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Data needs and Statistics compilation for macro-prudential analysis

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Brussels, Belgium, 18–19 May 2017

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Data needs and statistics compilation for macroprudential analysis

Overview of the workshop

Jose Maria Serena and Bruno Tissot[1]

Introduction

Macroprudential policy: new data needs after the Great Financial Crisis

The Great Financial Crisis (GFC) of 2007–09 showed that a **system-wide perspective** is needed to properly assess financial stability risks that would otherwise remain buried in institution-level metrics.[2] This lesson reflects two major characteristics of the financial system. One is its procyclicality: fragilities had increased largely unnoticed over a long period of time before the GFC, as rising leverage sustained valuations. The ensuing financial bust was precipitated by a general deleveraging and sharp corrections in asset prices. The second characteristic is the "cross-sectional" dimension of systemic risk. In particular, interlinkages between institutions played a key role in triggering the GFC, as disruptions from major counterparties hit entities with seemingly sound financial positions.

The implication, as clearly recognised in the aftermath of the GFC, is that a specific set of policy actions are needed to address systemic risk. So-called macroprudential tools have thus become an important element of the toolkit in supporting financial stability. They complement more "traditional" policy tools, such as those used for microprudential supervision, monetary policy, liquidity provision etc. Comprehensive **macroprudential policy frameworks** now set clear objectives, such as strengthening the financial system against shocks, dampening the financial cycle, and identify the relevant instruments.[3]

Data issues have, however, substantially hindered the operationalisation of these frameworks. For instance, the construction of useful systemic risk indicators requires

1 Respectively, Economist, BIS Monetary and Economic Department (jose.serena@bis.org); and Head of Statistics and Research Support, BIS and Head of the IFC Secretariat (bruno.tissot@bis.org). The views expressed here are those of the authors and do not necessarily reflect those of the Bank for International Settlements or the Irving Fisher Committee on Central Bank Statistics or the National Bank of Belgium. This overview benefited from comments by Andre Dias, Robert Kirchner, Olga Monteiro and Stephan Müller.

2 See J Caruana, "Macroprudential policy: what we have learned and where we are going", Keynote speech at the Second Financial Stability Conference of the International Journal of Central Banking, Bank of Spain, Madrid, 17 June 2010.

3 See CGFS, "Macroprudential instruments and frameworks: a stocktaking of issues and experiences", *CGFS Papers*, no 38, 2010.

a large amount of granular information on the financial system, in order to cover its various segments, participants and instruments. Unfortunately, existing statistical sources have shown important limitations in terms of data availability, quality and timeliness, thereby limiting their usefulness. The development of new macroprudential frameworks has thus been accompanied by major efforts to design and collect new data sets. Cases in point have been the actions undertaken in the context of the G20 Data Gaps Initiative (DGI), with close coordination among the various international bodies associated in the Inter-Agency Group on Economic and Financial Statistics (IAG).[4] These international efforts to close data gaps have accompanied various domestic initiatives; for instance, several national authorities have taken steps to set up useful indicators of procyclicality in the financial system, monitor vulnerabilities at the firm- and household-level, and measure interconnectedness among participants in the financial system.

The workshop: stocktaking after 10 years of data collection

A decade after the GFC, authorities are showing an increasing interest in taking stock of the various post-crisis data collection initiatives. This is particularly true for central banks, which have witnessed a **huge increase in the statistics** they collect. They have also been at the forefront of efforts to ensure greater consistency between new micro-level data sets and more traditional aggregates,[5] adapt data frameworks to the rapidly evolving financial system,[6] and exploit granular firm-level data sets for financial stability work.[7]

Three reasons underscore the **importance of taking stock** of the recent data initiatives undertaken to support macroprudential frameworks. First, several projects have come to fruition, and many new data sets are now available for analysis. Second, the process has revealed new data gaps, prompting additional waves of data collection. Finally, the various initiatives have been truly multidisciplinary, involving statistical, economic, monetary and financial stability departments. All this calls for a comprehensive and holistic review.

Against this backdrop, a workshop in Brussels was co-organised by the Irving Fisher Committee on Central Banks Statistics (IFC) with the National Bank of Belgium (NBB) in May 2017. The aim was to share views on strategies, successes and challenges in data collection for macroprudential analysis, revisiting the earlier stocktaking exercises undertaken just after the GFC.[8] Almost 100 participants from 38 jurisdictions took part, coming from various institutions and backgrounds. As argued by Claudia Buch, IFC Chair and Vice President of Deutsche Bundesbank, in her keynote remarks, this was a timely opportunity to evaluate the post-crisis financial sector reform agenda, and the contribution of statistics collected in the context of the DGI. Three

[4] See FSB-IMF, "The financial crisis and information gaps", 2009, for the first phase of the DGI; and IMF and FSB, "The financial crisis and information gaps – sixth implementation progress report of the G20 Data Gaps Initiative", 2015, for its second phase (2016–20).

[5] See IFC, "Combining micro and macro statistical data for financial stability analysis", *IFC Bulletin*, no 41, May 2016.

[6] See IFC, "Statistical implications of the new financial landscape", *IFC Bulletin*, no 43, March 2017.

[7] See IFC, "Uses of central balance sheet data offices' information", *IFC Bulletin*, no 45, October 2017.

[8] For similar discussions at an early stage of the process, see IFC, "Initiatives to address data gaps revealed by the financial crisis", *IFC Bulletin*, no 34, December 2011.

aspects seem crucial. First, the success of the evaluation of financial sector reforms post-implementation will depend on the availability of granular data. Second, assessing risks in the shadow banking sector will call for more intensive use of existing data infrastructure, and the simultaneous development of adequate analytical tools – especially to strengthen the understanding of transmission channels. Third, evaluating shock propagation across borders requires timely entity-level data, putting a premium on accessing and sharing sufficiently granular information and on using common identifiers to link different micro data sets.

The meeting comprised four parts. The first part discussed the implications for statistics of the new macroprudential frameworks. The second part focused on areas where substantial data gaps still constrain macroprudential analyses: namely, the measurement of prices in the real estate sector, the assessment of household vulnerabilities, shadow banking and, more generally, the new patterns of financial intermediation that have emerged post-crisis. The third part was devoted to derivatives markets, with a focus on making use of the new data collected by trade repositories (TRs). The last part dealt with the increasing use of granular, loan-by-loan data sets for macroprudential analysis. The workshop closed with a policy panel discussion, chaired by Marcia De Wachter (NBB), which presented a useful opportunity to review the policy usefulness of the data collected since the GFC.

Key takeaways

The various experiences presented at the workshop highlighted a number of important messages for central bank statisticians:

- Many authorities have **successfully managed to adapt in-house data sets** for new macroprudential purposes. For instance, existing statistics designed to fulfil a specific function have been successfully used to assess certain financial stability risks. Examples include work with credit registers, monetary statistics, financial institutions' supervisory records, or household finance surveys. However, the repurposing of these data sets did require substantial methodological work.
- The data collection exercises launched after the GFC have helped to **close several data gaps**, especially in the areas of shadow banking and large institutions. Particularly in the context of the DGI, globally harmonised information has been made available on non-bank entities involved in financial intermediation[9] and on systemically important institutions.[10] Moreover, many of these new data sets are highly granular, and can thus shed useful light on the distribution of risks within the financial system.
- **Important data needs remain** despite these efforts. Cases in point are real estate markets, especially as regards information on commercial property

9 See the results of the last annual FSB survey on shadow banking in FSB, *Global Shadow Banking Monitoring Report 2016*, May 2017.

10 See E Bese Goksu and B Tissot, "Monitoring systemic institutions for the analysis of micro-macro linkages and network effects", International Statistical Institute 61st World Statistics Congress, July 2017; and Senior Supervisors Group, "Senior Supervisors Group progress report on counterparty data", January 2014.

prices,[11] and derivatives markets, for which there is a clear need to make a better use of the various information collected on derivatives contracts and reported to TRs. Perhaps more importantly, given the growing impact of economic and financial globalisation, the monitoring of global corporations remains challenging: their activities straddle (reporting) borders and are difficult to capture with current residency-based statistical frameworks.[12] There is in particular a clear need to improve the measurement and understanding of cross-border financial and non-financial linkages.

- There is rising demand for **empirical analysis using granular data** to support financial stability work. For instance, understanding how shocks propagate themselves within the financial system may require entity-level information on interlinkages and spillover effects – domestically and even more so internationally. Effective use of such granular data depends on two key requirements. One is well established data-sharing frameworks, both within and between countries,[13] supported by adequate data dissemination standards.[14] The other is the broader use of global identifiers, such as the Legal Entity Identifier (LEI):[15] this is a clear requirement if granular data sets are to be matched across different sources, so that useful financial stability analyses can be developed.
- A key policy issue is that all these data gaps still significantly hinder the **effective assessment of the impact of the post-crisis reforms**.
- Analysing the new statistics collected since the GFC has raised **a number of important challenges**. A major one is that ensuring consistency between micro and aggregated data sets is often difficult. Moreover, a number of the newly developed granular data sets are very large and require substantial quality checks, with important implications for IT systems. Furthermore, processing and interpreting complex data sets calls for sophisticated techniques and tools. It also puts a premium on rationalising existing data collections through unified reporting schemes as well as on matching existing data sets that can be used as complementary sources.
- Lastly, rapid innovations in financial markets and technology call for **vigilance**. Despite important progress in setting up comprehensive macroprudential frameworks post-crisis and collecting the associated statistics, a fully detailed, real-time heat-map of financial system risks is still far out of reach.

11 Despite the recent expansion of the related indicators disseminated by the BIS (following up on the DGI recommendations) on prices for residential properties and, more recently, commercial property; see www.bis.org/statistics/pp.htm.

12 See in particular Inter-Agency Group on Economic and Financial Statistics, "Consolidation and corporate groups: an overview of methodological and practical issues", IAG reference document, October 2015.

13 See IFC, "The sharing of micro data – a central bank perspective", December 2016.

14 In particular the key Statistical Data and Metadata Exchange (SDMX) standard supported by the international community; see IFC, "Central banks' use of the SDMX standard", March 2016.

15 See Legal Entity Identifier Regulatory Oversight Committee, "Collecting data on direct and ultimate parents of legal entities in the Global LEI System – Phase 1", 10 March 2016.

Part 1: Databases for macroprudential analysis and policy

The first part of the meeting, chaired by Aurel Schubert, IFC Vice Chair and ECB, discussed the **impact of recent macroprudential frameworks on statistics**. Many jurisdictions are setting up new macroprudential tools, requiring adequate indicators to gauge the build-up of systemic risks and guide appropriate policy responses. One example has been the growing policy need to assess the state of the credit cycle. Other indicators are also urgently needed, for instance, to identify risks in sectors that are critical from a financial stability perspective, such as real estate markets.[16] Yet gathering the data to construct such indicators is not always easy. In many cases, there is a lack of sufficiently long and varied historical statistical series to properly assess developments in the financial cycle. Furthermore, effective macroprudential frameworks require early warning indicators, the definition of adequate policy measures, and ways of assessing their impact. To this end, several authorities have embarked on ambitious compilation exercises to document the various macroprudential tools that have been set up, implemented and assessed.

The first paper, co-authored by the NBB, the ECB and the European Systemic Risk Board (ESRB), reviewed the **indicators set up to guide macroprudential policy** in the European Union (EU). Many relevant macroprudential statistics are already available and compiled by a variety of producers – eg central banks, financial supervisors, international financial institutions as well as commercial data providers. The so-called Macroprudential Database comprised 275 indicators, harmonised across the 28 EU countries and released on a regular basis. However, some important data gaps remained in Europe, especially as regards residential and commercial real estate markets as well as on non-bank financial intermediation. Another important consideration was that the Macroprudential Database had to be updated regularly to effectively capture the evolving financial system.

Several years of macroprudential policy implementation in the EU have also increased the need to track authorities' policy actions. In this regard, the second presentation described the ESRB **database on macroprudential measures**, collected since 2014. This database provides several dimensions, such as the type and timing of each measure implemented, the authority involved, and the intended purpose. A key priority is that the available information is promptly disseminated to support the assessment of the impact of specific measures (including across sectors and borders). For instance, a specific webpage provides updated information on banks' countercyclical capital buffers.

Yet the compilation of macroprudential databases is often **challenging**, as highlighted by the experience of the Central Bank of Montenegro in computing the credit-to-GDP gap – a key indicator used to guide the activation and deactivation of countercyclical capital buffers.[17] The difficulties arose from the short history of the credit series, the need to take into consideration the impact of financial deepening, and the measurement of the financial cycle itself. To deal with these challenges, the central bank was considering a wider set of alternative indicators to assess the build-up of risks in the financial sector and guide countercyclical capital requirements – eg

[16] See CGFS, "Operationalising the selection and application of macroprudential instruments", *CGFS Papers*, no 48, December 2012.

[17] See also the BIS statistics on credit-to-GDP gaps, www.bis.org/statistics/c_gaps.htm?m=6%7C380%7C670.

the actual level of credit provided to the economy, the degree of maturity transformation, and the importance of foreign lending.

The fourth presentation, by Eurostat, discussed the **specific data required to identify risks in the real estate sector**, which can play an important role from a macroeconomic and a financial stability perspectives. There was a need to consider various price indicators for rental properties because of different methodologies and measurement methods – eg weights based on transactions or stocks; standard or quality-adjusted prices etc. For instance a simple transaction-weighted index of unadjusted prices could be useful in tracking the emergence of asset price bubbles in real estate markets. But assessing banks' default risk would require the residual value of their collateral, and thus also of the depreciation of the underlying asset over time to be measured. To this end, it was more pertinent, first, to use quality-adjusted property price indexes and, second, to look at stocks instead of transactions.

Part 2: Identifying and closing data gaps

The second part of the meeting comprised four sub-sessions devoted to areas where data gaps were the most severe for macroprudential frameworks: the real estate sector; the assessment of households' financial vulnerabilities; shadow banking; and new patterns of financial intermediation.

The real estate sector

This session, chaired by Pedro Duarte Neves (Bank of Portugal), discussed the **financial stability implications of property market developments**. From this perspective, one should distinguish between residential real estate (RRE) and the commercial real estate (CRE) sectors. First, the RRE sector was characterised by large investor exposures, since housing represents a large fraction of households' liabilities. In contrast, overall investor exposure to the CRE sector was smaller and more concentrated among specific institutions, such as banks, pension funds and insurance companies. Second, both sectors were subject to significant price movements over the financial cycle, but the CRE sector had tended to display much higher procyclicality. In both cases, authorities were working to close existing data gaps, in particular by making more intensive use of surveys.

The first presentation, by the ESRB, Bank of Italy, and the French Prudential Supervision and Resolution Authority, discussed the **EU agenda to close data gaps** in RRE and CRE markets. This agenda comprised three steps. The first was to precisely define the boundaries between the RRE and CRE markets, which may vary according to the relevant policy perspective. The second step was to select the appropriate indicators to be monitored, such as concentration of loan portfolios; measures of lending standards (eg collateral values, loan-to-value ratios (LTVs)); and indicators of borrower income (eg loan-to-income ratios (LTIs)). Ideally, these indicators should be considered for both the RRE and the CRE sectors; in practice, however, information was scarcer and less harmonised across jurisdictions in the latter case. The third step was to progressively implement an adequate data collection strategy.

Statistics from **commercial data providers** can be successfully explored to address these data gaps, as highlighted in the second presentation, by the Bank of

France. While authorities had relatively good data on the French RRE sector, official information was lacking on CRE. To fill this gap, data on office prices provided by major real estate agencies could be useful for policy purposes. The aim was to use additional sources of information such as notarial databases.

The third presentation, by the NBB, analysed information from the European **Household Finance and Consumption Survey** (HFCS) to assess risk in the Belgian mortgage market. The HFCS is a euro area-wide survey on financial behaviour that provides household-level information on liabilities and assets. The exercise underlined the importance of using such granular data, for instance, to identify households with high mortgage debt but little in the way of liquid assets, or the proportion of mortgage debt at risk in case of macroeconomic shocks.

The fourth presentation, by the Central Bank of the Republic of Austria, also used the HFCS to **simulate the impact of macroprudential policies** on house prices and credit availability. The results suggested that capping borrower income ratios (eg LTIs) had a greater effect on credit take-up than did restrictions on lending standards (eg LTVs). It also underlined that the high granularity of the data allowed the impact of macroprudential policies to be investigated effectively – for instance to assess their specific impact on highly indebted households, on housing prices etc.

Finally, the last presentation by the ECB and the Central Bank of Ireland (CBI), looked at the usefulness of **property market indicators in guiding policy decisions** to activate and deactivate countercyclical capital buffers. It suggested that, for macroprudential authorities seeking to curb the credit cycle in small open economies, housing prices appeared more useful as indicators than, for example, credit-to-GDP gaps.

Households' financial vulnerabilities

The second session, chaired by João Cadete de Matos (Bank of Portugal), discussed the **financial stability risks posed by households' vulnerabilities**. Central banks, especially in Europe, have long-standing experience in surveying household financial behaviour and this has proved of particular interest for assessing the resilience of households to adverse shocks.

The first presentation, by the Czech National Bank, described **stress-testing exercises** to measure households' ability to service debt in case of macroeconomic shocks, such as a rise in interest rates or a fall in incomes. The analysis was based on a specific survey, complemented by other data sources, eg micro-level data sets on mortgage payments and the European HFCS. Such complementarity can be quite useful since the data can provide different types of information (eg transactions versus stocks) and differ significantly in terms of timeliness.

The **importance of using timely data** for vulnerability analyses was reinforced in the second presentation by the ECB. The starting point was the fact that the HFCS represents a rich source of harmonised information on income, wealth and debt, covering many EU countries. It also allows pockets of vulnerability to be identified according to standard metrics, and provides relevant information on the types of household surveyed: size, income, type of debt, employment status etc. But the interest of HFCS data for policy purposes is limited by the survey's three-year publication lag, which could put a premium on timelier but less granular alternative data sets (eg national accounts) or on the use of microsimulation techniques to simulate the behaviour of individual households over time.

The third presentation, by the Central Bank of Luxembourg, nevertheless confirmed the usefulness of the HFCS data set for **measuring household indebtedness** (eg debt-to-assets, debt-to-income, or debt-service) **and liquidity** (eg liquid assets-to-income) ratios. Overstretched households were identified using ad hoc thresholds, and tended to be associated with specific characteristics, eg education. Yet one limitation of this approach was the sensitivity of the estimates to the choice of the selected thresholds.

Similarly, the fourth presentation, a joint work by the Deutsche Bundesbank, the ECB and academic researchers, showed how household-level information can be used to shed light on **households' responses to macroeconomic policies**. In particular, the HFCS survey helped to identify heterogeneous patterns that were useful in clarifying aggregate dynamics.

Lastly, the HFCS can also be used to **investigate the risks of financial exclusion**, as argued by the fifth presentation, from the Bank of France. Financial exclusion, defined as the lack of access to certain basic financial services, was found to be positively correlated with specific households' characteristics such as age, unemployment, income and wealth. Moreover, using the successive waves of the HFCS survey allowed for assessing the contribution of these factors over time.

Shadow banking

Several post-crisis initiatives seek to increase the information available on non-banks' involvement in financial intermediation and their contributions to **maturity and liquidity transformation in the financial system**. In particular, the FSB's annual survey on shadow banking has since provided regular harmonised information on the structure and scale of shadow banking in major jurisdictions. However, and as highlighted in the session chaired by Charles Thomas (US Federal Reserve Board of Governors), these initiatives have not closed all data gaps, especially regarding the measurement of financial innovation, the assessment of interconnectedness at the firm level, and the capturing of country specificities.

The first presentation, by the ECB, analysed the recent **work on shadow banking** conducted in the EU and described ongoing initiatives to close remaining data gaps there. The ESRB measure of the shadow banking sector is based primarily on general financial accounts and monetary statistics data, zooming in on entities actively engaged in credit intermediation. This is complemented by specific efforts to use balance sheet data from securities and derivative dealers (SDDs) and financial corporations involved in lending (FCLs), which is collected through a harmonised Eurosystem survey. Looking ahead, the availability of the additional micro-level data sets compiled in response to new regulatory initiatives – in particular the European Market Infrastructure Regulation (EMIR), the Alternative Investment Fund Managers Directive (AIFMD) and the Securities Financing Transactions Regulation (SFTR) – will further contribute to closing the data gaps related to shadow banks.

The second presentation, by the Bank of Canada, focused on how to monitor **peer-to-peer lending companies**. These institutions are entities that match borrowers and lenders online, frequently outside the boundaries of regulated institutions. Gathering information on this particular activity has become pressing, because it is expanding briskly and because stress episodes have already occurred. These companies provide substantial information on their websites, which can be mobilised using "big data" techniques (ie web scraping).[18] An alternative way would be for authorities to organise new targeted data collections, through direct reporting by peer-to-peer institutions or indirect reporting by the group of regulated financial institutions participating in such peer-to-peer platforms.

The third presentation, by the ECB, highlighted the significant contribution made by **the OFIs[19] sector** to general shadow banking activities. Usually, this kind of analysis is done by ranking the various sectors according to their direct interlinkages so as to measure interconnectedness – a key element when assessing the systemic importance of a given sector. The ECB analysis was based on a broader measure of interconnectedness between institutional sectors, using "from-whom-to-whom" financial accounts data[20] in order to capture the indirect exposures related to the OFIs sector.

The fourth presentation, by the BIS, presented an exercise to **identify relationships** between non-financial institutions and their various types of creditor. The starting point was that information on creditors is absent in firms' financial statements. But such entity-level records can be matched with security-level data sets, in turn providing information on lenders to corporates. The resulting information allows the situation of a given corporate to be analysed in a very granular way, depending on its funding structure and exposure to specific lenders – including "non-bank" funding providers.

The fifth presentation, by the Bank of Italy, discussed the importance of **retained securitisation by financial vehicles**, which should be included in shadow banking assets under the approach proposed by the FSB. Yet it was important to carefully consider country-specific situations. In Italy, for instance, retained securitisation activity often reflects banks' debt issuance to obtain securities that could be eligible as collateral in refinancing operations. In that case, the related assets are recorded on bank balance sheets and are thus within the scope of regulators. Moreover, one issue is the valuation of these assets, which can differ markedly, for instance, for securitised non-performing loans that are valued at a discount by the banks but at nominal value by the financial vehicles involved (with the result that the size of the Italian shadow banking sector can be overstated).

New patterns of intermediation

Traditional statistics also face challenges related to **the evolving way the financial system is intermediating between savers and borrowers** – irrespective of the issue of the financial stability risks involved, as analysed above in the session related to shadow banking.[21] The session, chaired by Bruno Tissot (BIS), was an opportunity to

[18] For an overview of central banks' ongoing initiatives in the use of big data techniques, see IFC, "Big data", *IFC Bulletin*, no 44, September 2017.

[19] Other financial intermediaries, except insurance corporations and pension funds (ICPFs).

[20] For an introduction to from-whom-to-whom tables, see B Tissot, "Development of financial sectoral accounts: new opportunities and challenges for supporting financial stability analysis", *IFC Working Papers*, no 15, November 2016.

[21] The issues analysed here – ie the impact of the changes in the way financial intermediation is being provided from lenders to borrowers – overlapped with the ones dealt with in the session on shadow banking. Shadow banks are understood to be "financial institutions that act like banks but are not

shed light on the new patterns of financial intermediation observed since the GFC and their statistical implications. In particular, there has been a growing demand for data on (non-bank) market-based finance as well as for measuring the interconnectedness of financial market participants. To do so, central banks are seeking to make the most of available granular data sets and combine information across various sources, as well as apply new techniques, eg machine-learning.

The first presentation, by the CBI, discussed the activity of bank-sponsored **special purpose vehicles** (SPVs). Foreign banks often use SPVs incorporated in Ireland to securitise their assets, resulting in sizeable cross-border debt financing. But this activity is unrelated to the financing of the domestic economy, thus calling into question the use of standard, residency-based statistics.[22] To better understand the new intermediation patterns, the CBI has been collecting data on debt issuance by SPVs that remains on the balance-sheet of their sponsor banks. This information suggested that foreign banks often used SPVs to circumvent capital flow management measures and high taxation in their home jurisdictions, underlying the importance of looking at those issues in a granular way.

The second presentation, by the NBB, was based on an entity-level analysis, using the Central Balance Sheet Office data set. This granular information showed that a significant part of non-bank financial intermediation in Belgium was provided by **private equity companies**, which should not be considered as being part of the shadow banking sector.

One issue related to the use of large micro databases to **identify new patterns** in financial markets. As argued in the third presentation, by the Deutsche Bundesbank, new "big data" techniques can be quite helpful in addressing the related challenges. In this particular case, machine-learning algorithms were successfully used to enhance the information content of the da ta set on German banks' securities holdings.

The fourth presentation, by the ECB, underlined the importance of **intra-group transactions**. This analysis was based on granular information, particularly sourced from monetary and financial institutions' balance sheets, which showed that EU intra-group loans were quite volatile and had significantly expanded in recent years, reflecting greater banking consolidation.

Part 3: Trade repositories

The lack of **information on derivative transactions** was considered as one of the major data gaps post-crisis. To close it, many jurisdictions have enforced central

supervised like banks": see L Kodres, "What is shadow banking?", *Finance & Development*, vol 50, no 2, IMF, Washington DC, 2013. The FSB definition is more detailed: "shadow banking is non-bank credit intermediation involving bank-like activities, such as maturity/liquidity transformation and/or leverage, that can become a source of systemic risk"; see FSB, op cit. A key policy objective is to ensure that new ways of financial intermediation would allow for the "transforming [of] shadow banking into resilient market-based finance", see FSB, "Recommendations to Strengthen Oversight and Regulation of Shadow Banking", October 2011.

22 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.

clearing requirements through central clearing counterparties (CCPs) and the reporting of standardised OTC transactions to TRs.[23] The resulting large expansion in the data collected has raised significant challenges, as highlighted in this part of the workshop chaired by Alejandro Gaytan (Bank of Mexico).

The first presentation, by the ECB, analysed the **derivatives data collection** process in the EU. In accordance with the European Markets Infrastructure Regulation (EMIR), both counterparties of an OTC derivative transaction must report to an authorised TR. But the processing of this information has raised many problems. One is the limited quality of the data, particularly due to missing values. Another is the difficulty of aggregating granular data points, reflecting the lack of common identifiers for the products, trades and counterparties involved in the transactions. Lastly, the management of the large volumes of data involved has proved technically difficult.

The second presentation, by the Dutch National Bank, argued that TR data can be **used for various policy purposes**, including microprudential supervision, macroprudential supervision, and statistical compilation. Given the sheer complexity of the information collected, a two-pronged approach has been followed. On the one hand, TR data are being exploited as a "regular" statistical source, by running adequate quality checks, aggregation mechanisms and monitoring exercises. On the other hand, ad hoc analysis is performed on specific segments – eg asset classes, instruments – to address specific information needs.

The last presentation, by researchers from University Paris 1 and Trinity College, Dublin, analysed the **importance of CCPs** in the EU. They have helped to increase transparency in OTC derivatives markets, thereby enhancing counterparty risk management. In addition to data quality aspects, an important issue has been the concentration of exposures in CCPs, and regulators have been taking steps to tackle this issue.[24]

Part 4: Credit register data

Many central banks manage a central credit register (CCR), ie a centralised system for collecting entity-level credit information on loans provided to the economy. As discussed in the last part of the meeting, chaired by Marcia De Wachter (NBB), **detailed loan-by-loan information** from CCRs can be used for many purposes, and particularly for macroprudential work.

The first presentation, by the NBB and ECB, showed how CCRs can be used to **monitor risks in the real estate sector** – eg by providing information on borrower risk profiles, the credit risk taken by lenders, exposure concentrations etc. This underlined the importance of the ongoing initiative to set up a European-wide CCR, AnaCredit.[25] One issue is that this new source of information will not comprise a long historical series, an important drawback when assessing the evolution of financial

[23] See IFC, "Central banks' access to and use of trade repository data", IFC Report, forthcoming.

[24] See CPMI-IOSCO, *Resilience of central counterparties (CCPs): Further guidance on the Principles for Financial Market Infrastructures (PMFI), Final Report*, July 2017.

[25] "AnaCredit" stands for *analytical credit datasets*.

risks over time – given that financial cycles usually have a long amplitude, at least compared with the traditional business cycle. Hence it will be important to combine the information from AnaCredit with data from national CCRs in several European countries. The difficulty is that such domestic sources are not harmonised and exhibit important cross-country differences in terms of data coverage, time span, instrument breakdown and sectoral definitions.

The second presentation, by the ECB, argued that AnaCredit will be instrumental in supporting the **identification of macroprudential risks**. For each loan provided to a corporate, there will be a wealth of information on the parties involved (eg creditor, originator, servicer, debtor). Moreover, this type of highly granular data set can be used flexibly depending on the policy question. It can shed light on distribution risks that are difficult to assess with aggregated data sets; and it could be linked to other granular data sets, multiplying the amount of information available for analysis.

The third presentation, by the Central Bank of the Republic of Turkey, also emphasised the value of **matching CCR data with complementary data sources**. The starting point was that the Turkish register contains detailed information on foreign exchange (FX) loans by residents but does not capture foreign bank lending or non-bank liabilities (eg debt securities). Moreover, it is compiled on a solo basis, ie not at the consolidated level of a firm. To address this gap, the central bank has started a complementary data collection to measure the open FX positions of non-financial firms with the highest FX debt.

The last intervention, by the Bank of Portugal, highlighted the **variety of possible uses for CCR data**. The Portuguese CCR contains detailed liability information (type, status, purpose, maturity, collateral etc) on a borrower-by-borrower basis. While it was initially set up to gauge the creditworthiness of borrowers, as in many central banks, it has since been used for various additional purposes: statistics, research, monetary policy implementation, microprudential supervision and, more recently, financial stability analysis.

IFC-National Bank of Belgium Workshop on "*Data needs and Statistics compilation for macroprudential analysis*"

Brussels, Belgium, 18-19 May 2017

Keynote
Data needs and statistics compilation for macroprudential analysis[1]

Claudia Buch,
IFC Chair and Vice President, Deutsche Bundesbank

[1] This keynote 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.

Speech

Prof Claudia Buch
Vice-President of the Deutsche Bundesbank and person accompanying the president at the ECB Governing Council

Data needs and statistics compilation for macroprudential analysis

Keynote Remarks IFC – National Bank of Belgium Workshop

Brussels | 18.05.2017

Good afternoon ladies and gentlemen and a warm welcome to the IFC – National Bank of Belgium's Workshop on "Data needs and statistics compilation for macroprudential analysis". I am happy to see the broad support of many researchers and practitioners contributing to progress in the area of statistics for financial stability. Thanks a lot to the organisers for putting together a very interesting programme.

The workshop continues discussions in several publications and previous conferences of the Irving Fisher Committee. Ideas developed in these discussions influence official statistics. Let me take the 2015 IFC report on data sharing as an example (IFC 2015). This paper has stimulated discussions at the G20 level. About two months ago, G20 Finance Ministers and Central Bank Governors endorsed recommendations for sharing and accessibility of granular data (G20 2017). Now, we need to implement these recommendations in line with the second phase of the G20 Data Gaps Initiative (DGI).

This workshop will underline the close connection between financial stability analysis and statistics. My talk today will focus on the contribution of statistics to the evaluation of the post-crisis financial sector reform agenda and the role of the G20 Data Gaps Initiative. Given that the goal of post-crisis reforms has been a more resilient financial system, let me begin with a broad overview of where we stand.

1 How resilient is the global financial system?

Resilience is a core theme of the German G20 presidency. The G20 recently endorsed resilience principles which complement the comprehensive financial sector reforms that were agreed upon in the aftermath of the global financial crisis. A stable financial system and a resilient real economy are two sides of the same coin. Almost ten years after the onset of the global financial crisis, its legacies continue to weigh on the world economy. Global growth is below its pre-crisis trends, debt levels remain high. Sustained resilience to shocks thus remains of key importance – for both the private and the public sectors.

So how can we make sure that the financial system is resilient and that risks to financial stability are contained? Let me start with a definition of systemic risk.

Systemic risks arise if the distress in one institution or a group of financial institutions threatens the functioning of the entire financial system. Systemic risk can arise through domino effects due to direct contractual linkages. Empirically, informational contagion leading to runs on assets of other financial institutions, even without any direct contractual linkages, is at least equally important. Resilience of the financial system thus depends on the ability of financial institutions to buffer shocks. It is affected by the magnitude of shocks, by amplification mechanisms, and by exposure to common shocks.

Recent indicators of systemic stress have remained low despite some bouts of market turbulence. Asset returns have become less correlated across classes, regions, and sectors. At the same time, political uncertainty has increased. The precise nature and timing of future policy changes and their impact remain unclear. Changes in the macroeconomic policy mix, a push for deregulation, or growing protectionist pressures could affect growth outcomes. Volatility could rise. If history is any guide, the potential for abrupt reversals of financial market conditions remains significant.

In particular, persistently low interest rates can encourage the build-up of risks to financial stability. The longer low interest rates persist, the larger the share of low-yielding assets on financial institutions' balance sheets will become. Low interest rates may induce investors to systematically underestimate risk, thus skewing risk premia downwards. This can encourage the build-up of latent risks across many sectors of the economy. Finally, low interest rates may trigger a credit-financed real estate boom. As a consequence, risks associated with a change in interest rates increase.

Hence, safeguarding against systemic risks remains a priority. Each market participant must ensure that contractual terms are appropriate and that risk buffers are sufficient to absorb losses from unexpected developments. Regulators need to ensure that capital buffers in the financial system as a whole are sufficient. And we need good data to monitor the build-up of systemic risk and to assess the effects of reforms.

Financial sector reforms have been set against threats to financial stability.

G20 Leaders committed to a fundamental reform of the financial system, and substantial progress has been made in four main reform areas:

- making banks more resilient,
- ending too-big-to-fail,
- transforming shadow banking into market-based finance, and
- making derivative markets safer.

Now, it is time to move on from implementation monitoring to the evaluation and possible refinement of reforms. We need to evaluate whether reforms are achieving their intended outcomes or whether they are having material unintended consequences. This is part of regulators' accountability to the public, and it is needed to ensure transparency.

Reform evaluation is challenging. We need to answer questions such as:

- Have reforms achieved their objectives? How can we isolate reform effects from other factors influencing financial market outcomes?
- What are the short-term and long-term costs and benefits of reforms? How do they differ across jurisdictions?
- And what are the overall effects of reforms?

Rather than exacerbating these challenges, a structured evaluation helps manage and address them. The Financial Stability Board (FSB) is currently working on a framework that will help gain a better understanding of reforms and provide a basis for informed policy decisions, without compromising on the reforms' objectives and the resilience of the system. This structured framework for post-implementation evaluation of the effects of financial regulatory reforms is explicitly welcomed by the G20 and underwent public consultation (FSB 2017).

Above all, reform evaluation needs to be based on good data. So let me turn to the role of the G20 Data Gaps Initiative.

2 The Role of the G20 Data Gaps Initiative

Let me illustrate what kind of information is required for effectively monitoring risks to financial stability – and to assess the effects of reforms in a structured way. I will focus on three areas: the real estate sector, shadow banking, and international capital flows.

2.1 The Real Estate Sector

The real estate sector plays an important role for the real economy and the financial system. Monitoring developments in real estate markets is, therefore, key to an early identification of vulnerabilities.

- More than two-thirds of all Europeans own the homes they live in.[1] Residential property typically forms the largest component of homeowners' wealth.
- The majority of households borrow to finance a home purchase. In many places, housing assets can be used as collateral to access funding. Mortgage debt is thus the main financial liability of the household sector.[2]
- Mortgage loans are also a major asset of the financial system. In advanced economies, about 60 percent of banks' total lending portfolios are held in the form of mortgage loans.

Given this large exposure of financial institutions, risks to financial stability can occur if a strong rise in house prices coincides with a strong expansion in mortgage loans and an easing of credit standards.

Risks can build up if market participants form overly positive expectations regarding future developments in debt sustainability. They may not give due consideration to the possibility that asset prices may fall and that interest rates may rise. If property prices subsequently decline, and if this is coupled with a simultaneous increase in default rates, banks may not be able to offset losses from mortgage lending.

The bursting of credit-driven real estate price booms does significant and long-lasting damage to the real economy (Jordà, Schularick, and Taylor 2016; Brunnermeier and Schnabel 2015, Taylor 2015). A fall in house prices may also affect financial institutions more directly through their specific investments in residential real estate assets.

The availability of data on real estate markets does not match the importance of these markets for financial stability. The European Systemic Risk Board (ESRB 2016) has thus recommended "closing real estate data gaps". Much work needs to be done to improve data on real estate in terms of coverage as well as of comparability across countries.

The lack of data is profound. For Germany, indicators are available only for (aggregated) prices and credits. Information on credit standards is insufficient for monitoring financial stability. Information is limited to the Eurosystem's quarterly Bank Lending Survey (BLS). But this survey includes only qualitative information, and it is constrained to a sample of 139 large banks. As regards markets for commercial real estate, reliable indicators on both price and lending volumes are lacking.

The G20 Data Gaps Initiative aims at improving the availability of Residential Property Price Indices (RPPI) (IMF and FSB 2016).[3] By the year 2021, G20 economies are to provide nationally available data on Commercial Property Price Indices to the BIS. In September 2016, the BIS had already published such data, including information on coverage and methodologies, for a number of countries.

The session on the real estate sector today provided illustrative country examples related to the connections between real estate data, statistical compilation methods, and financial stability analysis.

2.2 Shadow Banking

The second area I want to comment on in the context of data needs is shadow banking, which was also a topic of our workshop in the morning. Shedding light on the shadow banking sector has been a priority for policymakers since the global financial crisis. Let me clarify upfront that the "shadow" in shadow banking refers to what is less visible from the point of view of both banking supervision and market participants; it does not refer to illegal activities.

Shadow banking "activities" cannot be measured directly. The easier task is identifying shadow banking intermediaries, or subsectors. The Financial Stability Board defines shadow banking as credit intermediation by intermediaries and activities outside the regular banking system (FSB 2011).

Over the past years, the Financial Stability Board, the European Systemic Risk Board, central banks, and macroprudential supervisors have set up monitoring systems for shadow banking sectors. The work of the FSB is linked to recommendation 5 of the second phase of the G20 Data Gaps Initiative: G20 countries are encouraged to contribute to the FSB monitoring process and the provision of sectoral accounts data. At the same time, the FSB initiated improvements of the conceptual framework at the global level in a way that is as consistent as possible with the traditional System of National Accounts (IMF and FSB Secretariat 2016).

The FSB provides two publicly available datasets within the frame of the Shadow Banking Monitoring Report: (1) globally and nationally aggregated figures, and (2) report-related data, including diagrams. Furthermore, the Bundesbank publishes data on the German shadow banking activities as part of its Financial Stability Reviews. These time series on the German shadow banking sector can be downloaded, and data on relevant sub-subsectors, for example on investment or money market funds, are updated on a regular basis.

Measuring financial stability risks arising from institutions of activities that are classified as "shadow banking" is difficult. Recall the definition of financial stability risks as arising through direct and indirect financial contagion. Measuring contagion arising from common exposures, for instance, requires empirical analysis. These risks cannot simply be read from official statistics.

The route taken by the FSB to address this issue is to start from broad, aggregate statistics, and then to "narrow down" in order to obtain more risk-related measures. For monitoring purposes, different statistics need to be combined, including flow of funds data, financial accounts, supervisory, and statistical data. For Germany, these sources include the statistics on investment funds, on financial vehicle corporations, or on securities holdings. Some of the related data gaps have been closed recently. The German investment fund statistics now also covers closed-end funds. Other data gaps are about to be closed, for example regarding so-called alternative investment funds or securities financing transactions.

One important next step will be to develop and use analytical approaches identifying sources of systemic risk arising from "shadow banking" activities: How do shocks hitting individual financial institutions propagate through the system? How important are linkages between different sectors, including the traditional banking sector, for the propagation of shocks? Has the strength of cross-border channels of contagion increased or decreased? And how relevant are common exposures?

All these questions cannot be answered looking at aggregate statistics only. They require drilling down to the granular level and meaningful aggregation across the system at the same time. This is extremely challenging analytically. But, fortunately, we have better data than before the crisis, we have improved methodologies for analysing those data, and we have international fora where experts get together.

We now have to deliver and exploit our international cooperation to improve upon our analysis of systemic risks.

The first step towards improved analysis is the ability to access and share granular data. The report on the Data Gaps Initiative and the Outcome of the Workshop on Data Sharing approved by the G20
Finance Ministers and Central Bank Governors on 17/18 March 2017 are important milestones in this regard (Inter-Agency Group on Economic and Financial Statistics 2017).

2.3 Global Financial Cycles

Today's workshop also deals with international debt and funding patterns. These patterns have changed noticeably over the last two decades. Global (gross) capital flows have outpaced global trade flows, and the importance of capital flows to emerging market economies has increased. From 1999 to 2015, the amount of global gross foreign assets grew from about USD 27 trillion to more than USD 130 trillion, which is about twice as high as global GDP.[4]

This higher degree of international financial integration can contribute to a more efficient allocation of capital, a wider range of funding opportunities, and better risk sharing. But it can also lead to an
overheating of sectors or markets, increase imbalances, and serve as a propagation mechanism during a crisis. There is evidence that global financial cycles have intensified and risks of capital flow reversals have increased (Eichengreen and Gupta 2016; Sahay et al. 2014). The first line of defence is a higher resilience of the financial system, both in the source and in the destination countries of global financial flows. The higher the leverage in the financial system is, the stronger propagation mechanisms are, and the more likely destabilising global capital flows become (Rey 2013).

Consequently, the design and use of macroprudential measures should be considered within the context of cross-border capital flows. Timely and granular data are the precondition for proper analysis and for the calibration of potential instruments. Results from a large cross-country study of the International Banking Research Network (IBRN) suggest that prudential policies spill over internationally through banks. But the transmission differs by types of banks and types of funding flows, and banks' responses to regulatory changes are heterogeneous (Buch, Bussiere, and Goldberg 2016).

The International Banking Research Network uses granular data that are available across central banks. However, it does not share the data, only the results of the common analytical research template. To gain the most value out of granular data, particularly in a cross-border context, different data sets need to be linked. Sharing data across sectors and jurisdictions is crucial for monitoring systemic risks. Shared data help bridge the divide between micro and macro analysis. And shared data allow taking a truly global – systemic – view where needed.

But to improve data sharing, the availability of sufficiently granular data is not enough. Beyond that, we need common global identifiers. The Legal Entity Identifier (LEI)[5] helps identify legally distinct entities that engage in financial transactions, and progress in implementing the LEI for financial corporations has been made through various legal acts.[6] Yet coverage of the LEI should be expanded to the non-financial corporations sector and to the identification of consolidated group-level structures.

Indeed a key recommendation on data sharing,[7] which was endorsed by the G20 Finance Ministers and Central Bank Governors in Baden-Baden (G20 2017), has been to encourage G20 economies to widen the scope of the LEI and enable a better coverage of the non-financial sector. At the European level, I welcome the initiative by the Committee on Monetary, Financial and Balance of Payments Statistics (CMFB 2017), which has published recommendations on business identifiers and business registers to advance the LEI's implementation.

The LEI-related expenses vary from country to country, depending on the competent contracting authority. The German "Bundesanzeiger", for example, charges EUR 140 for the initial registration covering the first year and EUR 90 for each subsequent year, excluding value added tax. A CMFB High Level Group, in cooperation with the LEI bodies, is currently investigating concrete cost reduction measures. Accordingly, the CMFB recommendations are an important step to further promote the propagation of the LEI, especially for non-financial corporations.

Finally, let me mention recent progress we have made in terms of improving our joint knowledge of macroprudential policy measures that have been taken across countries. The IMF, in consultation with the FSB and the Bank for International Settlements (BIS), is working on a publicly available macroprudential policy database which could serve as an information basis.

3 Summing Up

Surveillance of risks to financial stability requires good data and information. The second phase of the G20 Data Gaps Initiative plays an important role for improvements in the statistical infrastructure. Apart from providing a conceptual framework for the collection of data, implementation of new concepts nationally and internationally will be crucial.

I have highlighted three specific points:

First, with its framework for the evaluation of financial sector reforms post-implementation, the FSB has started an ambitious project. The success of this project will depend crucially on the timely and comprehensive availability of granular data. Now is the time to start developing protocols defining how statistical and policy evaluation work can be integrated more closely.

Second, we have made much progress in the surveillance of non-bank finance or "shadow banking". Assessing risks in this area requires drilling down further, using the infrastructure that we have in terms of data and methodologies. But it also requires further developing our analytical tools, especially in order to strengthen our understanding of shock transmission channels and the relevance of common exposures and inter-sectoral linkages for the latter, including those that extend across borders.

Third, international capital flows have many positive effects – but can also propagate shocks across borders. To address this concern, timely and granular data are needed for policy use. An improved sharing of and accessibility to sufficiently granular data is crucial for monitoring systemic risk. This implies the use of common identifiers in order to allow a better linking of different micro datasets and a more refined analysis of channels of propagation.

4 References

Brunnermeier, M. and I. Schnabel(2015). Bubbles and Central Banks: Historical Perspectives, CEPR Discussion Paper No. 10528, April 2015.
Buch, C.M., M. Bussière, and L. Goldberg (2016). Prudential policies crossing borders: Evidence from the International Banking Research Network.
http://voxeu.org/article/prudential-policies-crossing-borders
CMFB (2016). Committee on Monetary, Financial and Balance of payments statistics opinion on business identifiers and business registers: recommendations for statistical production, 2 December 2016, available at: http://www.cmfb.org/publications/opinions
Eichengreen, B. and P. Gupta (2016). Managing Sudden Stops, World Bank Policy Research Working Paper 7639, April 2016.
European Systemic Risk Board (2016). Recommendation on closing real estate data gaps (ESRB/2016/14), October 2016.
Eurostat (2017). Distribution of Population by Tenure Status, Type of Household and Income Group – EU-SILC Survey, http://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=ilc_lvho02&lang=en, accessed 3 April, 2017.
Financial Stability Board (2011). Shadow Banking: Strengthening Oversight and Regulation, Recommendations of the Financial Stability Board, 27 October 2011.
Financial Stability Board (2017). Proposed Framework for Post-Implementation Evaluation of the Effects of the G20 Financial Regulatory Reforms, Consultation document on main elements, 11 April 2017.
G20 (2017). Communiqué of the G20 Finance Ministers and Central Bank Governors Meeting, Baden-Baden, Germany, 17-18 March 2017.

