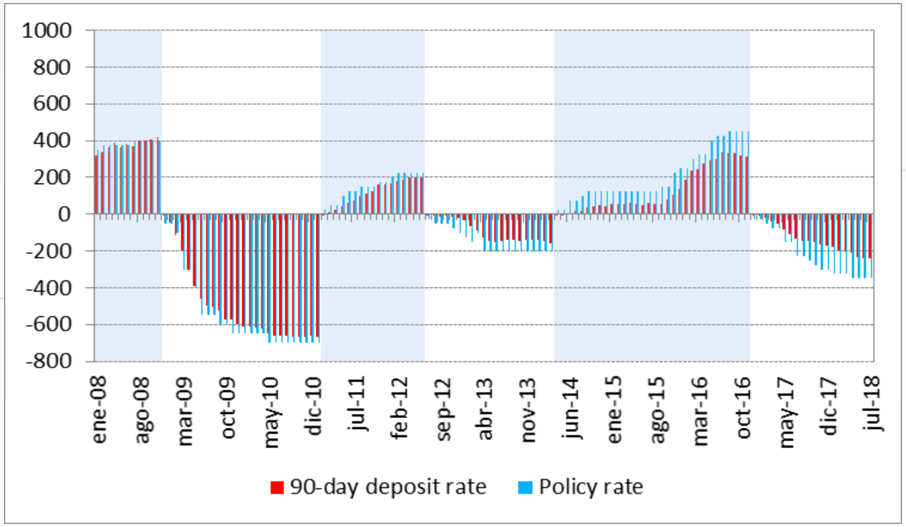
Banco de la República de Colombia

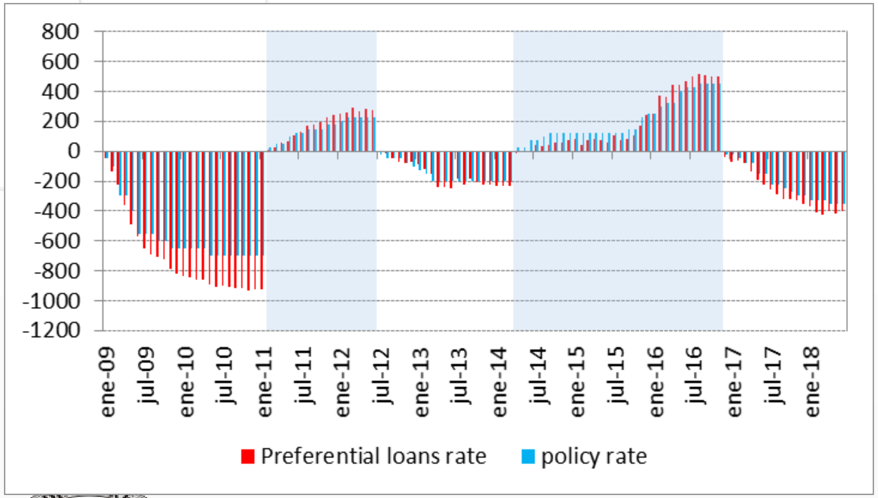
August, 2018

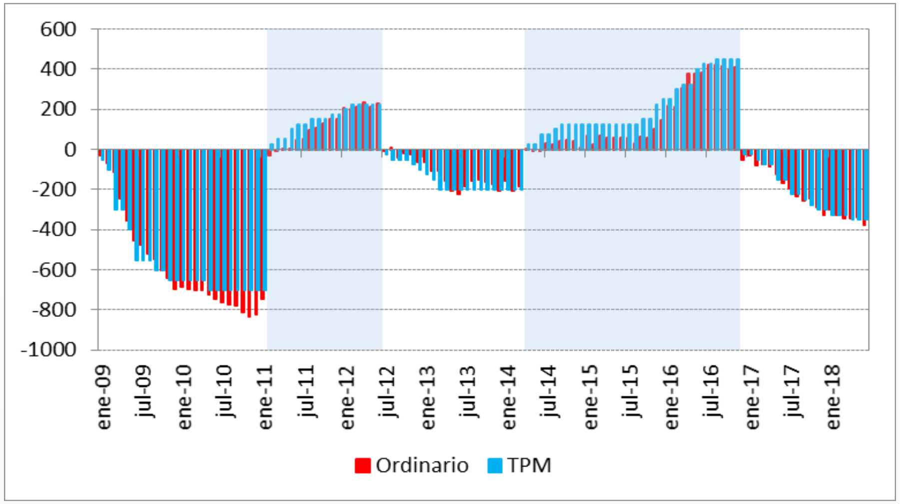
MARKET INTEREST RATES AND MONETARY POLICY RATE



Cummulative change since the change in monetary policy stance(BP)







installed capacity

The effect of unanticipated monetary policy shocks

$$\Delta i_t = \alpha_0 + \alpha_1 \Psi_t + \epsilon_t$$

1. Estimación of monetary policy shocks as one-period forecasting errors from the model:

$$i_t^p = f(Y, \bar{\pi}, \pi^{USA}, \Delta s, ICI, CCI)_{t-p} + \Psi_t$$

$$\Psi_t = i_t^p - \ i_{t/t-1}^p$$