International Monetary Fund and Financial Stability Board (2016). The Financial Crisis and Information Gaps, Second Phase of the G20 Data Gaps Initiative (DGI-2), First Progress Report, September 2016.
Inter-Agency Group on Economic and Financial Statistics (2017). Update on the Data Gaps Initiative and the Outcome of the Workshop on Data Sharing, March 2017.
Irving Fisher Committee on Central Bank Statistics (2015). Data-sharing: issues and good practices, Report to BIS Governors prepared by the Task Force on Data Sharing, January 2015.
Jordà, Ò., M. Schularick, and A. M. Taylor (2016). "The Great Mortgaging: Housing Finance, Crises, and Business Cycles," Economic Policy, Vol. 31 No. 85, pp. 107–152.
OECD (2017). Households' Financial Assets and Liabilities, http://stats.oecd.org/Index.aspx?DataSetCode=QASA_7HH, accessed April 4, 2017.
Rey, H. (2013). Dilemma not Trilemma: The global financial cycle and monetary policy independence. VoxEU, 31 August 2013.
Sahay, R., V. Arora, T. Arvanitis, H. Faruqee, P. N'Diaye, and T. Mancini-Griffoli (2014). Emerging market volatility: Lessons from the taper tantrum, IMF Staff Discussion Note 14/09, September 2014.
Taylor, A.M.(2015). Credit, Financial Stability, and the Macroeconomy, NBER Working Paper No. 21039, March 2015.

Footnote

1. Home ownership rates in Germany are somewhat lower. In 2015, a little more than 50 percent of households owned the houses they lived in. See Eurostat (2017).
2. Mortgage debt amounts on average to about two-thirds of household liabilities in euro-area countries. In Germany, mortgages accounted for about 70 percent of total household debt in 2016. See OECD (2017).
3. More specifically, recommendation 17 of the second phase of the Data Gaps Initiative addresses this issue. In addition, recommendation 18 was set up to "enhance the methodological guidance on the compilation of Commercial Property Price Indices (CPPI) and encourage dissemination of data on commercial property prices via the BIS website".
4. Source: IMF databases, own calculations.
5. For details, see https://www.gleif.org/de/about-lei/introducing-the-legal-entity-identifier-lei/.
6. For details, see https://www.gleif.org/en/about-lei/regulatory-use-of-the-lei. Broader coverage is expected through the forthcoming Markets in Financial Instruments Directive (MiFID II) and Regulation (MiFIR) https://www.gleif.org/en/about-lei/how-to-get-an-lei-find-lei-issuing-organizations/registration-agents, which will cover trading venues, investment firms and intermediaries.
7. Inter-Agency Group on Economic and Financial Statistics (2017).

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IFC-National Bank of Belgium Workshop on "*Data needs and Statistics compilation for macroprudential analysis*"

Brussels, Belgium, 18-19 May 2017

Panel presentation
Statistical reporting and macroprudential analysis: Banco de Portugal experience[1]

Pedro Duarte Neves,

Vice Governor, Bank of Portugal

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.

Statistical Reporting and Macroprudential Analysis: Banco de Portugal experience

BANCO DE PORTUGAL
EUROSYSTEM

Pedro Duarte Neves • Banco de Portugal Vice-Governor
Brussels, 19 May 2017

Workshop on "Data needs and statistics compilation for macroprudential analysis"
Jointly organized by the BIS Irving Fisher Committee on Central Bank Statistics and National Bank of Belgium

Panel discussion
Chair:
- **Marcia De Wachter**, Executive Director, Member of the Board of the National Bank of Belgium

Panellists:
- **Claudia Buch**, IFC Chair and Vice President, Deutsche Bundesbank
- **Pedro Duarte Neves**, Vice Governor, Bank of Portugal
- **Philip Lane**, Governor, The Central Bank of Ireland
- **Jan Smets**, Governor of the National Bank of Belgium and former IFC Chair

1. Financial crisis aftermath and macroprudential policy
2. BdP experience on micro-databases
3. BdP experience on using granular information for macroprudential purposes
4. Looking ahead

The financial crisis has shown the importance of:

- sharing key information across banking, insurance and financial markets supervisors;
- complementing macro-data with micro-data.

The objective is to:

- better monitor the risks to financial stability;
- signal when a specific macroprudential instrument should be activated;
- evaluate the impact of macroprudential policy.

Examples of BdP micro-databases

Central Credit Register (CCR)

Enabled BdP to compile comprehensive statistics on credit, to assess credit concentration and distribution and to measure overdue loans and overdue loans' ratio, with a view to better understand the risks underlying bank's balance sheet.

Central Balance Sheet Database (CBSD)

Gives a complete view on non financial corporations assets and liabilities allowing the BdP to monitor and conduct detailed studies on businesses and entrepreneurial dynamics.

Securities Statistics Integrated System (SSIS)

A powerful tool to measure exposures of banks and non-banks to specific issuers and in complement with the CCR give a more complete overview of the indebtedness of the economy.

BdP experience in fostering the use of granular information for macroprudential purpose

- Loans to non-financial corporations
- Real estate loan-by-loan information
- In-house credit assessment system (ICAS)
- Research Laboratory on Microdata (BPLim)

3.1 Loans to non-financial corporations

Micro-data

Data Sources: Central Credit Register (CCR) and Central Balance Sheet Database (CBSD)

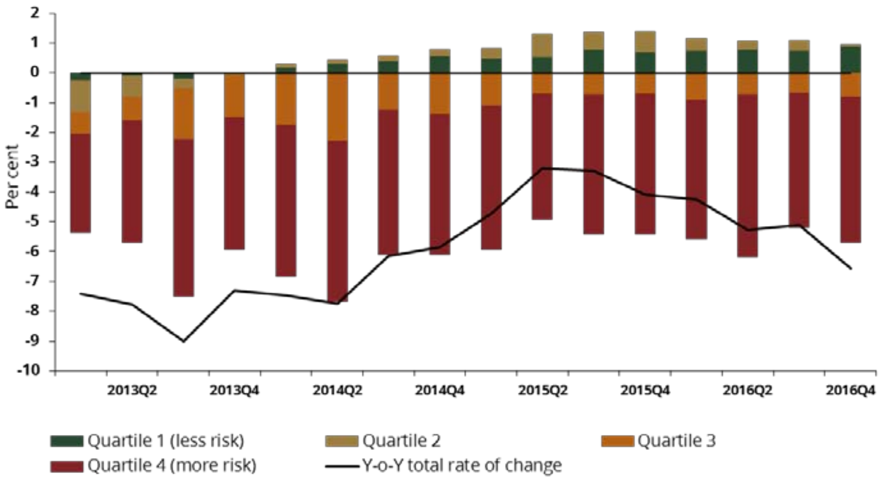
CCR is a database containing granular information on credit on a borrower-by-borrower basis and, in some cases, including details which provide loan-by-loan information, with a virtually complete coverage. CBSD contains yearly balance sheet information on firms with almost complete coverage.

Data Treatment

Loans to NFC were distributed among quartiles, according with the respective risk class, with quartile 1 corresponding to the less risky NFC.

Macroprudential use

Disagregate the evolution of total loans to NFC in order to grasp if the there has been diferent evolutions according to risk profiles.

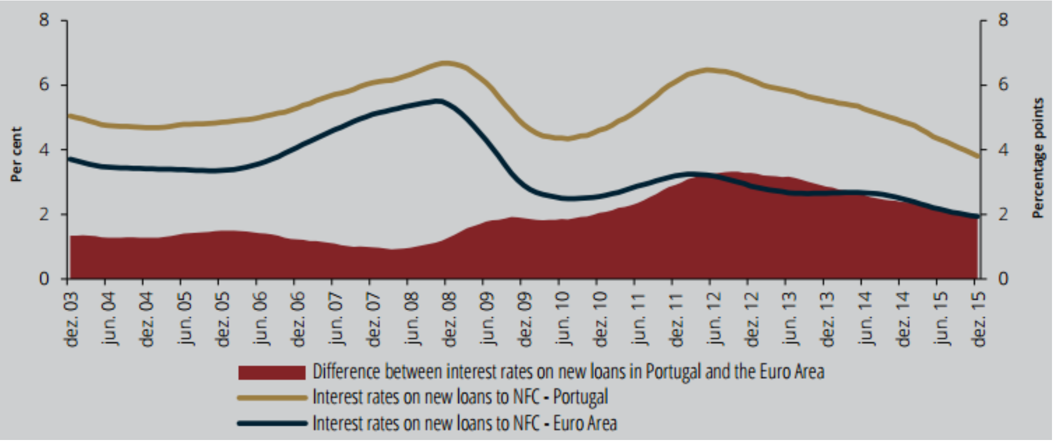


Macro-prudential policy implications

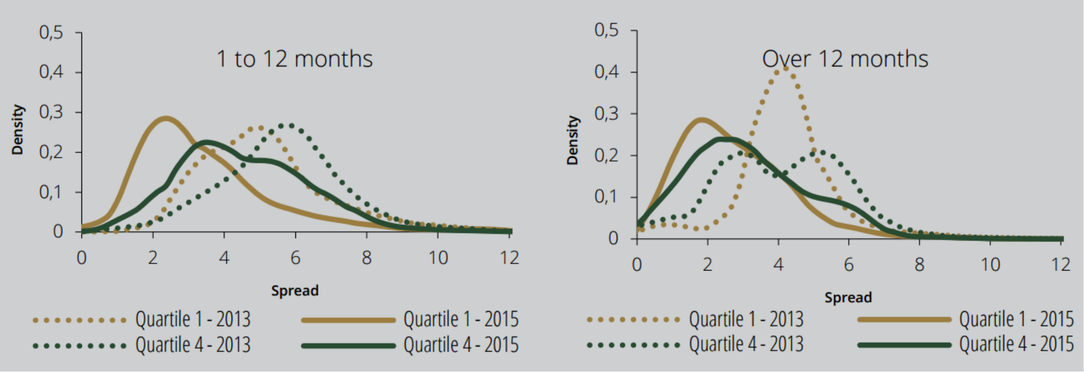
- After the financial crisis there has been a continued deleveraging process of the Portuguese banking system. In 2016 the annual growth rate of NFC loans was still negative.
- Neverthless, we can observe that the contribution to the reduction of the exposure of domestic banks to NFC comes from loans to companies included in the higher risk quartiles.

3.1 Loans to non-financial corporations (cont.)

Interest rates on new bank loans to NFCs – Portugal, euro area and difference between both series



Average spreads on new bank loans to NFCs – Loans by maturity for the first risk quartile (lower risk) and the fourth risk quartile (higher risk) in 2013 and 2015



Macro-prudential policy implications

- The spread between interest rates in loans to NFC in Portugal and in the euro area has been declining steadily since 2012.
- There is differentiation in returns on new loans.
- Risk premia accuracy improved during period 2013-2015, especially in longer term loans.
- Analysis published in the Financial Stability Report May 2016.

3.2 Real Estate loan-by-loan information

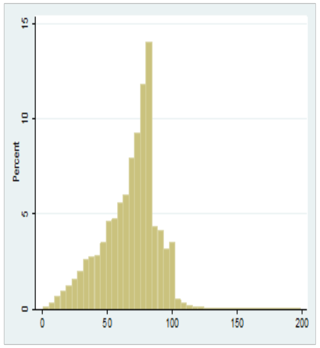
Micro-data

Data Source
Loan-by-loan information on conditions, collateral and debtor’s income, reported under Circular-Letters 6/2016/DES and 107/2015/DSC.

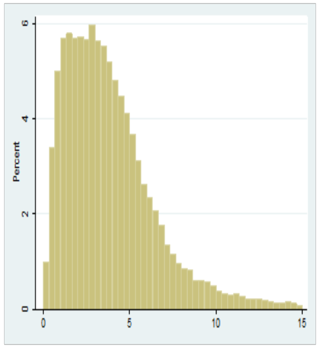
Data Treatment
Loans are aggregated by borrower of the property in order to calculate indicators such as LTV, LTI, DSTI on the origination and on current date.

Macroprudential use
Monitoring of the real estate market and the exposure of the financial system.
High levels of indicators (LTV, LTI, DSTI) may signal the potential building up of imbalances.

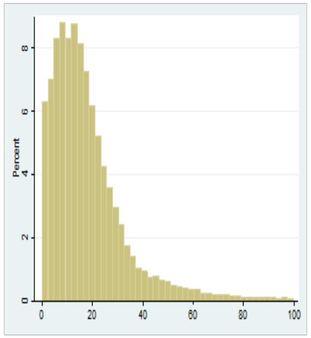
Loan by loan infomation
(year of origination 2015)



LTVo based on appraisal



LTIo



DSTIo

Macro-prudential policy implications

- Although the evolution of LTV, LTI and DSTI reflects the result of relative strict credit standards in the last years, data for 2015 new contracts shows that there are still contracts with high indicators.
- Mortgages for properties owned by the banks and for properties of distressed companies which are clients of the bank usually display higher LTV ratios.

3.3. Funding and Capital Plans

Micro-data

Description

FCPs focus on the solvency, liquidity and profitability of the institutions, include detailed historical and prospective accounting and prudential information (overall strategies pursued in a 3-4 year time horizon) and are built over harmonized macro scenarios, guidelines and restrictions, which allow for full consistency among institutions.
As such, this instrument is much suited for the pre-emptive nature of macroprudential policy.

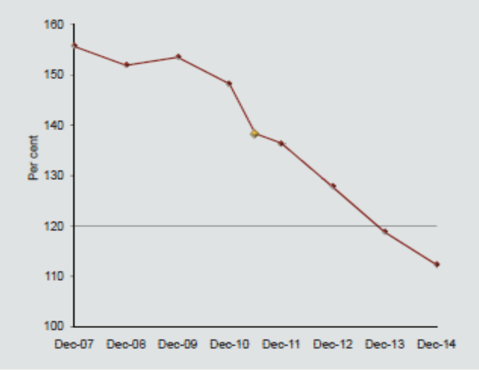
Data Source and Treatment

Plans are submitted by institutions to BdP followed by several interactions between the supervisory and financial stability teams.

Macroprudential use

On top of its direct relevance for supervision, the analysis of FCP contribute to the prospective assessment of the intermediate objectives of the macroprudential policy and namely to assess the coherency and sustainability of the projected aggregate trends on credit, funding, financing to the economy and profitability.

Credit to deposits ratio
(FCP projections)



Macro-prudential policy implications

This tools was very useful under the Economic and Financial Assistance Program.

Example from Financial Stability Report Nov 2011
There has been a reduction in the credit to deposits ratio since 2009 which fell to around 140 per cent in June 2011 (156 per cent in December 2007). In aggregate terms, the plans point towards a gradual reduction of the ratio, to levels of less than 120 starting from the end of 2013.

3.4 Internal Credit Assessment System (ICAS)

ICAS use

Monetary policy use

- To assess the credit quality of eligible assets.

Micropudential use

- Benchmark to gauge the assessment provided by institutions with their own internal notation systems;
- To assess the quality of individual credit portfolios, while potentially contributing to an early identification of specific risks to which institutions may be exposed to.

ICAS data source

Macro-prudential policy implications

Monitoring tool of the developments of the non-financial sector and the potential building up of imbalances, namely to assess the fragility of specific sectors of the economy, in particular through the economic and financial analysis of the companies that constitute each of the sectors.

3.5 BPLim

Research Laboratory on Microdata (BPLim)

Research Laboratory on Microdata (BPLim) is a research structure integrated in the Economics and Research Department, whose chief objective is to support the production of research projects and studies on the Portuguese economy, both by the Bank's economists and authorized external users.

BdP microdata used by BLim

- Central Credit Register
- Central Balance-Sheet Database
- Securities Statistics Integrated System

Main purposes

- providing scientific and computational support for microdata-backed research;
- promoting training actions in micro-econometrics and panel econometrics;
- disclosing econometric estimation techniques applied to microdata.

4. Looking ahead

Data needs put forward by macroprudential functions should be regarded as an opportunity to explore synergies between financial stability and statistical activities:

- integrating supervisory and statistical information generates benefits both to the reporting entities and to the data compliers;
- micro-data enables a wider range of analytical studies that reveal the heterogeneity hidden behind aggregate numbers and that can be of importance for macroprudential purposes.

To maximize the usefulness of all the new information that will be available further work should focus on its analysis and integration to ensure that the higher reporting standards are reflected in a sounder framework for financial institutions supervision, thus fostering financial stability.

Statistical Reporting and Macroprudential Analysis: Banco de Portugal experience

BANCO DE PORTUGAL
EUROSYSTEM

Pedro Duarte Neves • Banco de Portugal Vice-Governor
Brussels, 19 May 2017

Workshop on "Data needs and statistics compilation for macroprudential analysis"
Jointly organized by the BIS Irving Fisher Committee on Central Bank Statistics and National Bank of Belgium

Panel discussion
Chair:
- **Marcia De Wachter**, Executive Director, Member of the Board of the National Bank of Belgium

Panellists:
- **Claudia Buch**, IFC Chair and Vice President, Deutsche Bundesbank
- **Pedro Duarte Neves**, Vice Governor, Bank of Portugal
- **Philip Lane**, Governor, The Central Bank of Ireland
- **Jan Smets**, Governor of the National Bank of Belgium and former IFC Chair

Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

IFC-National Bank of Belgium Workshop on "*Data needs and Statistics compilation for macroprudential analysis*"

Brussels, Belgium, 18-19 May 2017

European Macroprudential Database[1]

Samo Boh, Stefano Borgioli, Andra (Buca) Coman, Bogdan Chiriacescu,
Anne Koban and Joao Veiga, European Central Bank;
Piotr Kusmierczyk, European Systemic Risk Board;
Mara Pirovano and Thomas Schepens, National Bank of Belgium

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.

European Macroprudential Database

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Abstract

This paper presents the Macroprudential Database (MPDB), as a part of the ECB's Statistical Data Warehouse, and encourages its use among external users. The paper explains the rationale for creating the MPDB and how it can contribute to fulfil the macroprudential data needs for the analysis conducted by the E(S)CB and by the ESRB, within the countries of the Single Supervisory Mechanism and also of the whole Europe Union. The structure of the database and a broad overview of indicators are also presented, dealing with data confidentiality issues and differences between the internal and the public version of the database. Examples illustrate how the MPDB is used for monitoring purposes and econometric modelling. Finally the paper discusses remaining data gaps and expected future enhancements of the MPDB.

Keywords: Macroprudential, statistics

JEL classification: C82, E60

Contents

1. Introduction

The financial crisis and its aftermath confirmed the need for system-wide surveillance of systemic risk and led to the establishment of macroprudential policy as a new key policy area with the objective of an early detection of systemic risk and, in case of materialisation, promoting actions to limit its contagion effects. Systemic risk can be described as the risk that the provision of necessary financial products and services by the financial system will be impaired to a point where economic growth and welfare may be materially affected. Systemic risk can derive from three sources: an endogenous build-up of financial imbalances possibly associated with a booming financial cycle; large aggregate shocks hitting the economy or the financial system; or contagion effects across markets, intermediaries or infrastructures. Financial stability is a state whereby the build-up of systemic risk is prevented. Whatever their origin, a primary role of macroprudential authorities is to identify, measure and monitor these systemic risks as early as possible and to consider macroprudential policies to mitigate them. The overarching goal of macroprudential policy is to preserve financial stability by (1) preventing the excessive build-up of risk, resulting from external factors and market failures, in order to smoothen the financial cycle (time dimension); (2) by increasing the resilience of the financial sector and limit contagion effects (cross-sectional dimension) and (3) by encouraging a system-wide perspective in financial regulation to create the right set of incentives for market participants (structural dimension).

An input partially missing in the macroprudential field was the availability of a strong and comprehensive common statistical basis to support macroprudential analysis and to stimulate research, to be used as a basis for conducting macroprudential policy by the ECB and national authorities, with the European Systemic Risk Board (ESRB) being in charge of the macroprudential oversight of the EU financial system and the prevention and mitigation of systemic risk. Establishing a comprehensive and unique Macroprudential Database (MPDB) is therefore essential to underpin quantitative and policy oriented analyses for both internal and external publications, and for a consistent cross-country analysis of systemic risk (see Box 1 for a comparison with IMF Financial Soundness Indicators).

The MPDB became operational in October 2015 and it is accessible through the ECB's Statistical Data Warehouse (SDW)[1]. It currently comprises around 275 relevant country level public indicators (and around 370 in the internal version) grouped into seven domains related to the macro economy and financial markets, debt and credit, residential and commercial real estate, the banking sector, the non-banking sector and interconnectedness. In order to meet continuously evolving user needs, the MPDB is already subject to a regular review process, making it a live and easily adjustable product. The majority of indicators are also publicly available, allowing further research outside the ESCB/ESRB community.

This paper is structured as follows: section 2 explains the motivation for the set-up of the MPDB and increasing user needs that triggered the project; section 3 describes the structure and key features of the database; section 4 points out ideas

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[1] The MPDB can be accessed in the public SDW via this link: http://sdw.ecb.europa.eu/browse.do?node=9689335

for future enhancements of the database; and finally, section 5 includes key concluding remarks.

2. Motivation for the set-up of the MPDB and user needs

Macroprudential policies address the emergence of possible systemic risks in the financial system, and thus aim at preserving financial stability. Originally, macroprudential powers in the European Union were established primarily at the national level[2], reflecting the need for a more tailored approach, due to the imperfect synchronisation of financial and business cycles in the European Union. Along with the harmonisation of microprudential supervision, the Single Supervisory Mechanism (SSM) Regulation also strengthens consistency of macroprudential policy. Hence, the Eurosystem is able to strengthen coordination and to address potential cross-country spill-overs of macroprudential policies at the national level[3].

In particular, the SSM Regulation[4] confers specific powers and responsibilities in the field of macroprudential policy upon the ECB and National Competent Authorities or National Designated Authorities.

The role of the ECB in this area is twofold. First, the ECB is involved in the decision making process of macroprudential policy in SSM countries. National authorities are required to notify the ECB before implementing or changing a national measure foreseen in EU laws[5]. The ECB is then required to assess the envisaged macroprudential measure and, if necessary, raise objections, which must be considered by the national authorities.

Second, the ECB has the right to apply more stringent measures at the national level for the instruments included in the EU laws. For example, the ECB may apply higher capital buffer requirements[6] compared to the level set by national authorities.

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[2] This is for example reflected in the ESRB Recommendation ESRB/2011/3 on National Macroprudential Mandates:

http://www.esrb.europa.eu/pub/pdf/ESRB_Recommendation_on_National_Macroprudential_Mandates.pdf?87d545ebc9fe76b76b6c545b6bad218c

[3] ECB Macroprudential Bulletin, Issue 1, 2016, https://www.ecb.europa.eu/pub/pdf/other/ecbmpbu201603.en.pdf

[4] Council Regulation (EU) No 1024/2013 of 15 October 2013 conferring specific tasks on the European Central Bank concerning policies relating to the prudential supervision of credit institutions.

[5] Capital Requirements Directive (CRD) IV (Directive 2013/36/EU) and Capital Requirements Regulation (CRR) (Regulation No 575/2013)

[6] Countercyclical capital buffer, systemic risk buffer, capital buffers for Global Systemically Important Institutions (G-SII) and Other Systemically Important Institutions (O-SII).

The shared responsibilities regarding macroprudential policies between national authorities and the ECB triggered the need to establish a common ground for macroprudential analysis. A comprehensive and unique database was therefore considered as essential for analytical and policy oriented work flowing into internal and external reports, and for a consistent cross-country analysis of systemic risk. The establishment of a comprehensive and harmonised database for macroprudential analysis – the Macroprudential Database (MPDB) - was therefore considered as a key priority.

Due to the multifaceted nature of systemic risk, a wide range of indicators is needed to identify vulnerabilities, assess the resilience of the financial system and capture both cyclical and structural developments. Naturally, banking sector variables play a key role for macroprudential policy, together with debt and credit variables. In addition, the macroeconomic environments, as well as the developments of relevant financial markets need to be taken into account. In addition, indicators reflecting developments of the housing market as well as the commercial real estate market are essential inputs. However, poor data availability and quality in this field often hamper the analysis.

To ensure that the MPDB would not only support the ECB's macroprudential functions at the euro area level but have a wider application, the ESRB joined the MPDB development work. As responsible for the macroprudential oversight of the EU financial system and the prevention and mitigation of systemic risks,[7] the ESRB has a broad remit, covering banks, insurers, asset managers, non-banks intermediaries (the so-called shadow banking), financial market infrastructures and other financial institutions and markets. By extending the relevant indicators to cover non-bank financial intermediaries and encompassing the EU to the extent possible, the new database also suits the broader perspective of the ESRB.

In this regard, the MPDB constitutes the statistical basis for conducting macroprudential analyses in the context of the ECB's macroprudential function, while also addressing the ESRB's data needs. By considering synergies between different users' requirements, the MPDB establishes a consistent, unique and harmonised database supporting relevant and well-informed macroprudential analyses as well as the policy discussions.

The MPDB should also stimulate macroprudential analysis and research both within and outside the European System of Central Banks, and should prove relevant for market-participants and academics (see Box 2 for confidentiality issues).

3. Structure and key features of the database

The MPDB provides a comprehensive set of harmonised, relevant and fit-for-use indicators to analyse the build-up of both cyclical and structural systemic risks.

The development of the database started with the compilation of a list of potential indicators to be included in the database — casting the net relatively wide

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7 See ESRB Regulation: Regulation (EU) No 1092/2010 of the European Parliament and of the Council of 24/11/2010

— based on relevant experience on macroprudential analyses and on the relevant academic literature. The list also included the indicators selected for the ESRB's quantitative risk analysis tools, such as the ESRB risk dashboard. Following the compilation of this list, the second and longest phase of the work consisted in an extensive inventory exercise. The desired indicators were to allow cross-country comparability (harmonisation), large cross-country availability and, to the extent possible, a long history. This inventory exercise showed that many of the "best available" time series for the desired indicators were already available in datasets included in the ECB's Statistical Data Warehouse (SDW),in databases of other international institutions (BIS, OECD, Eurostat, IMF) or in commercial data providers (Bloomberg, Thomson Reuters, Datastream, iBoxx, etc.).

A relatively large number of indicators were ultimately integrated in the MPDB, which is structured around the following seven domains[8]:

- Macroeconomic and financial market variables
- Debt and credit variables
- Residential real estate variables
- Commercial real estate variables
- Bank sector variables
- Non-bank variables
- Interconnectedness variables

The MPDB comprises around 275 relevant country level public variables and indicators (and around 370 in the internal version). A catalogue encompassing all indicators together with underlying SDW codes and indicators calculations is available in the SDW. In addition, the catalogues are also available at domain level. These catalogues also include references to few time series that cannot be shown in the SDW, but are available in the other data sources.

The following sections present a summary of the main features of the various MPDB domains.

3.1 Macroeconomic and financial market variables

This first domain covers a very wide range of macroeconomic and financial market variables that can be used to measure the build-up of cyclical and structural systemic risks in the financial system or in the real economy, both on a national and European level (i.e. euro area as well as the EU). The indicators included in this domain aim to cover financial stability risks stemming from macroeconomic developments (inflation, growth) and imbalances (current account,

[8] See Annex 1 for an overview of the full MPDB structure.

competitiveness), from household, corporate and public sector debt or from financial markets (equity, bond, foreign exchange:), encompassing:

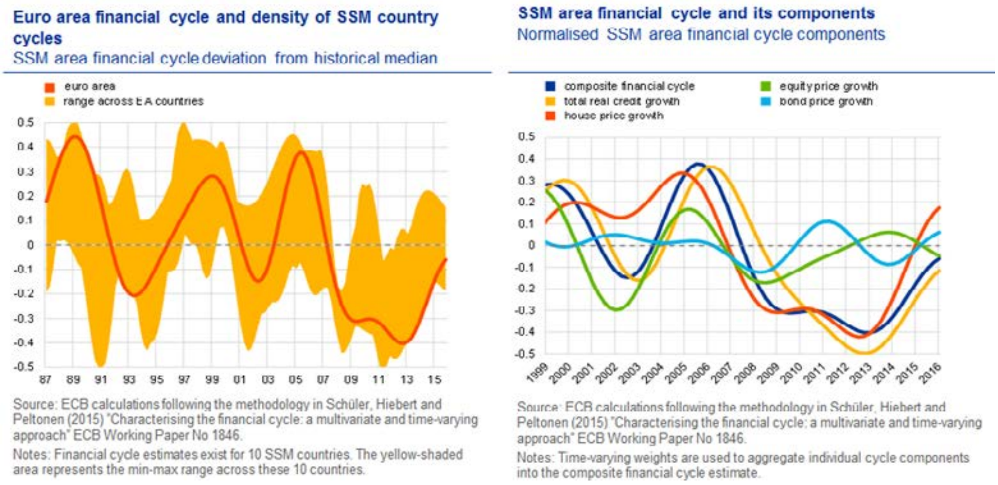
- Macroeconomic aggregates (monetary and real variables)
- Financial market variables
- Risk and uncertainty variables
- Financial condition indicators for the main economic sectors (government sector, households, non-financial corporations)
- Borrowing and lending conditions

These indicators can be used to characterise and estimate financial cycles for European countries and the euro area as a whole. Based on the methodology of Schuler, Hiebert and Peltonen[9], the financial cycle is a widely used measure in financial stability analysis and macroprudential policy.

The financial cycle summarises the (co)-movements over time of a range of financial sector variables, covering quantities and prices. To identify financial cycles, attention is given to common cyclical fluctuations across total credit, residential property prices, equity prices and benchmark bond yields. The indicators used for estimating the financial cycle are included in MPDB (credit, house prices, equity prices, bond yields, real GDP, unemployment, inflation).

In order to estimate the financial cycle and the trend evolution, long time series are needed and the MPDB therefore contains several indicators with significant historical data. In addition, the full euro area country coverage of MPDB indicators allows for decomposition of the cycle, as well as of its components, also at the individual country level. Chart 1 illustrates the euro area financial cycle and the components, including also the min-max range across euro area countries. The cycles and it subcomponents are not stored in the MPDB, but can be calculated on the basis of the time series included in the MPDB.

Chart 1: Euro area financial cycle and its components, as well as density of euro area country cycles



11 See "Characterising the financial cycle: a multivariate and time-varying approach", Y. Schuler, P. Hiebert, T. Peltonen, ECB Working Paper Series, No. 1846 / September 2015

3.2 Debt and credit variables

According to the Basel Committee on Banking Supervision (BCBS, 2010) an important goal of macroprudential policy relates to the prevention of periods of excess aggregate credit growth that have often been associated with the build-up of leverage and system-wide risk. It is also well documented that variables related to the cyclical dimension of credit are among the best performing indicators in signalling (banking) crises in a broad set of countries (in particular during the upswing of the economic cycle[10]). Such indicators include, for example, (i) the credit-to-GDP gap[11] (e.g., Babecký et al., 2014; Drehmann and Juselius, 2014; Detken et al., 2014; Behn et al., 2016), (ii) the deviation of household credit to GDP from its long-run trend (e.g. Detken et al., 2014; Anundsen et al., 2016), (iii) the deviation of non-financial corporation credit to GDP from its long-run trend (e.g. Anundsen et al., 2016), (iv) total or bank credit growth (e.g., Schularick and Taylor, 2012; Anundsen et al., 2016; Behn et al., 2016), (v) household credit growth (e.g., Büyükkarabacak and Valev, 2010; Detken et al., 2014), (vi) non-financial corporations credit growth (e.g., Büyükkarabacak and Valev, 2010). While excessive cyclical credit developments might reflect growing optimism in economic boom periods, potentially leading to risk illusion and excessive risk-taking by financial actors, high indebtedness of the non-financial private sector increases vulnerability to economic shocks. The empirical literature has emphasised the ability of indicators such as the credit to GDP ratio (e.g., Behn et al., 2016) and the debt service ratio (e.g., Detken et al., 2014; Drehmann and Juselius, 2014) in signalling banking crises well in advance.

The debt and credit domain of the MPDB considers a wide range of variables aimed to timely detect the build-up of periods of excessive credit growth or the possible emergence of credit bubbles in the economy that might pose a threat to the resilience of the financial sector. Complementing the financial condition indicators of the first domain, this second domain provides time series covering various aggregates and breakdowns of:

- Total credit (loans plus debt securities) granted to households, non-financial corporations and (private) non-financial sector;
- Bank credit (loans) to various types of counterparties;
- Cross-border exposures;
- Information on credit exposures in banks' balance sheet (data from the consolidated prudential COREP and FINREP reports);
- Bank Lending Survey indicators related to the bank's practices and expectations regarding credit standards and lending conditions[12].

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[10] For further details see Borio and Lowe (2002, 2004), Borio and Drehmann (2009), Behn et al (2013) and Drehmann and Juselius (2014), BCBS (2010) and Dekten et al. (2014), Alessi and Detken (2014).

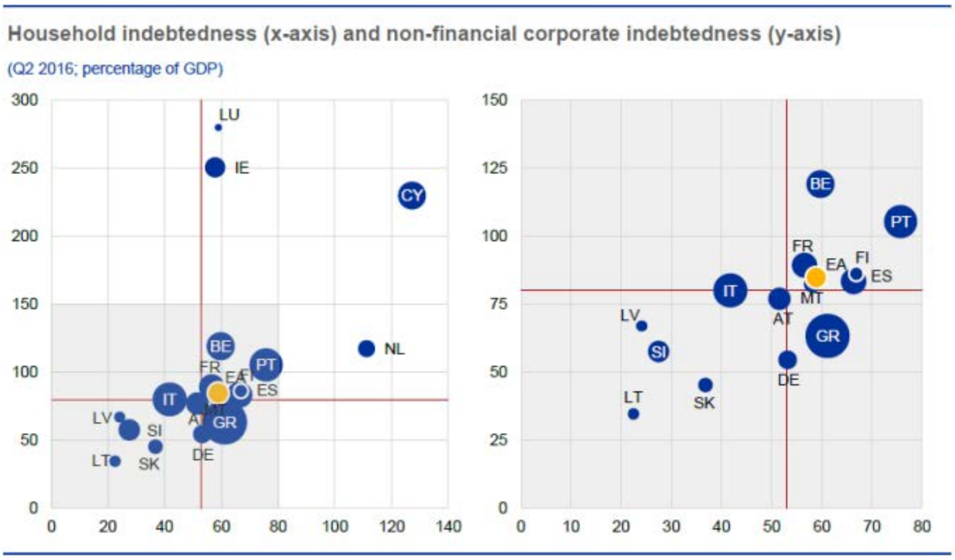
[11] The credit-to-GDP gap is defined as the deviation of credit to GDP from its long-run trend.

[12] See also https://www.ecb.europa.eu/stats/money/surveys/lend/html/index.en.html

Credit variables are particularly relevant in the context of the setting of the Countercyclical Capital Buffer (CCyB). This macroprudential instrument was introduced in the EU law by the Capital Requirement Directive IV (CRD IV) and needs to be assessed and set on a quarterly basis by the designated authority.

Among these variables, which aim at capturing cyclical systemic risk, the credit-to-GDP gap (as suggested by the Basel Committee of Banking Supervision) plays the most prominent role, although it is not supposed to lead to any automatic setting of the buffer. As its performance over time and in different countries can be heterogeneous, it is important to rely on a broader set of indicators, including qualitative information. The ESRB recommendation explicitly requires national authorities to monitor and consider a broader set of variables in addition to the credit-to-GDP gap, when setting the countercyclical capital buffer: real estate overvaluations, measures of credit developments, measures of external imbalances, measures of the strength of bank balance sheets, measures of private sector debt burden, measures of potential mispricing of risks, and measures derived from models which combines the credit-to-GDP gap[13]. Many of these indicators used at the national level can be found in the MPDB. Chart 2 illustrates indebtedness of households and non-financial corporates in euro area countries as an example. Apart from a comparison with historical value, the cross-country dimension of the database can also be used to compare developments in a cross-country and cross-time dimension.

Chart 2: Indebtedness across sectors



Sources: European Commission and ECB.
Notes: The size of the bubble reflects the level of general government debt as a share of GDP. Non-financial corporate debt is consolidated. Consolidated non-financial corporate debt figures include cross-border inter-company loans, which tend to account for a significant part of debt in countries where a large number of foreign entities, often multinational groups, are located (e.g. Belgium, Cyprus, Ireland, Luxembourg and the Netherlands). The horizontal and vertical lines represent the estimated macroeconomic imbalance procedure (MIP) benchmarks of 80% of GDP for consolidated non-financial corporate debt and 53% of GDP for household debt. The 133% of GDP MIP limit for fully consolidated non-financial private sector debt is split between firms and households based on their average past shares in the stock of non-financial private sector debt.

[13] See ESRB/2014/1.

3.3 Residential real estate variables

Imbalances in residential real estate markets (RRE) have played a significant role in several past financial crises[14]. Often, housing booms coincided with (broad-based) credit booms and, as documented in Crowe, Dell'Ariccia, Igan and Rabanal (2013), almost all the countries that experienced a "twin boom" ended up suffering a financial crisis or a severe contraction of GDP. The severe impact on the real economy of financial and economic crises related to real estate stems from the central role of the real estate sector in the economy and the predominance of bank credit in financing this sector.

Several empirical studies confirmed the importance of indicators related to residential real estate as useful early-warning indicators of banking crises or vulnerabilities related to real estate markets (e.g., Barrell et al., 2010; Reinhart and Rogoff, 2013; Detken et al., 2014; Ferrari et al (2015); Anundsen et al., 2016; Behn et al., 2016, Ciocchetta et al. (2016)). Imbalances in real estate markets are therefore also used as input for the more general assessment of cyclical systemic risks (see Section 3.2).

The potentially important role of RRE markets in the build-up of financial vulnerabilities also helps to explain why several macroprudential instruments have been implemented to target risk stemming from RRE. These include instruments targeting banks (e.g. sectoral capital requirements) and borrowers (e.g. loan-to-value (LTV), loan-to-income (LTI) and debt-service-to-income (DSTI) caps). Indicators related to credit conditions (LTV, LTI and DSTI) could also be useful to signal the emergence of vulnerabilities in the real estate sector driven by too lax lending standard. In fact, Crowe et al (2013) find that LTV ratios are significantly associated with real estate price developments. However, the empirical testing of the signalling properties of such indicators was so far hampered by significant data gaps and a lack of harmonised definitions[15].

The MPDB includes times series on variables that have been identified as potential leading indicators for RRE crises and/or that are the basis for the above-mentioned macroprudential instruments. Some of these areas are however still characterised by important gaps in the availability of comprehensive and comparable data for various countries (see Section 4)[16].

Against this background, the MPDB has identified a broad set of indicators for the RRE domain:

- A first set of indicators looks at the domestic household sector's balance sheet and its mortgage liabilities.

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[14] See for example Crowe et al. (2013) and Hartmann (2015).

[15] The ESRB Recommendation on Closing Real Estate Data Gaps (ESRB/2016/14) lays the foundations for a more harmonised and widespread availability of lending standards indicators for residential real estate loans in the EU, thereby allowing to overcome this issue in the future.

[16] See for example ESRB (2015), Report on residential real estate and financial stability in the EU, December.

- The second set of indicators covers time series that provide information on mortgage loans' key features, such as the interest rate cost of these loans. In the future, these should be complemented with comprehensive and comparable data on mortgage loan maturities and LTV, DSTI or LTI ratios.
- A third group of indicators focuses on time series providing information on house prices and house price valuation.
- The fourth group of indicators relates to time series that provide information on the supply side of the residential real estate market.

The MPDB puts a strong emphasis on cross-country comparability and therefore provides a very good basis for the horizontal analysis of vulnerabilities across European countries. Examples of how the MPDB was used for such a horizontal and indicator-based assessment of vulnerabilities can be found in the ESRB report on "Vulnerabilities in the EU residential real estate sector" published in November 2016.[17]

Table 1 presents the residential real estate scoreboard for European countries for Q3 2016. The indicators are grouped in three different categories according to the type of vulnerability they aim to capture, namely a "collateral stretch" (reflecting house price developments and measures of potential overvaluation of prices), "lending conditions" (signalling availability and pricing of mortgages), and "household stretch" (capturing the households' financial situation and ability to service its debt). Moreover, in addition to the single indicators, also summary measures are constructed to facilitate a comparison and ranking across countries and arrive at composite vulnerability scores.

It should be noted that an indicator-based horizontal analysis of vulnerabilities can only serve as a starting point of a more detailed analysis, which takes into account country-specific structural and institutional factors as well as expert judgement.

[17] The report is available on the ESRB website: https://www.esrb.europa.eu/pub/pdf/reports/161128_vulnerabilities_eu_residential_real_estate_sector.en.pdf?d1a536823a87796fcc0d06428343fe11

Table 1: Residential real estate scoreboard for European countries

Vulnerabilities in RRE across the EU: results from the indicator-based horizontal analysis

	Indicators										Summary measures	
	Collateral Stretch				Lending Indicators			Household Stretch				
Country	Residential real estate price index, 12m growth, %	Residential price index relative to peak prior to 2014	RRE valuation measure, house price to income	RRE valuation measure, econometric model	Loans to HH for house purchases, 12m growth, %	Loans to HH for HP relative to peak prior to 2014	HH Loan spread	HH debt, % of GDP	HH financial assets to debt, %	Debt service to income ratio for HH, %	Average rating across indicators	Composite indicator
AT	8.1	1.1	26.0	14.0	4.9	1.1	2.1	51.2	350.8	10.2	1.4	0.3
BE	2.3	1.0	26.0	4.0	8.1	1.2	1.8	59.6	500.2	10.7	1.5	0.2
BG		0.8	-9.0	-11.0	0.6	1.0	5.6	23.8	552.6	8.1	0.0	-0.9
CY	-1.6	0.7	-16.0	-3.0	-1.8	0.9	3.2	127.3	206.0	28.8	0.9	0.3
CZ		1.0	8.0	2.0	8.7	1.1		30.3	360.4	8.2	0.8	-0.1
DE	4.7	1.1	4.7	-2.0	3.7	1.1	1.9	53.4	338.1	9.4	0.8	0.1
DK	3.5	0.9	19.0	4.0	1.2	1.0	1.4	122.8	248.5	20.4	1.5	0.6
EE	0.8	0.9	8.0	-7.0	4.6	1.0	2.3	40.6	270.4	7.6	0.4	-0.2
ES	6.3	0.7	-6.0	5.0	-3.5	0.8	1.9	66.4	275.8	12.9	0.5	-0.1
FI	-0.1	1.0	10.0	3.0	2.6	1.0	1.4	66.7	210.9	11.4	1.4	0.2
FR	0.3	0.9	14.0	4.0	3.2	1.0	1.7	56.5	394.1	10.0	1.0	0.0
GR	-5.0	0.6	-25.0	-5.0	-3.6	0.8	2.7	61.8	218.3	21.8	0.7	-0.2
HR	-2.1	0.8	-11.0	-16.0	-4.8	0.8	4.4	36.9	302.7	8.8	0.0	-0.6
HU	4.3	0.9	-7.0	-15.0	-3.3	0.6	4.6	21.2	563.5	7.6	0.1	-0.9
IE	7.4	0.7	-3.0	-23.0	-4.2	0.6	3.4	57.8	237.3	19.9	0.7	-0.4
IT	-1.2	0.8		-5.0	0.9	1.0	1.6	42.1	581.5	11.8	0.3	-0.3
LT	10.5	0.7	-3.0	-8.0	6.6	1.0	1.9	22.3	414.2	5.1	0.6	-0.4
LU	4.5	1.1	18.0	9.0	7.0	1.2	1.7	57.4	242.1	10.8	1.8	0.4
LV	7.4	0.7	-6.0	-19.0	-2.2	0.7	3.3	24.3	430.8	5.7	0.2	-0.8
MT	10.0	1.1	10.0	-9.0	7.9	1.2	2.3	57.8	462.8	12.8	1.6	0.1
NL	4.4	0.9	-4.0	2.0	6.2	1.1	2.8	111.4	296.7	21.5	0.9	0.3
PL	1.8	0.9	-9.0	-17.0	0.7	1.1	1.4	36.2	268.6	13.4	0.5	-0.2
PT	5.0	0.9	-9.0	-3.0	-3.5	0.8	2.0	76.3	269.5	16.4	0.6	0.0
RO	3.6	0.7	-20.0	-29.0	16.5	1.3	2.8	17.2	414.6	6.5	0.6	-0.6
SE	12.9	1.3	69.0	47.0	8.7	1.1		84.7	333.4	16.0	2.2	1.2
SI	0.8	0.8	-10.0	-8.0	3.2	1.0	2.0	27.5	367.4	5.8	0.1	-0.4
SK	1.0	0.8	-6.0	-15.0	13.8	1.3	2.3	35.8	213.9	10.0	1.0	-0.1
UK	8.7	1.0	30.0	11.0	4.6	1.1		87.0	372.9	18.4	1.7	0.6
EAA	2.4	1.0	4.7	-1.0	2.1	1.0		59.3	356.1		0.5	0.0
EAM	4.5	0.9	-3.0	-3.0	3.2	1.0	2.0	57.4	296.7	10.8	0.8	0.0
EUA		1.0									1.0	0.4
EUM	4.4	0.9	-3.0	-3.0	3.2	1.0	2.1	54.9	335.8	10.8	0.7	-0.1
T1	4.0	0.9	2.5	2.5	5.0	1.0	1.5	50.0	220.0	10.0	1.0	0.0
T2	6.5	1.0	5.0	5.0	7.5	1.1	1.8	70.0	240.0	15.0	1.2	0.2
T3	9.0	1.1	7.5	7.5	10.0	1.2	2.0	90.0	260.0	20.0	1.7	0.5
TR	4.0	0.9	2.5	2.5	5.0	1.0	2.0	50.0	260.0	10.0		

Source: MPDB, see Annex B of ESRB report on vulnerabilities in residential real estate markets, November 2016 for details.
Notes: EAA is the euro area average; EAM is the euro area median; EUA is the EU average; EUM is the EU median; T1, T2, T3 and TR are the risk thresholds. See Box 1 and Annex B of ESRB report on vulnerabilities in residential real estate markets, November 2016 for a description of the methodology underlying these results. In Finland, the household financial asset-to-debt indicator excludes earnings-related pension assets. Including assets held by the Finish employment pension scheme, the ratio would be around 337%.

3.4 Commercial real estate variables

Excessive developments in the commercial real estate (CRE) sector can harm the stability of the financial sector and have negative consequences for the real economy. CRE markets are inherently more pro-cyclical than RRE markets, due to more inelastic supply conditions, stronger co-movements with broad macroeconomic developments and the more international investor base (ESRB, 2015). Furthermore, providers of CRE financing are diverse, encompassing both bank and non-bank entities, such as insurance companies and asset managers. In addition, the CRE sector is heterogeneous both with respect to the type of property being financed (e.g. retail, industrial, office, residential…) and for the underlying purpose underlying the acquisition of CRE property. In fact, commercial property is more often bought as a speculative investment by professional investors than residential property, which often serves as accommodation for its owners.

The analysis of risks and vulnerabilities related to CRE is still hampered by severe data gaps and, until recently, by the absence of a commonly agreed definition of CRE. However, the 2016 ESRB Recommendation on Closing Real Estate Data Gaps (ESRB/2016/14) sets the stage for overcoming these limitations and lays the foundations for an effective monitoring framework for CRE markets in the EU. First, the ESRB Recommendation provides a definition of CRE, namely "any income-producing real estate, either existing or under development, excluding social housing, property owned by end-users and buy-to-let housing"[18] (Section 2.1.4). Secondly, the Recommendation provides detailed guidance on the set of indicators necessary for the monitoring of emerging CRE risks, covering several dimensions, including the physical market for CRE properties, the financial sector's exposures to CRE and related lending standards.

However, the MPDB currently, covers a very limited number of CRE-related variables, encompassing mainly available CRE price indicators and information on CRE-related exposures in the financial sector (even if these exposures may only be considered to be broad proxies of what would fall under a more precise definition of CRE).[19] Enhancing the availability of CRE-related indicators is one of the priorities for the future enhancement of the database.

3.5 Bank sector variables

The recent financial crisis demonstrated that the financial system in general and the banking sector in particular can be an important source and propagation channel of shocks. In fact, while vulnerabilities can materialise within the banking sector, the degree of banks' resilience determines the degree to which adverse developments are transmitted to the real economy and potentially amplified. More specifically, a banking sector characterised by high capitalisation, low leverage and low degree of

[18] Buy-to-let housing, defined in the Recommendation as "any residential real estate property directly owned by a private household primarily for letting to tenants", falls under the scope of residential real estate.

[19] See for example ESRB (2015), Report on commercial real estate and financial stability in the EU, December.

liquidity mismatch is better able to withstand negative shocks, and to limit their propagation to the real economy.

Several studies in the early-warning literature reveal that the probability of banking crises is reduced when the banking sector is characterised by low leverage (e.g. Barrell et al., 2010; Anundsen et al., 2016; Behn et al., 2016) lower liquidity mismatch (e.g. Barrell et al., 2010; Drehman and Juselius, 2014; Anundsen et al., 2016), and a high capital ratio (Betz et al. 2014). Betz et al (2014) also find that, at the country level, rapid growth in non-core liabilities, a high debt-to-equity ratio as well as a large banking sector, are associated with higher probabilities of bank distress. The role of the banking sector in both originating and transmitting adverse shock is the subject of a vast body of theoretical studies. According to the literature, two important transmission channels are the bank balance sheet and the liquidity channel.[20]

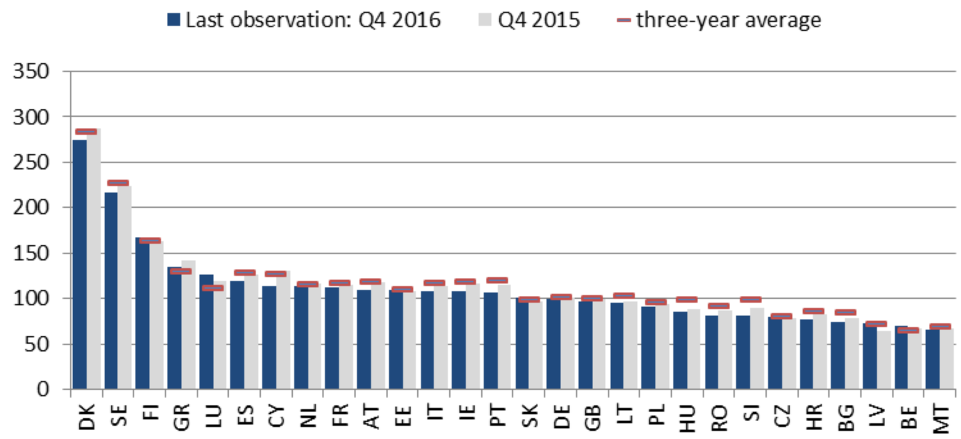
The MPDB includes several indicators used to measure banking sector performance and vulnerabilities in the different EU countries as well as at the EU and euro area level, which are grouped under the following categories:

- Banking structure: This set of indicators shows the degree of financial intermediation and banking concentration to support the identification of structural risks.
- Main elements of the income statement: In this section basic components of the profit and loss account are shown.
- Profitability: Based on the main elements of the income statement this section includes various ratios concerning profitability and efficiency.
- Main elements of the balance sheet: The section on elements of the balance sheet covers the structure of assets and liabilities on a detailed basis.
- Liquidity and funding: These indicators aim at assessing the resilience of banks' liquidity position, the diversification of funding sources and maturity mismatches between assets and liabilities so as to reduce liquidity risk and cover any unforeseen funding requirements. A high value of the loan-to deposit ratio, implying that the financing of the stock of loans has to rely on additional wholesale funding, could signal higher aggregated liquidity risk for those banking systems, since wholesale funding tends to be more volatile than deposits.

[20] See BCBS (2011).

Chart 3: Loan to deposit ratio of EU banking sector

Percentages



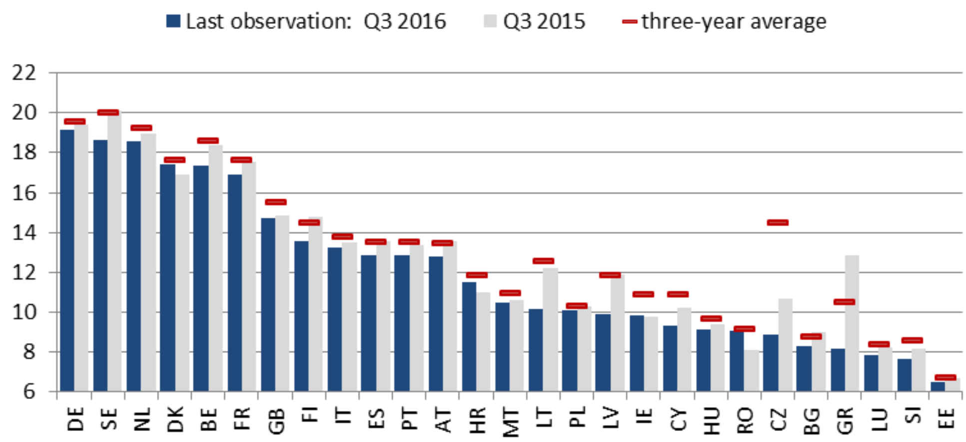
Source: ECB, ESRB Risk Dashboard

Notes: MFIs sector excluding the ESCB. Data refers to the ratio between total loans and total deposits vis-à-vis the domestic and euro area households, NFCs and non-MFI residents excluding the general government. Mortgage banks in Denmark, which represent around 55% of total MFI loans to domestic NFCs, are not allowed to take deposits owing to regulations, but must fund their lending through issuance of covered bonds only. Excluding mortgage banks from the indicator, the loan-to-deposit ratio for DK is equal to 0.75 for Q4 2016 and 0.79 for Q4 2015.

- Lending and leverage: Indicators in this category allow to assess different types of risks related to the provision of credit to the real economy, such as risks from lending in foreign currency, variable rate loans, large exposures and loan concentration per sector, as well as risks related to the excessive build-up of leverage (leverage ratio indicator).

Chart 4: EU banking sector leverage

Total assets, as multiple of capital



Sources: ECB.

Notes: Share of total assets in capital for domestic banking groups and stand-alone credit institutions. Consolidated data

- Capital: This category assesses the capacity of the financial sector to absorb shocks on both asset and liability sides of their balance sheets. Indicators cover the main regulatory capital ratios, the quality of regulatory capital as well as the composition of the risk-weighted assets.
- Asset quality: The indicators assess the credit quality of the loan portfolio and banks' related provisioning.
- Locational funding indicators: This section complements indicators provided in other sections.

3.6 Non-bank variables

As systemic risks can also emerge outside the banking sector, other segments of the financial system also warrant monitoring. This is even more relevant given the shift to market-based financing or to more lightly regulated intermediaries. Identifying the build-up of systemic risk in the so called "shadow banking" sector is a priority on the international policy agenda, as illustrated by the work of the Financial Stability Board.[21]

Monitoring the non-bank sector is not an easy task, principally because of the very heterogeneous entities and activities which it encompasses. Besides insurance companies and pension funds, the non-bank sector also comprises entities such as money market funds, real estate investment trusts, special purpose vehicles and hedge funds, just to name a few. As outlined by Doule et al. (2016), potential risks in the non-bank sector might arise from liquidity and maturity mismatches, excessive leverage and pro-cyclicality of margins and haircuts.

The ability to monitor risks in the non-bank sector is severely hampered by data gaps. However improvements are being made in this respect. An important step forward in the monitoring of the shadow banking sector has been marked in 2016 by the publication of the ESRB "EU Shadow Banking Monitor"[22] and the paper by Grillet-Aubert et al (2016). In addition, oversight of the EU insurance sector has been recently significantly improved by the availability of new data based on the Solvency II reporting. [23]

The MPDB includes a domain containing variables to assess risks to financial stability originating from outside the banking sector. The indicators deal for example with structural features of insurance corporations and pension funds and their exposures to sovereigns. It also covers information on financial vehicle corporations (FVCs).

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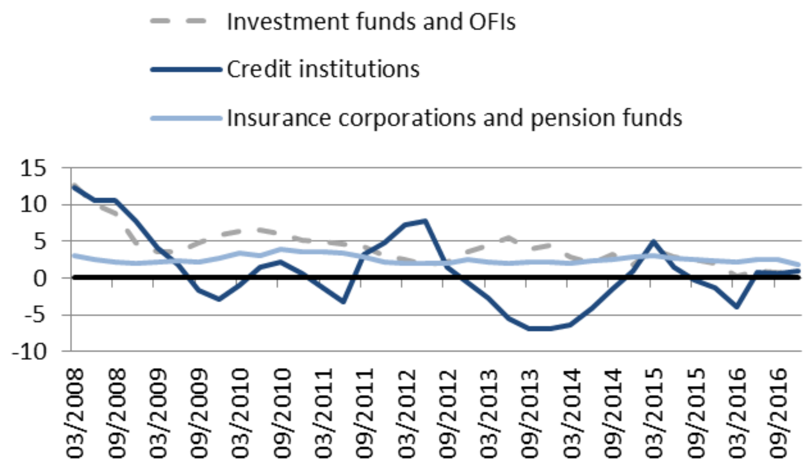
[21] See for instance the last FSB Global Shadow Banking Monitoring Report, http://www.fsb.org/2015/11/global-shadow-banking-monitoring-report-2015/

[22] https://www.esrb.europa.eu/pub/pdf/.../20160727_shadow_banking_report.en.pdf

[23] This data is available to the ESRB on aggregated basis, based on agreement with EIOPA. First transmission, comprising insurance data for Q3 2016, took place in March 2017

Chart 5: Growth of components of the EU financial sector

EU; percentages; total assets annualised growth rates; last observation: Q4 2016



Sources: ECB.

Notes: Data based on financial accounts and monetary statistics. Data refer to the non-consolidated balance sheets of the respective entities

3.7 Interconnectedness variables

Interconnectedness plays a major role in the propagation of financial distress both within the financial sector and across countries. The recent financial crisis made evident that direct and indirect financial linkages (i.e. bilateral contractual obligations or exposures to common assets) may result in a contagion cascade with the potential of spreading financial distress worldwide.. Recent studies have confirmed that the network structure matters in both the origination (Allen et al., 2011) and the transmission of systemic risk (e.g., Gai and Kapadia, 2010; Georg, 2013).

The MPDB includes variables that capture interconnectedness within the financial system, among which indicators that have been selected for the ESRB's quantitative risk analysis tools. The Financial Stability Board for instance developed a common data template to be reported by global systemically important banks (G-SIBs).[24] The MPDB encompasses indicators such as total bank assets relative to GDP, banks' interbank liabilities (in addition to their interbank assets) and positions in derivatives, among others.

[24] See the FSB Data Gaps Initiative on a Common Data Template for G-SIBs: http://www.fsb.org/2013/04/r_130418/

Box1: Comparison between MPDB and IMF Financial Soundness Indicators (FSI)

The IMF Financial Soundness Indicators (FSIs) project was the first structured initiative aimed at compiling a database specifically tailored to macroprudential statistical needs and analysis. The regular data collection started in 2008, following two preliminary implementation phases: a) the development of the compilation guide meant to set the methodological standards to derive the FSIs, and b) an initial pilot data collection exercise that began in 2006. Work is currently ongoing on revising the list of FSIs in response to the global financial crisis.

The main characteristics of the MPDB and FSIs are summarised in the table below. FSIs currently cover around 40 indicators (52 in the revised list of indicators foreseen to be implemented), mainly focused on the financial system and their corporate and household counterparts. The MPDB is much broader in scope (around 275 indicators), also encompassing the macroeconomic environment, financial markets, debt/credit developments and government sector. Such broader coverage results from the availability of a large variety of in-house statistics. On the other hand, the country coverage is significantly higher for FSIs compared to MPDB (103 countries vs 28 EU countries).

Another relatively notable difference is that all data in the MPDB is fully harmonised across countries in terms of statistical methodologies. In the case of the FSIs, given the much higher coverage of countries, there is still scope in enhancing the comparability and homogeneity of data across all countries, the FSIs compilation guide plays an important role in this respect.

Comparison of MPDB and IMF FSIs

	MPDB	IMF FSIs
Country coverage	28 (EU countries)	103
Number of indicators	275	40
Overlapping	~30 indicators (however significant methodological differences may exist for the same indicator between the two datasets)	
Harmonisation	Fully harmonised data	Scope to enhance comparability of cross-country data
Data collection	Selected data already available at the ECB	Dedicated data collection
Frequency	Depends on the underlying data (generally monthly or quarterly)	Generally quarterly (other frequencies depending on the indicator)
Release year	2015	2006 pilot exercise/2008 regular reporting

Source: ECB, IMF

Box2: Confidentiality protection and the three layers of MPDB

The MPDB follows the dissemination policy in place for the datasets already available in the ECB SDW, thereby being fully compliant with the confidentiality features of the underlying data.

In this regard, the MPDB has three different layers, which differ in the data availability:

- ECB internal MPDB
- ESCB layer of MPDB
- Public MPDB

ECB internal MPDB

ECB users can access the entire content of the MPDB, including data sourced from commercial data providers. In some cases, access to particular datasets is granted on the principle of business-related "need to know", so as to ensure that given data are only accessed by authorised individuals who need these resources in order to undertake their work.

ESCB layer of MPDB

Data are visible to the European System of Central Banks and also associated institutions for which a memorandum of understanding is in place: the European Banking Authority (EBA), the European Commission, the European Insurance and Occupational Pensions Authority (EIOPA), the European Securities and Markets Authority (ESMA), the European Stability Mechanism (ESM), the European Systemic Risk Board (ESRB) and the Bank of International Settlements (BIS). In this layer, some of the data from commercial data providers are not available to the users, due to contractual limitations. If the variables coming from third institutions (e.g. OECD and BIS) are not available in this layer, the MPDB catalogues gives clear instructions on where and how to obtain this data.

Public MPDB

Since the start of the project much effort has been put in making as much data as possible available to the general public.

Admittedly, the coverage of the MPDB available for the general public is limited compared to the ECB or even the ESCB layer, as a significant amount of data reported to the ECB from national authorities, is flagged as non-publishable and thereby can only be shared within the ESCB.

Nevertheless, the public layer of the MPDB is expected to be a useful reference, providing as much information as possible presented in one place. As in the ESCB layer, the MPDB catalogues provides clear instructions where and how to obtain certain time series from commercial providers or third institutions (e.g. OECD and BIS).

4. Future enhancements

4.1 Regular reviews and closing of data gaps

The creation of the MPDB was accompanied by a data gap analysis. The most relevant areas affected by data gaps identified in this analysis are real estate (both commercial and residential), non-banking intermediaries and interconnectedness measures. Following an in-depth assessment, carried out in close collaboration with NCBs/NCAs, some of these gaps were deemed "possible to be addressed" by collecting information already available at national level.

Within this set of missing statistical information, a number of relevant indicators for macroprudential analysis (labelled as "Orange Indicators") could in principle be derived from the information reported within the banking supervisory reports (EBA Implementing Technical Standards on Supervisory Reporting (FINREP/COREP templates), available with the national authorities.

While a decision on the collection of these data by the ECB is still to be finalised, the actual implementation would close some of the data gaps related to both commercial and residential real estate in the short run, even though only to a limited extent (around 15 new indicators) compared to the actual data needs in this area. These indicators mainly refer to different measures that are relevant for the assessment of credit risk, provisioning and solvency for various real estate type of exposures.

In addition to the potential implementation of these indicators, further improvements towards the closing of data gaps in the real estate sector could likely be expected around 2020 in the context of the implementation of the ESRB Recommendation on closing real estate data gaps and of the AnaCredit project, which will provide granular loan information covering the non-financial corporations sector.

Data gaps in the area of residential and commercial real estate are difficult to bridge in a satisfactory fashion through ad hoc surveys. A good and comparable dataset on very important parameters for the macro-prudential analysis of RRE (such as LTV ratios) will require establishing common definitions and co-ordinated collections of data that are at least representative for the domestic mortgage and housing markets, which is exactly what the ESRB recommendation on closing real estate data gaps aims at.

Apart from the already foreseen expansions and enhancements, the MPDB is being regularly reviewed to keep up with evolving users' needs. It is fair to add that such developments may imply costs for the compilers in NCBs/NCAs as well as lead to additional reporting from industry. The ESCB and ESRB will take a cost-conscious and effective approach prior to any significant increase in coverage, and the more so the more costly such extensions may be.

4.2 Further expanding coverage in the area of non-banks

While many systemic crises are characterised by bank failures or bail-outs, experience shows that financial instability is not always triggered by traditional banking intermediation. As the Regulation that establishes the ESRB provides it with a mandate to oversee systemic risk in the financial system as a whole, a further development of the MPDB to measure risks stemming from outside the banking sector would support the ESRB in its tasks. One example of the direct application of the non-banking data is the ESRB Heatmap - risk analysis tool, currently in the development phase. The heatmap should help policy makers and financial stability analysts to monitor the EU financial system and the potential build-up of systemic risks. To achieve this, input of high quality data covering non-banking sectors is essential.

Non-bank entities and activities contributed to the propagation of the global financial crisis. The securitisation of mortgages prior to the crisis increased vulnerabilities and led to over-borrowing. Money market funds following the failure of Lehman Brothers played an amplifying role in the global financial crisis. So too did the near-failure of AIG, an insurer which had become 'too big to fail'.

Identifying and addressing such risks and assessing the resilience of the financial system are becoming ever more important with the recent growth of the non-bank financial system in the EU.

In addition, the drive toward greater market financing – a key goal of the European capital markets union (CMU) – will likely spark further growth among non-banks.

4.3 Type of indicators

The materialisation of systemic risks emanating from non-banks can be understood in similar terms to those from banking. The impact, sources and transmission channels, however, may vary substantially across sectors.

4.3.1 Credit growth and leverage

By providing services to the real economy some financial firms may take on leverage and undertake maturity transformation. Excessive leverage amplifies the financial cycle, allowing more borrowing to take place, and may lead to a reduction in the resilience of market players. In addition, reliance on short-term and unstable funding may lead in case of dry-up to fire sales, market illiquidity and contagion as firms seek to meet withdrawals.

4.3.2 Interconnectedness

Links between financial institutions can help manage risk and distribute funds to where they can be deployed more effectively. Interlinkages between entities may also reduce the system's ability to withstand stress given direct and indirect contagion channels. Risks may materialise also when banks provide financial support to non-bank financial entities beyond contractual obligation.

4.3.3 Too big to fail

Non-bank entities can become systemically important. On the one hand, mandatory clearing of standard derivatives through CCPs has the potential to increase transparency and the stability of the network. On the other hand it also creates new networks and concentrates risks at CCPs. Due to their central position in the network; CCPs may themselves become systemically important.

5. Conclusions

A suitable statistical basis for macroprudential analyses and policies comprises a comprehensive and high-quality set of data and indicators. A wide set of statistics on macroeconomic variables, financial and real estate markets, credit, debt and funding patterns are needed. Moreover, in order to detect possible contagion risks, created by increasing interconnectedness and herd behaviour, also interconnectedness variables have to be monitored.

This paper describes a major initiative undertaken by the E(S)CB, in cooperation with the ESRB, to build such a statistical repository with the creation of the Macroprudential Database (MPDB). The rationales for setting up the MPDB are put forward, together with the structure of the database and a broad overview of its indicators. Relevant confidentiality issues are dealt with.

As a by-product, the design and implementation of the MPDB showed how cooperation and mutual involvement of financial stability experts and statisticians can create relevant synergies and value added in terms of conceptual analysis, technical infrastructures, collection and compilation of data.

With the creation of the MPDB a first important step was taken, but more has to be done. Data gaps are still there, especially in some domains of the MPDB and they will have to be filled, always keeping an eye on the burden to data compilers and matching merits and costs of additional data. Data gaps appear to be relevant for instance in the area of residential and commercial real estate. A further important challenge will be expanding the coverage in the area of non-banks credit intermediation, given the growing relevance of the so-called "shadow-banking" sector. Progress in the EU-driven project of developing a Capital Market Union will make this area even more relevant. More in general, the MPDB will be regularly reviewed to ensure a robust and harmonised data system capable of satisfying the information needs of macroprudential analysts and policymakers.

Annex 1 - MPDB structure

The database consists of seven domains with various sub-domains and has the following structure:

Macroeconomic and financial market variables

- Monetary indicators
- Macroeconomic indicators
- GDP indicators
- Foreign exchange indicators
- Financial market indicators
- Risk and uncertainty indicators
- Financial condition indicators
- Borrowing and lending indicators

Debt and credit variables

- Total credit and debt service indicators
- Bank credit indicators
- Financial sector credit by sub-sector (whom-to-whom accounts)
- Cross border / currency / securities exposures
- Credit exposure of banks (FINREP data)
- Credit exposure of banks (COREP data)
- Credit conditions according to bank lending survey

Residential real estate variables

- Mortgage debt and household balance sheet
- Mortgage loan features / credit standards
- House price and house price valuation indicators
- Housing transactions and supply side

Commercial real estate variables

- CRE market: risk indicators
- Financial sector exposure to CRE

Bank sector variables

- Banking structure

- Main elements of the P&L
- Profitability
- Main elements of the balance sheet
- Liquidity and funding
- Lending and leverage
- Capital
- Asset quality

Non-bank variables

- Insurance companies and pension funds
- Other financial institutions

Interconnectedness variables

- Interconnectedness variables

References

Alessi, Lucia and Detken, Carsten, Identifying Excessive Credit Growth and Leverage (August 8, 2014). ECB Working Paper No. 1723

Allen, F., Beck, T., Carletti, E., Lane, P., Schoenmaker, D., Wagner, W., 2011. "Cross-Border Banking in Europe: Implications for Financial Stability and Macroeconomic Policies", CEPR Report.

Anundsen, A., Gerdrup, K., Hansen, F., Kragh-Sørensen, K., 2016. Bubbles and Crises: The Role of House Prices and Credit. Journal of Applied Econometrics 31(7), 1291-1311.

Babecký, J., Havránek, T., Matějů, J., Rusnák, M., Šmídková, K., Vašíček, B., 2014. Banking, debt and currency crises in developed countries: Stylized facts and early warning indicators. Journal of Financial Stability 15, 1-17.

Barrell, R., Davis, E.P., Karim, D., Liasdze, I., 2010. Bank regulation, property prices and early warning systems for banking crises in OECD countries. Journal of Banking and Finance 34(9), 2255-2264.Basel Committee on Banking Supervision (2010), Guidance for national authorities operating the countercyclical capital buffer.

Basel Committee on Banking Supervision (2011), "The transmission channel between the financial and the real sectors: a critical review of the literature", BIS Working Paper No.18, February 2011.

Behn, M, C Detken, T Peltonen and W Schudel (2013): "Setting countercyclical capital buffers based on early warning models: would it work?", ECB Working Paper Series, no 1604, November.

Behn, M., Detken, C., Peltonen, T., Schudel, W., 2016. Predicting vulnerabilities in the EU banking sector: the role of global and domestic factors. International Journal of Central Banking, forthcoming.

Betz, F., Oprica., S., Peltonen, T.A., Sarlin, P., 2014, "Predicting distress in European banks", Journal of Banking and Finance, Vol.45, pp. 225-241.

Borio, C and P Lowe (2002): "Assessing the risk of banking crises'", BIS Quarterly Review, December, pp 43–54

Borio, Claudio E. V. and Lowe, Philip William, Securing Sustainable Price Stability: Should Credit Come Back From the Wilderness? (July 2004)

Borio, Claudio E. V. and Drehmann, Mathias, Assessing the Risk of Banking Crises – Revisited (March 2, 2009). BIS Quarterly Review, March 2009

Büyükkarabacak, B., Valev, N.T., 2010. The role of household and business credit in banking crises. Journal of Banking and Finance 34(6), 1247-1256.

Ciocchetta, F., Cornacchia, W., Felici, R., Loberto, M., 2016. Assessing financial stability risks arising from the real estate market in Italy. Banca d'Italia Occasional Papers No. 323.

Crowe, Christopher & Dell'Ariccia, Giovanni & Igan, Deniz & Rabanal, Pau, 2013. "How to deal with real estate booms: Lessons from country experiences," Journal of Financial Stability, Elsevier, vol. 9(3), pages 300-319.

Council Regulation (EU) No 1024/2013 of 15 October 2013 conferring specific tasks on the European Central Bank concerning policies relating to the prudential supervision of credit institutions.

Directive 2013/36/EU of the European Parliament and of the Council of 26 June 2013 on access to the activity of credit institutions and the prudential supervision of credit institutions and investment firms, amending Directive 2002/87/EC and repealing Directives 2006/48/EC and 2006/49/EC Text with EEA relevance

Dekten, C., O. Weeken, L. Alessi, D. Bonfim, M. Boucinha, C. Castro, S. Frontczak, G. Giordana, J. Giese, N. Jahn, J. Kakes, B. Klaus, J. Lang, N. Puzanova and P. Welz (2014), "Operationalising the countercyclical capital buffer: indicator selection, threshold identification and calibration options", ESRB Occasional Paper Series, No. 5, June.

Drehmann, M., Juselius, M., 2014. Evaluating early warning indicators of banking crises: Satisfying policy requirements. International Journal of Forecasting 30(3), 759-780.

ECB (2016): Macroprudential Bulletin, Issue 1.

ESRB (2011/3), "Recommendation on the macro-prudential mandate of national authorities". December, 2013.

ESRB (2014/1), "Recommendation of the European Systemic Risk Board of 18 June 2014 on guidance for setting countercyclical buffer rates", June 2014.

ESRB (2016/14): "Recommendation on Closing Real Estate Data Gaps", October 2016.

ESRB Report "Vulnerabilities in the EU residential real estate sector", November 2016.

Ferrari, S., Pirovano, M., Cornacchia, W., 2015. Identifying early warning indicators for real estate-related banking crises. European Systemic Risk Board Occasional Paper No. 8.

Financial Stability Board (2015), Global Shadow Banking Monitoring Report 2015.

Gai, P., Kapadia, S., 2010, "Contagion in financial networks", Proceedings of the Royal Society A: Mathematical, Physical and Engineering Science, rspa20090410.

Georg, C.-P., 2013, "The effect of the interbank network structure on contagion and common shocks", Journal of Banking & Finance 37 (7), pp. 2216-2228.

Grillet-Aubert, L., Haquin, J., Jackson, C., Killeen, N., Weistroffer, C., 2016, "Assessing shadow banking- non-bank financial intermediation in Europe", ESRB Occasional Paper No 10/July 2016.

International Monetary Fund, 2006. Financial Soundness Indicators: Compilation Guide.

International Monetary Fund, 2013. Modifications to the Current List of Financial Soundness Indicators (FSIs); IMF Policy Paper.

Regulation (EU) No 575/2013 of the European Parliament and of the Council of 26 June 2013 on prudential requirements for credit institutions and investment firms and amending Regulation (EU) No 648/2012 Text with EEA relevance

Regulation (EU) No 1092/2010 of the European Parliament and of the Council of 24/11/2010 on European Union macro-prudential oversight of the financial system and establishing a European Systemic Risk Board

Reinhart, C.M., Rogoff, K.S., 2013. Banking crises: An equal opportunity menace. Journal of Banking and Finance 37(11), 4557-4573.

Schularick, M., Taylor, A., 2012. Credit booms gone bust: Monetary policy, leverage cycles and financial crises, 1870–2008. American Economic Review 102(2), 1029–1061.

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European Macroprudential Database[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.

European Macroprudential Database (MPDB)

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Disclaimer: The views expressed are those of the authors and do not necessarily reflect those of the ECB, ESRB and NBB

Topics addressed in this presentation

Macroprudential Database

- **Macroprudential Database (MPDB)** - Statistical basis for ECB macroprudential policy and also covering ESRB data needs
  - ➢ comprehensive and harmonised dataset of indicators selected on the basis of institutions' experience, information about indicators used in various macroprudential tools and relevant academic literature.

- A first large dataset went *live in October 2015* and can be consulted in the **ECB's Statistical Data Warehouse (SDW):** ***Link to the MPDB***

- **Semi-annual review** of the indicator list to meet evolving user needs and potential availability of new data sources
  - ➢ Criteria: relevance, availability, quality and confidentiality of the data

The rationale for the MPDB (1)

- The financial crisis confirmed need for system-wide surveillance of systemic risk and led to establishment of macroprudential policy as key policy area with objective of early detection of systemic risk and, in case of materialisation, promoting actions to limit its contagion effects

- Originally, macroprudential powers in the European Union were established primarily at the national level, but …

- … the implementation of the Single Supervisory Mechanism (SSM) Regulation also strengthens consistency of macroprudential policy at EU level.

- *Background information*: SSM Regulation - Council Regulation (EU) No 1024/2013 conferring specific tasks on the ECB concerning policies relating to the prudential supervision of credit institutions in the EU

The rationale for the MPDB (2)

- In particular, the **SSM Regulation** confers specific powers and responsibilities in the field of macroprudential policy upon the ECB and National Competent Authorities or National Designated Authorities.

- The role of the ECB in this area is twofold:

1. **First**, the ECB is involved in the decision making process of macroprudential policy in SSM countries.

2. **Second**, the ECB has the right to apply more stringent measures at the national level for the instruments included in the EU laws.

The rationale for the MPDB (3) - EU Macroprudential Framework

Macroprudential tasks and tools of the ECB in the context of the SSM

- *Coordinating with national macroprudential authorities*
  - The concerned authority of Member States shall duly notify its intention to the ECB prior to taking a decision
  - Where the ECB objects, it shall state its reasons in writing within five working days
  - The concerned authority shall duly consider the ECB's reasons prior to proceeding with the decision as appropriate

- *Taking macroprudential actions*
  - Instead of national authorities of the participating Member State, or jointly with them, the ECB may apply
    - ✓ higher requirements for capital buffers
    - ✓ apply more stringent measures aimed at addressing systemic risks

Measures are subject to procedures set out in ***CRR/CRD IV and SSM Regulation***

The rationale for the MPDB (4)

- The shared responsibilities regarding macroprudential policies between national authorities and the ECB triggered the need to establish a common ground for macroprudential analysis.

- A comprehensive and harmonised database was essential for analytical and policy oriented work flowing into internal and external reports, and for a consistent cross-country analysis of systemic risk.

- The Macroprudential Database (MPDB) became operational in October 2015 and is available publicly, accessible through ECB's Statistical Data Warehouse (SDW)

MPDB in ECB's Statistical Data Warehouse

Statistical Data Warehouse
EUROPEAN CENTRAL BANK

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- Financial markets and interest rates
- Macroeconomic and sectoral statistics
- Balance of payments and other external statistics
- **Supervisory and prudential statistics**
  - Consolidated banking data
  - **Macroprudential Database**
    - Macroeconomic and financial market variables
    - Debt and credit variables
    - Residential real estate variables
    - Commercial real estate variables
    - Bank sector variables
    - Non-bank variables
    - Interconnectedness variables
  - Banking supervision
- Payments statistics
- ECB surveys

Macroprudential Database

The Macroprudential Database (MPDB) is a comprehensive and harmonised dataset of indicators covering various sub-categories of indicators judged relevant for macroprudential analysis. The database focuses on the indicators that can be used to explain and predict financial crisis episodes. The indicators were selected based on institutions' experience of using time series for macroprudential analyses, information about indicators used in macroprudential tools and relevant academic literature. They include indicators selected for the ESRB's quantitative risk analysis tools, such as the ESRB Risk Dashboard, and the indicators used to monitor developments in national banking markets. The indicators in the database are grouped into seven categories, each of which include various sub-categories, according to the below structure (see overview tab).

The list of indicators, together with the underlying SDW codes and indicator calculations, can be accessed in the MPDB catalogue. The catalogue may also include references to time series that cannot be shown in the SDW but are available from other data sources.

Download the MPDB catalogue

Overview | Publications and Dashboards

Macroeconomic and financial market variables

Monetary indicators | Macroeconomic indicators | GDP indicators | Foreign exchange indicators | Financial market indicators | Risk and uncertainty indicators | Financial condition indicators | Borrowing and lending indicators

MPDB – Structure

- **MPDB coverage**: ~370 variables internal SDW (~275 public SDW)
  - ➢ Grouped in 7 domains/ 34 sub-domains

MPDB Structure

- Macroeconomic and financial market
- Debt and credit
- Residential real estate
- Commercial real estate
- Bank sector variables
- Non-bank variables
- Interconnectedness

Underlying MPDB data sources (~40 different sources)

- Consolidated banking data – 34%
- Quarterly sector accounts – 12%
- Financial market data – 10%
- Balance sheet data – 9%
- Other datasets (each ≤ 3%)

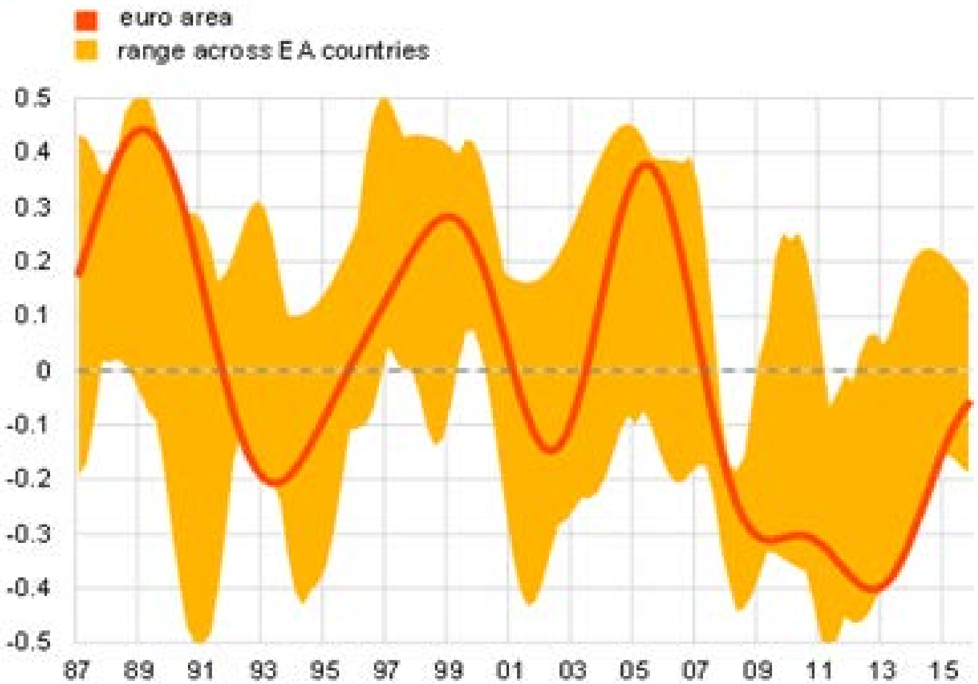
Some Data Gaps

Structure and key features (1)

- **Macroeconomic and financial market variables:** very wide range of macroeconomic and financial market variables that can be used to measure build-up of cyclical and structural systemic risks in financial system or in real economy, both on a national and European level.
  - Macroeconomic aggregates (monetary and real variables)
  - Financial market variables
  - Risk and uncertainty variables
  - Financial condition indicators for the main economic sectors (government sector, households, non-financial corporations)
  - Borrowing and lending conditions

Structure and key features (1 - continued)

Euro area financial cycle and density of SSM country cycles
SSM area financial cycle deviation from historical median



Source: ECB calculations following the methodology in Schüler, Hiebert and Peltonen (2015) "Characterising the financial cycle: a multivariate and time-varying approach" ECB Working Paper No 1846.

Notes: Financial cycle estimates exist for 10 SSM countries. The yellow-shaded area represents the min-max range across these 10 countries.

Structure and key features (2)

- **Debt and credit variables:** a wide range of variables aimed to timely detect the build-up of periods of excessive credit growth or the possible emergence of credit bubbles in the economy that might pose a threat to the resilience of the financial sector.

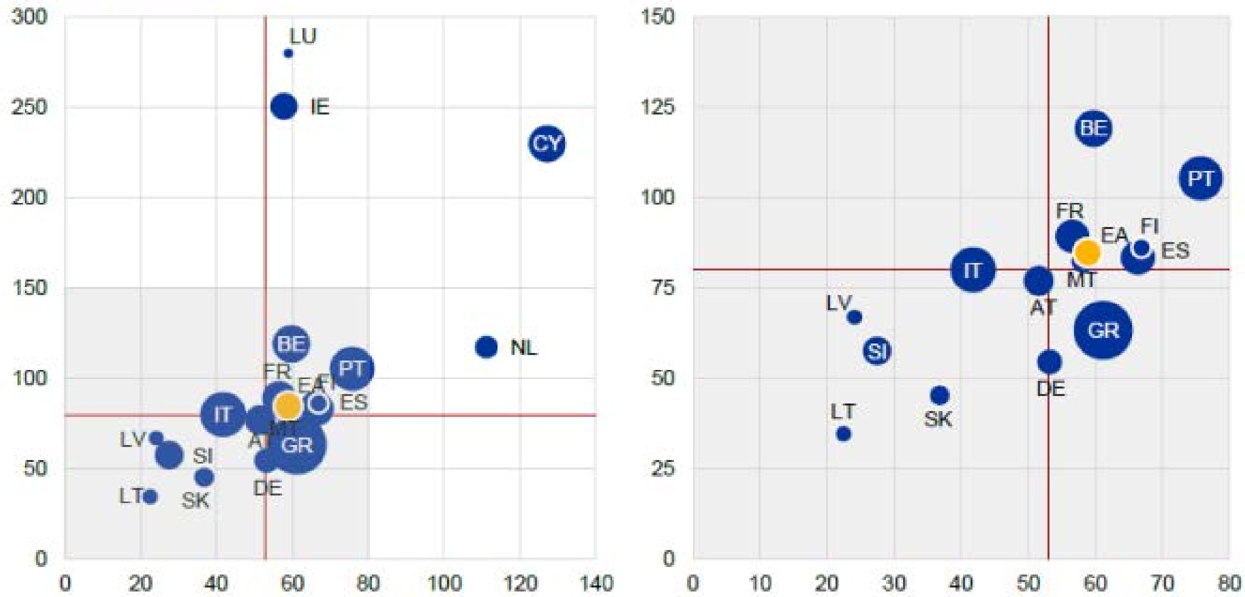
  - Total credit (loans plus debt securities) granted to households, non-financial corporations and (private) non-financial sector;
  - Bank credit (loans) to various types of counterparties;
  - Cross-border exposures;
  - Information on credit exposures in banks' balance sheet (data from the consolidated prudential COREP and FINREP reports);
  - Bank Lending Survey indicators related to the banks' practices and expectations regarding credit standards and lending conditions

Chart 1.26

High indebtedness across sectors remains a cause for concern in some countries

Household indebtedness (x-axis) and non-financial corporate indebtedness (y-axis)

(Q2 2016; percentage of GDP)



Sources: European Commission and ECB.
Notes: The size of the bubble reflects the level of general government debt as a share of GDP. Non-financial corporate debt is consolidated. Consolidated non-financial corporate debt figures include cross-border inter-company loans, which tend to account for a significant part of debt in countries where a large number of foreign entities, often multinational groups, are located (e.g. Belgium, Cyprus, Ireland, Luxembourg and the Netherlands). The horizontal and vertical lines represent the estimated macroeconomic imbalance procedure (MIP) benchmarks of 80% of GDP for consolidated non-financial corporate debt and 53% of GDP for household debt. The 133% of GDP MIP limit for fully consolidated non-financial private sector debt is split between firms and households based on their average past shares in the stock of non-financial private sector debt.

Structure and key features (3)

- **Residential real estate (RRE) variables:** include times series on variables that have been identified as potential leading indicators for RRE crises.

  - indicators for the domestic household sector's balance sheet and its mortgage liabilities.

  - indicators that provide time-series information on mortgage loans' key features (i.e the interest rate of these loans). In the future, these should be complemented with comprehensive and comparable data on mortgage loan maturities and LTV, DSTI or LTI ratios.

  - indicators with time series information on house prices and house price valuation.

  - indicators with time series that provide information on the supply side of the residential real estate market

Still significant data gaps!

Structure and key features (4)

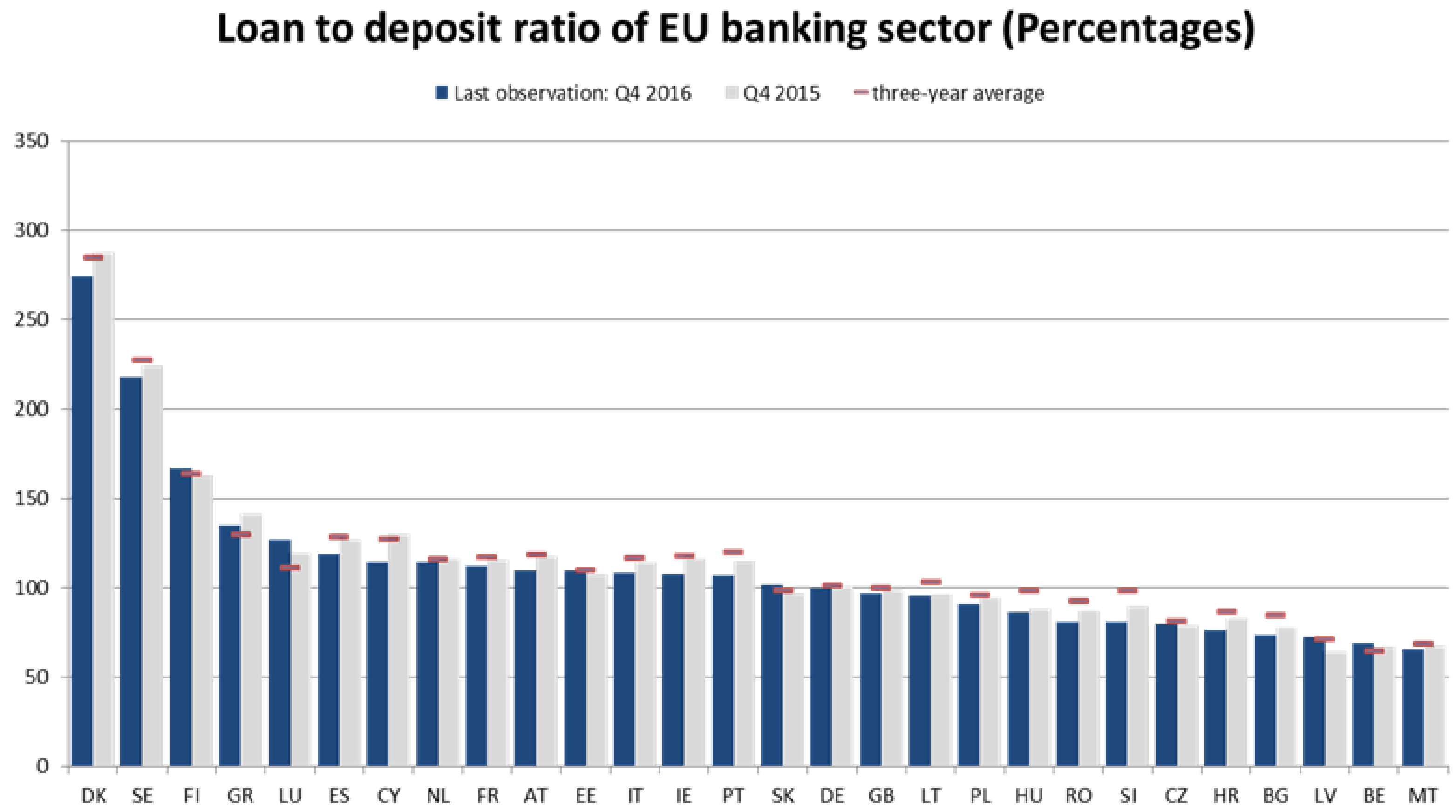
- **Commercial real estate (CRE) variables:** currently MPDB covers very limited number of CRE-related variables, encompassing mainly available CRE price indicators and information on CRE-related exposures in financial sector (even if these exposures are only broad proxies of what would fall under a more precise definition of CRE)

Significant data gaps!

Structure and key features (5)

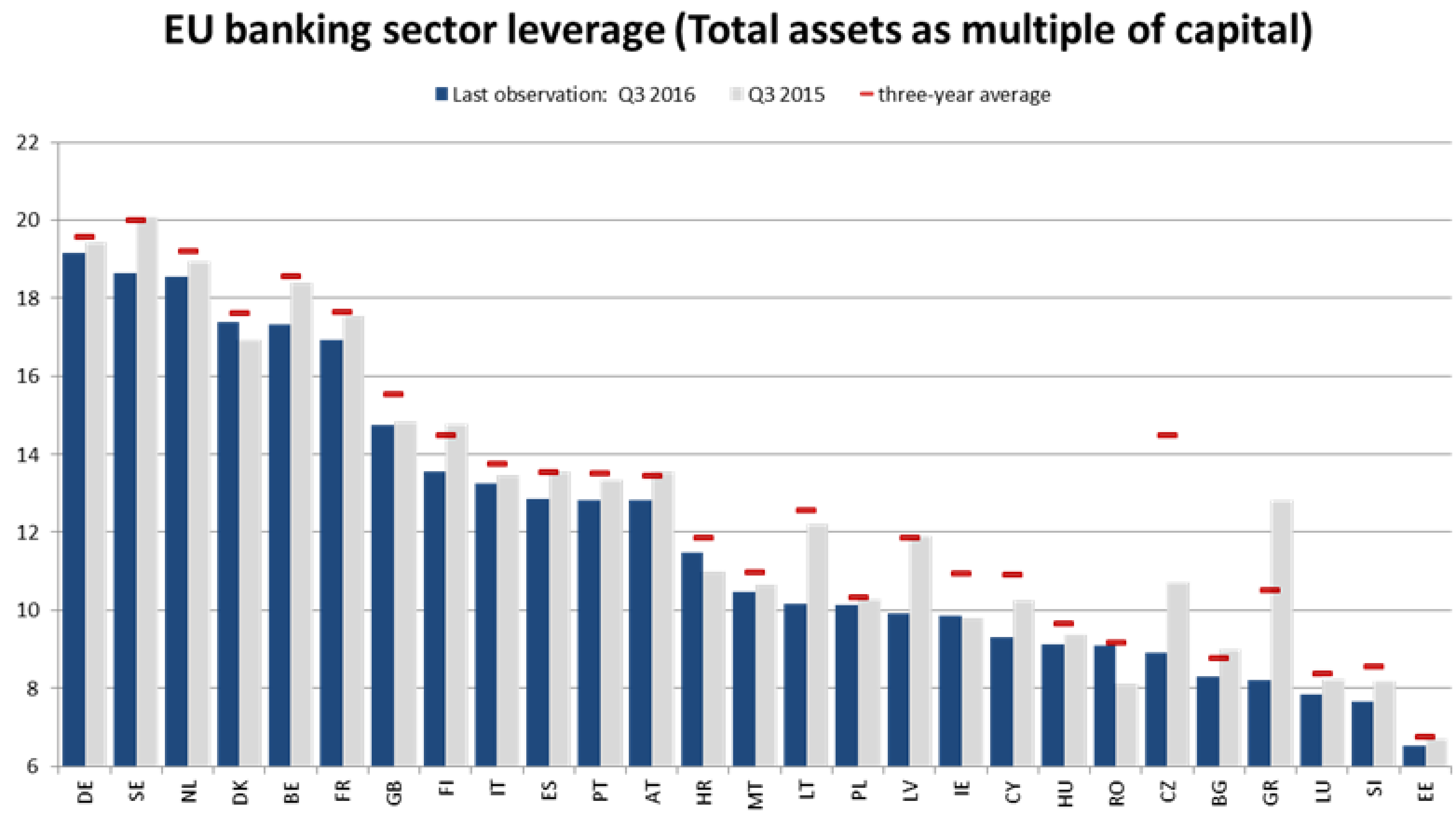
- **Bank sector variables** measure banking sector structure, performance and vulnerabilities in the different EU countries
    - Banking structure
    - Main elements of the income statement
    - Profitability variables
    - Main elements of the balance sheet
    - Liquidity and funding
    - Lending and leverage
    - Capital
    - Asset quality
    - Locational funding indicators

Structure and key features (5 - continued)



Source: ECB, ESRB Risk Dashboard.
Notes: MFIs sector excluding the ESCB. Data refers to the ratio between total loans and total deposits vis-à-vis the domestic and euro area households, NFCs and non-MFI residents excluding the general government. Mortgage banks in Denmark, which represent around 55% of total MFI loans to domestic NFCs, are not allowed to take deposits owing to regulations, but must fund their lending through issuance of covered bonds only. Excluding mortgage banks from the indicator, the loan-to-deposit ratio for DK is equal to 0.75 for Q4 2016 and 0.79 for Q4 2015.