Where Y : Output gap, $\bar{\pi}$: Inflation gap from target, π^{USA}: USA Inflation, Δs : Nominal devaluation, installed capacity index, consumer confidence index.

The effect of unanticipated monetary policy shocks

2. Estimation of monetary policy shocks as forecasting errors from the monetary policy rate expectations (survey of experts)

$$\Psi'_t = i_t^p - E_{t-1}\left(i_t^p\right)$$

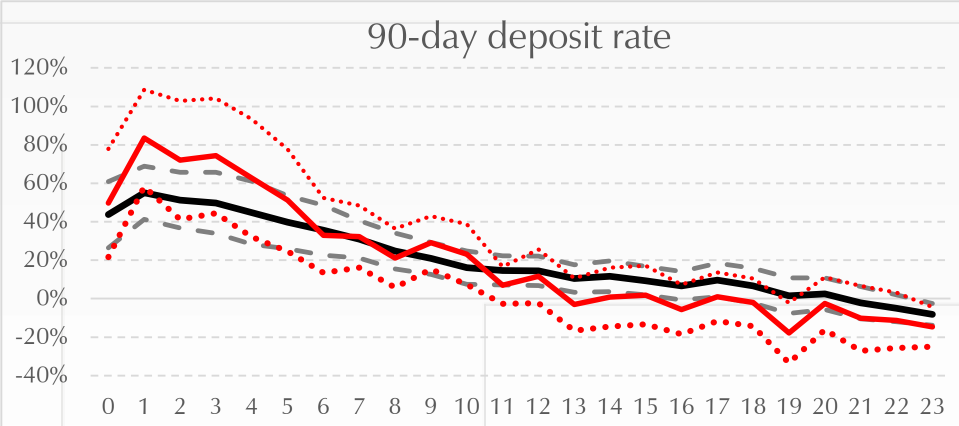
90-day Deposit rate

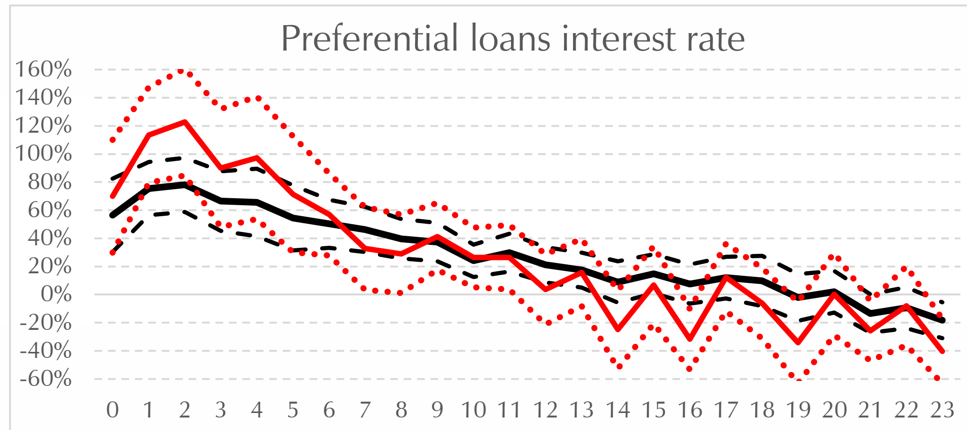
Coeficient	1	2
Shock	0.44	0.49
	(0.11)	(0.17)
constant	-0.005	-0.003
	(0.00)	(0.00)
Adjusted R^2	0.28	0.11