Structure and key features (5 - continued)

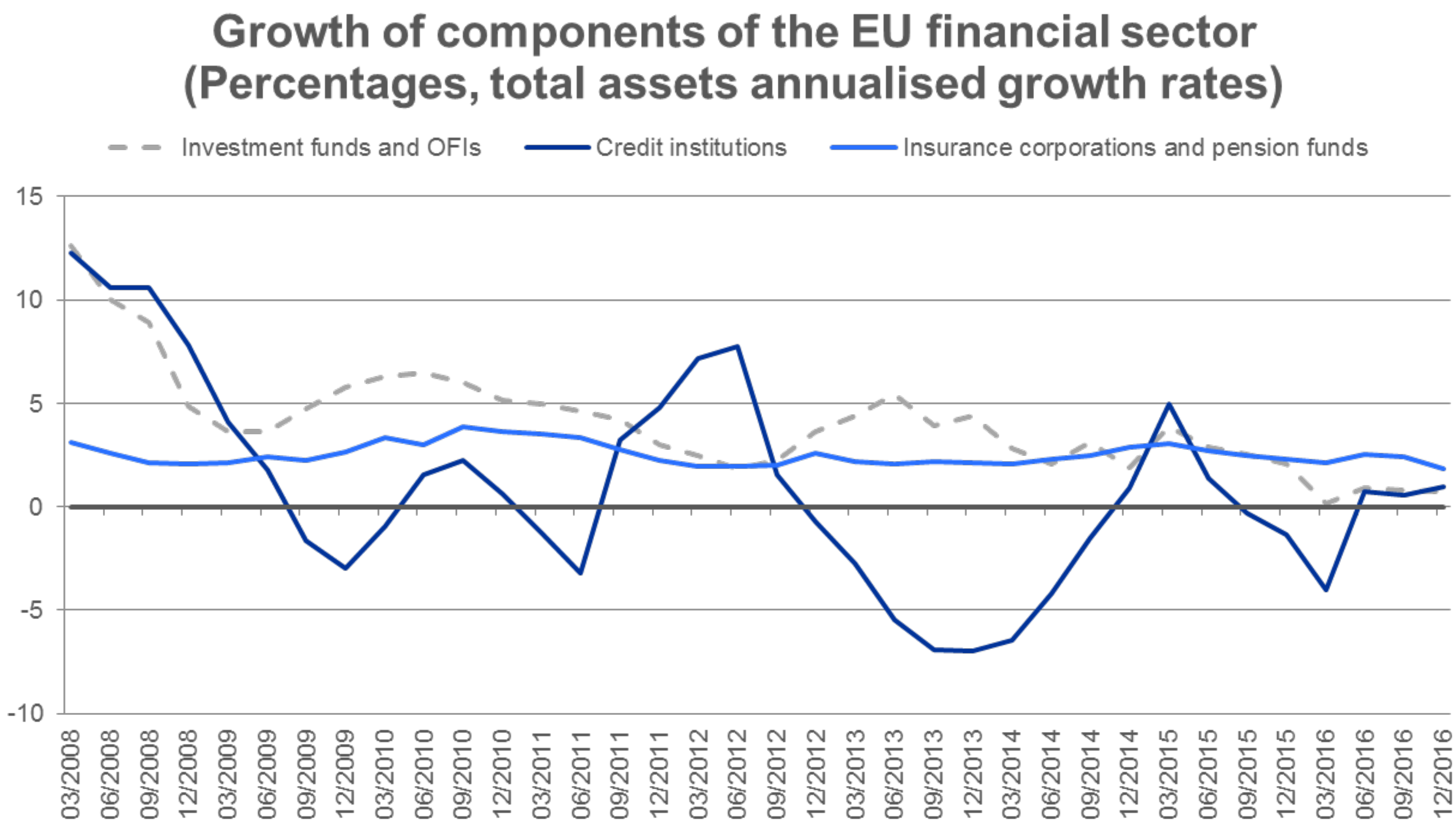


Source: ECB.
Notes: Share of total assets in capital for domestic banking groups and stand-alone credit institutions. Consolidated data.

Structure and key features (6)

- **Non-bank variables:** a domain containing variables to assess risks to financial stability originating from outside the banking sector.
- The indicators deal for example with structural features of insurance corporations and pension funds and their exposures to sovereigns.
- It also covers information on financial vehicle corporations (FVCs)

Structure and key features (6)



Source: ECB.
Notes: Data based on financial accounts and monetary statistics. Data refer to the non-consolidated balance sheets of the respective entities.

Structure and key features (7)

- **Interconnectedness variables:** Interconnectedness plays a major role in the propagation of financial distress both within the financial sector and across countries (*cross-sectional dimension of systemic risk*).
  - MPDB comprises variables that capture interconnectedness within the financial system.
  - Includes indicators dealing for example with total bank assets relative to GDP, banks' interbank liabilities (in addition to their interbank assets) and positions in derivatives, among others.

Data gap analysis

- Creation of MPDB was accompanied by a **data gap analysis**. The most relevant areas affected by data gaps are :
  - commercial and residential real estate
  - non-banking intermediaries
  - interconnectedness measures.
- To close these data gaps, a number of relevant indicators (labelled as "**Orange** Indicators") could in principle be derived from information already available at national level within banking supervisory reports (EBA ITS).
- This would at least close some of the data gaps for both commercial and residential real estate (even though only to a limited extent)

Data gaps - RRE and CRE (1)

- Important data gap: **residential and commercial real estate**
- **Goal:** Need for a comparable/harmonised dataset of highly relevant indicators (such as LTV ratios) for enhancing the statistics for macroprudential analysis of RRE and CRE
- **No short-term solution:** rather difficult to bridge in a satisfactory manner through *ad-hoc surveys*, because of the lack of data harmonisation
- **Way forward: closing data gaps** could be achieved through *common definitions* and *coordinated* data collections

Data gaps - RRE and CRE (2)

- First step in this direction: **ESRB recommendation on closing real estate data gaps (ESRB/2016/14)**
  - Goal: Implement a risk monitoring framework for domestic RRE and CRE, based on a recommended set of indicators by end-2020
  - Guidance provided: Detailed templates, definitions and methodologies
  - Timeline – National macroprudential authorities (NMA) have to deliver:
    a) an interim report *by end-2018* on data available or expected to become so,
    b) a final report on the implementation of this recommendation *by end-2020*
- **Criteria** for the implementation of the Recommendation:
  - ESRB recommendations are subject to a “comply or explain” mechanism
  - Due regard should be paid to the principle of proportionality: a) size and development of the CRE/RRE market in each MS, b) powers of each NMA

Data gaps – Non-bank sector (1)

- Currently, MPDB gives prominence to the banking sector, but …
- … experience shows that financial instability is not always caused by traditional banking intermediation, and …
- *… Non-bank entities* and *activities* contributed to the propagation of the global financial crisis
  - Securitisation of mortgages increased vulnerabilities and led to over-borrowing
  - MMFs played an amplifying role following Lehman Brothers failure
  - Near-failure of AIG, an insurer which had become “too big to fail”

Data gaps – Non-bank sector (2)

- The transmission channels of systemic **risks from non-banks** may vary substantially from the ones stemming from banking intermediation
- Growing relevance of non-bank financial intermediation, relative to the banking sector
- Capital Market Union will make this area even more relevant
- Type of indicators required for monitoring non-banks:
  - Credit growth and leverage – excessive leverage amplifies the financial cycle
  - Interconnectedness – interlinkages between banks and non-banks may reduce system ability to withstand stress
  - Too big to fail – non-bank entities can be systemically important (e.g. CCPs)
- **Ongoing work** in this field is led by the ESRB, which has an explicit mandate in the area of non-banks

Conclusions

- A suitable statistical basis for macroprudential analyses and policies requires a comprehensive and high-quality set of data and indicators.
- MPDB - major initiative undertaken by the E(S)CB, in cooperation with the ESRB, to build such a statistical repository
- Successful creation of the MPDB is an significant development in the area of statistics for macroprudential purposes
- Data gaps need to be addressed as part of future MPDB development

Thank you for your attention!

Questions?

Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

IFC-National Bank of Belgium Workshop on "*Data needs and Statistics compilation for macroprudential analysis*"

Brussels, Belgium, 18-19 May 2017

The ESRB macroprudential measures database[1]

Urszula Kochanska,

European Systemic Risk Board Secretariat

[1] This paper 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.

The ESRB Macroprudential Measures Database[1]

Urszula Kochanska[2]

Abstract

This paper describes the new European Systemic Risk Board (ESRB) database that contains information about the macroprudential measures applied by the authorities in the Member States of the European Union (EU) and in two countries[3] of the European Economic Area. The database currently covers mainly measures related to the banking sector, namely: i) *capital buffers* i.e. the capital conservation buffer (CCoB), the countercyclical capital buffer (CCyB), the systemic risk buffer (SRB) and buffers for global/other systemically important institutions (G-SII and O-SII buffers respectively); ii) *reciprocation (recognition) measures*; and iii) *other measures*. Information on how the measures have been applied dates back to the early 2000s. However, the database focuses primarily on the period since 2014, when the Capital Requirements Directive IV[4] and the Capital Requirements Regulation[5] (CRD/CRR) came into force, setting a milestone in the development of a macroprudential policy framework in the EU. More recently the ESRB has increasingly devoted work on macroprudential policy beyond the banking sector[6] and, in principle, the content of the database is expected to reflect this in future.

Keywords: Macroprudential measures, Macroprudential policy, Macroprudential indicators, European Systemic Risk Board

JEL classification: G210

[1] The author would like to express her thanks to Frank Dierick and Tuomas Peltonen for their comments on the paper. The work carried out by Romain Calleja and Daniel Karpati on developing and setting up the database is greatly appreciated. Thanks are also extended to Stéphanie Stolz and Anna Dobrzanska. The views expressed are those of the author and do not necessarily reflect the views of the European Systemic Risk Board or of the European Central Bank. The author would also like to thank the participants and organisers of the workshop at the Irving Fisher Committee on Central Banking Statistics and the Nationale Banque van België/Banque Nationale de Belgique, where the paper was presented.

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[3] The two countries are Norway and Iceland, which are involved as non-voting members in the work of the ESRB following Decision No 198/2016 of the Joint Committee of the European Economic Area of 30 September 2016.

[4] Directive 2013/36/EU of the European Parliament and of the Council of 26 June 2013 on access to the activity of credit institutions and the prudential supervision of credit institutions and investment firms (OJ L 176, 27.6.2013, p. 338).

[5] Regulation (EU) No 575/2013 of the European Parliament and of the Council of 26 June 2013 on prudential requirements for credit institutions and investment firms and amending Regulation (EU) No 648/2012 (OJ L 176, 27.6.2013, p. 1).

[6] See ESRB (2016), Macroprudential policy beyond banking: an ESRB strategy paper, July, available at https://www.esrb.europa.eu/pub/pdf/reports/20160718_strategy_paper_beyond_banking.en.pdf

Contents

1. Introduction

The global financial crisis highlighted the need for a macroprudential policy framework. Such a framework would equip the authorities responsible for overseeing the financial system with appropriate mandates, analytical tools and instruments to address systemic risk. In the EU, a number of important steps have been taken to address this issue. One such step was the establishment in 2010 of the European Systemic Risk Board (ESRB), which has responsibility for macroprudential oversight of the EU financial system. Since its establishment the ESRB has actively promoted the development of macroprudential policy frameworks. In 2011 it recommended that Member States should establish national macroprudential authorities[7]; and in 2013 it recommended that Member States should identify clear intermediate macroprudential objectives and assign concrete tools to achieve these objectives[8].

The entry into force on 1 January 2014 of the new prudential rules for banks set out in the CRD/CRR was pivotal in the development of a macroprudential policy framework in the EU and the flow of information on the use of macroprudential tools. The new prudential rules provided Member States with a common legal framework and a set of macroprudential instruments to mitigate systemic risk in the banking sector. The CRD/CRR framework set in motion the requirement for macroprudential authorities (designated authorities, competent authorities and/or Member States) to notify the ESRB of macroprudential measures. Moreover, certain ESRB recommendations[9] include additional notification requirements. These notification requirements have contributed to the collating of information and the setting-up of the Macroprudential Measures Database (MPMDB).

In March 2014 the ESRB published its Handbook on operationalising macroprudential policy in the banking sector[10], which contributed to the further development of macroprudential policy and analytical framework in the EU. This Handbook is targeted at the macroprudential authorities and provides detailed instrument-specific advice on how to design and implement macroprudential policy for the banking sector. The Handbook's discussion of data largely forms the basis for the design of the MPMDB. The information in the MPMDB is used by the ESRB in several of its outputs, notably the yearly reviews of macroprudential policy in the EU[11, 12, 13].

7 Recommendation of the European Systemic Risk Board of 22 December 2011 on the macroprudential mandate of national authorities (ESRB/2011/3) (OJ C 41, 14.0.2012, p. 1).

8 Recommendation of the European Systemic Risk Board of 4 April 2013 on intermediate objectives and instruments of macroprudential policy (ESRB/2013/1) (OJ C 170, 15.6.2013, p. 1).

9 ESRB 2013/1, Recommendation of the European Systemic Risk Board of 11 December 2015 on recognising and setting countercyclical buffer rates for exposures to third countries (ESRB/2015/1) (OJ C 97, 12.3.2016, p. 1), and Recommendation of the European Systemic Risk Board of 15 December 2015 on the assessment of cross-border effects of and voluntary reciprocity for macroprudential policy measures (ESRB/2015/2) (OJ C 97, 12.3.2016, p. 9).

10 Available at https://www.esrb.europa.eu/pub/pdf/other/140303_esrb_handbook_mp.en.pdf

11 ESRB (2015), *A review of macroprudential policy in the EU one year after the introduction of the CRD/CRR*, June, available at https://www.esrb.europa.eu/pub/pdf/other/150625_review_macroprudential_policy_one_year_after_intro_crdcrr.en.pdf

The objective of this paper is to contribute to the analytical availability of the up-to-date, comprehensive database and derived datasets on macroprudential instruments used in the EU and the European Economic Area (EAA).

2. Main features of the ESRB Macroprudential Measures Database

2.1 Handling information

The ESRB MPMDB was built[14] with the aim of storing information on macroprudential measures and making this information available for analysis. The macroprudential measures are notified to the ESRB by the respective authorities in the EU in accordance with the notification requirements. Notifying authorities use the common ESRB/European Central Bank (ECB)/European Banking Authority (EBA) notification templates[15], of which there are currently nine. The templates cover G-SIIs, O-SIIs, the SRB, the CCyB, risk weights, minimum loss given default (LGD), so-called national flexibility measures[16], reciprocation measures, and other measures not covered by the CRD/CRR.

All templates contain the following items of information:

- the name of the notifying national authority
- a description of the measure, including information on the institutions concerned, as identified by the name and legal entity identifier (LEI)
- the time frame of the measure
- the reason for activating the measure, including details on the methodology and indicators used
- the cross-border and cross-sectoral impact of the measure
- details of any other connected measures.

[12] ESRB (2016), *A Review of Macroprudential Policy in the EU in 2015*, May, available at https://www.esrb.europa.eu/pub/pdf/other/20160513_esrb_review_of_macroprudential_policy.en.pdf

[13] ESRB (2017), *A Review of Macroprudential Policy in the EU in 2016*, April, available at http://www.esrb.europa.eu/pub/pdf/other/20170413_esrb_review_of_macroprudential_policy.en.pdf?c41913d3d8dcd6f87545cfc2efabea90

[14] The contributions from R. Calleja and D. Karpati are greatly appreciated.

[15] The notification templates are available at http://www.esrb.europa.eu/national_policy/html/index.en.html

[16] "National flexibility measures" under Article 458 of the CRR are a set of measures allowing national authorities to impose stricter prudential requirements in order to address systemic risks. They include the level of own funds, large exposure limits, public disclosure requirements, the level of the CCoB, liquidity requirements, risk weights for the RRE and CRE, and measures for intra-financial sector exposures. These instruments may only be used if the national authority can establish that the measure is necessary, effective and proportionate and that other specified measures cannot adequately address the identified systemic risk. The instruments are subject to a notification and non-objection process. They include the level of own funds, large exposure limits, public disclosure requirements and the level of the capital conservation.

Notifications submitted to the ESRB are stored on its internal document management system and published on its website. The relational MPMDB is populated with the information from the templates in accordance with an established data-recording and managing process. An exception to this is information on the CCyB, which is directly entered into a separate database schema by the reporting authorities using an online survey tool. Such an arrangement was put in place in the case of the CCyB, since it is the most frequently reassessed and notified measure (in principle, on a quarterly basis). The introduction in the near future of a survey programme for non-CCyB measures is currently under consideration.

The relational MPMDB comprises four main areas: i) notifications; ii) measures; iii) banks; and iv) measure levels (see the Annex for the relationship structure of the MPMDB tables). As at end-March 2017 there were 259 notifications recorded and 35 measure types covering 213 individual banking entities (either on a solo or consolidated basis). Collection of the data began in January 2015 and covers notifications received since 2014 and some older ones dating back to 2010.

The ESRB Secretariat is the owner of the dataset and carries out regular revisions and publications of the information derived from the MPMDB. The Secretariat is also responsible for analytical support to the ESRB committees[17], and uses the MPMDB (also querying via a user-friendly interface (see Figure 1) to produce reports and notes[18].

17 See the ESRB's organisational chart, available at https://www.esrb.europa.eu/shared/pdf/Organisational-Chart.pdf?65c63facfb31dff9e723be9f668d93b9

18 See, for example, the reports and notes available at https://www.esrb.europa.eu/pub/html/index.en.html

Figure 1. User interface of the MPMDB

Source: ESRB MPMDB.

2.2 Overview of the MPMDB

The ESRB has identified a number of macroprudential instruments to achieve its so-called intermediate objectives of financial stability[19]. The four intermediate objectives are preventing or mitigating systemic risks that may arise from the following sources:

1. *excessive total/sectoral credit growth*, which may be a key driver of financial crises, with leverage as the amplifying feature
2. *excessive maturity mismatch* with overreliance on short-term and unstable funding, which may lead to *market illiquidity*, fire sales and contagion
3. direct and indirect *exposure concentrations* that make a financial system vulnerable to common shocks
4. *misaligned incentives*, which arise from moral hazard and the negative effect of (implicit) government guarantees.

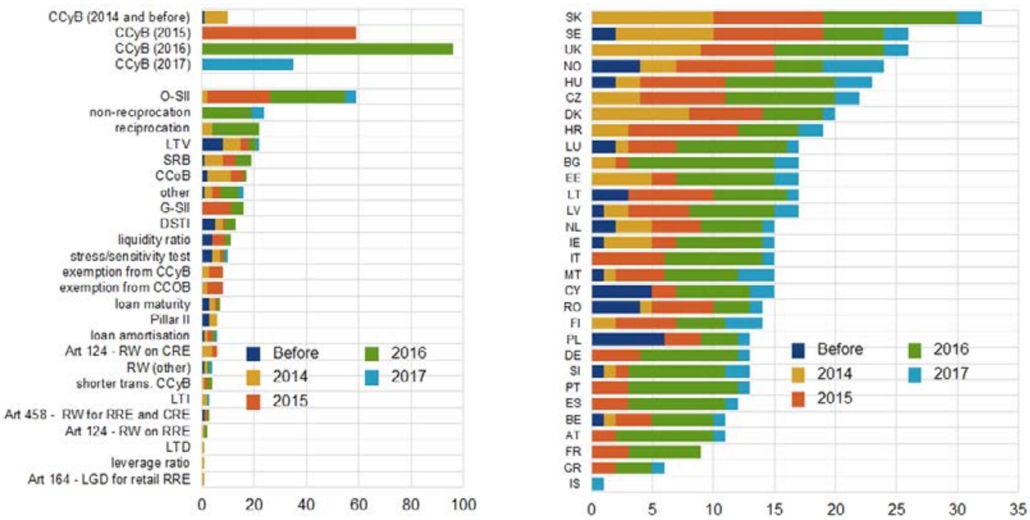
[19] See Recommendation ESRB/2013/1.

The following is a selection of the suite of macroprudential instruments used for addressing the intermediate objectives of financial stability[20]:

- for objective 1: *total scope*: the CCyB, the SRB, leverage ratio, increased CCoB and own funds requirement; *sectoral scope*: risk weights (RW), loss given default (LGD) floors, and limits for: loan-to-value (LTV), loan-to-income (LTI) or debt servicing-to-income (DSTI)
- for objective 2: liquidity charges, loan-to-deposit (LTD) limit, liquidity buffers, net stable funding ratio (NSFR) and other stable funding requirements
- for objective 3: the SRB, large exposures requirements, increased own funds requirement, measures for intra-financial sector exposures
- for objective 4: capital buffers for G-SIIs and O-SIIs, the SRB, increased CCoB, own funds requirements.

Macroprudential authorities have opted to use some of the measures from the suite of instruments[21] (see Figure 2). The measures used have most frequently been directed at addressing excessive credit growth and limiting the systemic impact of misaligned incentives. The focus on these two intermediate objectives is a reflection of the many policy initiatives that concern lending to the real estate sector and systemically important institutions.

Figure 2. Measures recorded in the MPMDB by type, country and year of initiative
(as at April 2017, number of measures by type (left-hand panel) and by country (right-hand panel))



Source: ESRB MPMDB.
Notes: “CRE” refers to commercial real estate, “RRE” to residential real estate, and “trans. CCyB” to transitional periods for CCyB. Art 124, Art 458 and Art 164 refer to those of CRR.

[20] For details on the instruments and transmission channels, see footnote 10 above.

[21] See footnotes 11, 12, 13.

2.3 Release of data on macroprudential measures

A host of information and several datasets derived from the MPMDB are regularly made available on the ESRB's website, including information on:

1. the CCyB (dedicated webpage and dataset)
2. measures beyond the CCyB (dataset)
3. capital measures targeting specific banks (dataset).

2.3.1. Overview of the CCyB on the ESRB's website and in the data extract

A page dedicated to information on the CCyB is available on the ESRB's website[22]. This capital buffer is designed to mitigate procyclicality in the financial system and is assessed on a quarterly basis. As the most frequently assessed measure, the related notification flow is automated via an online survey tool (see Section 2.1 above), which feeds the database that in turns populates the website. All EU Member States as well as Iceland and Norway[23] report into the database. The ESRB has also developed a set of principles and guidelines on activating and calibrating the CCyB[24].

With regard to the published dataset, historical data on how the authorities in Europe have set the CCyB can be retrieved from a dedicated file. This file contains details on the CCyB rates, the timing of the decisions and the dates of application. It also contains links to relevant press releases or other publicly available information, with explanatory notes and background analyses. Finally, any new items of information are flagged, as and when they become available, for the benefit of users.

The MPMDB contains a broader set of data than the above-mentioned file. The macroprudential authorities report on the leading indicator – the credit-to-GDP gap (credit gap) – and also on additional indicators[25] and the powers exercised following the principles of guided discretion in setting the CCyB. In particular, the authorities provide additional information on the credit-to-GDP ratio, buffer guide[26], and any justifications, elaborating on exceptional circumstances.

[22] See the relevant page on the ESRB's website (https://www.esrb.europa.eu/national_policy/ccb/applicable/html/index.en.html).

[23] Reporting from Liechtenstein is forthcoming.

[24] See the relevant page on the ESRB's website (https://www.esrb.europa.eu/news/pr/date/2014/html/pr140630.en.html).

[25] See ESRB (2016), "Implementation of the countercyclical capital buffer regime in the European Union", *Macroprudential Commentaries*, Issue 8, December, available at https://www.esrb.europa.eu/pub/pdf/commentaries/ESRB_commentary_1612.en.pdf?e68d4dbc5f50fc80032371dc28bcf34b

[26] For definitions and more information, see the sections entitled "Recommendation B" and "Implementation of the ESRB Recommendation ESRB/2014/1". "Buffer guide" means a benchmark buffer rate, selected in accordance with recommendation B(4); "additional credit-to-GDP gap" means a credit-to-GDP gap measured and calculated in accordance with Recommendation B(2).

2.3.2 Overview of measures beyond the CCyB

Information on the overview of the macroprudential measures beyond the CCyB is extracted on a monthly basis from the MPMDB and posted in the Overview of national macroprudential measures file, on the ESRB's website[27]. The following information is provided about such measures:

- *geographical specifications* (region, country, authority)
- *timing and communication strategy* (year that the macroprudential measure was initiated, dates of publication and notification, time frame for the measure, links to the communication materials)
- targeted *intermediate objective* of financial stability
- *legal basis*
- *status of the measure* (information about revocation or replacement)
- *description* of the measure, including links to relevant public information
- *reciprocation*[28], including ESRB recommended reciprocation.

The measures covered in the file can be grouped as follows:

1. capital buffers
2. reciprocation measures
3. other measures.

With regard to the **capital buffers**, the CRD equips the macroprudential authorities with several buffers which form part of the combined capital buffer requirement. More specifically, the combined buffer requirement means the total common equity tier 1 (CET1) capital needed to meet the requirement for the CCoB and, if applicable, the CCyB, the G-SII buffer, the O-SII buffer and the SRB. The CRD/CRR capital buffer framework was implemented on 1 January 2014, with derogations in place until 1 January 2016 and a phasing-in period lasting until 2019.

The CCoB is required for a bank to meet its own funds requirements[29]. The CCyB is designed to mitigate procyclicality in the financial system and to build a capital buffer during periods of excessive credit growth, which is then released when a systemic risk abates. The SRB targets structural systemic risks of a long-term non-cyclical nature. The SRB can be used to prevent or mitigate long-term non-cyclical systemic or macroprudential risk not covered by the CRR. Buffers for G-SIIs and O-SIIs address banks that, from an international and domestic perspective, are considered too big to fail.

Information on all additional capital buffers is extracted from the MPMDB and made available in the Overview of national macroprudential measures file. In particular, the file provides useful information on the buffers' features, namely:

- for the CCoB: transitory buffer rates, if applicable; coverage (system-wide, bank-specific, group of banks that fulfil certain criteria); consolidation

27 Available at https://www.esrb.europa.eu/national_policy/html/index.en.html

28 For further details, see the following section of this paper.

29 See Article 92 of the CRR.

scope; and exceptions for small and medium-sized investment firms from the requirements

- for the SRB: buffer rates; coverage; consolidation scope; type of exposures; and any other condition for applying the measure
- for the O-SII and G-SII buffers: designated banks with corresponding buffer rates; and phasing-in, if applicable.

Building a more resilient banking system in the EU requires authorities to recognise[30] macroprudential measures set by other Member States and to set or recognise the CCyB rates for so-called third countries[31]. Information on such **reciprocation framework**, which is essential to the effectiveness of the macroprudential measures, is recorded in the MPMDB.

Information on reciprocation or non-reciprocation is contained in the Overview of national macroprudential measures file as are the cross-links between the measures in the so-called matrix of reciprocation.

Macroprudential authorities have several **other measures** at their disposal. Among the most prominently used are measures targeting real estate lending, as developments in this area continue to be high on the agenda of macroprudential policymakers in Europe. A variety of such measures were applied at the national level and introduced into the MPMDB with details on their modalities.

Key features of such measures covering DSTI, LTI, payments-to-income (PTI), LTV, LTD, loan amortisation, risk weights, LGD floors, maturity restrictions, leverage ratio, liquidity ratio, stress tests of lender or borrower and amortisation requirement are included in the Overview of national macroprudential measures file. Further details of the measures are available in the Review of macroprudential policy in Europe in 2016 (for example, in Tables 1-3)[32].

The authorities also used Pillar 2 additional own funds requirements to address systemic risks related to specific banks. These additional own funds requirements can be used as an "add-on" to the other buffers.

2.3.3 Overview of measures targeting specific banks

Macroprudential authorities are responsible for setting measures targeting specific banks and deciding on the modalities of these measures. Information on such bank-specific capital buffer requirements is collected in the MPMDB and a subset is made public on the ESRB's website[33].

When analysing capital buffer requirements, it is important to consider general conditions for combining capital buffers (additivity versus a "higher of" approach), rules on combinations arising from the application of capital buffers on different

[30] See Recommendation ESRB/2015/2.

[31] See Recommendation ESRB/2015/1.

[32] See footnote 13 above.

[33] See *Overview of national capital-based measures*, available at https://www.esrb.europa.eu/national_policy/html/index.en.html

levels of consolidation (parent versus subsidiary) and principles that apply when transitional periods do not coincide.

The main feature of the CCoB is that it consists of an additional CET1 capital fixed at 2.5% of a bank's total risk exposure on an individual or consolidated basis, which effectively serves as a minimum capital requirement. Phasing-in over time has been available with rates of 0.625%, 1.25%, and 1.875% in 2016, 2017 and 2018 respectively.

In the case of the CCyB, the rate is set at between 0% and 2.5% of total risk exposure but may also be set higher if justified by the underlying risk. The institution-specific CCyB rate consists of the weighted average of the CCyB rates that apply in the jurisdictions where the relevant credit exposures of the institution are located. This buffer should be assessed on a quarterly basis.

The SRB rates can vary depending on banks' contribution to the specific structural systemic risk and geographical location of their exposures. The measure should be reviewed at least every other year and there is no maximum buffer limit. Furthermore, in practice the measure is often linked to the O-SII buffer, as some countries use the SRB as an alternative or as a supplement to the O-SII buffer.

With regard to the SIIs, which are designated in accordance with a prescribed methodology[34] and supervisory judgement, the G-SII buffer rate varies within five categories of SIIs with a starting rate of 1% increasing in increments of 0.5% up to 3.5%. For the O-SIIs, the authorities may require a buffer of up to 2%. Phasing-in of the buffers is possible, as the authorities could move the application date from 1 January 2014 to 1 January 2016, with reductions to 25%, 50% and 75% of the buffer rate in 2016, 2017 and 2018 respectively.

Granular information on the banks that are subject to the bank-specific measures of macroprudential authorities is available in the MPMDB. In particular, the identification of entities with LEIs enables information about the measures to be combined with bank-level and other data, as well as with the information on other macroprudential measures. Finally, it should be cautioned that focusing on the macroprudential measures the MPMDB does not contain information on the capital requirements resulting from the Supervisory Review and Evaluation Process (SREP) and Pillar 2 measures[35].

[34] Further information is available on the website of the European Banking Authority (EBA), at http://www.eba.europa.eu/risk-analysis-and-data/global-systemically-important-institutions. See also the EBA methodology for O-SIIs, available at http://www.eba.europa.eu/risk-analysis-and-data/other-systemically-important-institutions-o-siis-

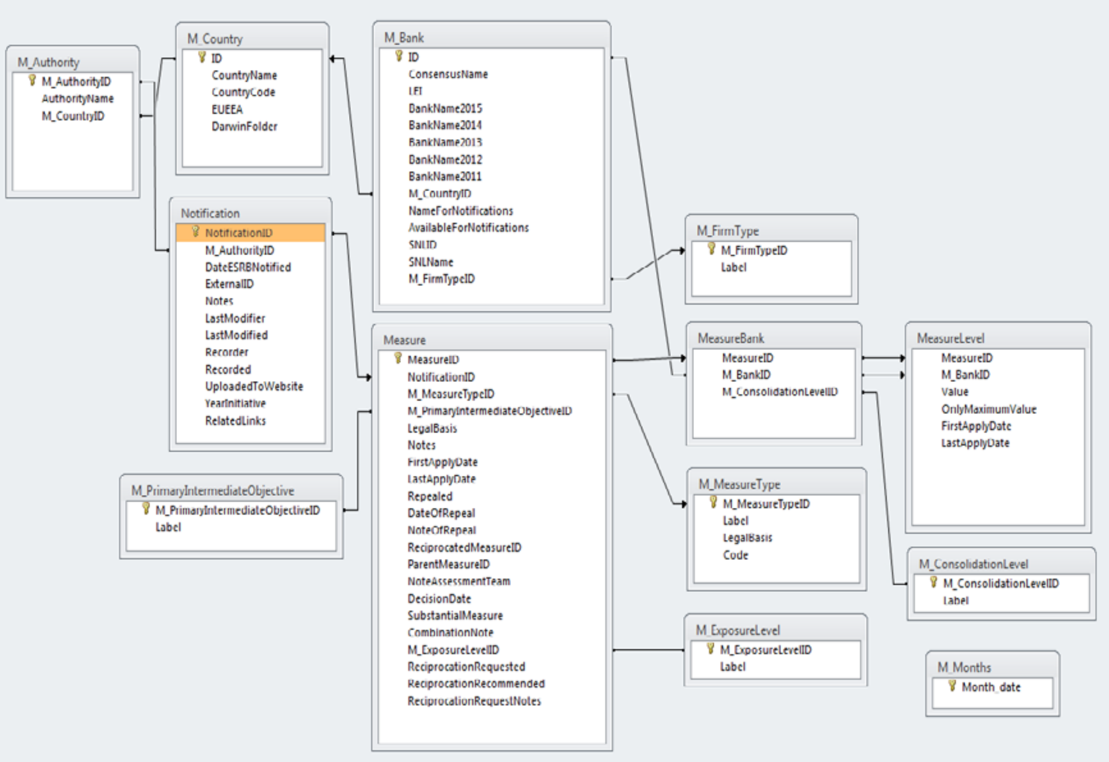
[35] Further information on the SREP and Pillar 2 is available at https://www.bankingsupervision.europa.eu/about/ssmexplained/html/srep.en.html

3. Conclusion

The ESRB MPMDB is a comprehensive and up-to-date database designed to store information on macroprudential measures in Europe and make that information available for analysis. The content of the database is based on the information provided by the macroprudential authorities to the ESRB in line with the notification requirements. The information in the database is used in several ESRB analyses and reports and is made available on the ESRB's website, where three data extracts are provided and updated on a regular basis. The standardised data extracts cover the CCyB, measures beyond the CCyB and bank-specific capital measures. The database constitutes a unique source of information for macroprudential policy. To promote analytical work and transparency in this area, further inclusion of information on non-banking sector measures and data releases are anticipated as is a deepening of the cross-country analysis of how measures are used.

Annex

Figure 3. Relationship structure of the MPMDB tables



Source: ESRB MPMDB.

Abbreviations

CCoB	capital conservation buffer
CCyB	countercyclical capital buffer
CET1	common equity tier 1
CRD IV	Capital Requirements Directive
CRE	commercial real estate
CRR	Capital Requirements Regulation
DSTI	debt service-to-income
DTI	debt-to-income
EBA	European Banking Authority
ECB	European Central Bank
ESRB	European Systemic Risk Board
EU	European Union
GDP	gross domestic product
G-SII	global systemically important institution
LEI	legal entity identifier
LGD	loss given default
LTD	loan-to-deposit
LTI	loan-to-income
LTV	loan-to-value
MPMDB	Macroprudential Measures Database
NSFR	net stable funding ratio
O-SII	other systemically important institution
PTI	payment-to-income
RRE	residential real estate
RW	risk weight
RWA	risk-weighted assets
SRB	systemic risk buffer
SREP	Supervisory Review and Evaluation Process

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BANK FOR INTERNATIONAL SETTLEMENTS

IFC-National Bank of Belgium Workshop on "*Data needs and Statistics compilation for macroprudential analysis*"

Brussels, Belgium, 18-19 May 2017

The ESRB macroprudential measures database[1]

Urszula Kochanska,

European Systemic Risk Board Secretariat

[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.

The ESRB Macroprudential Measures Database (MPMDB) and indicators of the usage of macroprudential instruments – paper

Urszula Kochanska

Disclaimer: This presentation should not be reported as representing the views of the European Systemic Risk Board (ESRB) or European Central Bank (ECB). The views expressed are those of the authors and do not necessarily reflect those of the ESRB or ECB.

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Introduction

i) Macroprudential policy framework and the ESRB

ii) Entering into force 1 Jan 2014 of the prudential rules for the banks in the *Capital Requirement Directive (CRD IV)* and *Capital Requirements Regulation (CRR)*

iii) envisaged notification requirements

iv) information flow about the use of the macroprudential tools

v) data collection which conduced to the set up of the Macroprudential Measures Database (MPMDB)

vi) *ESRB Handbook on operationalising macroprudential policy in banking sector* - a base for the design of the MPMDB

vii) Information from the MPMDB used in several ESRB outputs, notably in two yearly reports:

Reviews of Macroprudential Policy in the EU in 2015 and 2016

Motivation behind the paper

1) to develop, make available and increase the analytical availability of the **database and derived datasets** on macroprudential instruments in Europe
   - with its comprehensive and consistent coverage (initiatives of the competent authorities in the European Union and in the European Economic Area)
   - and timeliness

2) to add to the research on the development of the indicators that gauge the use of macro-prudential tools

Content of the presentation

1. Main features of the ESRB Macroprudential Measures (MPMDB) database

A. Handling of information

B. Overview of macroprudential measures in the MPMDB

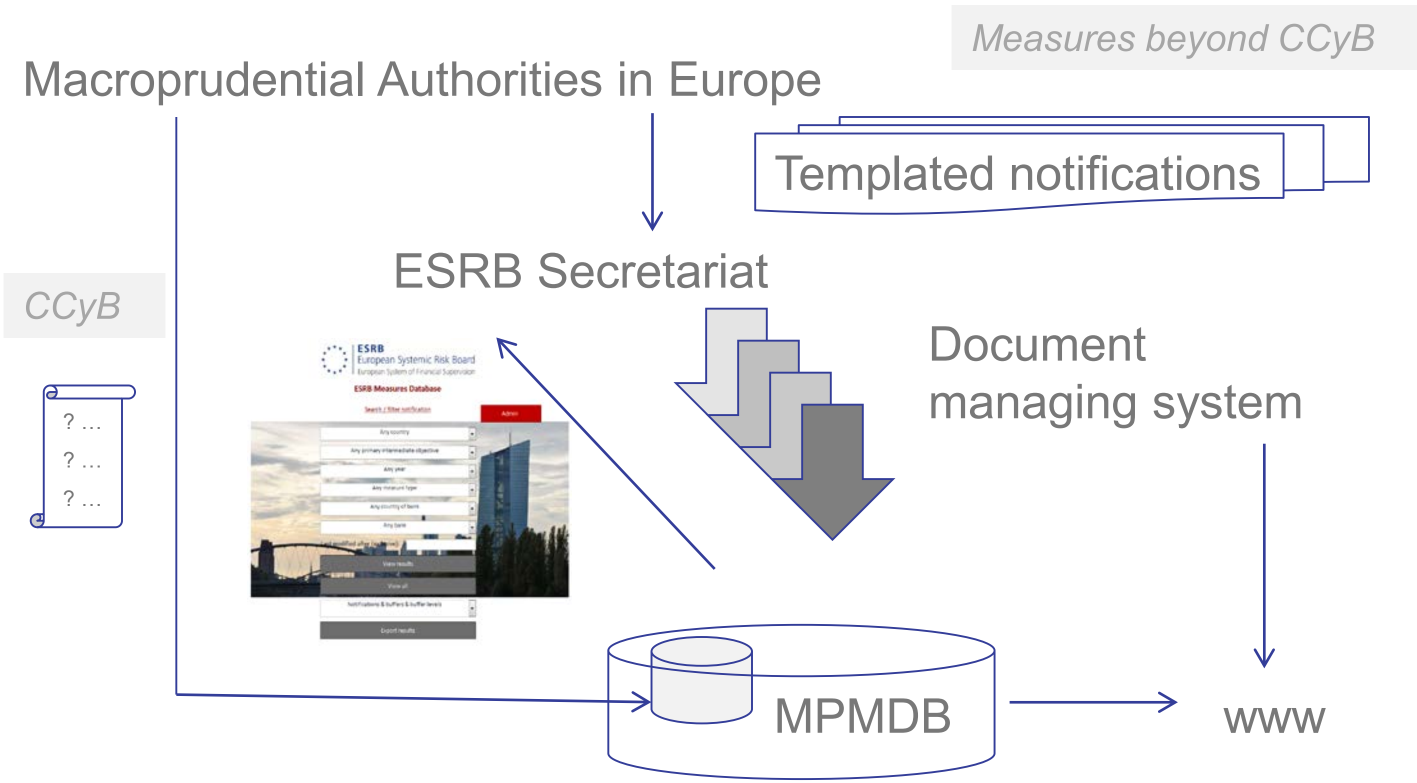
C. Release of data on macroprudential measures
   a. Webpage and data dedicated to the CCyB
   b. Overview of the measures beyond the CCyB
   c. Overview of bank specific measures

2. Indicators based on MPMDB

Composite of Secondary Indicators Guiding the CCyB (CSIG)

1. Main features of the ESRB Macroprudential Measures (MPMDB) database

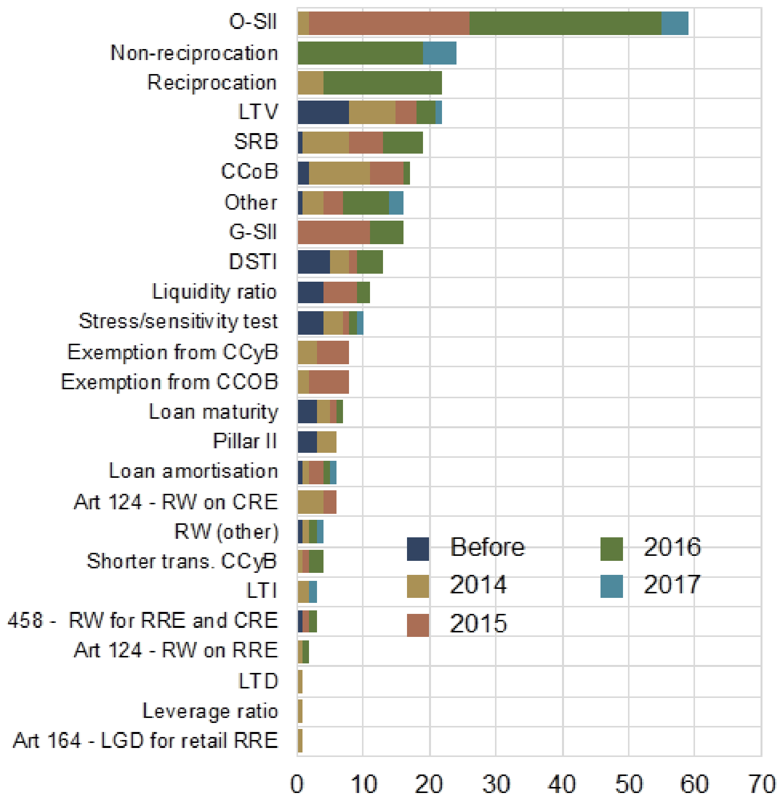
A. Handling the information

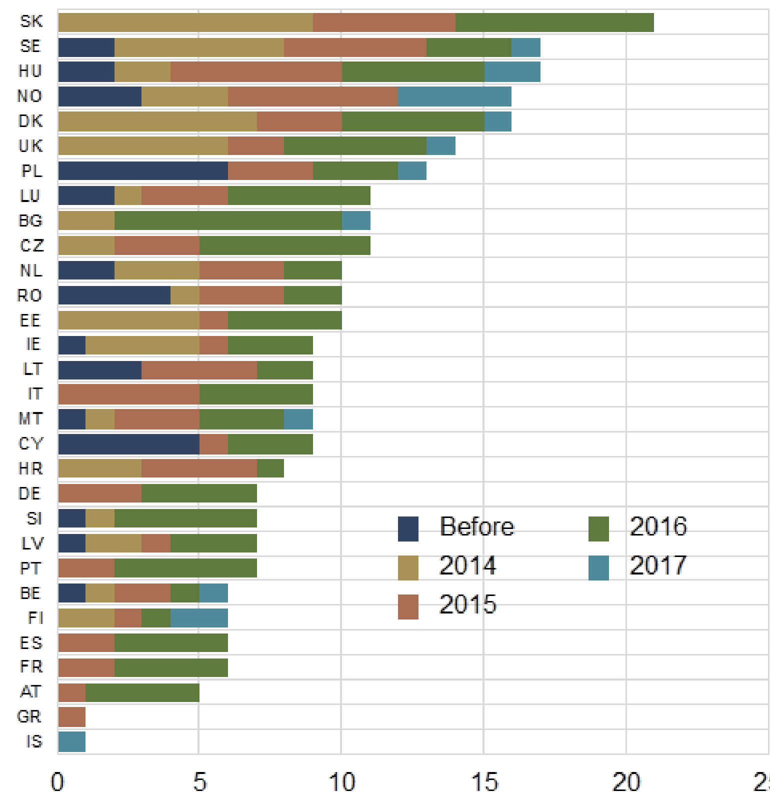


B. Overview of measures

Measures recorded in the MPMDB by year of initiative and country

(Number of measures by type (left panel) and by country (right panel))





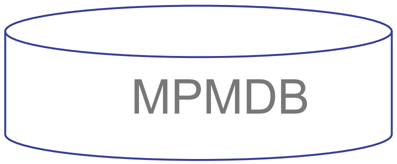
Source: ESRB MPMDB.