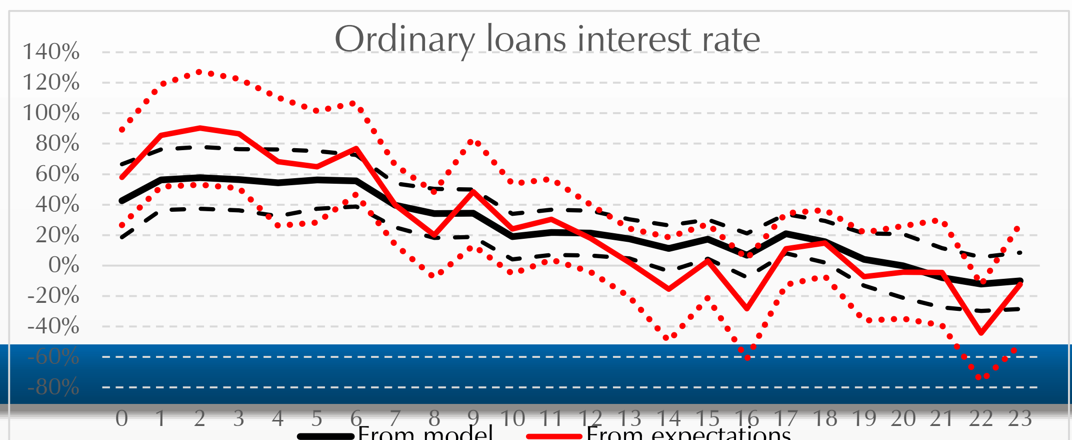
Commercial credit rates

	Ordinary loans		Preferential loans	
	1	2	1	2
Shock	0.43	0.58	0.56	0.7
	(0.11)	(0.22)	(0.11)	(0.22)
constant	-0.003	-0.004	-0.005	-0.003
	(0.00)	(0.00)	(0.00)	(0.00)
Adjusted R^2	0.11	0.06	0.17	0.08

Impulse-response function of an unanticipated monetary policy shock







UNANTICIPATED MONETARY SHOCKS ESTIMATED AS THE AVERAGE OF SHORT-RUN EXPECTATIONS

$$i_t^{90-day} = \frac{1}{3}\left(i_t^{mp} + E_t\left[i_{t+1}^{mp}\right] + E_t\left[i_{t+2}^{mp}\right]\right)$$

$$\Delta i_t^{90-day} = \frac{1}{3}\left(i_t^{mp} - E_{t-1}\left[i_t^{mp}\right]\right) + \frac{1}{3}\left(E_t\left[i_{t+1}^{mp}\right] - E_{t-1}\left[i_t^{mp}\right]\right) + \frac{1}{3}\left(E_t\left[i_{t+2}^{mp}\right] - i_{t-1}^{mp}\right)$$

$$\Delta i_t^{90-day} = \alpha_1\left(i_t^{mp} - E_{t-1}\left[i_t^{mp}\right]\right) + \alpha_2\left(E_t\left[i_{t+1}^{mp}\right] - E_{t-1}\left[i_{t+1}^{mp}\right]\right) + \alpha_3 E_t\left[i_{t+2}^{mp} - i_{t-1}^{mp}\right] + \epsilon_t$$

$$unanticipated\ monetary\ policy\ surprise = i_t^{mp} - E_{t-1}\left[i_t^{mp}\right]$$

$$expectations\ revision = E_t\left[i_{t+1}^{mp}\right] - E_{t-1}\left[i_{t+1}^{mp}\right]$$

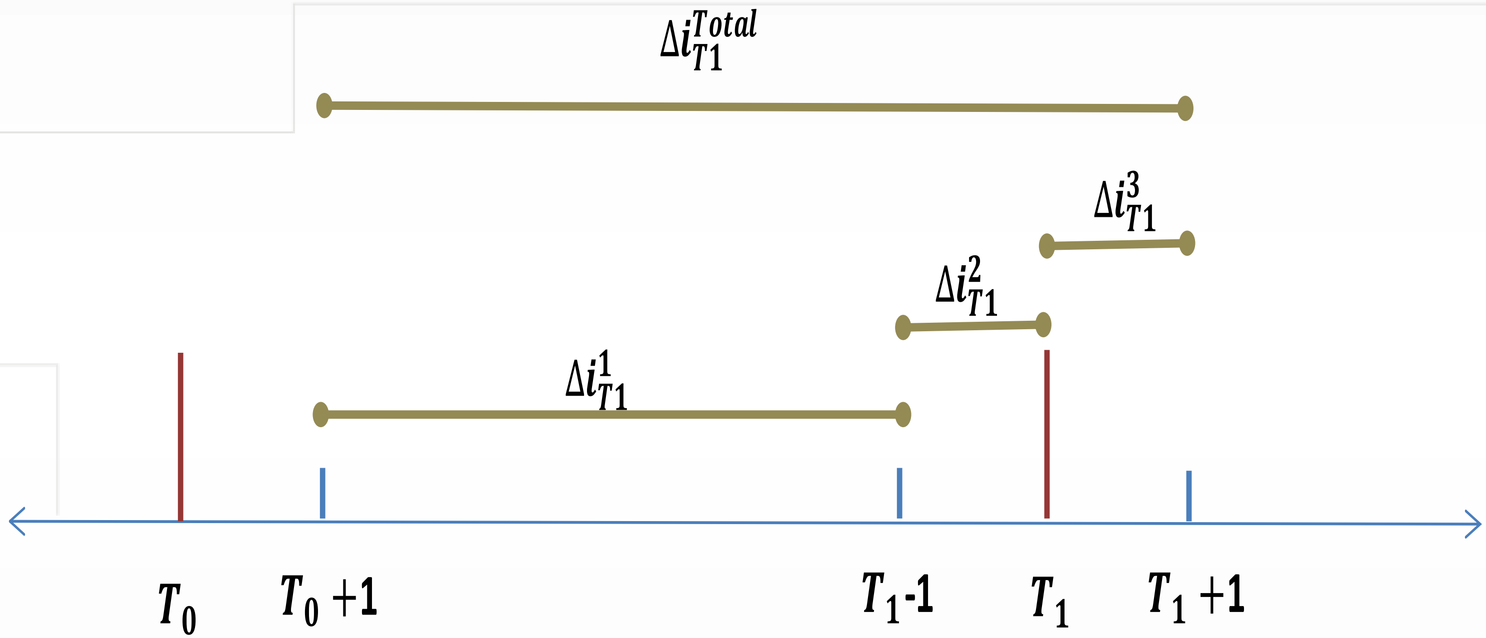
$$expectations\ of\ the\ \text{change in}\ MP\ rate\ in\ the\ whole\ period = E_t\left[i_{t+2}^{mp} - i_{t-1}^{mp}\right]$$

$$= E_t\left[\Delta i_{t+2}^{mp} + \Delta i_{t+1}^{mp} + \Delta i_t^{mp}\right]$$

Estimation results

	Coeficient	Estimate	std error
Monetary policy surprise	α_1	0.188	0.089
expectation revision	α_2	0.124	0.121
expectation of total change in the polity rate	α_3	0.465	0.095

How does the daily deposit interest rate change with The monetary policy decisions



$$\Delta i_T^j = \phi_0 + \phi_1 \Delta TI_T + \nu_T \quad with\ j = 1,2,3,4$$

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	(0,0004)	(0,0004)	(0,0004)	(0,0003)