C. Release of data on macroprudential measures

a) The webpage and data dedicated to the CCyB

b) The overview of measures beyond the CCyB

c) The overview of bank capital measures

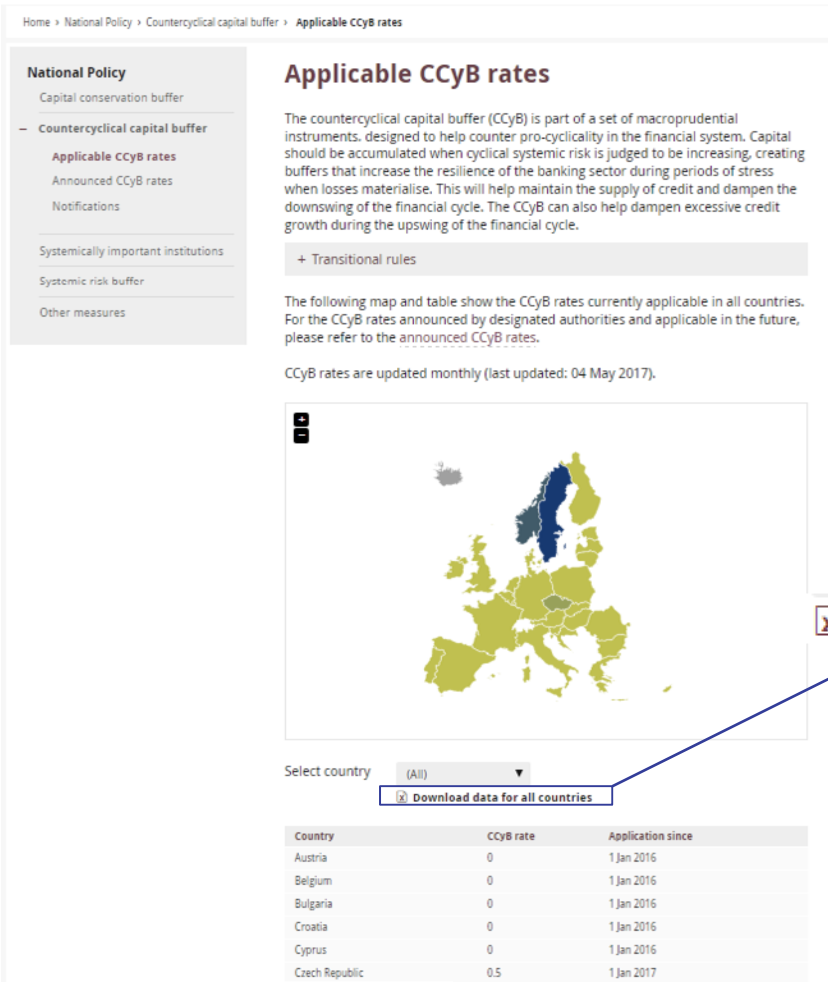


Download data for all countries

Overview of national macroprudential measures

Overview of national capital-based measures

a) The webpage and data dedicated to the CCyB



Home › National Policy › Countercyclical capital buffer › **Applicable CCyB rates**

National Policy
- Capital conservation buffer
- – **Countercyclical capital buffer**
  - **Applicable CCyB rates**
  - Announced CCyB rates
  - Notifications
- Systemically important institutions
- Systemic risk buffer
- Other measures

Applicable CCyB rates

The countercyclical capital buffer (CCyB) is part of a set of macroprudential instruments, designed to help counter pro-cyclicality in the financial system. Capital should be accumulated when cyclical systemic risk is judged to be increasing, creating buffers that increase the resilience of the banking sector during periods of stress when losses materialise. This will help maintain the supply of credit and dampen the downswing of the financial cycle. The CCyB can also help dampen excessive credit growth during the upswing of the financial cycle.

+ Transitional rules

The following map and table show the CCyB rates currently applicable in all countries. For the CCyB rates announced by designated authorities and applicable in the future, please refer to the announced CCyB rates.

CCyB rates are updated monthly (last updated: 04 May 2017).

Select country (All)

Download data for all countries

Country	CCyB rate	Application since
Austria	0	1 Jan 2016
Belgium	0	1 Jan 2016
Bulgaria	0	1 Jan 2016
Croatia	0	1 Jan 2016
Cyprus	0	1 Jan 2016
Czech Republic	0.5	1 Jan 2017

Additional data:
- Credit-to-GDP
- buffer guide
- justification

Download data for all countries

- buffer rates
- timing
- links

b) Overview of measures beyond CCyB

Overview of national measures

Measures covered:

- Capital buffers (CCoB, G-SIIs, O-SIIs, SRB)
- Reciprocation
- Other measures (real estate related e.g DSTI, LTV, risk weights etc, and others)

Information provided:

- *Geographical specifications* (region, country, authority)
- *Timing and communication strategy* (year of initiative, dates of publishing and notifying, timeframe for the measure, links to the communication materials)
- Targeted *intermediate objective* of financial stability
- *Legal basis*, information about revocation or replacement, status of the measure
- *Description* of the measure
- *Reciprocation* including ESRB recommended reciprocation
- *Notes*

c) Overview of bank specific measures

Overview of national capital-based measures

Combined buffer requirements as of 3 April 2017
in Europe (EU countries and Norway)

(At the individual bank level, all banks subject to individual structural buffers (G-SII, O-SII, SRB) are included)
Please use '+' on the sidelines to view individual banks in specific countries and
'1' and '2' at the top on the left margin to toggle between country and indiviudal bank view.

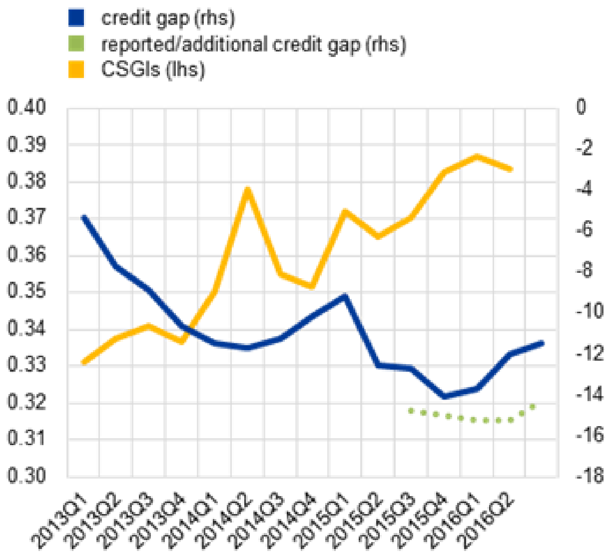
Country Decision-making authority *Bank name*	CCoB 1) CRD 129	CCyB 2) CRD 130	The higher of G-SII buffer CRD 131	 O-SII buffer 3) CRD 131	 SRB 4) CRD 133	Combined buffer requirement 5)	Details phasing in
Austria Finanzmarktaufsicht	**1.25%**	**0%**		**7 banks: 0.25%-0.5%**	**12 banks: 0.5%-1%**	**1.25%-2.25%**	**O-SII fully loaded by 01.01.2019** **SRB fully loaded by 01.01.2019**
BAWAG P.S.K.	1.25%	0%		0.25%	0.5%	1.75%	O-SII fully loaded by 01.01.2019 SRB fully loaded by 01.01.2019
Erste Group Bank AG	1.25%	0%		0.5%	0.5%	1.75%	O-SII fully loaded by 01.01.2019 SRB fully loaded by 01.01.2019
Raiffeisenlandesbank Niederösterreich-Wien AG	1.25%	0%		0.25%	0.5%	1.75%	O-SII fully loaded by 01.01.2019 SRB fully loaded by 01.01.2019
Raiffeisen Bank International AG	1.25%	0%		0.5%	0.5%	1.750%	O-SII fully loaded by 01.01.2019 SRB fully loaded by 01.01.2019
Raiffeisen Zentralbank Österreich AG	1.25%	0%		0.5%	0.5%	1.75%	O-SII fully loaded by 01.01.2019 SRB fully loaded by 01.01.2019
Raiffeisenlandesbank Oberösterreich AG	1.25%	0%		0.25%	0.5%	1.75%	O-SII fully loaded by 01.01.2019 SRB fully loaded by 01.01.2019
UniCredit Bank Austria AG	1.25%	0%		0.5%	0.5%	1.75%	O-SII fully loaded by 01.01.2019 SRB fully loaded by 01.01.2019
Hypo NOE Gruppe Bank AG	1.25%	0%			1.0%	2.25%	SRB fully loaded by 01.01.2019
Vorarlberger Landes- und Hypothekenbank Aktiengesellschaft	1.25%	0%			1.0%	2.25%	SRB fully loaded by 01.01.2019
Hypo Tirol Bank AG	1.25%	0%			1.0%	2.25%	SRB fully loaded by 01.01.2019
Oberösterreichische Landesbank Aktiengesellschaft	1.25%	0%			1.0%	2.25%	SRB fully loaded by 01.01.2019
Sberbank Europe AG	1.25%	0%			0.5%	1.75%	SRB fully loaded by 01.01.2019
Belgium National Bank of Belgium	**1.25%**	**0%**		**8 banks: 0.5%-1%**		**1.25%-2.25%**	**O-SII fully loaded by 01.01.2018**
AXA Bank Europe SA	1.25%	0%		0.5%		1.75%	O-SII fully loaded by 01.01.2018
Argenta Spaarbank NV	1.25%	0%		0.5%		1.75%	O-SII fully loaded by 01.01.2018

- ***Entity identification by LEI*** in MPMDB enables integration between various datasets
- important to consider the ***conditions on combinations*** of the individual types of capital buffers depending on the consolidation scope, exposures coverage, timeframes of application

2. Indicators based on MPMDB

Composite of Secondary Indicators Guiding the CCyB (CSIG) (work in progress)

Chart A1. Credit-to-GDP gaps and CSIG for the EU countries (Q1 2013 – Q3 2016)



Source: ESRB RDB, MPMDB and ESRB calculations. Note: aggregated credit gaps (standardised; reported/additional credit gap in MPMDB) weighted by GDP.

- measure the build-up of systemic risk
- build on the set of complementary indicators recommended by the ESRB
- categories 1) property prices, 2) credit growth, 3) external imbalances, 4) strength of bank balance sheets 5) private sector debt burden, 6) mispricing of risks.
- indicators homogenised and transformed based on their empirical cumulative distribution function (CDF) involving order statistics
- transformed indicators can be interpreted as probabilities of systemic risk being build-up
- they are aggregated into country specific as well as the overall for the EU
- further testing of the indicator needed

Thank you for your attention!

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BANK FOR INTERNATIONAL SETTLEMENTS

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Brussels, Belgium, 18-19 May 2017

Towards identification of gaps in data availability for maintaining financial stability – the case of Montenegro[1]

Maja Ivanović, Marijana Mitrović-Mijatović and Milena Vučinić,
Central Bank of Montenegro

[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.

TOWARDS IDENTIFICATION OF GAPS IN DATA AVAILABILITY FOR MAINTAINING FINANCIAL STABILITY – THE CASE OF MONTENEGRO

Marijana Mitrović-Mijatović

Maja Ivanović

Milena Vučinić

Abstract

The recent crisis pointed to an importance of building a strong and stable financial system, which is resilient to potential risks and imbalances. Macroprudential policy is used to identify, monitor and asses systemic risks to financial stability. In an attempt to create effective and efficient macroprudential policy, it is crucial to build a strong institutional framework and effective and applicable databases. Without strong macroeconomic and financial analysis it is almost impossible to accurately predict and assess macro and financial risks and vulnerabilities.

Bearing in mind Montenegro's small size and a short history as an independent state, there are many gaps in data availability and the associated challenges. Montenegro is still in the process of catching up, which implies financial deepening and macroprudential policy are not easy to apply. Thus, our intention in this paper is to identify data gaps which hamper the ability of central bank to identify indicators with good early warning properties (credit to GDP gap) for Montenegro. Furthermore, we will try to propose indicators which may complement the credit to GDP gap for decisions to release the countercyclical capital buffer.

JEL classification: E58; E61; G21; G28.

Key words: financial stability, data gaps, macroprudential policy

CONTENTS

1. Introduction

The recent financial crisis showed that price stability alone is not enough to ensure macroeconomic stability. There are countries where dangerous imbalances are developed under low inflation and small output gaps. In order to safeguard macroeconomic stability, the policy should involve financial stability as an additional objective. Thus, the introduction of macroprudential policy and its tools should be introduced in order to target specific sources of financial imbalances. Macroprudential policies (MAPs) have received greater attention with the recent financial crisis. Building effective macroprudential policy provides risks identification ex ante while building buffers to absorb shocks ex post (IMF, 2013). Macroprudential policy requires the ability to asses systemic risk, monitor and close regulatory, data and information gaps. According to the IMF (2013, a) strong institutional and governance frameworks are crucial for macroprudential policy conduct and require appropriate strength of powers and clear responsibility.

An importance of building a strong and stable financial system resilient to potential risks and imbalances is crucial in order to guarantee safe and stable financial and economic atmosphere. The macroprudential policy objective is to prevent systemic risk from forming and spreading in the financial system. Systemic risk has two different dimensions. The time dimension reflects the build-up of systemic risk over time due to the procyclical behaviour of financial institutions contributing to the formation of unbalanced financial trends. The second dimension is cross-sectional and reflects the existence of common exposures and interconnectedness in the financial system. The two dimensions of systemic risk cannot be strictly separated. Actually, they are expected to evolve jointly over the financial cycle. In general, macroprudential policy can be defined as the application of a set of instruments with a potential to increase preventively the resilience of the system in the future by: creating capital and liquidity buffers; limiting procyclicality in the behaviour of the financial system; containing risks that individual financial institutions might create for the system as a whole.

The need for macroprudential policy has increased notably in the recent period. Economic costs arising from the financial crisis either through excessive financial cycles or spillovers through interconnectedness are highly recognized. A large number of countries have introduced various institutional arrangements as well as macroprudential indicators and tools (instruments). The European Systemic Risk Board (ESRB) has identified four intermediate objectives for safeguarding financial stability and thus maintaining the ultimate objective of macroprudential policy. Those are: excessive credit growth and leverage, excessive maturity mismatch and market illiquidity, direct and indirect exposure concentrations, misaligned incentives with a view to reducing moral hazard. There are available instruments for each of the intermediate objectives. Considering excessive credit growth as the key predictor of a financial crisis, the macroprudential instrument should be designed to limit excessive credit growth. Thus, the ESRB (2014) developed the Countercyclical capital buffer in order to counter the procyclicality in the financial system, then loan to value, loan to income, debt service-to-income, sectoral requirement, systemic risk buffer, etc.

Countercyclical capital buffer (CCyB) is considered a genuine macroprudential tool proposed by Basel III. The aim of the CCyB is twofold. Firstly, it requires building up a buffer of capital in good times which may be used to maintain flow of credit to the real sector in difficult times. Secondly, it achieves the broader macroprudential aim of protecting the banking sector from indiscriminate lending in the periods of excessive credit growth that have often been associated with the building up of system-wide risk (BCBS, 2015).

In order to implement effective macroprudential policy, it is important to adopt the policy tailored to the country's characteristics, including its structural, institutional and financial market characteristics and exposures to shocks and risks. There is no one-size-fits-all approach. The effectiveness of the policy could depend on the effectiveness of structural, fiscal, and monetary policies. There are countries which can use monetary policy to affect the financial cycle while others that are in a monetary union or use pegged exchange regimes cannot use this option. There are countries with high public debt and less possibility to conduct countercyclical fiscal policy. According to the IMF (2014), open economies are highly exposed to external effects and can be easily affected by external shocks and prone to spillovers.

Country practices show that macroprudential policy requires powers that ensure the ability to act. These powers allow policymakers to obtain information from other responsible authorities. With these powers policymakers can ensure to fill data gaps (information powers); guide the activation and calibration of regulatory constraints (calibration powers); affect the designation of individual institutions as systemically important (designation powers) (IMF-FSB-BIS, 2016).

Montenegro is in the process of developing macroprudential policy and its strategy. A number of country specific factors influence the creation of macroprudential policy framework. Particularly, this is relevant for Montenegro given that country is euroised and small open economy strongly influenced by external factors. In the absence of an independent monetary policy, the key objective of the Central Bank of Montenegro (CBCG) is the preserving of financial stability. Even though it is not yet explicitly stated in the regulation, with financial stability as the main objective of the CBCG, there is not much need for discussion on the mandate for macroprudential policy, which would reside in CBCG. In 2010, the Financial Stability Council was established with the aim of analysing and monitoring financial stability situation in Montenegro. The Council has soft powers that include providing recommendations on measures and actions for preserving financial system stability (CBCG, 2010).

Strong macroeconomic and financial analyses are very important for accurate predictability and assessment of the macro and financial risks and vulnerabilities.

However, Montenegro has a short history as an independent country so there are short data series with data gaps. There is a need for closing data gaps that can compromise the reliability of analysis. Data analysis and systemic risk monitoring will strongly benefit from reliable statistics, such as statistics on real estate indices, capital flows, and flow of funds. In order to achieve its primary goal, the safeguarding of financial stability, the CBCG is developing a set of indicators on credit growth, lending standards and leverage, which would enhance the quality and effectiveness of risk monitoring and assessment.

Therefore, this paper aims to identify data gaps which hamper the ability of the central bank to identify indicators with good early warning properties for Montenegro, in particular to analyse the credit-to-GDP gap proposed under Basel III for the countercyclical capital buffer, and to discuss how to overcome the potential issues of the credit gap in the Montenegro context. In particular, we will try to propose indicators which may complement the credit to GDP gap for decisions to release the countercyclical capital buffer and to identify a set of fundamental factors that could provide a solid guidance for setting this instrument in Montenegro and using it in an efficient way.

2. Macroprudential indicators

2.1. Assessing credit to GDP gap in Montenegro

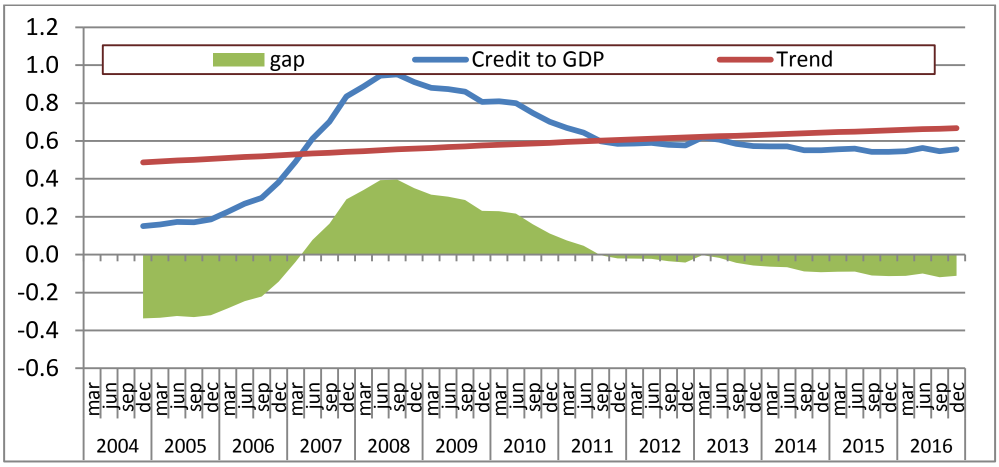
There have been growing concerns about the implications for macroeconomic and banking stability where rapid credit growth has coincided with vulnerabilities in the domestic financial systems. Minsky (1972) argues that credit booms tend to sow the seeds of crises. According to the empirical studies, the fast growth in bank lending during the upswing of the business cycle and the corresponding accumulation of debt in the non-financial sector increases banks' credit risk and the occurrence of non-performing loans and, consequently, fragility in the banking sector. This generates instability, amplifies the danger of financial crisis occurrence and increases systemic risk.

However, defining a credit boom might be sensitive. What was the “normal” or “satisfactory” level of credit? Was the fast credit growth just a result of the structural changes associated with the process of transition or the process of catching-up?

The Basel III framework proposes the countercyclical capital buffer as an extension to the regulatory capital framework for banks which policymakers should use in order to mitigate systemic risk. The countercyclical capital buffer is a time-vary macroprudential instrument which should be used with the aim to enhance the resilience of the banking system and over-exuberance in the supply of credit by discouraging the build-up of financial imbalances that might otherwise have led to a systemic banking crisis (Bank of England (2009), CGFS (2010), Borio (2011), FSB/IMF/BIS (2011) and IMF (2011) among others). Basel III assigns the credit-to-GDP ratio gap a prominent role for accumulating countercyclical capital buffers. The credit-to-GDP gap is defined as the difference between the credit-to-GDP ratio and its long-term trend (BCBS, 2010). Furthermore, the BCBS suggests that the long-run trend should be calculated by a one-sided, or ‘real-time’, Hodrick-Prescott (HP) filter with a smoothing parameter of 400,000.

Figure below illustrates this measure for Montenegro, showing that the broad measure would have signalled the need to tighten the countercyclical capital buffer ahead of the crisis in 2008.

Figure 1 Credit to GDP Indicator



Source: Central bank of Montenegro

The impressive growth in the Montenegrin banking sector in the pre-crisis period resulted in an increasing share of total credits in gross domestic product (GDP). This phase is represented in figure 1; by a positive gap i.e. the level of loan is above the long-term trend. 'Excessive' credit growth in the pre-crisis period, primarily financed by high external borrowing, posed a threat to banking sector stability, given that all sectors of the Montenegrin economy had a high level of debt. Namely, a strong credit growth from 2003 to 2008 led to an unsustainable boom that suddenly ended with the occurrence of the global financial crisis (GFC). Subsequently, the deep recession pointed to a number of accumulated problems, including the poor quality of many of the loans on banks` books.

Due to the influence of the GFC and restrictions on credit activities of the banking sector, the credit to GDP ratio growth slowed and fell below the trend line. Looking at figure 1, we can notice that there is still a negative gap at the end of 2016 (even higher than in the previous year), i.e. the level of loans is below the long-term trend, which points to the need to mitigate the situation in the market through the stimulation of adequate regulations and measures which will positively affect the expectations in the economy.

Even though the credit-to-GDP gap has received attention and critiques from both academics and practitioners, most of them have confirmed its usefulness as an indicator of financial vulnerabilities. Namely, as explained by the Bank of England (2013), it is difficult to find an indicator which could provide a perfect guide to systemic risks, given the complexity of financial inter-linkages, the tendency for the financial system to evolve over time, and time lags before risks become apparent.

In this section we tend to analyse whether the credit–to-GDP gap is a good measure for Montenegro, given that it has very short history as an independent country. Basel III recommends that at least 20 years of data is necessary in order to properly assess the forecasting ability of the credit gap. Thus, our first disadvantage is being limited by data availability. Furthermore, due to the short time horizon, the number of cycles and crises is very small compared with cross-country studies. Particularly, Montenegro experienced only one episode of the banking system crisis over the past 15 years. Similar to other countries, this crisis shared some common characteristics: a rapid credit growth which fuelled real estate prices and banks that encountered liquidity problems as funding markets dried up. As described by Drehman (2014), a common challenge in implementing the credit to GDP gap in emerging countries is problematic, as credit statistics are either not available for longer time spans or they are plagued by structural breaks.

Assessing the credit to GDP gap might be tricky in a developing country such as Montenegro as it may hinder the beneficial financial deepening. Namely, the increasing trend in credits might be viewed as a positive consequence of the deepening and restructuring of the financial system, given that most of developing countries like Montenegro were, and some of them still are, in a transition phase (Ivanovic et al, 2016). Thus, as highlighted by Drehman (2014), to the extent that credit growth exceeds past norms, it could trigger increases in the CCyB that could be a drag on further deepening and slow the process of catching up with financially more advanced economies.

Orphanides and van Norden (2002), Edge and Meisenzahl (2011), and Giese et al. (2014) argue that the reliability of the credit-to-GDP gap in real time might be questionable, as revisions to the underlying data used to calculate the credit-to-GDP ratio may lead to significant policy error. This may be a more significant problem in Montenegro, due to the significant changes in methodologies for the coverage of credits and calculating GDP. Quarterly data of GDP in line with the concept of ESA 2010 exists only from 2012 because national definitions had been used before that. Thus, the relevance of GDP might be problematic not only for the purposes of credit to GDP gap but also in econometric models (macro models, stress tests, etc.) Furthermore, the coverage of total credits has changed from January 2013 pursuant to new regulations; banks are obliged to implement internal methodologies for measuring impairment of financial assets in accordance with the IAS. Changes in regulations necessitated changes in the chart of accounts. The most substantial changes are the following:

- Transfer of receivables classified in E category from off-balance to on-balance sheet.
- Loan receivables category is substantially expanded (funds and deposits from banks, factoring, accruals and prepayments)
- Introduction of accounts for recording impairments for all balance sheet asset items, and provisions for off-/on-balance sheet items, pursuant to the IAS.

Furthermore, this issue is linked to the stability of the filter's outcome as new data points become available. Namely, Basel III suggests that the credit-to-GDP ratio should be calculated by means of a one-sided (i.e. backward-looking) HP filter. Actually, this means that the HP filter is run recursively for each period, and the ex post evaluation of performance of the credit gap is based only on this recursive calculation. Thus the problem might appear when future data points become available. In addition, a similar problem might appear due statistical revisions in the underlying data, causing concerns that it can impair its signalling performance. Edge and Meisenzahl (2011) discuss that the backward revision of the trend renders the credit gap unreliable as a guide for the CCyB. Namely, they argue that the 'true' underlying trend, measured using a two-sided HP filter, may differ substantially from real-time estimates of the trend, measured using a one-sided filter, as one-sided filter uses only data available up to each observation, whereas the two-sided filter calculates the trend over the entire sample. Finally, they find that this makes a substantial difference to estimates of the gap in the US. However, Borgy et al. (2009) find that the one-sided filter leads the two-sided filter because it is influenced more by the latest observation and hence it becomes more pro-cyclical. However, since the trend lags behind the actual observations, this implies that the credit gap crosses the one-sided trend earlier than the two-sided trend, making the credit gap based on the one-sided trend more useful as a leading indicator.

From Montenegro`s perspective, it would be impossible for the policymaker to apply a two-sided filter since the future of a country like Montenegro is difficult to forecast. Namely, Montenegro is a small and open economy with very limited monetary policy since the euro is its official currency. Furthermore, Montenegro is service-oriented economy and highly dependent on foreign capital flows. Thus, it would be difficult to extend the sample by recommended five years (Gerdrup et al., 2013) with forecasts of the credit-to-GDP ratio and calculate a two-sided filter for this augmented series.

Drehman (2014) stresses that a similar problem arises at the beginning of the time series used to compute the credit gap in several emerging countries with short data series. Geršl and Seidler (2012) find that the trend calculation can depend significantly on the starting point of the data. This could be a problem in Montenegro, since at the beginning of the observed period, Montenegro experienced an expansive credit growth, which coincided with the privatization of several banks, mergers and was followed by the entry of foreign banking groups, amplifying the banks' lending process and increasing competition in this sector (Ivanovic, 2016). This means that the sample starts near the peak or the trough of the financial cycle. In these circumstances, the trend stays too high for a long period. For these situations Drehman (2014) recommends that policymakers should consider dropping some initial data points, although it still remains an issue for the ex post assessment of performance of the credit gap.

2.2. Other macroprudential indicators complementing the credit to GDP gap effectiveness

In this section we will discuss how to overcome potential issues of the credit gap in the Montenegrin context. In particular, we will try to propose indicators which may complement the credit to GDP gap for decisions to release the countercyclical capital buffer. Summarising the relevant empirical literature, we will try to identify fundamental indicators which could provide a solid guidance for identifying the systemic risk and setting the countercyclical capital buffer in Montenegro.

1. Level of credit and growth rates of credit

As suggested by the literature (Borio and Lowe (2004), Mendoza and Terrones (2008, 2012), Drehmann et al (2011), Dell'Ariccia et al. (2012), Drehmann and Tsatsaronis (2014), BCBS (2010), and IMF (2011), a high level of credit has been recognized as an indicator for the build-up of financial imbalances. Credit expansion is often considered to increase the possibility of a banking crisis.

Drehmann et al. (2011) argues that the credit-to-GDP gap is slow to decline once crises materialize. Namely, he explains that the stock of credit may not fall immediately in a downturn because corporates may have undrawn credit lines available. Also GDP may fall at a quicker pace, potentially even leading to an increase in the ratio. Thus, growth rate of credit variables may provide a timelier alternative to the credit gap in identifying turning points of the financial cycle.

However, as already mentioned, in periods of high levels of credit policymakers have to assess whether in these situations levels of credits are sustainable or whether they are a source of aggregate vulnerability.

Furthermore, it may be useful to look at sectoral splits to understand where exuberance might be building. Namely, Claessens et al. (2013) noted that while aggregate credit growth was less pronounced before the global financial crisis, reflecting slower corporate credit expansion, household indebtedness in the United States rose rapidly after 2000, driven largely by increased mortgage financing, with historically low interest rates and financial innovation contributing.

Figure 2 Total credits by the household and corporate sectors in Montenegro

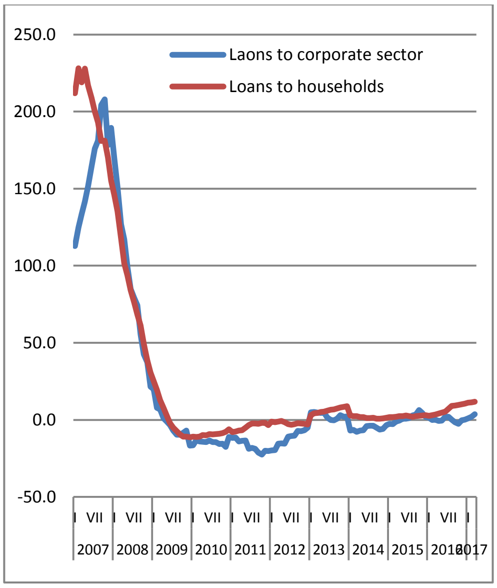


Figure 3 Total credits by sectors of the economy in Montenegro

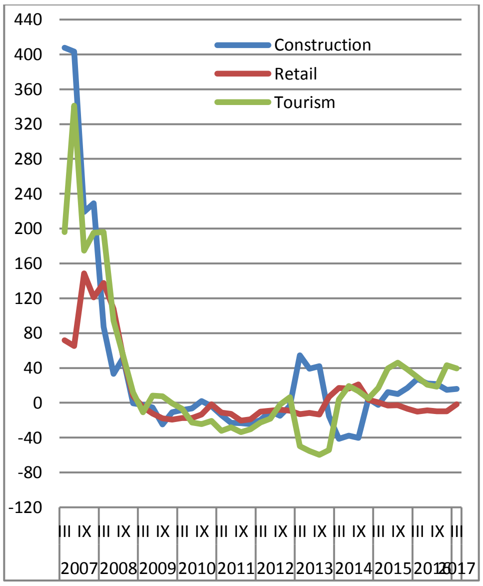


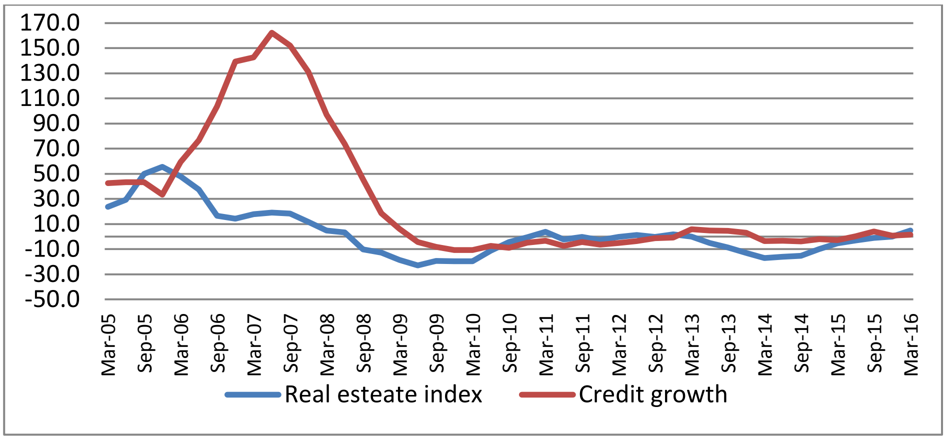
Figure 2 illustrates that loans to the corporate sector in Montenegro increased more rapidly than loans to households. Analysing the growth rate of household and corporate loans separately is useful particularly given that after the crisis, the share of non-performing loans of corporate sector in total loans was higher that the share of household non–performing loans. Furthermore, the sectoral structure of total amount of banking loans (Figure 3) shows that the largest portion of loans was granted to the retail sector, followed by the construction and tourism sectors. Thus, analysing leverage to these sectors and prescribing adequate measures for their monitoring would be beneficial.

As we have already identified data limitations, we would propose that the identification of systemic risk in Montenegro should mainly rely on analysing and monitoring credit developments. In particular, focusing on individual indicators which are grouped into a sectoral index would improve the quality of risk monitoring. Besides indicators of credit growth, developments in lending standards should be observed, as deterioration in lending standards can provide an early indication of an increase in systemic risk.

2. The quality of credit matters-house prices

House prices have typically been linked to financial crises (Drehmann et al. (2010), Claessens et al. (2010), Mendoza and Terrones (2008), Riiser (2005)) and they tend to lead volume-based credit indicators. As reported by Claessens et al. (2010) house prices increased dramatically before the crisis, in particular in the United States, the United Kingdom, Iceland, Ireland, Spain and most of the other markets that subsequently ran into problems. These booms in real estate prices were generally fuelled by fast rising credit, resulting in sharply increased household leverage. As seen in previous crises, the combination of rapid house prices increases and increased leverage turned out to be the most dangerous elements. According to (Crowe et al., 2011), real estate boom-bust patterns preceded more than two thirds of 46 systemic banking crises for which house price data are available.

Figure 4 Credit growth and real estate index (Hedonic index)



Source: Central Bank of Montenegro

The existing empirical literature finds that the loan-to-value ratio would be a good indicator for the quality of credits. Loan to value is defined as the cap on the ratio of the value of the loan relative to the value of underplaying collateral (real estate). Namely, Kuttner and Shim (2012) assess the degree of effectiveness of macroprudential instruments in mitigating housing price and credit cycles using data from 57 countries. Employing panel techniques, they find that caps on loan-to-value (LTV) and debt-to-income (DTI) ratios attenuate housing credit growth and are related to lower house price inflation. Wong et al. (2011) investigate the policy effectiveness using panel data across 13 economies and find caps on LTV ratios effective in mitigating boom and boost cycles. Furthermore, Crowe et al. (2011) explore the effects of these instruments on real estate booms and busts, and find caps on loan-to-value (LTV) ratios related to the real estate cycle have the best chance to curb a real estate boom, whilst dynamic provisioning, although ineffective in avoiding the boom, can help during the bust.

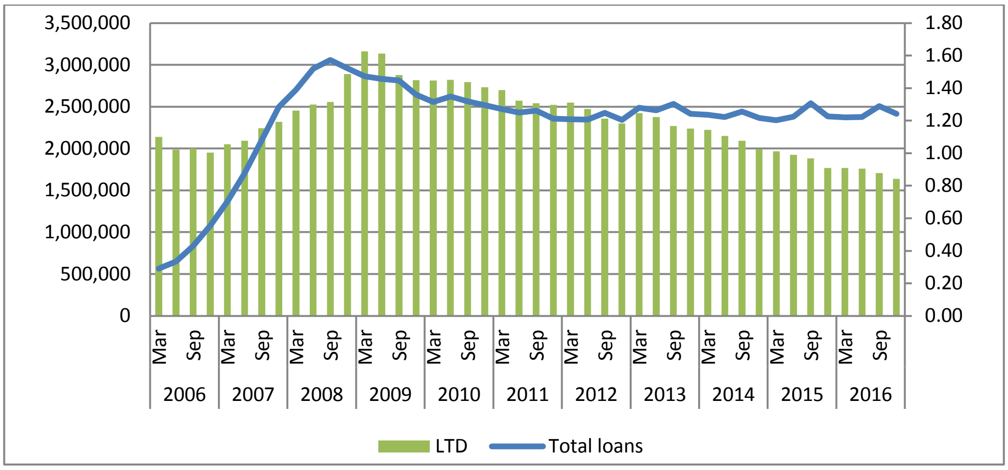
However, this ratio might be problematic in Montenegro given that the available information on developments in property prices is limited and fragmented. Furthermore, a transactions-based indicator of housing prices is only available for newly built apartments (from 2010) and in the central bank`s Hedonic index for real estate price is calculated only for the capital city. In addition, there is no information on transactions in commercial real estate.

The quality of systemic risk monitoring would benefit significantly from a comprehensive database of price indices for real estate. However, closing these data gaps will take time and require substantial capacity from the central bank and other state institutions. In the meantime, macroprudential measure like higher capital requirements or limits on mortgage loans might tackle excessive bank risk-taking associated with real estate booms. However, the calibration of these measures will be a learning process. Namely, excessive changes in the limits may lead to confusing signals and carry the risk of generating policy-induced real estate cycles (Dell'Ariccia, 2012).

3. *The way lending is funded is important*

Stabile bank funding is important. Widely used indicator to measure funding risk in banks is the ratio of loans to deposits. A high and increasing loan-to-deposit ratio would signal a weakening in banks' funding. Thus, the loan-to-deposit ratio should be observed carefully in order to control funding and thus limit increases in lending in the periods when economy is booming and prepare banks for liquidity shortages during crises.

Figure 5 Loan to Deposit Ratio in Montenegro



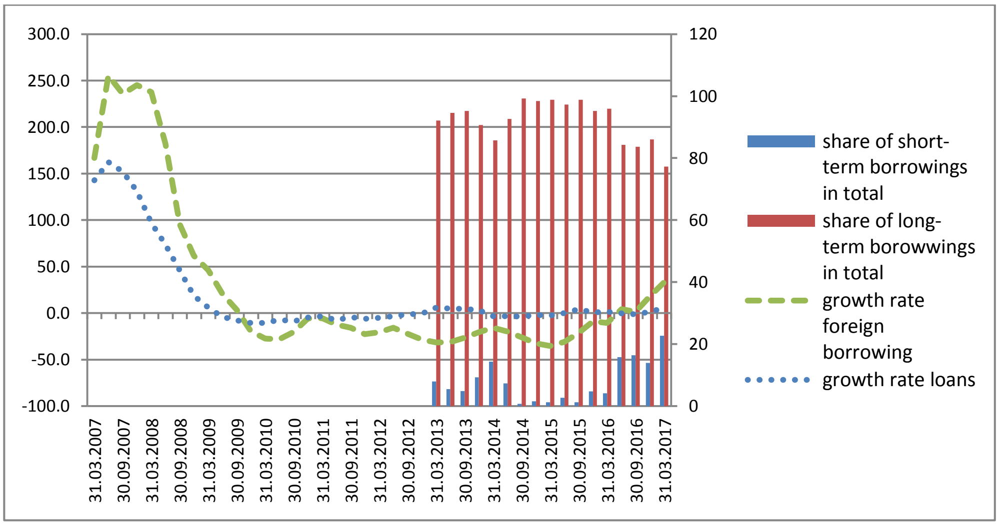
Source: Central Bank of Montenegro

As shown in Figure 5, until 2007, credit growth was supported by an increase in deposits related to high capital inflows. However, from 2007 credit growth significantly exceeded deposit growth. The loan to deposit ratio (LtD) has been extremely high until 2013, suggesting that deposits in that period have not been able to meet loan demand. This has led to an increasing dependency on foreign funding, which has mainly been channelled through the banking sector. Additional reason for the high LtD was that due to the global financial crisis, total deposits declined significantly. Significant withdrawals of deposits have been compensated with an increase in borrowings and credits (see Figure 6).

From 2012, both citizens and corporates restored their confidence into the banking system of Montenegro, and deposits have been growing continually. As a result of strong inflow of deposits and low growth rates of loans, corporate and household sectors have become net creditors as of 2015. Namely, as of 2015, the loans to deposit ratio has improved significantly in comparison with previous years, and it has remained below 1 percent, suggesting that banks have enough available funds to grant loans.

Extremely high LtDs have led to a growing dependency on foreign funding, which mainly involve borrowing from foreign parent banks, whose subsidiaries dominate the Montenegrin banking sector. For example, financing from parent banks constituted 76 percent of total borrowings at end-2008, exposing the banking sector to liquidity shocks in the case where parent banks were unable to sustain financing to their subsidiaries (Ivanovic, 2016). Thus, indicators such as the share of non-deposit funding and the share of FX funding might be useful to impede excessive maturity mismatch and market illiquidity.

Figure 6 Borrowings and their maturity



Source: Central bank of Montenegro

Differentiation of data for short-term and long-term borrowings, which is available in Montenegro only from 2013, might be useful as when the credit is funded by high levels of short-term debt, it is likely to make the financial system more prone to liquidity crises.

Generally, banks are considered by being construction fragile taking in account the maturity transformation that they undertake. Banks should constantly hold enough liquid assets in order to minimize liquidity risk. As Nikolaou states (2009) liquidity risk lies in the heart of banking. Banks' main role in the financial system is to provide liquidity through intermediation between depositors and investors. Banks provide liquid funding to investors by transforming short term maturities, deposits, into long term maturities and thereby promoting efficient allocation of resources in the system. That is the reason why banks become exposed to maturity mismatch. Further, it can result in instability of banking system because banks can fail in providing liquidity to depositors or borrowers (Nikolaou, 2009).

For liquidity purpose, banks in Montenegro have liquid assets available mainly in a very short term. Namely, Montenegrin banks are funded mainly through deposits, except during the periods around the credit boom. However, demand and short term deposits have a dominant part in total deposits. For example, at the end of 2016, short term deposits (with maturity of up to and including one year) comprised 77% of total deposits, while long-term deposits refer only to 23%. Furthermore, with regard to highly emphasized long term structure of credit portfolio, we may recognize a potential vulnerability as banks miss stable long term deposit potential.

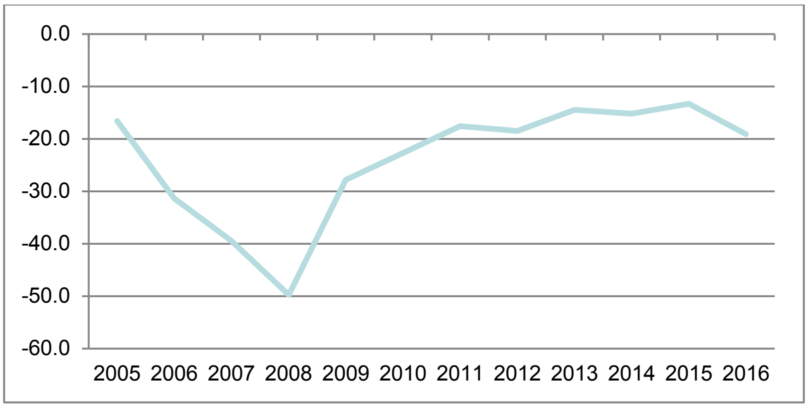
As the ESRB Handbook of operationalizing macroprudential policy in banking sector (ESRB, 2014a) states that application of instruments, aimed to address excessive credit growth and counter pro-cyclicality in the financial system, will help to prevent the systemic risks to materialize. However, the last financial crisis has evidenced that the implementing only prudential rules and strengthening capital buffers are not enough to address liquidity risk. There are instruments designed to address excessive maturity mismatch and market illiquidity. Both sides of banks' balance sheets are subject to illiquidity, market illiquidity on the asset side, and funding risk on the liability side. Materialization of these risks can lead to problems such as fire sales and contagion. In the scope of CRR/CRD, Liquidity Coverage Ratio (LCR) and Net Stable Funding Ratio (NSFR) are proposed. We currently have prescribed the minimum liquid assets ratio; however, the LCR and NSFR are not defined in our regulation. The liquidity coverage ratio by the Basel Accords defines how much liquid assets have to be held by financial institutions. The NSFR limits overreliance on short-term wholesale funding, encourages better assessment of funding risk across all on- and off-balance sheet items, and promotes funding stability (BCBS, 2014). Furthermore, they also propose indicators that are under national jurisdiction such as Loan to Deposit (LTD) Ratio and Stable Funding Requirements (SFR) (ESRB, 2014).

4. Large and persistent current account deficits

Large and persistent current account deficits might be seen as a warning sign of building vulnerabilities in financial sector (Reinhart and Reinhart (2008)). Large current account deficits are of concern, as they pose financing risks if capital inflows stop. In most cases, similar to that in Montenegro, credit booms are funded by capital inflows from abroad. According to Vamvakidis (2008), deterioration in the current account balances in emerging Europe was driven by an increase in investment, as high investment was expected to improve these countries' growth prospects and then, eventually, help reduce their current account deficits. By the end of 2007, these vulnerabilities were recognized. Namely, the IMF (2008, p. 15) warned that *"...the heavy dependence on foreign capital leaves the region exposed to an abrupt retrenchment of capital inflows"* and *"economies with large current account deficits or high external debt ratios would be especially vulnerable if foreign financing dried up."* As reported by the ECB (2009), strong growth in housing loans and rising housing prices contributed to the output boom in the construction sector, stimulating demand for particular imported goods such as white goods, furniture, and the like. In addition, they reported that housing loans have raised the overall ability of households to finance consumption; thus, these loans may have also contributed to rising inflationary pressures and/or current account deficits. Even though in situation where foreign lending was directly extended to end-users but domestic banks took part in excess lending, resilience of the financial sector might also weaken (Giese et al., 2014).

Figure below shows that Montenegro ran huge current account deficit before the current banks' crisis.

Figure 7 Current account deficit in GDP%



Source: Central Bank of Montenegro

During the period 2006–2010, net FDI financed 70 per cent of the current account deficit, on average. Even though access to capital was retained through foreign banks' increased financial support to their Montenegrin subsidiaries, this contributed to a rise in external debt which also poses a threat to the system. Owing to euroisation, a high level of external debt, and large debt service requirements Montenegro is prone to a slowdown in capital inflows and this requires the CBCG to pursue a macroprudential policy as soon as possible.

A significant limitation to the national statistics refers to firms` foreign leverage data. The measure of foreign leverage represents the value of foreign financial liabilities extended to firms by foreign banks. Unfortunately, due to the absence of any regulation and, consequently, no obligation by a borrower to inform the CBCG about the loan structure and other loan related information, there is no possibility for a more detailed analysis of these flows. Furthermore, based on Montenegro`s experience, it is sometimes difficult to make a difference between FDIs and firms` foreign leverage, as some companies register their investment financing as an intercompany debt, which is turned into capital after some time. Thus, with a lack of firms` foreign leverage data we cannot grasp the actual indebtedness of firms in Montenegro given that their credit history is not complete and their leverage is not properly registered.

Conclusion

Like many other transition countries, Montenegro has a financial system with the dominant role of the banking sector. Therefore, a sound banking system is fundamental for financial stability, macroeconomic stability, and economic development. Furthermore, in its process of European integration as an EU candidate country, Montenegro is adopting necessary regulation to align with EU requirements and standards. In that context, the banking sector regulation is in the process of compliance with the Basel III and CRD IV. New legislation and standards will grant more powers to the CBCG to address structural and countercyclical systemic risks. Until that, there are still macroprudential instruments other than those specified in the CRD that the national authorities have to propose and implement.

The existing empirical literature shows that macroprudential policy instruments can be effective in mitigating systemic risk. In the paper we analysed the credit-to-GDP gap which is used as a tool in setting the countercyclical capital buffer. Applying this measure for Montenegro, we find that the credit to GDP gap would have signalled the need to tighten the countercyclical capital buffer ahead of the crisis in 2008. However, the forecasting ability of the credit gap might be questionable due to a very short available data series and underlying quality of the data. Furthermore, given the short time horizon, the number of cycles and crises is very small compared to cross-country studies. Thus, in this paper we proposed indicators which may complement the credit to GDP gap for decisions to release the countercyclical capital buffer.

Other indicators, credit levels or growth ratios and sectoral credit ratios, might provide useful indications of credit quality. Namely, focusing on individual indicators which are grouped into a sectoral index would improve the quality of risk monitoring. In order to prevent excessive credit growth and leverage, it is also possible to apply capital requirements (sectoral), risk weights (sectoral), and limits on credit growth. However, the calibration of these measures has to be prescribed in regulation. Furthermore, indicators of housing prices such as loan-to-value are important as housing prices tend to lead volume-based credit indicators. In addition, indicators related to banks' balance sheets, such as the leverage ratio or the loan-to-deposit ratio would provide information how credit booms are financed. Given that credit is funded mainly by short term debt, the financial system might be prone to liquidity crises. Thus, indicators such as the share of non-deposit funding and the share of FX funding might be useful to impede excessive maturity mismatch and market illiquidity.

In the analysis of macroprudential policy, the limitations mainly relate to short data series with data gaps. Thus, there is a necessity for closing data gaps as they may endanger the reliability of analysis.

References:

1. Bank of England (2009) 'The Role of Macroprudential Policy', Discussion Paper, November 2009.
2. Basel Committee on Banking Supervision (BCBS) (2010), 'Countercyclical capital buffer proposal – consultative document', July 2010.
3. Basel Committee on Banking Supervision (BCBS) (2014), 'Basel III: The Net Stable Funding Ratio – Consultative Document', April 2014.
4. Basel Committee on Banking Supervision (BCBS) (2015), 'Frequently asked questions on the Basel III Countercyclical Capital Buffer', October 2015.
5. Borio, C. and P. Lowe (2004), 'Securing Sustainable Price Stability: Should Credit Come Back from the Wilderness? ', BIS Working Papers No. 157.
6. Borio, C. (2011), 'Implementing a Macroprudential Framework: Blending Boldness and Realism', *Capitalism and Society*, Vol. 6(1).
7. Central Bank of Montenegro, Financial Stability Council Law, OGM 44/10, (2010), http://www.cbcg.me/eng/slike_i_fajlovi/fajlovi/fajlovi_o_nama/regulativa/financial_stability_council_law.pdf
8. Claessens, S., M. K. Ayhan and M. E. Terrones (2010) 'The Global Financial Crisis: How Similar? How Different? How Costly?'TÜSİAD-Koç University, Economic Research Forum Working Paper Series, No. 1011.
9. Claessens, S., M. K. Ayhan, M., L. Laeven, F. Valencia (2013) 'Understanding Financial Crises: Causes, Consequencesand Policy Responses', Koç University-Tüsiad Economic Research Forum, Working Paper, No. 1301.
10. Crowe, C., G. Dell'Ariccia, D. Igan, and P. Rabanal (2011) 'Policies for Macrofinancial Stability: Options to Deal with Real Estate Booms' I*MF Staff Discussion Note* No. 11/02.
11. Dell'Ariccia, G. (2012) Property Prices and Bank Risk Taking *in Property Markets and Financial Stability, Heath, A., F. Packer and C. Windsor Eds., Reserve Bank of Australia, available at: www.rba.gov.au/publications/confs/2012/dellariccia.pdf*
12. Dell'Ariccia, G., Bakker, B.B., Laeven, L., Vandenbussche, J., Deniz Igan, D., and H. Tong, (2012) 'Policies for Macrofinancial Stability; How to Deal with Credit Booms' IMF Staff Discussion Notes, No. 06.
13. Drehmann, M. and K. Tsatsaronis (2014), 'The credit-to-GDP gap and countercyclical capital buffers: questions and answers', *BIS Quarterly Review*.
14. Drehmann, M., C. Borio and K. Tsatsaronis (2011), 'Anchoring countercyclical capital buffers: the role of credit aggregates', *BIS Working Papers*, No 355.
15. Drehmann, M., C. Borio, L. Gambacorta, G. Jiménez and C. Truchart (2010), 'Countercyclical capital buffer, exploring options', *BIS Working Paper* No317.
16. Edge, R. and R. Meisenzahl, (2011), 'The Unreliability of Credit-to-GDP Ratio Gaps in Real Time: Implications for Countercyclical Capital Buffers', *International Journal of Central Banking*.
17. ESRB, (2014), *Handbook of operationalizing macroprudential policy in banking sector*, https://www.esrb.europa.eu/pub/pdf/other/140303_esrb_handbook_mp.en.pdf
18. Financial Stability Board, International Monetary Fund, Bank for International Settlements (2011), 'Macroprudential Policy Tools and Frameworks: Progress Report to G20', 27 October.

19. Geršl, A. and J. Seidler (2012) 'Excessive Credit Growth and Countercyclical Capital Buffers In Basel III: An Empirical Evidence from Central and East European Countries', Economic Studies and Analyses, No 6(2).
20. Giese, J., H. Andersen, O. Bush, C. Castro, M. Farag and S. Kapadia (2014) the Credit-To-GDP Gap and Complementary Indicators for Macroprudential Policy: Evidence from the UK, *International Journal of Finance & Economics*, Vol. 19(1), pp. 25–47.
21. International Monetary Fund – Financial Stability Board-Bank for International Settlements (2016), *Elements of Effective Macroprudential Policies Lessons from International Experience,* available at: https://www.imf.org/external/np/g20/pdf/2016/083116.pdf
22. International Monetary Fund (2011), *Macroprudential Policy: An Organizing Framework*, available at: https://www.imf.org/external/np/pp/eng/2011/031411.pdf
23. International Monetary Fund (IMF) *(*2013a), *The Interaction of Monetary and Macroprudential policies, available at:* https://www.imf.org/external/np/pp/eng/2013/012913.pdf
24. International Monetary Fund (IMF), (2013), *Key Aspects Of Macroprudential Policy*, available at: https://www.imf.org/external/np/pp/eng/2013/061013b.pdf
25. International Monetary Fund, (IMF) (2014), *Macroprudential Policies to Mitigate Financial System Vulnerabilities*, available at: https://www.imf.org/external/pubs/ft/wp/2014/wp14155.pdf
26. Ivanovic, M. (2016), 'Determinants of Credit Growth: The Case of Montenegro', *Journal of Central Banking Theory and Practice*, Vol. 5(2), pp. 101-118.
27. Kuttner, K., and I. Shim, (2012) 'Can Non-Interest Rate Policies Stabilize Housing Markets? Evidence from a Panel of 57 Economies'. *National Bureau of Economic Research Working Paper, No. 19723.*
28. Mendoza, E. and M. Terrones, (2008), 'An Anatomy of Credit Booms: Evidence from Macro Aggregates and Micro Data', *NBER Working Paper*, No. 14049.
29. Mendoza, E. and M. Terrones, (2012), 'An Anatomy of Credit Booms and Their Demise', *NBER Working Paper*, No. 18379.
30. Nikolaou, K. (2009) 'Liquidity (risk) Concepts Definitions and Interactions', *ECB Working Paper Series,* No. 1008.
31. Orphanides, A. and S. Van Norden, (2002), 'The Unreliability of Output-Gap Estimates in Real Time', *Review of Economics and Statistics* Vol. 84(4), pp. 569-583.
32. Riiser, M. (2005), 'House Prices, Equity Prices, Investment and Credit – What Do They Tell Us About Banking Crises? A Historical Analysis Based on Norwegian Data', *Norges Bank Economic Bulletin* No. 05 (Q3), pp. 145-154.
33. Wong, E., Fong, T., K. Li and H. Choi., (2011) 'Loan-to-Value Ratio as a Macroprudential Tool – Hong Kong's Experience and Cross Country Evidence'. Hong Kong Monetary Authority, Working Paper.

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Towards identification of gaps in data availability for maintaining financial stability – the case of Montenegro[1]

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Central Bank of Montenegro

[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.

TOWARDS IDENTIFICATION OF GAPS IN DATA AVAILABILITY FOR MAINTAINING FINANCIAL STABILITY – THE CASE OF MONTENEGRO

Authors: Marijana Mitrović-Mijatović
Maja Ivanović
Milena Vučinić

Content

- Introduction
- Objectives of the paper
- Macroprudential policy and countercyclical capital buffer
- Assessing the credit to GDP gap in Montenegro
- Other indicators complementing the credit-to-GDP gap
- Concluding remarks

Introduction

- Montenegro is in the process of developing macro-prudential policy. The country is still in a catching-up process, which implies financial deepening, thus macroprudential policy is not easy to apply.

- Number of country-specific factors influence creation of macro-prudential policy framework.

1. It is a small euroizied and open economy strongly influenced by external factors. In the absence of independent monetary policy, key ***objective of Central bank of Montenegro (CBM) is preserving financial stability***.

2. Montenegro has a financial system with dominant role of banking sector. Therefore, healthy and sound banking sector is fundamental for stability of financial system.

3. Montenegro is a country with short history as independent state, thus there are many ***gaps in data availability and the associated challenges***. There is a necessity for closing data gaps which can endanger the reliability of analysis.

4. In order to achieve its primary goal, safeguard financial stability, the CBM ***is developing a set of indicators on credit growth, lending standards and leverage***, which would enhance the quality and effectiveness of risk monitoring and assessment.

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Objectives of the paper

1. To identify data gaps which hamper the ability of central bank to identify indicators with good early warning properties for Montenegro.
   - To analyse the credit-to-GDP gap proposed under Basel III for the countercyclical capital buffer.
2. To discuss how to over come the potential issues of the credit gap in the Montenegro context.
   - In particular, we will try to propose indicators which may complement the credit to GDP gap for decisions to release the countercyclical capital buffer.
   - To identify a set of fundamental factors that could provide solid guidance for setting this instrument in Montenegro and using it in efficient way.

Macro-prudential policy

- The macroprudential policy objective is ***to prevent systemic risk*** from forming and spreading in the financial system.
- ***Systemic risk has two different dimensions***:
  - ***The time dimension*** reflects the build-up of systemic risk over time due to the pro-cyclical behaviour of financial institutions contributing to the formation of unbalanced financial trends.
  - The second dimension is ***cross-sectional*** and reflects the existence of common exposures and interconnectedness in the financial system.
- The two dimensions of systemic risk cannot be strictly separated, actually they evolve jointly over the financial cycle.
- In general, macroprudential policy can be defined as the application of a set of instruments that have the potential to:
  - increase preventively the resilience of the system, in the accumulation phase, against the risks of emergence of financial instability in the future by
    - creating capital and liquidity buffers,
    - limiting procyclicality in the behaviour of the financial system,
    - containing risks that individual financial institutions may create for the system as a whole.
  - mitigate the impacts, in the materialization phase, of previously accumulated risks if prevention fails.

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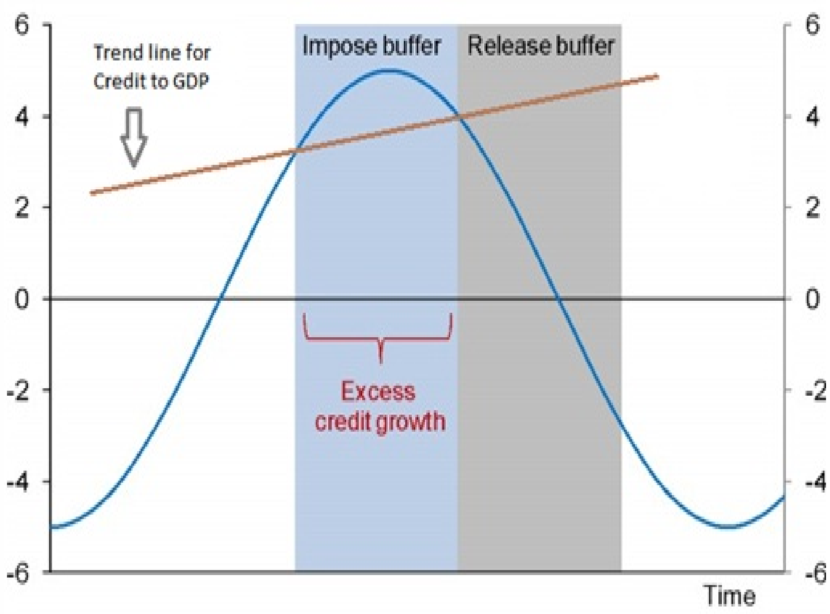
Countercyclical capital buffer (CCB)

- **Countercyclical capital buffer (CCB) - genuine macroprudential tool, proposed by Basel III**
- The aim of the CCB is twofold:
  1. it requires the build up a buffer of capital in good times which may be used to maintain flow of credit to the real sector in difficult times.
  2. it achieves the broader macro-prudential aim of protecting the banking sector from indiscriminate lending in the periods of excessive credit growth that have often been associated with the building up of system-wide risk.

- The common reference guide (BCBS , 2010) for setting the CCB is based on the aggregate private sector credit-to-GDP gap.



- A gap between currently observed value and the calculated long-term trend of private sector credit to GDP.
- BCBS suggests that the long-run trend should be calculated by a one-sided, or ‘real-time’, Hodrick-Prescott (HP) filter with a smoothing parameter of 400,000.

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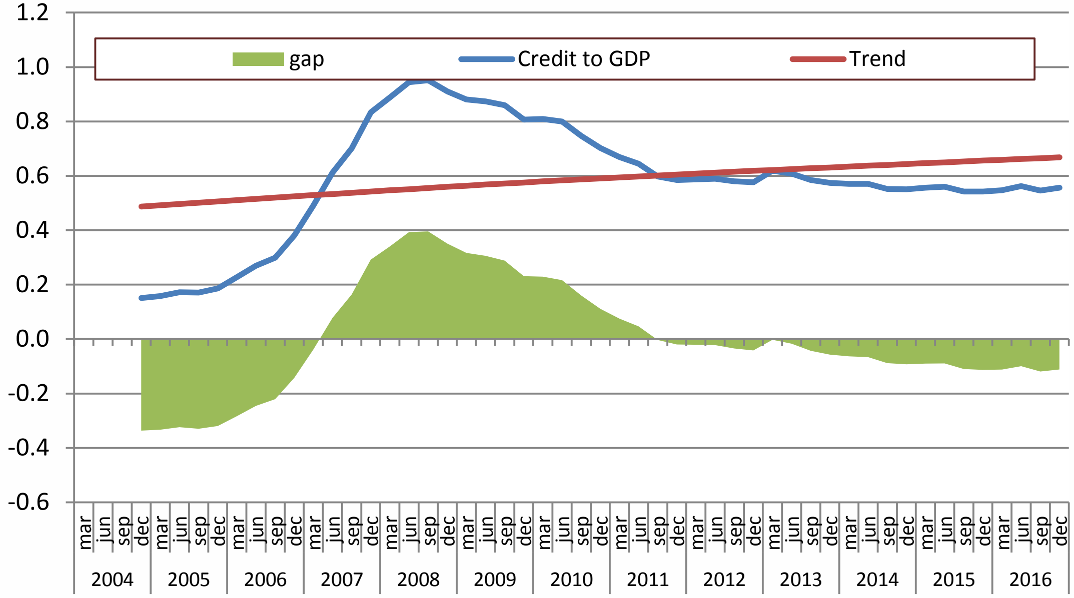
Assessing the credit to GDP gap in Montenegro

- In pre-crisis period an excessive risk was overtaken and it had been materialised,, immediately after the crisis hit banks` balances.
- Figure below illustrates this measure for the Montenegro, showing that the broad measure would have signalled the need to tighten the countercyclical capital buffer ahead of the crisis in 2008.

Figure: Credit to GDP Gap



Source: CBM

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Assessing the credit to GDP gap in Montenegro

- Whether the Credit to GDP gap is appropriate measure for Montenegro?
- Potential problems:

1. Data availability limitations: Montenegro has very short history.
   – Basel III recommends that at least 20 years of data is necessary in order to properly assess the forecasting ability of the credit gap.

2. The number of cycles and crises is very small compared with cross-country studies.
   – Particularly, Montenegro experienced only one episode of banking system crisis over the past 15 years.
   – Fast credit growth is incorporated in the trend

3. Assessing the credit to GDP gap might be tricky in developing country as Montenegro, as it may hinder the ***beneficial financial deepening***.

4. Orphanides and van Norden (2002), Edge and Meisenzahl (2011) and Giese et al. (2014) argue on the reliability of the credit-to-GDP gap in real time is questionable as ***revisions to the underlying data*** used to calculate the credit-to-GDP ratio may lead to policy error.
   – significant problem in Montenegro, due to the significant ***changes in methodologies for the coverage of credits and for calculating GDP.***

Assessing the credit to GDP gap in Montenegro

- Changes into the methodology:

  - ***Changes in GDP compilation – quarterly data exists only from 2012 in line with the concept of ESA 2010.***
    - *Before 2012 national definitions were used, data with many structural breaks.*
    - *Thus the relevance of GDP might be problematic not only for the purposes of credit to GDP gap but also in econometric models (macro models, stress tests, etc.)*

  - ***The coverage of total credits*** has changed from January 2013 pursuant to new regulations, banks are obliged to implement internal methodologies for measuring impairment of financial assets in accordance with the IAS. Changes in regulations conditioned change of the chart of accounts. The most substantial changes are the following:
    - ***Transfer of receivables classified in E category from off-balance to on-balance sheet.***
    - ***Loan receivables category is substantially expanded (funds and deposits from banks, factoring, accruals and prepayments,…)***
    - ***Introduction of accounts for recording impairments for all balance sheet asset items, and provisions for off/balance items, pursuant to IAS.***

- Discussions in the literature: one-sided (i.e. backward-looking) HP filter vs : two -sided (i.e. forward looking) HP filter.

  – the future in country like Montenegro is difficult to provide precise forecast, due to the facts that it is small, open and euroised economy, service oriented and highly depended from foreign capital flows.

Other indicators complementing the credit-to-GDP gap

- **Level of credit in the economy** - ***robust indicator for the build-up of financial imbalances.***
  - Drehmann et al. (2011) argues that the **credit-to-GDP gap is slow to decline once crises materialize**. The stock of credit may not fall immediately in a downturn because corporates may have undrawn credit lines available. Also GDP may fall at a quicker pace, potentially even leading to an increase in the ratio. Thus, ***growth rate of credit variables may provide a more timely alternative to the credit gap in identifying turning points of the financial cycle.***
  - In addition, it may be helpful to look at sectoral splits to understand where exuberance might be building.

Figure: Households vs Corporate Sector

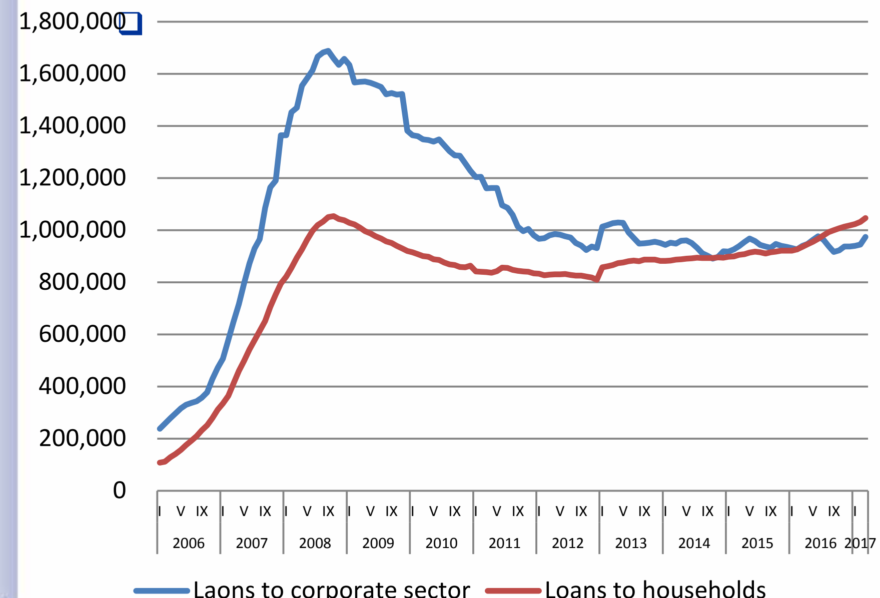
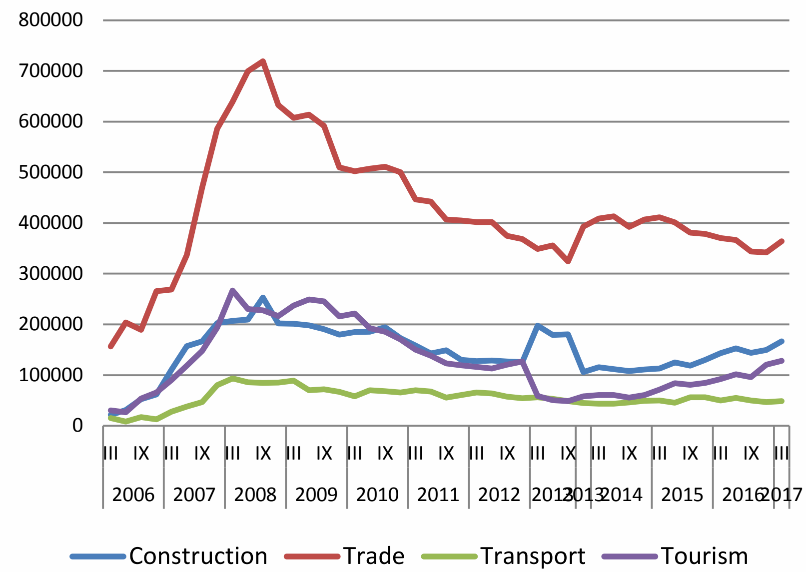


Figure: Sectoral split – most indebted sectors in economy

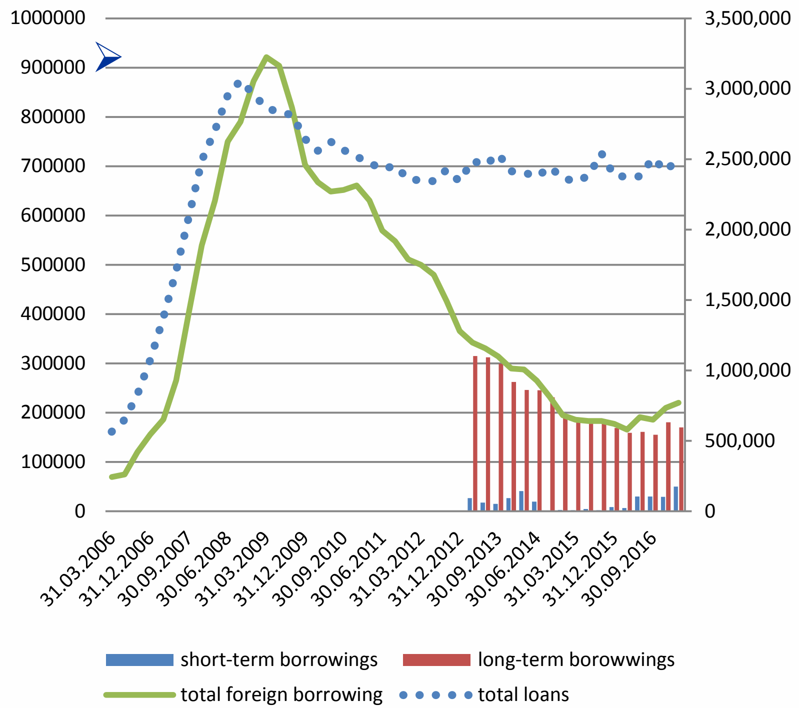


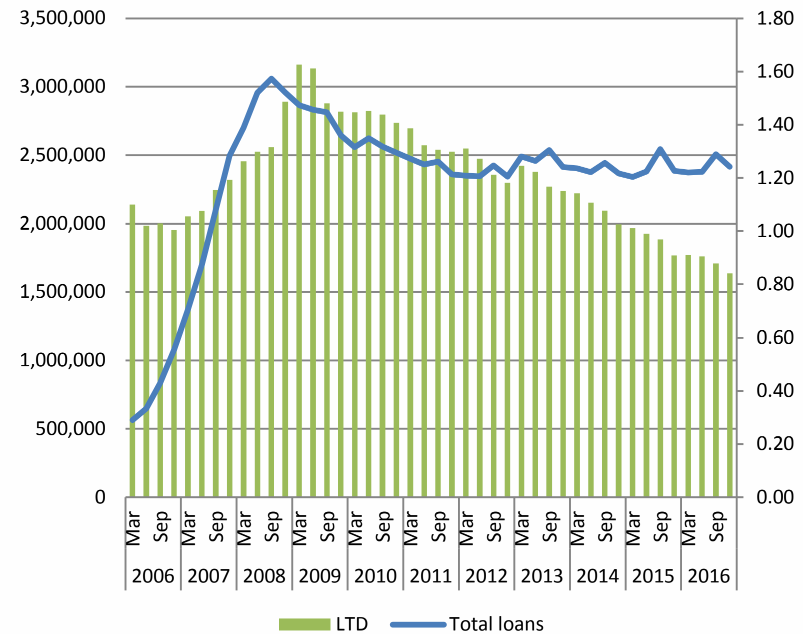
Source: CBM

Other indicators complementing the credit-to-GDP gap

❑ The sources of credit - the way lending is funded

- highly leveraged financial system is fragile,
- ***maturity transformation***, when the credit is funded by high levels of short-term wholesale debt, is likely to make the financial system more prone to liquidity crises,
- high and increasing loan-to-deposit ratio would then signal a weakening in banks' funding.

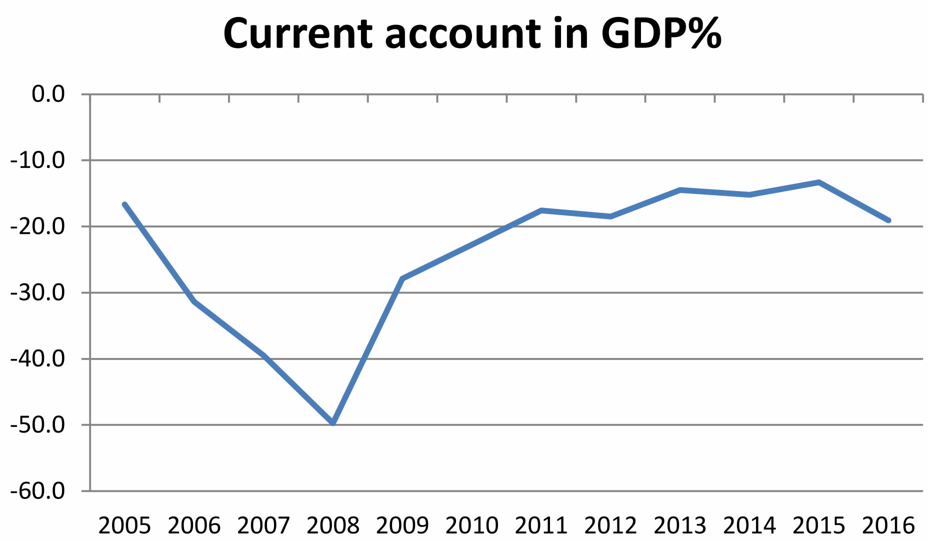




Source: CBM

Other indicators complementing the credit-to-GDP gap

- If foreign lending was directly extended to end-users but domestic banks took part in excess lending, resilience might also weaken. Large and persistent current account deficits are therefore also often seen as a warning sign of building vulnerabilities (Giese et al., 2014).



Source: CBM

- Significant limitation to national statistics and firms leverage data – there is no data of foreign indebtedness of Montenegrin companies.

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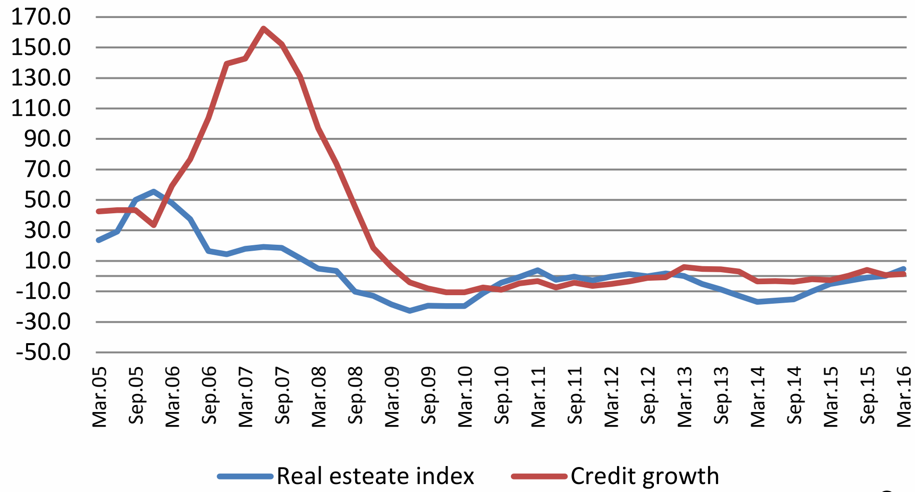
Other indicators complementing the credit-to-GDP gap

- **The quality of credit matters**
  - House prices have typically been linked to financial crises (see, among others, Barrell et al. (2010), Drehmann et al. (2010), Claessens et al. (2011), Mendoza and Terrones (2008) and Riiser (2005)) and they tend to lead volume-based credit indicators.
  - Loan-to-value ratios were a good leading indicator of stress.
  - However this is a problem in Montenegro:
    1. the available information on developments in property prices is limited and fragmented.
    2. A transactions-based indicator of house prices is only available for newly built apartments (from 2010) and in the CBM Hedonic index for real estate price is calculated only for the capital city)
    3. There is no information on transactions in commercial real estate.



Source: CBM

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Proposed indicators for Macroprudential framework

Intermediate objectives	Potential macroprudential indicators	Potential CBM policy tools	
		Currently available	Available from CRR/CRD IV
Excessive credit growth and leverage			
Aggregate	Credit to GDP gap Credit growth Growth in credit to GDP	Capital requirements (sectoral) Risk weights (sectoral) Limits on credit growth Limits on DSTI and LTV ratios for new lending	Countercyclical capital buffer Leverage ratio
Households	Growth in household credit (cash loans, housing loans)[a] Debt to income[b] Debt service to income (new lending)[c] Loan to value ratio (new housing loans)[a]		
Non-financial corporates	Growth in corporate credit (total and by industry)[d] Share of Foreign Exchange (FX) loans		
Financial sector	Bank capital ratios Bank leverage ratio		
Real estate	Growth in real estate lending[a] House price growth Price to income[b] Commercial property price growth		
Excessive maturity mismatch and market illiquidity	Loan to deposit ratio Share of non-deposit funding Share of FX funding	Minimum liquid assets ratio Stable funding requirement Reserve requirements Constraints on FX funding	Liquidity Coverage Ratio Net Stable Funding Ratio

a. Data is available in the credit registry. For some indicators, loan or borrower characteristics may have to be added to the credit registry reporting template (e.g., borrower income).
b. Income data is available from Monstat.
c. Data is available in the credit registry. Borrower income could be added as an extra attribute to the credit registry reporting template, alternatively income data from Monstat can be used
d.This should include foreign lending and could be based on the information that the CBM uses to compile the BoP statistics.

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Concluding remarks

- The ability of the CBM to monitor and assess systemic risk is limited by substantial data gaps. That limits the usefulness of indicators that strongly rely on the availability of long time-series, such as the credit gap.
- Central bank should develop own judgments about the sustainable level of credit in the economy.
- Credit-to-GDP ratio should serve as a guide.
- Other indicators should be tested as to their signaling properties for a built-up of systemic risk.

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Thank you for your attention!

References

- Bank of England (2009) 'The Role of Macroprudential Policy', Discussion Paper, November 2009.
- Basel Committee on Banking Supervision (BCBS) (2010), 'Countercyclical capital buffer proposal – consultative document', July 2010.
- Drehmann, M, C Borio and K Tsatsaronis (2011): 'Anchoring countercyclical capital buffers: the role of credit aggregates', BIS Working Papers, No 355.
- Drehmann, M. And Tsatsaronis, K. (2014) 'The credit-to-GDP gap and countercyclical capital buffers: questions and answers', BIS Quarterly Review,
- Edge, R and Meisenzahl, R (2011), 'The Unreliability of Credit-to-GDP Ratio Gaps in Real Time: Implications for Countercyclical Capital Buffers', International Journal of Central Banking.
- Julia, G., Andersen, H., Bush, O., Castro, C., Farag, M. and S. Kapadia (2014) 'The credit-to-GDP gap and complementary indicators for macroprudential policy: Evidence from the UK', International Journal of Finance & Economics, 19.1: 25-47.
- Orphanides, A and van Norden, S (2002), 'The unreliability of output-gap estimates in real time', Review of Economics and Statistics 84.4: 569-583.

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How should we measure residential property prices to inform policy makers?[1]

Jens Mehrhoff,
Eurostat

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[1] This paper 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.

How should we measure residential property prices to inform policy makers?

Jens Mehrhoff, Eurostat

Contents

1 Motivation and introduction

Data on house prices provide valuable information as a key macroeconomic indicator for identifying price signals, as an indicator for monetary policy impact analyses via the monetary transmission mechanism and, furthermore, as a tool for measuring an economy's real property assets. The data are also used to assess asset price bubbles as well as weaknesses and sources of potential risks in the financial sector, thus forming a basis for financial stability.

In order to make a statement about the residential real estate market as a whole, aggregation of the available price information is required. This can be done by forming the average using weights covering two different populations. On the one hand, the building stock – that is, all residential buildings existing in an economy – can be used as a basis; this results in a wealth perspective. On the other hand, the calculation can be made using transactions. This reflects market activity. It is appropriate to use different measurement approaches and weights depending on the specific analysis objective. Therefore, a single indicator cannot satisfy all user requirements equally.

This paper examines the various motivations for the analysis of house prices and the alternative measures to be applied in each case. Since for short-term business cycle analysis, the most recent developments are at the centre of attention, aggregation should be performed using transactions. In the case of national accounts, housing price data are needed to convert nominal values into real values. If the price-induced change in the property stock is to be measured, as a component of an economy's assets, and not just traded properties, it is appropriate to apply stock weighting. From a financial stability point of view, the potential build-up of asset price bubbles and the risks of banks' credit exposures associated to the financial soundness of private households are most relevant. Much like in short-term business cycle analyses, transactions can be used as a proxy for financings in order to provide valuable clues on the build-up of risks in banks' new business. It should be noted however, that important information on the regional heterogeneity is lost through aggregation.

2 Conceptual framework

The market value of a specific building depends on a variety of factors, such as the location, fittings, age and size of the property. The breakdown of this value[1] into its three main components – price, quality and quantity – can be shown as follows.

$$\text{Value} = \underbrace{\text{Price} \times \overbrace{\text{Quality}}^{}}_{\text{Unit value}} \overbrace{\times \text{Quantity}}^{\text{Volume}}$$

In the calculation, quantity is measured in square metres, for example. The unit value is calculated as the value divided by quantity, ie as the value in euro per square metre. It is thus dependent on the quality of the building concerned and contains not just pure price movements but also changes in quality over time. The quotient of value and price is termed volume and describes the real change in value, adjusted for pure price movements. It can also express, for example, an increase in effective expenditure if this comes about due to energy refitting or modernisation (ie improved quality).

The price in euro per square metre shown in the equation is given with all quality factors eliminated, so that quality appears as a dimensionless mark-up (or mark-down). The intertemporal comparison of prices therefore shows how much more or less would have to be spent today compared with previously under the assumption that the same property would have identical price-relevant fittings and characteristics.

[1] The derivation of this breakdown is based to a lesser extent on theoretical model considerations, eg portfolio theory, on the value of a reproducible, durable consumer good such as a residential building, but more on the breakdown of the value into a price and quantity component while taking into account changes in quality, as is customary in index theory (and hence for consumer prices as well).

In order to make a statement about the residential real estate market as a whole, aggregation is required. This can be done by forming the average using weights covering two different populations. On the one hand, the building stock – that is, all residential buildings existing in an economy – can be used as a basis; this results in a wealth perspective. On the other hand, the calculation can be made using transactions. This reflects market activity.

3 Macroeconomic perspective

3.1 Identification of price signals to allocate resources

In a market economy, prices provide signals about relevant shortages through the balance of supply and demand. In this way, enterprises and consumers receive important indications for their production and purchase decisions. Prices and the changes in them thus play a role in the saving and investment decisions of households and commercial investors.

Housing prices are also a key macroeconomic indicator. Rising housing prices tend to stimulate construction activity. What is more, there are indications that inflation in housing prices is linked to transaction frequency. In particular, price rises for housing, which entail increases in value for the owners, can indirectly boost household consumption via wealth effects.

As an indicator for monetary policy, housing prices constitute a key component of headline inflation measurement.[2] By 31 December 2018, the Commission should prepare a report addressing the suitability of the owner-occupied housing price index for integration into the harmonised index of consumer prices coverage. As with other durable consumer goods, the net acquisition approach is also to be applied here. This takes as its basis expenditure on the acquisition of new housing and on the maintenance and insurance of existing apartments and houses.

Measuring prices based on constant quality and quantity of a well-defined good is crucial to identifying undistorted signals. The measurement objective of a price index is not to portray the development of average expenditure on the acquisition of houses and apartments, which also incorporates higher or lower spending on changes in quality or quantity. Rather, the measurement objective is to record pure price developments under the assumption of identical price-relevant fittings and characteristics. To do this, prices have to be normalised to a uniform standard, which means eliminating quality-related differences.

Aggregation on the basis of transactions, which only incorporates price information on properties actually sold, should be undertaken for business cycle analysis. Ideally, the relevant purchase transactions would be used here as a weighting matrix, which reflect structural differences in the transaction frequency for different property types or regions. Cyclical fluctuations in the weights should be avoided, however.

[2] The same applies to interregional and international comparisons.

3.2 Uses in the national accounts

Housing price data are also needed to convert nominal values into real values (deflating) in the national accounts.[3] In simplified terms,[4] the volume can be derived as follows.

$$\text{Volume} = \frac{\text{Value}}{\text{Price}}$$

This requires a pure price index for this asset class, which is also termed a deflator.

If the price-induced change in the property stock[5] is to be measured, as a component of an economy's assets, and not just traded properties, it is appropriate to apply stock weighting.[6] In conceptual terms, a prerequisite for this is the availability of price information on both sold and unsold properties. Depending on the source of the price data, it is possible that information will only be available for sold properties; however, their price development can differ from that of unsold properties.

Deflators are additionally used in other sections of the national accounts. First, for overall sales of housing, to depict the real production value of real estate and housing services. Second, a price index for the production value of new buildings is needed, which forms part of gross (fixed) capital formation.[7] Deflating these variables requires a transaction-weighted price index which comprises only the prices of new properties for the new buildings component.

4 Application to financial stability

From a financial stability perspective, besides the possible emergence of asset price bubbles, the market risk associated with households' debt sustainability posed to lending banks is of particular relevance. In this connection, the change in value of the financed properties must be noted, taking into account two dimensions: risks involved in newly granted loans and changes in the value of properties in the loan portfolio.

3 Naturally, the nominal figures are also justified in their own right as a key indicator.

4 This document does not address the problem of breakdown into a land and structure component in further detail.

5 The value of the property stock is a significant component of an economy's assets. In Germany, for example, gross domestic capital stock as reported at replacement cost at year-end 2016 in the area of dwellings constitutes around 266% of nominal gross domestic product for the same year.

6 This approach would also be appropriate in terms of estimating wealth effects, as the values of households' individual asset portfolios are influenced by changes in housing prices, which diverge between regions.

7 There is a link between the definitions of stock and transaction values. The stock value at the beginning of the period plus the net change in that period gives the stock at the beginning of the subsequent period. Depreciation (devaluations and disposals) and write-ups (owing to construction and renovation, for example) also have to be taken into account.

However, aggregation can result in important information about regional heterogeneity being lost.[8] After all, in line with the experiences of other countries with exaggerations in the housing market, regional trends can definitely develop systemic relevance. Ultimately, undesirable regional developments in lending that initially arise in isolation can multiply, allowing the rise in housing prices to continue gaining ground.[9] Disaggregated price levels are therefore required to examine geographical transmission channels in more detail.

4.1 Assessment of the emergence of asset price bubbles at the current juncture

The emergence of asset price bubbles is often associated with misallocations, for example on account of a significant increase in construction investment and the corresponding capacities which, in the case of a trend reversal, involves higher default risk in the non-financial corporate sector, amongst other things. However, the acquisition of housing by households, which is credit-financed to a significant degree, merits particular attention. In this context, the value of a property at the time of purchase plays a particular role in lending to households. Thus, for example, the initial ratio of the loan amount to the market value is a key figure in macroprudential analysis.[10] The price dynamics have to be assessed in connection with additional financing indicators. The concurrent increase in lending and easing of lending standards, which can be observed in typical house price booms, is especially risky.

Like the user requirements for business cycle and price analysis, transaction weighting of the properties sold on the market, as an approximation value for financing and construction investment,[11] can provide important information for assessing the build-up of risk positions in new business.

[8] For further details, see Deutsche Bundesbank, The determinants and regional dependencies of house price increases since 2010, Monthly Report, October 2013, pp 13-29.

[9] For further details, see Financial Stability Committee, Erster Bericht an den Deutschen Bundestag zur Finanzstabilität in Deutschland, June 2014.

[10] This kind of monocausal analysis falls short of prudential practice in that there are more factors between property appraisal and customer rating than just the loan-to-value ratio, such as the posting of collateral. Furthermore, the normal loan-to-value ratio in Germany is not necessarily a good measure of a property's actual value, as this "may not exceed the value resulting from a prudent appraisal of the future marketability of a property" pursuant to section 16 (2) of the Pfandbrief Act (Pfandbriefgesetz).

[11] For the construction sector, however, there are vastly more suitable indicators available to directly measure activity.

4.2 Observation of the development of financed properties over time

Another relevant variable that is an important indicator is the change in value over time – changes in price including quality. This is because, with respect to the banks' default risk, the residual value of a property is only of interest when there is a default on loan payments (exposure), as the property would then revert to them and might have to be sold on the market.[12]

As shown above, the value of an individual property is made up of the three variables of price, quality and quantity. The quantity (eg living space) of a property is generally approximately constant over time. However, the price and quality change over time. Thus, the change in value from the time of house purchase until possible default of the loan amounts to:

$$\text{Change in value} = \text{Price change} + \text{Change in quality}$$

The condition of the house, ie its quality, is not a fixed variable in the equation, however; rather, a discount is subsequently assumed as a constant annual depreciation factor. A property's value is thus correlated with the price change on the market.[13]

Consequently, only the price developments of bank-financed properties would be relevant from a macroprudential perspective. Equally, the portfolio to be analysed should incorporate only these properties into the weighting scheme. This is crucial in that its composition changes over time. Newly financed buildings and apartments are added, and others are removed, as the loans granted for them were paid off.

For the purposes of financial stability, supplementary institution-specific data for the identification of sources of potential risk are therefore imperative.[14] The question of the breakdown's borders naturally cannot be answered using the available data. The weighting scheme which comes closest to the measurement objective discussed in this section is probably weighting based on the building stock.[15]

12 Of course, this is only weighed against the average probability of default in the loan portfolio. In principle, the market value of a property can also fall below the loan amount. As long as households can still make the interest and redemption payments, however, these non-defaulted loans do not play a role in the effectiveness of banks' risk management.

13 In this context, the absolute residual value of the property is not the decisive factor, but rather the ratio to the outstanding loan amount at the time of the possible loan default. Particularly in the first few years of the mortgage term, however, the principal component of the annuity is very low, while the rate of depreciation here was assumed to be constant, which means that the outstanding loan amount/residual value ratio normally initially deteriorates compared with the time the loan was granted.

14 In addition, developments broken down by year of loan granting are interesting as these can express the prevailing regime at the time in the form of lending standards.

15 Nonetheless, this approximation is rough at best. For example, the situation regarding households' ownership of real estate property is as follows, based on the German income and consumption sample for 2008: just over half of all households live in rented housing and another fifth own the property without a mortgage loan on it; only around one-quarter of households own housing for which they still have to settle an outstanding loan.

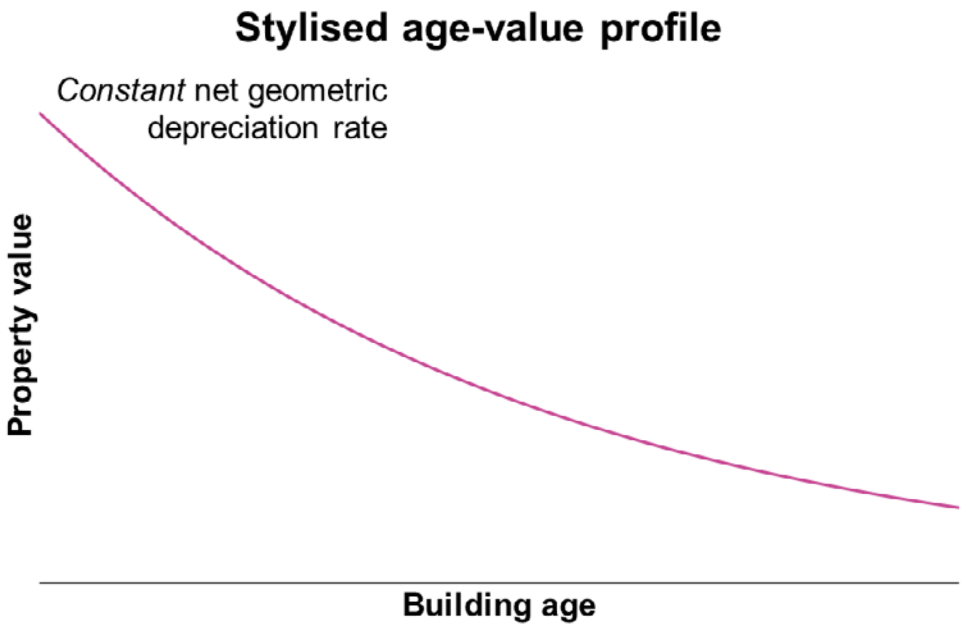
5 Conclusions and policy messages

Whether or not a price index should be adjusted for depreciation depends on the use. From a macroeconomic point of view, the pure, i.e. quality adjusted, price change is desirable as the target (and also as the headline). Having said that, however, for macroprudential purposes one might need to take into consideration deprecation since this affects the collateral value, too. This is exactly why the recommendation of the European Systemic Risk Board on closing real estate data gaps (ESRB/2016/14) demands the "application of a suitably chosen mark-down to account for the depreciation of the property" in the estimation of its current loan-to-value ratio when a price index is used.

Hence, for macroprudential purposes we need something like the age-price profile in the System of National Accounts. According to the *basic builder's model*[16] the value of the property decreases as the structure ages one additional period:

$$p_i^t = \beta^t L_i^t + \gamma^t \left(1 - \delta^t\right)^{A_i^t} S_i^t + \varepsilon_i^t,$$

where the parameter δ^t reflects the net geometric depreciation rate. The graph visualises this relationship, for simplicity ignoring major renovations and vintage effects.



[16] For further details, see Eurostat, Handbook on Residential Property Prices Indices (RPPIs), 2013 edition.

IFC-National Bank of Belgium Workshop on "*Data needs and Statistics compilation for macroprudential analysis*"

Brussels, Belgium, 18-19 May 2017

How should we measure residential property prices to inform policy makers?[1]

Jens Mehrhoff,
Eurostat

[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.

European Commission

How should we measure residential (and commercial) property prices to inform policy makers?

Jens Mehrhoff, Eurostat

IFC – NBB Workshop

Brussels, 18 – 19 May 2017

Structure of the presentation

1. Motivation and introduction

2. Conceptual and methodological framework

3. Conclusion

"Nowadays people know the price of everything and the value of nothing."
(Oscar Wilde in *The Picture of Dorian Gray*)

1. Motivation and introduction

- Recommendation of the European Systemic Risk Board on closing real estate date gaps (ESRB/2016/14):
    - [T]he **current value of the property** can be estimated using a **real estate <u>value</u> index** sufficiently granular with respect to geographical location and type of property; if such real estate value index is also not available, a **real estate <u>price</u> index** sufficiently granular with respect to geographical location and type of property can be used after application of a suitably chosen **mark-down to account for the depreciation** of the property.

1. Motivation and introduction

- The observation of **values and prices generally yields different results**.
- The change in market values between two consecutive periods does not necessarily reflect the **pure, i.e. quality-adjusted, change in prices**.
- It is rather a *mixtum compositum* **of quality changes** due to depreciation and renovation as well as the **quality-adjusted change in prices**; if quantities remain the same.

1. Motivation and introduction

- Let, for example, the **population be equal in the two periods** under consideration.
- **Due to depreciation the quality of all buildings will be lower** on average.
- Comparing the value of the same house over time is **not comparing apples with apples**, or it is **but a fresh apple with a rotten apple**.
- While **values might have decreased** due to depreciation, **quality-adjusted prices would have remained the same**.

2. Conceptual and methodological framework – Setting the stage

- The **market value provides a nominal measure** for residential property. If quantities in square metres, say, are available, dividing the value in euro by that quantity yields a so-called **unit value in euro per square metre**. Thus, the value can be split up as follows:

(1) Value = Unit Value x Quantity.

- However, the unit value in Equation (1) **depends on the quality of the building and not only its size**.

European Commission

2. Conceptual and methodological framework – Setting the stage

- Since price indices aim for a quality-adjusted indicator **prices here denote a constant quality *numéraire***. It is possible to decompose the value into a **constant-quality price** and a volume measure that inherits quality changes:

(2) Value = Price x Volume.

- Therefore, an index for property prices in its pure form will reflect **movements in prices that are stripped of quality changes**. The latter are included in the volume as shown in Equation (2).

2. Conceptual and methodological framework – Setting the stage

- Eventually, the ultimate statistical goal is splitting up the value into a **quality-adjusted price**, the quality component itself and a quantity measure independent of quality:

$$\text{(3)} \qquad \text{Value} = \underbrace{\text{Price} \times \overbrace{\text{Quality}}^{}}_{\text{Unit Value}} \hspace{-4em} \overbrace{\phantom{\text{Quality}} \times \text{Quantity}}^{\text{Volume}}$$

European Commission

2. Conceptual and methodological framework – Setting the stage

- Following Equation (3), the value is obtained via **multiplying the constant-quality price of a unit by a dimensionless mark-up (or mark-down) for the desired level of quality and the nominal quantity** of the structure or the land.
- This **mark-up can reflect characteristics such as the age of the building or its year of construction**.

2. Conceptual and methodological framework – Macro-economic use

- In a market economy, **prices give signals about relative scarcities** through equilibria between supply and demand.
- In this way, both enterprises and consumers gain important insights into their production and consumption decisions, respectively, so that **scarce resources are allocated to where they are most efficiently used**.
- Real estate prices are a significant economic indicator and **rising house prices are often associated with economic growth**.
- They **stimulate construction activity and promote house sales**. Not least, price increases **support private consumption via the wealth effect**.

2. Conceptual and methodological framework – Macro-economic use

- For **monetary policy making, house price indices** are an **integral part of inflation measurement**.
- By 31 December 2018, the Commission should prepare a report addressing the suitability of the **owner-occupied housing** price index for **integration into the harmonised index of consumer prices coverage**.
- For the **identification of pure price signals**, a **price index at constant quality is a condition *sine qua non***.
- Since for **short-term business cycle analysis**, the most recent developments are at the centre of attention, **aggregation** should be performed **using transactions** (albeit not necessarily in terms of chain-linked indices).

2. Conceptual and methodological framework – Macro-prudential use

- Apart from the **potential build-up of asset price bubbles**, the **risks of banks' credit exposures** associated to the **financial soundness of private households** are most relevant.
- Here, the **change in values of financed objects** needs to be tracked over time – from newly granted loans to properties in the credit stock.
- An important indicator is the **change in values – price changes including quality changes – of financed objects over time**.

2. Conceptual and methodological framework – Macro-prudential use

- This is because, from the banks' perspective, the **residual value of a home is of interest only should the debtor default**, since then the bank would have to sell the home on the market (possibly in a forced sale).
- Since the quantity, i.e. floor space or number of bedrooms, is constant in general, the **change in the property's value between the time of purchase and a potential foreclosure** is:

(4) Value change = Price change + Quality change.

2. Conceptual and methodological framework – Macro-prudential use

- The **quality of the house**, however, is not fixed but it is assumed to be **subject to a constant annual depreciation rate**.
- The **sole exogenous variable in the model** then would be the **quality-adjusted price**.
- Still, it is **not the absolute residual value of the house** that matters **but its ratio to the residual mortgage in the event of credit default**.
- In the **first years of the life of the loan**, though, the **amortisation rate of the annuity is rather low**, so that the **loan-to-value ratio worsens**.

2. Conceptual and methodological framework – Macro-prudential use

- From a macro-prudential view, **only prices of financed objects** would be relevant.
- A **bank's credit portfolio** would, furthermore, have a **changing composition**; newly financed objects enter, others exit due to repayments of the loans.
- For financial stability purposes, additionally, **institution-specific figures are indispensable** for the identification of risk potentials.
- The **tails of the distribution need close examination** as do **credit vintages which reflect then-effective lending standards**.

European Commission

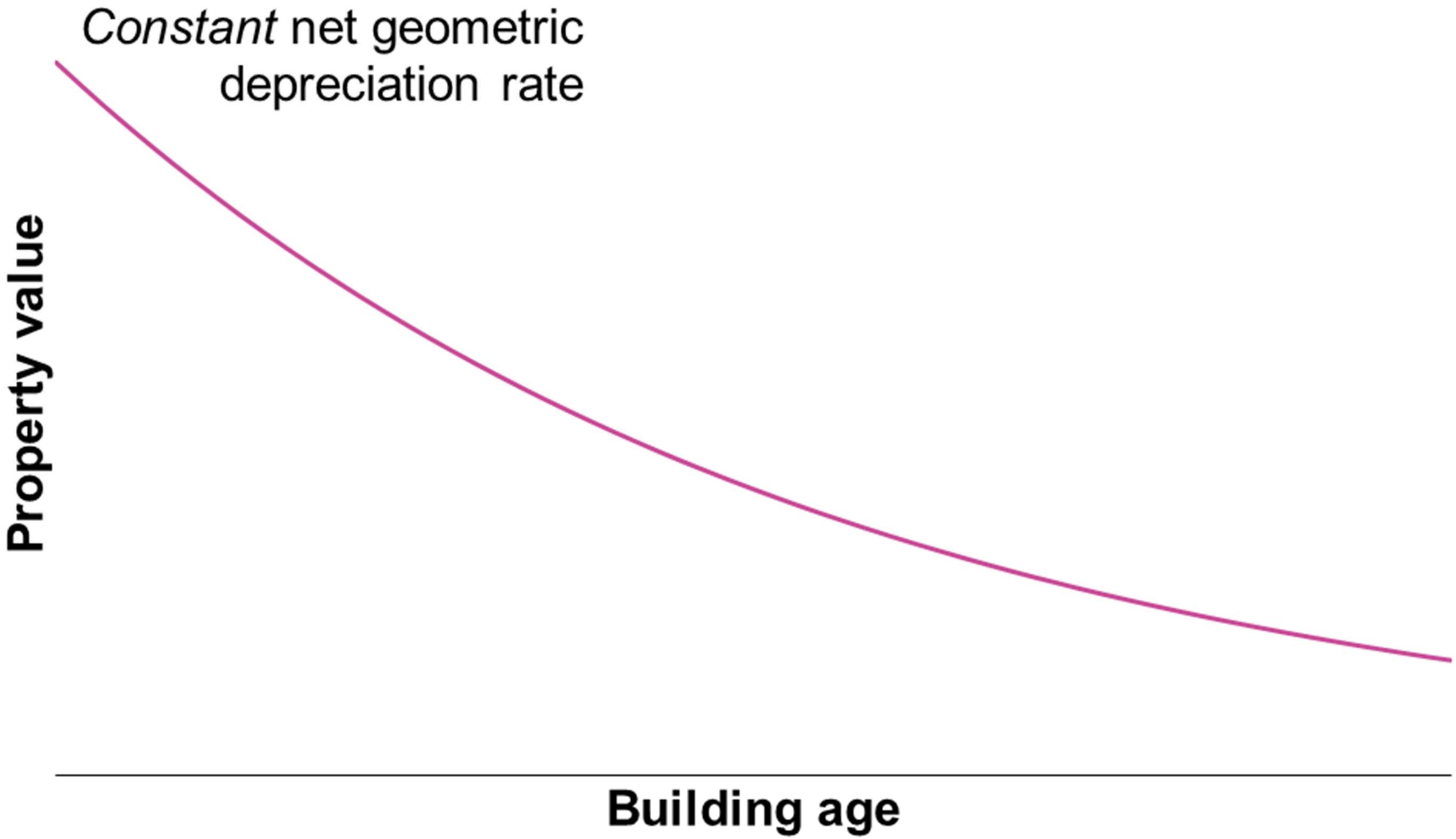
3. Conclusion

- **For macro-prudential purposes we need something like the age-price profile** in the SNA.
- **Basic builder's model** (see Eurostat, 2013, *Handbook on Residential Property Prices Indices*):

(5) $$p_i^t = \beta^t L_i^t + \gamma^t \left(1 - \delta^t\right)^{A_i^t} S_i^t + \varepsilon_i^t,$$

where the parameter δ^t reflects the ***net* geometric depreciation rate** as the structure ages one additional period.

Stylised age-value profile



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What is 'commercial property'?[1]

Jens Mehrhoff,
Eurostat

[1] This paper 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.

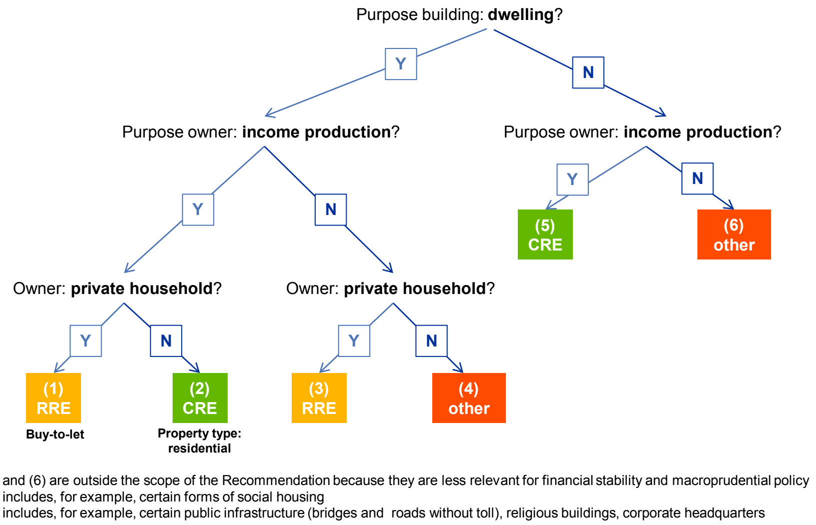
What is ‘commercial property’?

Jens Mehrhoff, Eurostat

Definitions of commercial real estate

Before considering commercial property price indicators, it is necessary to define ‘what is commercial property?’ Property represents one of the most significant, non-financial assets owned by households, firms, and governments. However, the use of property and its economic role changes depending on the entity that owns and uses it. In the European context, Dierick and Point (2017) discuss the delineation of residential and commercial property for the application of the European Systemic Risk Board (ESRB) recommendation on data gaps in the real estate field.[1] They highlight that these definitions are to be seen for the specific purpose of financial stability monitoring and macroprudential policy-making. It is duly and therefore rightly noted by them that the definitions in the recommendation do not coincide with the ones used in the Capital Requirements Regulation (CRR) and analytical credit database (AnaCredit) Regulation.

Figure 2 of Dierick and Point (2017), in particular, provides an overview of the categorisation in the form of a decision tree. First differentiating between residential properties (dwellings) and non-residential properties, the second level is whether or not the owner’s purpose is ‘income production’, followed by a third level, in the case of dwellings, whether or not the owner is a private household. This figure is reproduced here as is.



[1] Dierick, F., and Point, E. (2017), ‘Closing real estate data gaps for financial stability monitoring and macroprudential policy in the EU,’ *IFC Bulletin*, 46; ESRB (2016), ‘Recommendation of the European System Risk Board of 31 October 2016 on closing real estate data gaps (ESRB/2016/14),’ *OJ*, C 31.

The internationally agreed definition of commercial real estate and the relation of the ESRB definition to it

Only very recently has an international definition of what constitutes commercial property in the first place been agreed – a harmonised breakdown (including selection criteria) according to property types like office or retail is still lacking. Eurostat prepared a complete system in the form of building blocks for different definitions according to the varying uses in macroeconomic and macroprudential policies. This work has been approved by the Inter-Secretariat Working Group on Price Statistics (IWGPS)[2] and will be elucidated in early 2018 as part of a 'statistical book' publication (in the context of the G20 Data Gaps Initiative) on commercial property price indicators. The building blocks are presented in the following table.

Assets / Activities	Residential properties (buildings together with the land on which they are situated)		Non-residential properties (buildings together with the land on which they are situated)
Selling and renting of real estate	**Rental housing** Residential properties rented at market rents	*of which* Owned by household	**Investment properties** Non-residential properties sold at market values or rented at market rents
Construction of buildings	**Residential buildings under construction** on own account for sale, or on a fee or contract basis	*of which* For use by owner-occupiers	**Non-residential buildings under construction** on own account for sale, or on a fee or contract basis
Own use	**Owner-occupied housing** Residential properties used as residences (dwellings)		**Corporate properties** Non-residential properties used in the production of goods and services (other than real estate) sold at market prices
Non-market	**Social housing** Residential properties rented below market rents		**Other non-residential properties** Non-residential properties used in the production of goods and services sold below market prices or provided for free

Typically, rental housing and investment properties are considered as 'commercial property'. The boxes shaded in grey are those building blocks which could form the broadest possible definition of commercial property, i.e. also including buildings under construction and corporate properties that are used in the production of (other) goods and services but moreover 'buy-to-let housing', i.e. if a private household acts as a landlord. On the other hand, even rental housing might be excluded from a user (rather than owner) point of view, leaving investment properties, only, in the narrowest definition of commercial property.

[2] Members of the IWGPS are UNECE, ILO, IMF, OECD, Eurostat and World Bank (current chair).

How does the definition in the ESRB recommendation relate to this new international standard? First of all, the express aim of the building blocks is two-fold:

1. Every property goes into one and only one building block, i.e. every property appears exactly once somewhere (technically speaking, it is a partition).
2. Since it is appropriate to use different measurement approaches depending on the specific analytical objective, the building blocks can be flexibly grouped.

Then, by looking at the decision tree is it evident that number[3] (2) is 'rental housing', while number (5) is 'investment properties'. Together with 'non-residential buildings under construction' – which are left out of the decision tree – these form commercial property for the sake of the ESRB recommendation. How 'residential buildings under construction' which are not for use by owner-occupiers, i.e. future rental or buy-to-let housing, shall be treated for the purpose of the ESRB recommendation remains unclear, though.

Number (1) refers to rental housing that is owned by households ('buy-to-let'). 'Owner-occupied housing' is equivalent to number (3). There is a vague relation of number (4) to 'social housing' and of number (6) to 'corporate properties' as well as 'other non-residential properties', which is not further elaborated (presumably for the reason that these three classes are not considered as commercial property).

It is undoubted that a decision tree helps a lot in the grouping of properties in one or the other class. The value might still be increased, though, if the new international standard would be incorporated and, thus, help in harmonising the approaches to measurement of commercial property price and associated indicators.

Conclusions and final remarks

The purpose of this note has been to discuss the definition of commercial property and set the ESRB recommendation in perspective to global efforts in this field. As such, this note necessarily fails short of providing the full background to the new international standard and this has to be left to the 'statistical book' publication on commercial property price indicators in early 2018 by Eurostat.

The evaluation here should also have been non-judgemental. Whether or not the definition applied by the ESRB recommendation is best for financial stability was out of the scope of this discussion. To reiterate this point, the buildings blocks are thought to be flexible enough to accommodate different definitions according to the varying uses of indicators in macroeconomic and macroprudential policies.

[3] In what follows the numbers relate to Figure 2 of Dierick and Point (2017), i.e. according to the ESRB definition.

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Closing real estate data gaps for financial stability monitoring and macroprudential policy in the EU[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.

Closing real estate data gaps for financial stability monitoring and macroprudential policy in the EU

Recommendation 2016/14 of the European Systemic Risk Board on closing real estate data gaps

Wanda Cornacchia (Banca d'Italia), Frank Dierick (ESRB Secretariat), Mara Pirovano (National Bank of Belgium) and Emmanuel Point (Autorité de Contrôle Prudentiel et de Résolution)

Abstract

On 31 October 2016, the European Systemic Risk Board (ESRB) adopted the Recommendation on closing data gaps in the residential and commercial real estate sectors addressed to the national macroprudential authorities in the EU. The aim of this Recommendation is to identify a common set of indicators that national macroprudential authorities are recommended to monitor along with some key definitions. This article describes the origins of the Recommendation and discusses its objectives, nature and scope. The article then presents the main indicators of the recommended monitoring framework for the residential and commercial real estate sectors and important conceptual issues related to their definition. It concludes by reviewing the next steps to be taken for the effective implementation of the Recommendation.

Keywords: Commercial real estate, Residential real estate, Data gaps, Financial stability, Macroprudential policy.

JEL classification: G18, G21, G31, G38

1. Introduction

The most recent and past financial crises underscored the importance of developments in the real estate sector for the financial system and the real economy. Adverse market developments in some countries of the European Union (EU), both in the residential real estate (RRE) sector and the commercial real estate (CRE) sector, resulted in large losses for some credit providers, with severe consequences for the real economy. This important economic impact stems from the tight interplay between the real estate sector, funding providers and other economic sectors, as well as the strong feedback loops that exist between the financial system and the real economy, reinforcing negative developments.

Against this background, analysing and addressing vulnerabilities in the real estate sector is a key responsibility of macroprudential authorities which therefore need to have the necessary analytical frameworks in place. Any risk assessment and policy implementation crucially depends on the availability of reliable, granular, timely and harmonised data on real estate markets. In particular, the effective monitoring of real estate markets requires information on a set of indicators that can signal the build-up of vulnerabilities well in advance and that encompass several dimensions.

The lack of commonly agreed working definitions across EU countries on the RRE and CRE sectors, along with limited data availability for a number of relevant indicators, hampers the reliability of financial stability analyses, making it difficult to accurately assess and compare risks across national markets. Earlier work undertaken under the aegis of the European Systemic Risk Board (ESRB) revealed the existence of important gaps in the availability and comparability of real estate indicators across EU countries.

On the RRE side, the ESRB[1] highlighted the lack of availability of comparable, high-quality data for RRE credit standards indicators, such as the Loan-to-Value (LTV) ratio, the Loan-to-Income (LTI) ratio, the Loan Service to Income (LSTI), the Debt-to-Income (DTI) ratio and the Debt Service to Income (DSTI) ratio. The absence of sufficient and harmonised data on these metrics affects both the financial stability surveillance of the RRE sector and the implementation of borrower-based macroprudential instruments targeting RRE vulnerabilities.

The assessment of the ability of these indicators to provide early warnings against the build-up of systemic risks has been hampered by the absence of reliable and harmonised time series. Furthermore, the data gaps impede the cross-country comparison of the prudential policy stance regarding borrower-based measures targeting RRE vulnerabilities.

On the CRE side, similar ESRB work[2] concluded that the absence of a harmonised working definition of commercial property and the lack of a granular and consistent data framework to capture broader market developments made the analyses of systemic risks problematic. Data gaps for CRE are more severe than for RRE and encompass several dimensions, such as the physical market, the exposures of funding providers and lending standards (i.e. indicators such as the Interest Coverage Ratio or ICR and the Debt Service Coverage Ratio or DSCR).

Against this background, ESRB Recommendation 2016/14 aims at providing the basis for closing existing gaps in the availability and comparability of data on RRE and CRE markets in the EU relevant for macroprudential purposes. It provides target working definitions of RRE and CRE, a common set of indicators that national macroprudential authorities are recommended to monitor, along with target definitions of these indicators.

This article provides an overview of the Recommendation, starting from the context that motivated its adoption (Section 2), describing its objectives and scope (Section 3), as well as the indicators and related definitions it introduces for the monitoring of the RRE and CRE sectors in the EU (Sections 4, 5 and 6). The article concludes with reviewing the different steps still required for the effective implementation of the Recommendation (Section 7).

[1] ESRB (2015a), *Report on residential real estate and financial stability in the EU*, December.

[2] ESRB (2015b), *Report on commercial real estate and financial stability in the EU*, December.

2. Background

2.1 The importance of the real estate sector for financial stability

The relevance of the RRE sector for financial stability lies in the dominance of RRE assets in households' wealth, the large contribution of the RRE sector to GDP and the key role of the financial sector (mainly credit institutions) in providing funding for RRE investments. According to the ECB's Statistical Data Warehouse (SDW) figures at end September 2016, mortgage loans account for 40% to 90% of total lending of monetary financial institutions (MFIs) to households in the different EU countries. The tight interplay between the housing market and the economy leads to strong transmission channels in a downturn (or upturn) phase: a steep fall in house prices negatively affects households' wealth and financial institutions' balance sheets through collateral and property values (asset valuation channel); it further increases the riskiness of households and of construction firms, resulting in the adoption of more stringent lending standards by banks (credit risk channel).

Developments in the CRE sector are also relevant for financial stability because of the highly cyclical nature of the sector, its concentration in a few EU countries and the size of banks' and other institutions' exposures to it. While less important in volume than RRE lending, CRE lending still represents a substantial share of EU banks' loan portfolio. According to the ECB's SDW figures at end September 2016, in most EU countries, lending to the construction sector and real estate related activities (a proxy for commercial real estate lending) makes up between around 20% to 50% of total lending by monetary and financial institutions (MFIs) to corporates.

In the past, adverse developments in CRE markets also played an important role in financial crises, most notably in the Nordic countries and in the United States in the early 1990s, in some Asian economies in the late 1990s, as well as in some EU countries during the recent global financial crisis.[3] Moreover, losses on banks' CRE lending exposures have often been higher than those on RRE lending even though RRE lending exposures are typically larger. The higher losses on CRE lending are due to the predominantly non-recourse basis of CRE loans and to the fact that CRE property is much less liquid than RRE property.

Due to the importance of the real estate sector for financial stability and for the economy, establishing a more harmonised framework for monitoring developments in the RRE and CRE markets is crucial to ensure the early identification of vulnerabilities that could lead to future financial crises.

[3] See Englund, P., "The Swedish Banking Crisis: Roots and Consequences", Oxford Review of Economic Policy, Vol.15, No 3, 2004; Richard J. Herring and Susan M. Wachter (1999), "Real Estate Booms and Banking Busts: An International Perspective", The Wharton School Research Paper and Liow Kim (2004), "Time-Varying Macroeconomic Risk and Commercial Real Estate: An Asset Pricing Perspective", Journal of Real Estate Portfolio Management.

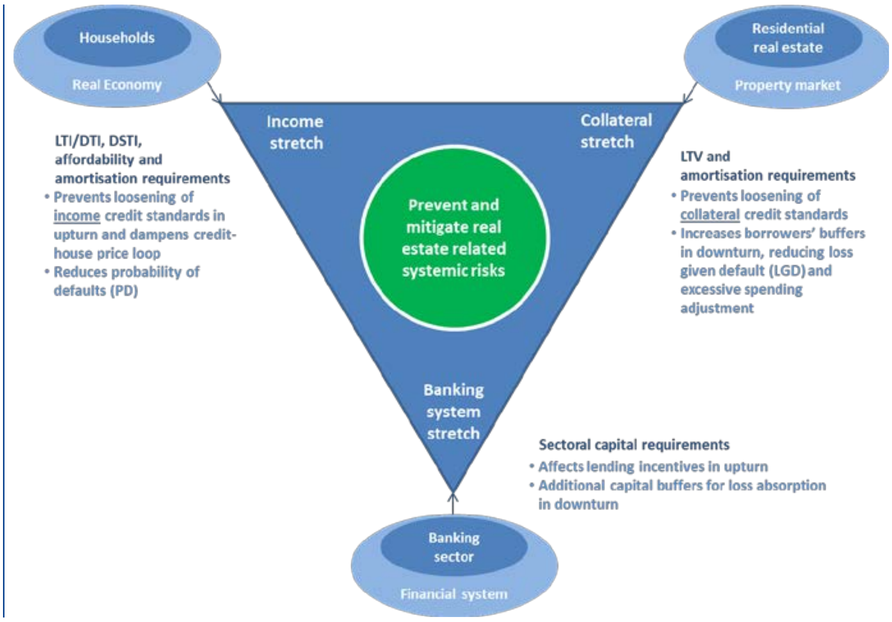
2.2 Real estate instruments and indicators on lending standards

Macroprudential policy aims at addressing the emergence of systemic risks in all or parts of the financial system, with the aim of increasing its resilience and preserving financial stability. Several macroprudential instruments have been designed to address vulnerabilities stemming from the real estate sector. A useful categorisation of real estate instruments is the so-called "three stretches model" (see Figure 1), which applies to both RRE and CRE. Many of these instruments take the form of limits to the values of certain indicators for lending standards, which are in turn particularly relevant for an effective monitoring framework as envisaged by the Recommendation. The three stretches are:

- **Household (or debtor / income) stretch instruments** refer to macroprudential measures aimed at addressing vulnerabilities rooted in borrowers' indebtedness. Instruments such as LTI, LSTI, DTI and DSTI limits can increase borrowers' resilience by restricting the loan amount relative to their income (households, in the case of RRE). By influencing borrowers' probability of default, these measures also improve the quality of banks' mortgage loan portfolios.
- **Collateral stretch instruments.** These include instruments such as LTV and amortisation requirements, which limit borrowers' leverage (LTV) or affect the modalities of loan repayment over time (amortisation requirements). They can be helpful in addressing vulnerabilities rooted in real estate markets, in particular in relation to property prices and valuation changes. Key aspects in the design of such instruments (and indicators) are the valuation approaches for the collateral and the coverage of the instrument.
- **Banking (or lender) stretch instruments** aim to increase the resilience of lenders by improving their loss-absorbing capacity (capital buffers) and thereby limit the impact of crystallising credit risk. The prudential rules for the EU's banking sector are laid down in the Fourth Capital Requirements Directive and the Capital Requirements Regulation (CRD4/CRR)[4]. These consist mainly of capital-based instruments targeting the capital structure of credit institutions and that can also be used to mitigate risks emerging in specific sectors, including real estate.

[4] Directive 2013/36/EU of the European Parliament and of the Council of 26 June 2013 on access to the activity of credit institutions and the prudential supervision of credit institutions and investment firms, amending Directive 2002/87/EC and repealing Directives 2006/48/EC and 2006/49/EC (OJ L 176, 27.6.2013, p. 338) ("CRD4"); Regulation (EU) No 575/2013 of the European Parliament and of the Council of 26 June 2013 on prudential requirements for credit institutions and investment firms and amending Regulation (EU) No 648/2012 (OJ L 176, 27.6.2013, p. 1) ("CRR").

Figure 1: Instruments by stretches related to real estate lending



Source: ESRB (2015), Report on residential real estate and financial stability in the EU, December, p. 89

Therefore, indicators such as the LTV, LTI, LSTI, DTI and DSTI ratios can be used to guide national authorities in the use of national macroprudential instruments targeting borrowers which are outside the scope of the CRD4/CRR (such as caps on LTV, LTI, LSTI, DTI and DSTI ratios). Furthermore, the indicators can also play an important role in determining whether and when to tighten or release the harmonised macroprudential instruments targeting lenders that are available under EU law. Some of these instruments have already been activated by EU countries[5], although the definitions of the instruments and indicators vary across jurisdictions. This hampers the comparability of macro-prudential policies targeting the real estate sector in different EU countries.

2.3 ESRB initiatives related to the real estate sector

In the aftermath of the 2007 financial crisis, national and supranational authorities have devoted increased attention to the identification of risks stemming from the real estate sector, and have designed macroprudential policy instruments to address the identified vulnerabilities. The ESRB, mandated to conduct macroprudential oversight of the financial system within the EU with the aim of contributing to the prevention or mitigation of systemic risks, has therefore from its very beginning devoted considerable attention to this sector[6].

The ESRB Recommendation on closing real estate data gaps is part of a broader effort to better understand and address risks related to real estate in the EU. Under

[5] For some examples, see ESRB (2016), Review of macroprudential policy in the EU, April.

[6] The ESRB's legal framework is governed by Regulation (EU) No 1092/2010 of the European Parliament and of the Council of 24 November 2010 on European Union macro-prudential oversight of the financial system and establishing a European Systemic Risk Board (EU) No 1092/2010 ("ESRB Regulation").

the aegis of the ESRB, several initiatives were taken to help guiding the macroprudential policy of national authorities, providing useful inputs to both the analysis of emerging risks at the EU level and to the implementation of macroprudential policy instruments. Four ESRB initiatives in particular need to be highlighted.

First, in 2014 the ESRB published its Flagship Report and the Handbook on Macroprudential Policy in the Banking sector[7]. The aim of these documents was to assist macroprudential authorities in the implementation of the new policy instruments that became available with the coming into force of the new EU prudential rules for banks on 1 January 2014. In particular, Chapter 3 of the Handbook is dedicated to the use of real estate instruments for macroprudential purposes, grouped into instruments that target banks (capital requirements) and instruments that target borrowers (LTV, LTI, DSTI limits).

Second, in 2015 the ESRB published two reports on the real estate sector and financial stability in the EU, focussing respectively on the RRE and CRE sector[8]. These reports investigate how structural features of, and cyclical developments in, these sectors may affect financial stability and how related risks can be addressed. The reports highlight that comparable high-quality data on some key metrics for financial stability monitoring and policymaking in this area are still not available. It was therefore recommended to develop harmonised definitions of key indicators for monitoring and cross-border comparison.

As follow-up to these two reports, the ESRB adopted, on 31 October 2016, Recommendation 2016/14 on closing real estate data gaps[9]. The aim of the Recommendation is to encourage national macroprudential authorities to implement a framework for monitoring developments in the RRE and CRE sectors relevant for financial stability, based on a set of recommended, commonly agreed target indicators and related definitions.

Finally, the ESRB has conducted an in depth analysis of RRE vulnerabilities across EU countries. This culminated, on 22 September 2016, with the issuance of warnings to eight EU countries on medium-term vulnerabilities in the RRE sector. The full documentation, including the warnings, the responses received from the "warned" countries and additional documents, was then published by the ESRB on 28 November 2016.[10]

[7] ESRB (2014), Flagship report on Macroprudential Policy in the Banking Sector, March; ESRB (2014), Handbook on operationalising Macroprudential Policy in the Banking Sector, March.

[8] See footnotes 1 and 2.

[9] ESRB Recommendation on Closing Real Estate Data Gaps (ESRB/2016/14): https://www.esrb.europa.eu/pub/pdf/recommendations/2016/ESRB_2016_14.en.pdf?641b03e63b2595 3a1ba16ed8973530ca

[10] The reader is referred to the ESRB report on "Vulnerabilities in the EU residential real estate sector" (November 2016) for the detailed country-specific vulnerability assessments

3. General features of the Recommendation

3.1 Objectives of the Recommendation

The Recommendation aims to address existing gaps in the availability and comparability of data on RRE and CRE markets in the EU relevant for financial stability and macroprudential policy. For these purposes, it provides target working definitions of RRE and CRE. In addition, it identifies a common set of indicators that national macroprudential authorities are recommended to monitor in order to assess risks resulting from the RRE and CRE sectors, along with target definitions of these indicators.

In carrying out its task, the ESRB should contribute to ensuring financial stability and mitigating the negative impacts on the internal market and the real economy. For these purposes, the availability of harmonised working definitions and a core set of comparable and timely available real estate indicators are of key importance. A better understanding of the structural and cyclical characteristics of RRE and CRE markets in the EU will be helpful in allowing macroprudential authorities to better track the dynamics of the real estate sector, to identify the threats it may pose to financial stability and to guide appropriate action.

The purpose of the Recommendation is to provide the basis for a harmonised framework for monitoring real estate markets in the EU: hence, it does not imply the EU-wide collection of data on the indicators identified. However, the ESRB expressed the view that in a next stage it would be beneficial for financial stability and macroprudential policymaking to regularly collect and distribute at EU level comparable country data on these indicators (see Section 7.2), to effectively close the data gaps in the real estate domain.

3.2 Nature and scope of the Recommendation

ESRB recommendations, like Recommendation 2016/14 discussed here, advise the addressees on policy actions to be taken to mitigate systemic risks identified by the ESRB. Recommendations are a soft law instrument subject to an "act or explain" mechanism, meaning that addressees either follow suit by implementing the recommendation or explain their non-action. In the case of Recommendation 2016/14, the addressees are the national macroprudential authorities of EU countries (and the European Supervisory Authorities - ESAs - for one sub-recommendation), in line with the earlier mentioned objectives of the Recommendation. Recommendations are adopted by the ESRB's decision making body, the General Board. The General Board membership includes high-level representatives of all central banks and financial supervisors of the EU as well as of the relevant European bodies (the ESAs, the European Commission and the Economic and Financial Committee - EFC).

While Recommendation 2016/14 introduces harmonised definitions and indicators for the macroprudential monitoring of RRE and CRE markets, it does not prevent national macroprudential authorities from relying, for their internal risk and policy assessment, on real estate indicators based on their own definitions and metrics, which may be better suited to accommodate national requirements. In that respect, there is a certain similarity between the Recommendation and the Basel Committee on Banking Supervision's guidance for the countercyclical capital buffer. In the latter case, the credit-to-GDP gap calculated according to a common methodology is seen as a useful common indicator; at the same time, it is recognised that this indicator does not need to play a dominant role in the information used by authorities to take and explain national buffer decisions.

The Recommendation is formally structured around five (sub)recommendations, two dealing with the RRE sector and three with the CRE sector. Especially for the CRE sector, data are in general scarce, incomplete or inconsistent, making it difficult to accurately describe and compare risks within and across national markets. Since the starting base for the RRE and CRE sectors is very different, the Recommendation is more detailed as regards data and indicators for the RRE sector compared to the CRE sector.

In order to provide a quick overview of the recommended indicators and breakdowns, the Recommendation includes in its annexes a number of templates for indicators on both sectors. These templates are only indicative, and they should not be considered as reporting templates. In a similar vein, the accompanying guidance on the methods for calculating the indicators used in the templates should not be seen as detailed technical instructions for completing the templates covering all possible cases, but rather as high-level direction.

3.3 Relationship with the AnaCredit project

The Recommendation takes into account other ongoing international and European initiatives in the area of data harmonisation and collection. The most relevant at the European level in the context of closing real estate data gaps is the AnaCredit project. "AnaCredit" stands for "*Analytical credit data standards*" and refers to a project aimed at establishing a dataset containing detailed information on individual bank loans in the euro area, harmonised across all the participating countries. This new dataset will support the European Central Bank (ECB) in performing its central banking and banking supervision functions, including in the area of financial stability. The ECB adopted a Regulation on the collection of granular credit and credit risk data, setting out the reporting requirements and reporting population for the AnaCredit project[11].

While AnaCredit will be a very important source of information for meeting the needs identified in the Recommendation, it cannot be relied on exclusively for closing real estate data gaps, due to some of its features.

First, the definitions of RRE and CRE provided in the Recommendation are more detailed and better suited for financial stability purposes than those outlined in the Anacredit Regulation, which refers to the (microprudential) definitions of the CRR (see Section 4). Second, information on some key indicators and market segments identified as important for financial stability in the Recommendation is not provided for in the Anacredit Regulation. Third, only euro area countries are within the scope of AnaCredit[12]. Fourth, AnaCredit is currently restricted to information on credit extended to legal persons and other institutional units, including non-financial

[11] Regulation (EU) 2016/867 of the European Central Bank of 18 May 2016 on the collection of granular credit and credit risk data (ECB/2016/13), OJ L 144, 1.6.2016, p. 44 ("AnaCredit Regulation").

[12] EU countries outside the euro area have the option to participate on a voluntary basis, but at this stage it is still unclear which countries will decide to do so.

corporations. Information on credit to natural persons is not yet within its scope and the timing of such extension is not yet defined. Fifth, AnaCredit collects loans held (or serviced) only by credit institutions. The importance of other market participants in real estate financing, in particular CRE property, requires a large collection of loans granted by these institutions. Sixth, in application of the proportionality principle, small banks may be excluded from the scope of AnaCredit[13] although a macroprudential authority might consider that also their activity in the real estate sector needs to be monitored for reasons of financial stability.

4. Definitions of residential and commercial real estate

The RRE and CRE definitions are key elements for delineating the scope of the Recommendation. These definitions should be seen in the context of the Recommendation's aim of addressing data gaps specifically for the purposes of financial stability monitoring and macroprudential policymaking. The latter also explains why the definitions do not always coincide with the ones used in the CRR or the AnaCredit Regulation.

The Recommendation defines RRE as any immovable property located in the domestic territory, available for dwelling purposes, acquired, built or renovated by a private household and that is not qualified as a CRE property. This definition is very similar to the one in the CRR (also used by AnaCredit)[14].

The Recommendation also classifies buy-to-let property under the RRE heading, depending on some conditions regarding its ownership and purpose. Specifically, buy-to-let housing or property is defined as any RRE directly owned by a private household primarily for letting to tenants (the CRR and the AnaCredit Regulation do not provide for such a sub-category). This type of activity is only significant in certain EU countries, such as the United Kingdom and Ireland, and is generally considered to be a riskier segment of the RRE sector warranting separate monitoring and stricter measures[15]. Since the buy-to-let activity is typically undertaken by part-time, non-professional landlords with a small property portfolio, it belongs more to RRE than CRE.

CRE is defined as any income-producing real estate, either existing or under development, with the exclusion of social housing, property owned by end-users, and buy-to-let housing. In contrast, the CRR and the AnaCredit Regulation do not provide a positive CRE definition, but rather define CRE in a negative way as real estate that does not meet the RRE definition. For financial stability monitoring and macroprudential policy making, this broadens the scope of the definition too much,

[13] National central banks may grant derogations to small credit institutions provided that the combined contribution of all credit institutions that are granted a derogation to the total outstanding amount of loans in the reporting Member State does not exceed 2%.

[14] See Article 4(1) (75) of the CRR. Residential property is defined as a residence which is occupied by the owner or the lessee of the residence, including the right to inhabit an apartment in housing cooperatives located in Sweden.

[15] See for example, Central Bank of Ireland (2015), Restrictions on residential mortgage lending, Information Note; Prudential Regulation Authority (2016), Underwriting standards for buy-to-let mortgage contracts, Supervisory Statement, SS13/16, September.

motivating the more specific CRE definition in the Recommendation. Under the CRR and AnaCredit definition, CRE would also include corporate headquarters, buildings owned by firms and used for their corporate activity, certain public building infrastructure such as non-toll paying bridges and roads, religious buildings, etc. These type of buildings typically do not raise concerns of unsustainable credit or asset price developments relevant for financial stability or macroprudential policymaking, nor do they raise the issue whether their cash-flow generating capacity is sufficient to repay the contracted loans (with leverage being a key element for financial stability). It should be noted, though, that the ESRB definition allows the inclusion of buildings not financed by debt since equity investments may also contribute to a real estate bubble.

CRE is generally quite distinct from RRE, as it is shown in Table 1. However, there are a number of border cases for which the distinction is not always clear-cut, such as property under development, social housing and buy-to-let housing (the latter was discussed above).

Table 1: Comparison of the RRE and CRE sectors along some key dimensions

	Residential real estate	Commercial real estate
Definitional and data issues	Comparatively fewer definitional and data problems	No commonly agreed definition and delineation concerns. Serious problems of data scarcity and data comparability
Purpose	Held for own use or for income-generating purposes ("buy to let")	Only held for income-generating purposes
Political sensitivity	Politically sensitive (households, access to housing)	Much less politically sensitive (professional participants)
Complexity and transparency	Simpler, more transparent and homogenous, and large scope for standardisation	Complex, opaque and heterogeneous market, which poses specific risk management issues
Size of exposures	Exposures are generally more significant in bank portfolio	Exposures are generally less important in bank portfolio
Concentration risk	Lower due to higher granularity	Higher due to low granularity
Cyclicality	Comparatively less cyclical	Comparatively more cyclical
Default risk	Lower (own use, more liquid and less volatile market, recourse financing)	Higher (commercial use, less liquid and more volatile market, non-recourse financing)
Role of other economic channels	Developments may impact consumption channel	Developments may impact investment channel
Market actors	Often domestic banks dominate the market	More important role of non-banks and foreign participants
Experience with use of instruments	More experience with use of macroprudential instruments	Scarce experience with use of macroprudential instruments

Source: ESRB (2016), "A Review of Macroprudential Policy in the EU in 2015", May, p. 20

Whether property under development should be considered as CRE can be debated and national practices vary. However, the experience during the recent financial crisis has demonstrated the importance of including the financing of this activity in financial stability monitoring. Moreover, new property under development is expected to increase the future stock of CRE once completed. For the purposes of the Recommendation, property under development is therefore considered to be a sub-category of CRE. National macroprudential authorities are also recommended to focus the monitoring on the riskiest developments of the activity, such as those

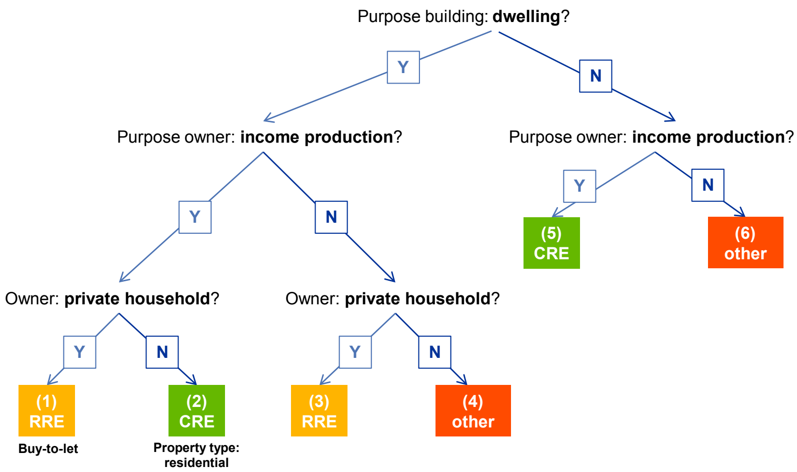
CRE projects with very low pre-let or pre-sale ratios, given the relevance for financial stability.

Social housing is a complex segment of the property market, as it may take different forms across and within countries. The Recommendation excludes it from the definition of CRE when the transaction value of properties or the rent applied to tenants in such properties are directly influenced by a public body, which results in rents being lower than those observed in the current market. National authorities are advised to determine the boundary between social housing and private rental sector in their country according to this criterion.

Given the large scale nature of multi-household dwellings that are not owned by a single private household, such dwellings belong more to CRE (albeit as a separate sub-segment) than to RRE, though it can be argued that this is a border case. The experience of countries such as Spain during the recent financial crisis, however, illustrate that developments in this segment of the real estate sector should be within the scope of financial stability monitoring.

Figure 2 provides an overview of the categorisation of real estate according to the Recommendation. The latter further specifies that if a property has a mixed CRE and RRE use (e.g. a building with shops at the ground floor and apartments on the upper floors), it should be considered as different properties (based for example on the surface areas dedicated to each use) whenever it is feasible to make such breakdown; otherwise, the property can be classified according to its dominant use.

Figure 2: Real estate classification according to the Recommendation



(4) and (6) are outside the scope of the Recommendation because they are less relevant for financial stability and macroprudential policy
(4) includes, for example, certain forms of social housing
(6) includes, for example, certain public infrastructure (bridges and roads without toll), religious buildings, corporate headquarters

Data challenges are much greater for CRE than RRE: data are scarcer, patchier and less comparable. Authorities therefore often rely on private sector data to supplement official statistics. In that case, they are expected to identify the differences in scope and definitions compared to those mentioned in the Recommendation and be able to provide details on the underlying methodology used by the provider and the data coverage.

5. Guidance for the monitoring of the RRE sector

5.1 Indicators for the RRE sector

The Recommendation provides the main elements of a monitoring framework for RRE loans, which are defined as loans to private households secured by RRE property independent of the loans' purposes. The majority of such loans are mortgage loans.

The Recommendation identifies two broad categories of RRE indicators necessary to close the RRE data gaps: indicators on the financial system's exposures to the RRE sector and indicators on RRE lending standards. The first describe the main features of credit providers' RRE loan portfolio and include the total RRE loans disbursed within a given period as well as their decomposition in sub-categories such as loans to first time buyers and for buy-to-let housing, foreign currency loans, amortising loans, loan maturities and the different interest fixation periods used for RRE loans. The second category includes indicators on lending standards which, according to the three stretches model discussed above, include collateral stretch indicators (LTV) and income stretch (LTI, LSTI, DTI, DSTI) indicators. In case a country has a significant buy-to-let market, it is expected to monitor a number of additional indicators for the buy-to-let loans (Interest Coverage Ratio or ICR, Loan-to-Rent ratio or LTR).

The indicators on RRE lending standards can refer to their value at the time of the origination of the loan (for loan flows) or their current value (for loan stocks). Flows provide the most recent information on how conditions in the RRE market are developing over a certain period. Stocks, or the accumulated net flows over time, by contrast evolve much more slowly but are also relevant as they provide a picture of the loan portfolio at a given point in time.

Furthermore, it is not sufficient for the macroprudential authority to have only information on the average value of the indicators. More granular information on the distribution of the indicators (i.e. the relative importance of the different intervals or "buckets" for the value of a certain indicator) is very helpful for identifying the riskiest segments of the market that are particularly relevant for financial stability. In addition to univariate distributions (i.e. each distribution of values corresponds to a single indicator), joint distributions (i.e. a distribution that combines the variation in values over two indicators together) are also particularly helpful as they allow authorities to monitor vulnerabilities combining different stretches (e.g. the segments that are vulnerable along both the collateral and the income stretch dimensions).

5.2 Guidance on the RRE indicators

The Recommendation provides high-level guidance on the methods for calculating the indicators. These methods may need to be adjusted to accommodate for the specificities of national markets or market segments. In addition, once authorities start actually compiling data on these indicators, more detailed technical instructions may still be needed. Key elements for the calculation of the indicators are the value of the property (for LTV), the value of the loan (LTV, LTI, LSTI), the income of the borrower (LTI, LSTI, DTI, DSTI), the debt of the borrower (DTI, DSTI) and the loan service/debt service cost (LSTI, DSTI). Although indicators like LTV and LTI are well-established and available in many EU countries, the way they are calculated can be very different, hence the need for harmonised guidelines.

The value of the property can refer to the value at the moment the loan was originated (used for credit flows) or its current value (used for credit stocks). The value at origination is measured conservatively by taking the lower of the transaction value and the value assessed by an independent external or internal appraiser. In case the property is still being constructed, the total value of the property up to the reporting data is considered, thus accounting for the value increases due to the progress of the construction works. In case of prior liens on the property, these are deducted from the property value.

In case the current value of the property is used, the value needs to be assessed by an independent external or internal appraiser. If such assessment is not available, the current value can be estimated using a granular real estate value index; in case this one is also not available, a granular real estate price index can be used provided one also takes into account the depreciation of the property (hierarchy of approaches). Any real estate value of price index should be sufficiently differentiated according to the geographical location of the property and the property type.

The value of the loan includes all loans or loan tranches secured by the borrower on the property. The value is measured on the basis of disbursed amounts and therefore does not include any undrawn amounts on credit lines. In case the property is still under construction, the loan value is the sum of all loan tranches disbursed up to the reporting date. Alternatively, if this calculation method is not available or does not correspond to the prevailing market practice, the LTV can also be calculated on the basis of the total loan amount granted and the expected value of the property upon completion. The loan servicing cost is the combined interest and principal repayment on the RRE loan as just defined.

The income of the borrower refers to the borrower's annual disposable income as registered by the lender. The disposable income can have various sources (e.g. employee income, unemployment benefits, pensions, etc.) and is net of any income taxes and health care/social security contributions. Only the income of the borrower should be taken into account, i.e. the signatory or cosignatory of the loan agreement and receiving financing from the lender, not that of any other family members that may reside in the same property.

The debt of the borrower covers the total debt of the borrower, whether or not it is secured by real estate, including all outstanding financial loans (i.e. granted by the RRE loan provider and by any other lenders). The debt servicing cost is then the combined interest and principal repayment on the borrower's debt as just defined.

6. Guidance for the monitoring of the CRE sector

6.1 Indicators for the CRE sector

The Recommendation provides for three broad categories of CRE indicators: (i) indicators related to the physical CRE market, (ii) indicators on the financial system's exposures to the CRE sector, and (iii) indicators on CRE lending standards. Some basic indicators describing the CRE market, such as price and rental indices, are still missing in many EU countries, hence the need for this additional category of indicators on the physical market compared to RRE. The strong cyclical nature of developments in CRE markets requires that some aspects of the monitoring (e.g. price indicators, credit and investment flows) should take place at a higher frequency than for the RRE sector (quarterly rather than annually).

The Recommendation also foresees breakdowns of the physical market and exposures indicators according to the type of the property and the location of the property. "Property type" refers to the primary use of a commercial property, such as residential (e.g. multi-household premises), retail (e.g. hotels, restaurants, shopping malls), offices (e.g. a property primarily used as professional or business offices), industrial (e.g. property used for the purposes of production, distribution and logistics), and other types of CRE. Which of these property types are actually relevant may vary from country to country. "Property location" refers to the geographical breakdown (e.g. by regions) or to real estate submarkets, which shall also include prime and non-prime locations. A prime location is generally considered the best location in a particular market, which is also reflected in the rental yield (typically the lowest in the market).

Equity investors are very important in the CRE sector: end 2014, debt financing represented 53% of total CRE financing in Europe, having declined since 2009[16]. Another distinct feature is that cross-border investments, including those from outside the EU, can be very substantial for certain CRE markets (e.g. in the United Kingdom). These market characteristics imply that macroprudential authorities need information on both lenders and investors for an adequate financial stability monitoring, in particular on the type of the lender/investor (e.g. banks, insurance companies, investment funds) and the nationality of the lender/investor (domestic, rest of the European Economic Area, rest of the world). Just like for RRE, another relevant breakdown is between stocks and flows of CRE lending but also for CRE investments.

The three stretches model discussed earlier can also be applied to the CRE sector. The Recommendation provides for collateral stretch and income stretch indicators, which are similar to their RRE counterparts: LTV ratio, ICR and DSCR. For credit flows, the indicators are calculated at the time of origination; for credit stocks, they refer to current values. In principle, authorities should also monitor the distributions of the indicators, but due to the lack of information on the levels of such indicators, the Recommendation does not provide any further guidance as regards the buckets to be used for the indicators. *Mutatis mutandis*, the methods for calculating these indicators is similar as for RRE. Finally, the Recommendation specifies that for CRE

[16] ESRB (2015), Report on commercial real estate and financial stability in the EU, 2015, p. 20.

property under development, authorities may monitor the Loan-to-Cost ratio (LTC) instead of the LTV at origination; the LTC represents the initial amount of all loans granted in relation to the costs associated with the construction of the CRE property until completion.

6.2 Publication requirement of the ESAs

The Recommendation includes a specific publication requirement on CRE exposures for the three ESAs, i.e. the European Banking Authority (EBA), the European Insurance and Occupational Pensions Authority (EIOPA) and the European Securities and Markets Authority (ESMA). Such public disclosure is expected to enhance the knowledge of national macroprudential authorities on the activity of entities from EU countries on their domestic CRE market. The Recommendation does not prescribe the format of this publication, but requires the ESAs to define the publication templates. In case there are any concerns about the scope or quality of the published data, the publication should be accompanied with the appropriate disclaimers.

More specifically, the ESAs are recommended to disclose at least annually aggregated information on the exposures to the different national CRE markets in the EU for the entities within the scope of their supervision. The Recommendation does not require any new data collection by the ESAs but rather specifies that they should draw on information already available from regulatory reporting templates, in particular regarding the geographical breakdown of credit exposures and/or (direct and indirect) investments.

When reporting templates provide a breakdown by NACE[17] codes, CRE could be referred to as both Section ‘F’ (construction, excluding civil engineering) and Section ‘L’ (real estate activities, excluding real estate agencies), although strictly speaking some sub-categories would need to be excluded following the Recommendation’s definition of CRE. The main drawback of using NACE classifications is that they focus on the economic sector of the borrower and not the purpose of the loan. For instance, a loan extended to a property company to buy a car fleet will be reported under Section L, even if it is not a CRE loan.

7. Next steps

7.1 Implementing the Recommendation

The Recommendation specifies the timeline for the follow-up by the addressees to the Recommendation. The national macroprudential authorities have until end 2018 to deliver to the ESRB and the Council of the EU[18] an interim report on the information already available, or expected to be available, for the implementation

[17] NACE is the classification of economic sectors in the EU and is derived from the French *Nomenclature statistique des activités économiques dans la Communauté européenne*.

[18] The involvement of the Council of the EU in the Recommendation and its follow-up are in line with the procedures provided for in the ESRB Regulation.

of the Recommendation. By end 2020, the ESRB and Council should receive the final implementation report.

The sub-recommendation which is only addressed to the ESAs provides for three deadlines: end 2017 for the definition of a template for the regular publication of exposure data of the entities under the scope of their supervision; end June 2018 for the first publication of data (reflecting the situation as of end 2017); and end March 2019, for the start of the regular (at least annual) publication of aforementioned exposure data.

The ESRB has well-established rules and procedures in place for assessing the implementation of Recommendations by addressees, which also apply to Recommendation 2016/14[19]. A few points need to be highlighted.

First, the principle of proportionality applies. This means that when proceeding with the implementation of the relevant indicators and methods for their calculation, the size and development of the national RRE and CRE markets should be taken into account. For example, only in countries where buy-to-let housing represents a significant source of risks needs the risk monitoring framework for the RRE sector to include additional indicators for this market segment. Similarly, CRE markets vary significantly across countries and the challenge of the Recommendation was to provide guidance relevant for both well developed and less developed CRE markets. Hence, also for the breakdowns of the CRE indicators according to CRE market segments, the proportionality principle applies (e.g. some break-downs may not be relevant for some countries).

Second, any assessment as regards the implementation of the Recommendation should consider the progress and constraints faced in the data collection at EU level mentioned in the next section. In particular, the final reports due by end 2020 may not necessarily include all key indicators if justified by such constraints.

7.2 Data collection at the EU level

The aim of the Recommendation is not to organise an EU-wide data collection on the indicators identified. Nevertheless, the ESRB indicated that in a next stage there would be merit in regularly collecting and distributing at EU level comparable country data on these indicators. Indeed, as indicated earlier, at present comparable data on key indicators are not available in the EU which complicates the cross-country comparison of risks and the use of instruments to address these risks. This is something the ESRB was confronted with when preparing the earlier-mentioned warnings to eight EU countries regarding medium-term vulnerabilities in the RRE sector.

The ECB is required to perform certain tasks regarding the functioning of the ESRB[20], in particular, it needs to provide analytical, statistical, logistical and administrative support to the ESRB. The ECB is therefore well-placed to coordinate such a data collection and distribution at EU level. Preparatory work on this was

[19] ESRB Secretariat (2016), Handbook on the assessment of compliance with ESRB recommendations, April.

[20] Council Regulation (EU) No 1096/2010 of 17 November 2010 conferring specific tasks upon the European Central Bank concerning the functioning of the European Systemic Risk Board.

initiated under the aegis of the ECB's Statistics Committee after the adoption of the Recommendation.

As macroprudential authorities start implementing the Recommendation and the actual data collection at EU level proceeds, further technical guidance and work on the target definitions and indicators will be needed to accommodate for the specificities of national markets or market segments and to ensure the statistical quality of the data. The Recommendation specifies that any such more detailed implementation guidance should not change the basic features and purpose of the target definitions and indicators as laid down in the Recommendation.

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Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

IFC-National Bank of Belgium Workshop on "*Data needs and Statistics compilation for macroprudential analysis*"

Brussels, Belgium, 18-19 May 2017

Closing real estate data gaps for financial stability monitoring and macroprudential policy in the EU[1]

Frank Dierick, European Systemic Risk Board Secretariat, and

Emmanuel Point, French Prudential Supervision and Resolution Authority

[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.

ESRB
European Systemic Risk Board
European System of Financial Supervision

Closing Real Estate Data Gaps for Financial Stability Monitoring and Macroprudential Policy in the EU

Frank Dierick (ESRB Secretariat) and Emmanuel Point (ACPR)

IFC – NBB Workshop
Data needs and Statistics compilation for Macroprudential Analysis

Brussels, 18 May 2017

PRESENTATION OUTLINE

1. Background
2. Residential real estate
3. Commercial real estate

1. BACKGROUND

BACKGROUND

- Importance of the real estate sector for financial stability
- ESRB work related to real estate and financial stability
- Warnings and recommendations as “soft law” tools of the ESRB
- Recommendation ESRB/2016/14 on closing real estate data gaps
- Objectives of the Recommendation:
  - Common set of indicators for monitoring framework
  - Harmonised indicators and definitions
  - Not (yet) actual data collection

2. RESIDENTIAL REAL ESTATE

DEFINITIONS OF RRE AND CRE

- **Definition of RRE**: any immovable property located in the domestic territory, available for dwelling purposes, acquired, built or renovated by a private household and that is not qualified as a CRE property

- **Definition of buy-to-let housing**: any RRE directly owned by a private household primarily for letting to tenants

  - This type of activity is only significant in certain EU countries (e.g. UK, Ireland) and is generally considered to be a riskier segment of the RRE sector warranting separate monitoring and stricter measures.

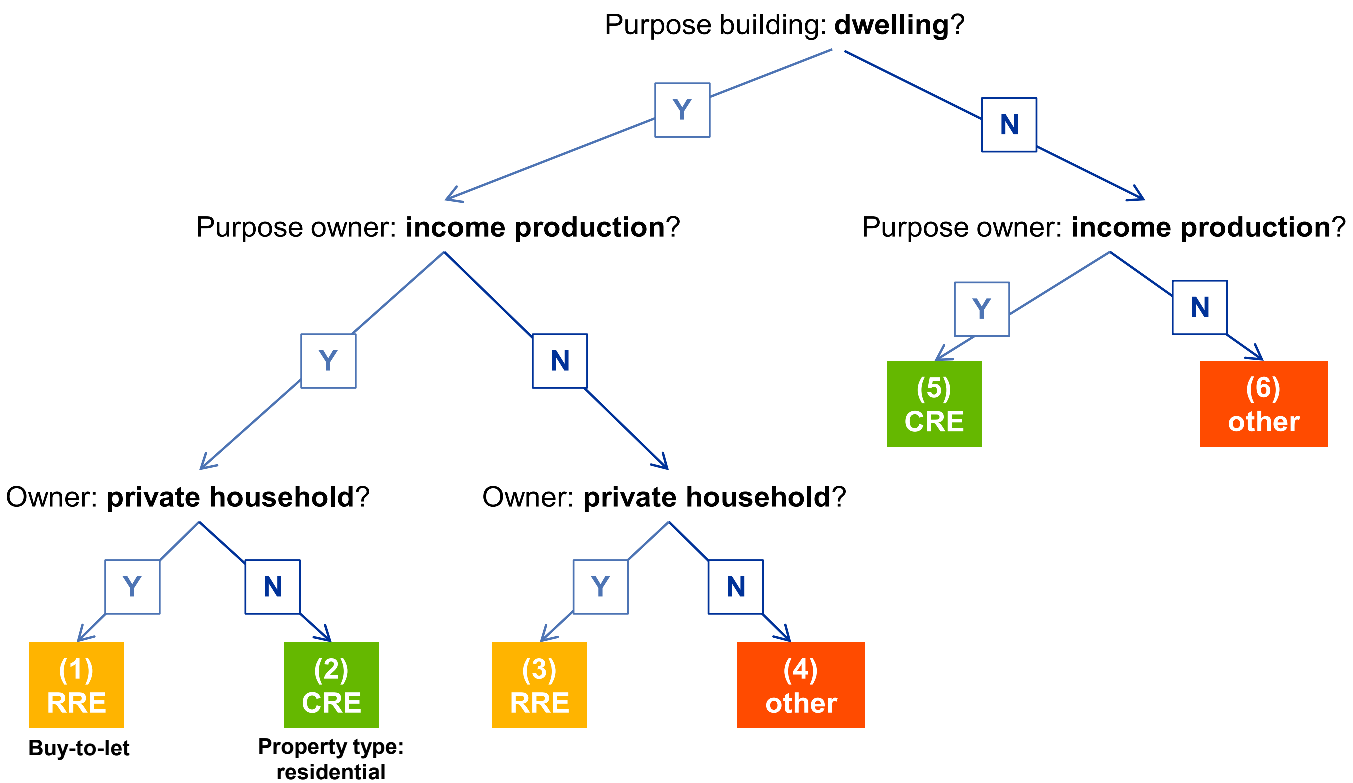
- **Definition of CRE**: any income-producing real estate, either existing or under development, with the exclusion of social housing, property owned by end-users, and buy-to-let housing

COMPARISON OF THE RRE AND CRE SECTORS

	Residential real estate	Commercial real estate
Definitional and data issues	Comparatively fewer definitional and data problems	No commonly agreed definition and delineation concerns. Serious problems of data scarcity and data comparability
Purpose	Held for own use or for income-generating purposes ("buy to let")	Only held for income-generating purposes
Political sensitivity	Politically sensitive (households, access to housing)	Much less politically sensitive (professional participants)
Complexity and transparency	Simpler, more transparent and homogenous, and large scope for standardisation	Complex, opaque and heterogeneous market, which poses specific risk management issues
Size of exposures	Exposures are generally more significant in bank portfolio	Exposures are generally less important in bank portfolio
Concentration risk	Lower due to higher granularity	Higher due to low granularity
Cyclicality	Comparatively less cyclical	Comparatively more cyclical
Default risk	Lower (own use, more liquid and less volatile market, recourse financing)	Higher (commercial use, less liquid and more volatile market, non-recourse financing)
Role of other economic channels	Developments may impact consumption channel	Developments may impact investment channel
Market actors	Often domestic banks dominate the market	More important role of non-banks and foreign participants
Experience with use of instruments	More experience with use of macroprudential instruments	Scarce experience with use of macroprudential instruments

Source: ESRB, A Review of Macroprudential Policy in the EU in 2015, May 2016, p. 20

REAL ESTATE CLASSIFICATION



(4) and (6) are outside the scope of the Recommendation because they are less relevant for financial stability and macroprudential policy
(4) includes, for example, certain forms of social housing
(6) includes, for example, certain public infrastructure (bridges and roads without toll), religious buildings, corporate headquarters

INDICATORS FOR THE RRE SECTOR

- **Two broad categories** of RRE indicators (template)
  - **Indicators on the financial system's exposures to the RRE sector:** total RRE loans disbursed within a given period and their decomposition in loans to first time buyers, buy-to-let housing, foreign currency loans, amortising loans…
  - **Indicators on RRE lending standards:** LTV, LTI, LSTI, DTI, DSTI

- In case a country has a significant **buy-to-let market**: Interest Coverage Ratio (ICR), Loan-to-Rent ratio (LTR)

- The indicators on RRE lending standards can refer:
  - to their value at the time of the origination of the loan (for loan flows);
  - their current value (for loan stocks)

- Information on the **average value** of the indicators BUT ALSO on the **distribution** of the indicators (i.e. "buckets")

- **Univariate** distributions BUT ALSO **joint** distributions (i.e. a distribution that combines the variation in values over two indicators jointly)

GUIDANCE ON THE RRE INDICATORS

- The Recommendation provides **high-level guidance** on the methods for calculating the indicators

- Key elements for the calculation of the indicators are (Annex IV):

  - **the value of the property** (for LTV)

    value at origination
    the lower of: 1. the transaction value (in notarial deed)
    2. the value assessed by independent appraiser

    current value
    value assessed by independent appraiser OR value estimated using a granular real estate value index

  - **the value of the loan** (LTV, LTI, LSTI): all loans or loan tranches secured by the borrower on the property; it is measured on the basis of disbursed amounts and does not include any undrawn amounts on credit lines

  - **the income of the borrower** (LTI, LSTI, DTI, DSTI): borrower's annual disposable income, net of taxes and health care/social security contributions

  - **the debt of the borrower** (DTI, DSTI): total debt of the borrower, whether or not it is secured by real estate, including all outstanding financial loans

  - **the loan service/debt service cost** (LSTI, DSTI): annual debt servicing cost of the RRE loan/total debt of the borrower

3. COMMERCIAL REAL ESTATE

INDICATORS FOR THE CRE SECTOR

- **Three broad categories** of CRE indicators
  - **Indicators on the physical CRE market:** prices, rents, yields, vacancy, construction starts
  - **Indicators on financial system's exposure to CRE:** both flows and stocks of credits (including NPLs and coverage) + focus on property under development (credit stocks)
  - **Indicators on lending standards:** LTV, ICR, DSCR

- Where **investments** represent a significant share of CRE financing:
  - Investment flows and stocks (both direct and indirect)
  - Valuation adjustments on CRE investment (both for flows and stocks)

- **Additional breakdowns:** property type, property location, funding providers' nationality

- Information on the **average value** of lending standards BUT ALSO on the **distribution** of the indicators (i.e. "buckets") – however no guidance on these buckets and no bivariate distributions

- template

GUIDANCE ON CRE

- Since monitoring of risks related to CRE is much less developed, the Recommendation provides guidance on various topics (Annex V):
  - Need for a **working definition** of CRE for macroprudential purposes
  - Lists of possible **data sources** for both physical market and financial system's exposures (proxies)
  - **Breakdowns:** property type, property location", investor type, lender type and nationality
  - Assessment of **CRE prices**
  - Assessment of the **financial system's exposures** (lending vs investment, double counting, foreign exposures…)
  - Key elements for the calculation of **lending standards** identical to RRE whenever possible:
    - LTV: syndicated loans, valuation of each individual property, distribution
    - ICR: income = net annual rental income on the property
    - LTC as a substitute to LTV for property under development
  - Annual **publication of data by ESAs**

NEXT STEPS

- Implementation of the Recommendation
- Actual data collection

Thank you for your attention !

www.esrb.europa.eu

UNIVARIATE DISTRIBUTION

Overview of RRE loan portfolio	FLOWS
Loans disbursed	ncu, #
o/w buy-to-let	ncu, #
o/w owner-occupied	ncu, #
o/w first-time buyers	ncu, #
o/w loans in foreign currency	ncu, #
o/w fully amortising	ncu, #
o/w partially amortising	ncu, #
o/w non-amortising*	ncu, #
o/w ≤ 1y initial interest rate fixation period	ncu, #
o/w] 1y; 5y] initial interest rate fixation period	ncu, #
o/w] 5y; 10y] initial interest rate fixation period	ncu, #
o/w > 10y initial interest rate fixation period	ncu, #
o/w renegotiated (optional)	ncu, #

Loan-to-value at origination (LTV-O)	FLOWS
WEIGHTED AVERAGE	Avg (in %)
o/w buy-to-let	Avg (in %)
o/w owner-occupied	Avg (in %)
o/w first-time buyers	Avg (in %)
o/w loans in foreign currency	Avg (in %)
o/w fully amortising	Avg (in %)
o/w partially amortising	Avg (in %)
o/w non-amortising*	Avg (in %)
DISTRIBUTION	
≤ 50%	ncu, #
]50% ; 60%]	ncu, #
]60% ; 70%]	ncu, #
]70% ; 80%]	ncu, #
]80% ; 90%]	ncu, #
]90% ; 100%]	ncu, #
]100% ; 110%]	ncu, #
> 110%	ncu, #
Not available	ncu, #

Current loan-to-value (LTV-C)	STOCKS
WEIGHTED AVERAGE	Avg (in %)
DISTRIBUTION	
≤ 50%	ncu, #
]50% ; 60%]	ncu, #
]60% ; 70%]	ncu, #
]70% ; 80%]	ncu, #
]80% ; 90%]	ncu, #
]90% ; 100%]	ncu, #
]100% ; 110%]	ncu, #
> 110%	ncu, #
Not available	ncu, #

Maturities at origination	FLOWS
WEIGHTED AVERAGE	Avg (years)
DISTRIBUTION	
≤ 5y	ncu, #
]5y ; 10y]	ncu, #
]10y ; 15y]	ncu, #
]15y ; 20y]	ncu, #
]20y ; 25y]	ncu, #
]25y ; 30y]	ncu, #
]30y ; 35y]	ncu, #
> 35y	ncu, #
Not available	ncu, #

Loan-service-to-income at origination (LSTI-O)	FLOWS
WEIGHTED AVERAGE	Avg (in %)
o/w buy-to-let	Avg (in %)
o/w owner-occupied	Avg (in %)
o/w first-time buyers	Avg (in %)
o/w loans in foreign currency	Avg (in %)
o/w fully amortizing	Avg (in %)
o/w partly amortizing	Avg (in %)
o/w non-amortizing*	Avg (in %)
o/w ≤ 1y initial interest rate fixation period	Avg (in %)
o/w] 1y; 5y] initial interest rate fixation period	Avg (in %)
o/w] 5y; 10y] initial interest rate fixation period	Avg (in %)
o/w > 10y initial interest rate fixation period	Avg (in %)
DISTRIBUTION	
≤10%	ncu, #
]10% ; 20%]	ncu, #
]20% ; 30%]	ncu, #
]30% ; 40%]	ncu, #
]40% ; 50%]	ncu, #
]50% ; 60%]	ncu, #
> 60%	ncu, #
Not available	ncu, #

Debt-service-to-income at origination (DSTI-O) (OPTIONAL)	FLOWS
WEIGHTED AVERAGE	Avg (in %)
DISTRIBUTION	
≤10%	ncu, #
]10% ; 20%]	ncu, #
]20% ; 30%]	ncu, #
]30% ; 40%]	ncu, #
]40% ; 50%]	ncu, #
]50% ; 60%]	ncu, #
> 60%	ncu, #
Not available	ncu, #

Loan-to-income at origination (LTI-O)	FLOWS
WEIGHTED AVERAGE	Avg
DISTRIBUTION	
≤3	ncu, #
]3 ; 3,5]	ncu, #
]3,5 ; 4]	ncu, #
]4 ; 4,5]	ncu, #
]4,5 ; 5]	ncu, #
]5 ; 5,5]	ncu, #
]5,5 ; 6]	ncu, #
> 6	ncu, #
Not available	ncu, #

Debt-to-income at origination (DTI-O)	FLOWS
WEIGHTED AVERAGE	Avg
DISTRIBUTION	
≤3	ncu, #
]3 ; 3,5]	ncu, #
]3,5 ; 4]	ncu, #
]4 ; 4,5]	ncu, #
]4,5 ; 5]	ncu, #
]5 ; 5,5]	ncu, #
]5,5 ; 6]	ncu, #
]6,5 ; 7]	ncu, #
> 7	ncu, #
Not available	ncu, #

JOINT DISTRIBUTION

FLOWS	Loan-service-to-income at origination (LSTI-O)		
	≤30%	]30% ; 50%]	>50%
LTV-O ≤ 80%			
Maturity at origination			
≤ 20y	ncu, #	ncu, #	ncu, #
]20y ; 25y]	ncu, #	ncu, #	ncu, #
> 25y	ncu, #	ncu, #	ncu, #
LTV-O]80%-90%]			
Maturity at origination			
≤ 20y	ncu, #	ncu, #	ncu, #
]20y ; 25y]	ncu, #	ncu, #	ncu, #
> 25y	ncu, #	ncu, #	ncu, #
LTV-O]90%-110%]			
Maturity at origination			
≤ 20y	ncu, #	ncu, #	ncu, #
]20y ; 25y]	ncu, #	ncu, #	ncu, #
> 25y	ncu, #	ncu, #	ncu, #
LTV-O >110%			
Maturity at origination			
≤ 20y	ncu, #	ncu, #	ncu, #
]20y ; 25y]	ncu, #	ncu, #	ncu, #
> 25y	ncu, #	ncu, #	ncu, #

FLOWS	Loan-service-to-income at origination (LSTI-O)		
Initial interest rate fixation period	≤30%	]30% ; 50%]	>50%
o/w ≤ 1y	ncu, #	ncu, #	ncu, #
o/w] 1y; 5y]	ncu, #	ncu, #	ncu, #
o/w] 5y; 10y]	ncu, #	ncu, #	ncu, #
o/w > 10y	ncu, #	ncu, #	ncu, #

FLOWS	Debt-to-income at origination (DTI-O)		
Loan-to-value at origination (LTV-O)	≤ 4	]4 ; 6]	> 6
LTV-O ≤ 80%	ncu, #	ncu, #	ncu, #
LTV-O]80% ; 90%]	ncu, #	ncu, #	ncu, #
LTV-O]90% ; 110%]	ncu, #	ncu, #	ncu, #
LTV-O >110%	ncu, #	ncu, #	ncu, #

* Where relevant, non-amortising loans for which redemption vehicles exist should be identified separately.

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1. **Template A: indicators on the physical market**

	Indicator	Frequency	Breakdown	
			Property type (1)	Property location (2)
Physical market	CRE price index	Quarterly	I	I
	Rental index	Quarterly	I	I
	Rental yield index	Quarterly	I	I
	Vacancy rates	Quarterly	R	R
	Construction starts	Quarterly	#	#

(1) Property type is broken down into office, retail, industrial, residential and other (all domestic market).
(2) Property location is broken down into domestic prime and domestic non-prime.
I = Index
R = Ratio
# = Square metres

2. **Template B: indicators on the financial system's exposures**

	Indicator	Frequency	Breakdown					Total
			Property type (1)	Property location (2)	Investor type (3), (8)	Lender type (4)	Investor (5) / lender nationality (5)	
Flows (6)	Investments in CRE (8)	Quarterly	nc	nc	nc		nc	**nc**
	— of which direct CRE holdings	Quarterly	nc	nc	nc		nc	**nc**
	— of which indirect CRE holdings	Quarterly			nc		nc	**nc**
	Valuation adjustments on CRE investments	Quarterly	nc	nc	nc		nc	**nc**
	Lending to CRE (incl. property under development)	Quarterly	nc	nc		nc	nc	**nc**
	— of which to property under development	Quarterly	nc	nc		nc	nc	**nc**
	Non-performing CRE loans (incl. property under development)	Quarterly	nc	nc		nc	nc	**nc**
	— of which to property under development	Quarterly	nc	nc		nc	nc	**nc**
	Loan loss provisions on CRE lending (incl. property under development)	Quarterly	nc	nc		nc	nc	**nc**
	— of which to property under development	Quarterly	nc	nc		nc	nc	**nc**

	Indicator	Frequency	Breakdown					Total
			Property type (1)	Property location (2)	Investor type (3), (8)	Lender type (4)	Investor (5) / lender nationality (5)	
Stocks (7)	Investments in CRE (8)	Annually	nc	nc	nc		nc	**nc**
	— of which direct CRE holdings	Annually	nc	nc	nc		nc	**nc**
	— of which indirect CRE holdings	Annually			nc		nc	**nc**
	Valuation adjustments on CRE investments	Annually	nc	nc	nc		nc	**nc**
	Lending to CRE (incl. property under development)	Annually	nc	nc		nc	nc	**nc**
	— of which non-performing CRE loans	Annually	nc	nc		nc	nc	**nc**
	Loan loss provisions on CRE lending	Annually	nc	nc		nc	nc	**nc**
	Lending to property under development (as part of CRE lending)	Annually	nc	nc		nc	nc	**nc**
	— of which non-performing loans	Annually	nc	nc		nc	nc	**nc**
	Loan loss provisions on lending to property under development	Annually	nc	nc		nc	nc	**nc**

(1) Property type is broken down into office, retail, industrial, residential and other.
(2) Property location is broken down into domestic prime, domestic non-prime, and foreign.
(3) Investor type is broken down into banks, insurance companies, pension funds, investment funds, property companies and others.
(4) Lender type is broken down into banks, insurance companies, pension funds, investment funds, property companies and others.
(5) Nationality is broken down into domestic, European Economic Area and rest of the world.
(6) Flows are on a gross basis for investments, lending and non-performing loans (only new loans/investments are covered without taking into account repayments or reductions on existing amounts).
Flows are on a net basis for valuation adjustments on investments and loan loss provisions.
(7) Stocks data for the stock of CRE investments, valuation adjustments on CRE investments, CRE (non-performing) loans and loan loss provisions on CRE lending at reporting date.
(8) Only in case investments represent a significant share of CRE financing.
nc = Amount in national currency

3. **Template C: indicators on lending standards** (1)

	Indicator	Frequency	Weighted average of ratios
Flows (2)	Loan-to-value at origination (LTV-O)	Quarterly	R
	Interest coverage ratio at origination (ICR-O)	Quarterly	R
	Debt service coverage ratio at origination (DSCR-O)	Quarterly	R
Stocks (3)	Current loan-to-value (LTV-C)	Annual	R
	Current interest coverage ratio (ICR-C)	Annual	R
	Current debt service coverage ratio (DSCR-C)	Annual	R

(1) Excludes property under development, which can be monitored using the loan-to-cost (LTC) ratio.
(2) Flows data for the new production of CRE loans over the reporting period.
(3) Stocks data for the stock of CRE loans at reporting date.
R = Ratio

ESRB
European Systemic Risk Board
European System of Financial Supervision

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IFC-National Bank of Belgium Workshop on "*Data needs and Statistics compilation for macroprudential analysis*"

Brussels, Belgium, 18-19 May 2017

Evaluating risks in the French office market with new sources of data on commercial property prices[1]

Edwige Burdeau,
Bank of France

[1] This paper 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.

Evaluating risks in the French office market with new sources of data on commercial property prices

Edwige Burdeau[1]

Abstract

As the link between real estate and credit cycles has been emphasized in the literature, following property prices appears crucial for financial stability monitoring. Nevertheless, property markets are heterogeneous, notably in terms of property uses. While the residential market is frequently analyzed, the commercial property market is rarely studied empirically due to the lack of data. However, in France, commercial property prices, especially office prices, raised concerns over the last few years; the commercial property market appeared bullish while other macroeconomic indicators were less buoyant. In this context, we take advantage of a new source of historical data on commercial property prices with a breakdown by country and business sector. These indicators are computed for the ECB by the private data provider *Investment Property Databank* and made available to euro area national central banks. As historical series on office market statistics are not always available, a database on office market indicators gathering information from publications of private entities was also built. From these market data enriched with macroeconomic indicators, the dynamic relationships between office property prices and its determining factors are modeled and a measure of overvaluation of office prices is derived. According to this measure, office prices were overvalued in 2008-2009 and from 2011 to 2016. Finally, the estimated measure of price overvaluation is used to compute a recession indicator for France which is shown to have predictive power.

Keywords: office prices, office market determinants, cointegrated vector autoregressive model, Granger representation, measure of price overvaluation, crisis indicator

JEL classification: R33, E32, E37

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Contents

Introduction

It is generally accepted that banking crises can be in many cases associated with an underlying real estate bubble. In this context, monitoring real estate crises reveal insights into causes of banking crises. Indeed, commercial real estate market is highly pro-cyclical. During an upswing period, commercial real estate lenders ease their lending standards such as loan-to-value ratio, increasing CRE lending. A higher demand for CRE properties pushes property prices upward. In this context, constructions of new buildings of commercial properties become profitable. Nevertheless, due to lags in constructions of several years, supply is inelastic and prices are not driven down. During a downturn period, the demand in physical space decreases, a larger share of commercial real estate buildings remains vacant and some commercial real estate investors no longer pay back their debt. A significant part of CRE loans turns out to be non-performing; property prices fall, triggering or worsening a banking crisis. In the past, several real estate crises, both in the residential and commercial segments of the real estate sector, triggered banking crises, notably in United Kingdom, France and Sweden during the 1990s and more recently, in Ireland, in 2007.

From these empirical facts, it is necessary, before setting macro prudential instruments, to identify a set of key indicators on both financial and physical views of the commercial real estate market calculated and monitored on a regular basis. As highlighted by the European Systemic Risk Board (ESRB), this objective is far from being achieved. Firstly, there is no common definition of the scope delineated by commercial real estate markets, especially whether commercial real estate properties encompass all income-producing properties[2]. Secondly, indicators actually available are scarce, generally published by private entities, and covering only on a limited scope of the market. Besides, the methodology underlying the calculation of indicators is not always made available. In October 2016, the ESRB[3] published a recommendation on closing real estate data gaps enumerating avenues of progress in terms of definitions and data collection on real estate markets. In particular, the ESRB highlighted a strong need to build a consistent data framework to gather information on both financial and physical real estate markets. In this document, an exhaustive list of indicators of the physical market and the financial system, such as credit exposures, lending standards, investment features, is given as well as the level of granularity needed to ensure a broad coverage of the market.

Considering this ongoing work at the European level, this article introduces the set of indicators already identified for monitoring French commercial property markets, especially on the physical segment of the market. In our case, few indicators are published by public institutions; in this context, private entities especially real estate agencies remain the main source of information. Since 2013, data from the major real estate agencies in France, BNP Paribas Real Estate, CBRE, Jones Lang LaSalle, have been retrieved to build time series on the physical market. Nevertheless, as emphasized by the ESRB, in some cases, data from private entities cover only a part of commercial property markets, such as the office sector in the

[2] ESRB Report on commercial real estate and financial stability in the EU – December 2015

[3] Recommendation of the European Systemic Risk Board of 31 October 2016 on closing real estate data gaps (ESRB/2016/14)

Paris region. Besides, we take advantage of a partnership between the European Central Bank (ECB) and the data provider Investment Property Databank (IPD) to get time series of French commercial property price indexes breakdown by sectors, such as the office sector. From this data collection exercise, evolutions of office prices can be analysed considering its key market determinants. As evolutions of commercial property prices convey early information on potential overheating of the financial sector; identifying potential overvaluation of commercial property prices appears crucial. In this context, a measure of the overvaluation is estimated by relying on an econometric approach. According to this measure, office prices were overvalued in 2008-2009 and from 2011 to 2016. The value added of this indicator is assessed by evaluating its predictive power of recession periods identified by the OECD.

Recent evolutions on French commercial property markets

A stocktaking exercise to identify potential sources of data on commercial property market

French institutions devoted substantial efforts to produce housing market indicators. As an example, French quarterly residential property price index is recognized for its high-quality, timeliness and historical depth. Nevertheless, these efforts do not yet cover commercial property markets. Indeed, these markets are highly heterogeneous, gathering diverse types of properties, from offices, high street retail, shopping centres, retail parks to specific properties such as industrial spaces and hotels. Besides, these properties are sparsely exchanged, these markets are generally considered illiquid. At this stage, French authorities only publish monthly building permits and construction starts breakdown by sector.

In this context, we dedicated our time to identify appropriate indicators published by private entities to store historical data on commercial property markets. In France, every quarter, several commercial real estate agencies such as BNP Paribas RE, CBRE, or Jones Lang LaSalle, publish a set of commercial property market indicators on both end-user and investment markets. Besides, for the Paris region, an economic interest group, Immostat, was formed in 2001 by the main real estate agencies, to share their data to cover a larger part of the commercial property markets to build robust market indicators. In practice, commercial properties are both physical spaces consumed by companies and investment products bought by entities to generate profits. As disequilibrium can occur in either market, gathering information on both markets is crucial. From the end-user side, measures on both volume and price are made available on a quarterly basis. Office take-up and vacancy rates are generally used as the volume measure of the demand on the end-user market, while average rents is the price measure on this market. Nevertheless, these indicators are generally made available only for the Paris region and the office sector. For the investment side, aggregate investment breakdown by sector, published every quarter, covers the whole French area. Price information on the investment market are also estimated by commercial real estate agencies, but mainly through measures of profitability such as a yield measure for each sector and certain type of properties, generally *prime* transactions. Recently, Immostat also made available the average price of investments, but only for the office sector and the Paris region. Indeed, information on prices are sparse and not representative of the different segments of the commercial property market.

In parallel with its exercise, the ESCB Working Group on General Economic Statistics (WGGES) launched in 2010 a stocktaking exercise on commercial property markets to identify potential sources of commercial property prices in each member state ultimately to design a commercial property price index for the euro area market. At that time, several countries such as Germany, Italy and Denmark already computed or collected price indexes on commercial property markets, while other countries such as France and Spain were not able to provide price indexes for these markets. To fill these data gaps, a partnership with the data provider MSCI/IPD was set up to obtain price indicators for member states for which no price index was available. For France, several indexes are made available on a quarterly basis. Appraisal values breakdown by sector, available on a bi-annual basis from other private data providers, are interpolated on a quarterly basis and made available each quarter. Nevertheless, price indexes built on appraisal values are frequently criticized, because of deceiving low volatility and difficulties to capture turning points. Therefore, for each sector, a semi-hedonic price index relying on both transaction prices and appraisal values is calculated every quarter. In fact, IPD gathers, from commercial real estate agencies, granular data, especially transaction prices, appraisal values and distinctive features of each property, accounting for around 40% of the French commercial property markets. The econometric methodology used to develop French semi-hedonic quarterly price indexes was primarily defined for the MSCI/IPD UK commercial property indexes from a partnership between MSCI/IPD and the University of Aberdeen[4]. These indicators, made available every quarter by the ECB to euro area member states, are retrieved to monitor French price developments on commercial property markets.

Gathering information from commercial real estate agencies, Immostat and MSCI/IPD, a reasonable set of indicators on both the end-user and the investment markets is gathered every quarter to monitor commercial property markets. Nevertheless, at this stage, some indicators only cover the office sector in the Paris region.

A confirmed recovery on both end-user and investment markets

Quarterly amounts of investments on commercial property markets are generally identified as the best proxy of the demand on the investment market and vacancy rates are privileged to measure the demand on the end-user market. Nevertheless, while indicators on the investment part of the market are available for France, those for the end-user market cover generally only the office sector for the Greater Paris region. In fact, investments in the Greater Paris region and in the office sector account for respectively around 75% and 60% of this aggregate.

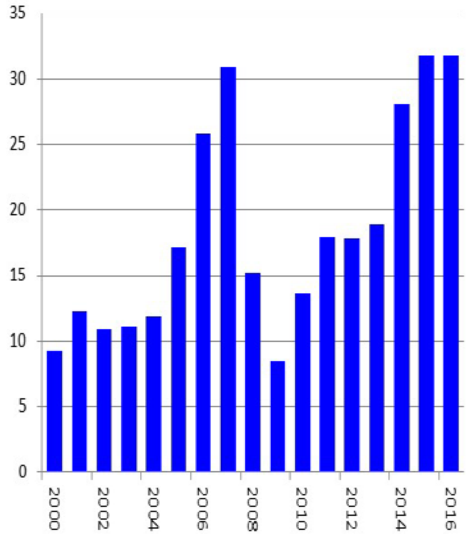
From 2000 to 2016, different market periods can be identified. In the early 2000s, investments in commercial property markets remained stable. Meanwhile, the end-user market was hit by the burst of the dotcom bubble, the office vacancy rate in the Paris region highly increased. From 2003 to 2007, both end-user and investment markets were in an upswing phase of their cycle: aggregate investments

4 Devaney & Diaz (2011)

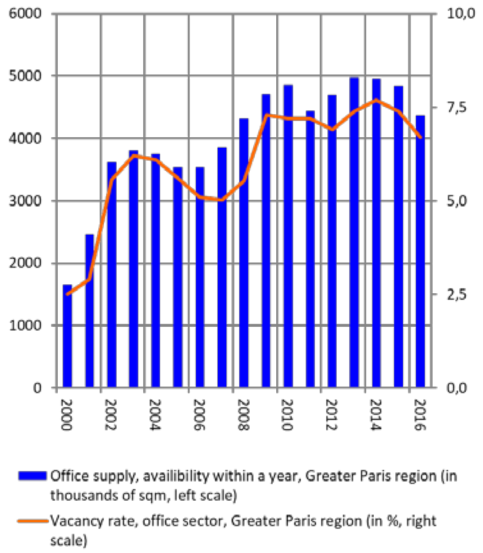
increased to reach a record level in 2007 while vacancy rate constantly decreased over this period. This flourishing period ended in 2008: the burst of the subprime crisis hit both markets. Nevertheless, the investment market displayed some signs of recovery as of 2010 while the end-user market remained sluggish. The investment market was recovering at a strong pace, and reached its highest level, 32 bn €, in 2015. Since mid-2015, the state of the end-user market has been improving; the office vacancy rate has been declining. Office space available for lease has reduced in some geographical areas such as the central business district of Paris and the business quarter La Défense.

Figure 1. Examples of key indicators on end-user and investor commercial real estate markets actually available

Aggregate investments, all sectors, France, in bn€



Office supply available within a year in thousands of sqm, vacancy rate in %, Greater Paris region



Sources: BNP Paribas Real Estate.

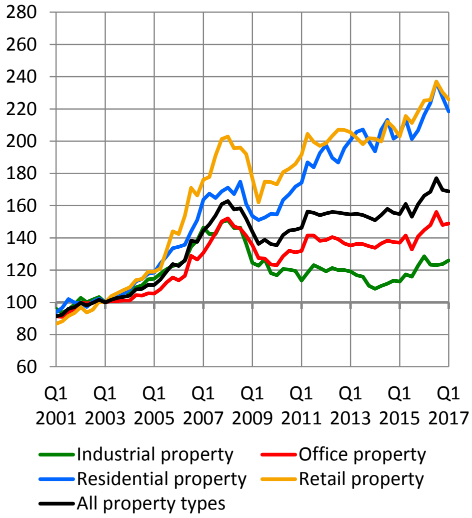
For all property sectors, prices have been rising since 2014

In France, property price index for the residential sector produced by the French national institute of statistics is well-known for its high quality. Nevertheless, the same methodology cannot be applied for commercial property markets: these markets are highly heterogeneous and illiquid. In this context, transaction data gathering information on prices and property characteristics cannot be the only source of information to build this type of indexes. At this stage, we rely on quarterly semi-hedonic MSCI/IPD price indexes built with both appraisal values and transaction prices and available as of Q1 1999.

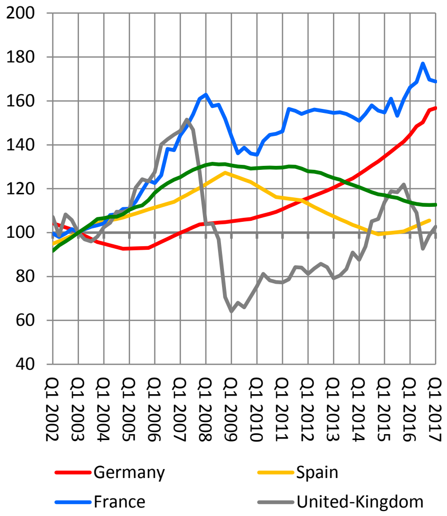
Evolutions of French commercial property price indexes share some similarities with those observed for the French residential real estate sector. From the end of the 1990s to 2008, commercial property prices doubled. In 2009, commercial property prices fell sharply on all property sectors but begun to recover as of 2010. Unlike residential property prices, commercial ones remained quite stable from 2011 to 2014. Property prices increased again in all sectors from 2014 to 2016, and remained relatively stable in 2016. Recent evolutions of French commercial property prices are singular compared to those of other European countries. In particular, French commercial property prices are higher in 2017 than their pre-crisis levels. This particular feature is shared only with German commercial property prices. Nevertheless, for this specific country, prices remained flat during the 2000s.

Figure 2. French commercial property price indicators by sector and commercial property price indicators by country, index base 100 in 2003

French commercial property price indicators, by sector, index base 100 in 2003



Commercial property price indicators, by country, index base 100 in 2003



Sources: ECB from MSCI/IPD, Bulwiengesa and vdp for Germany, Banca d'Italia for Italy.

In this context, monitoring French commercial property prices is crucial especially to assess the probability of a commercial real estate bubble. At this stage, only the office sector is reasonably covered by indicators at our disposal. Indeed, the econometric evaluation of a possible overvaluation of commercial property prices can be carried out only for the office sector.

A model of market interactions to evaluate risks on the office sector

In France, evolutions of the office sector, for which we have a reasonable set of indicators, raised concerns as of 2010. The end-user market remained sluggish, while the investment market recovered in 2010, boosting office prices. From this diverging path taken by office markets, it appeared crucial to evaluate whether the investment market was not in an overheating state, by assessing whether office prices were overvalued. For this purpose, we defined a model combining information from both end-user and investment markets. While there are few empirical papers on commercial property markets, several theoretical papers describe how end-user and investor office markets interact. Among them, DiPasquale & Wheaton (1992) and Wheaton, Torto & Evans (1997) proposed a general framework describing interactions between these markets in both the short and long run. The end-user and investment markets interact on these time horizons through levels of rents and new constructions of office space.

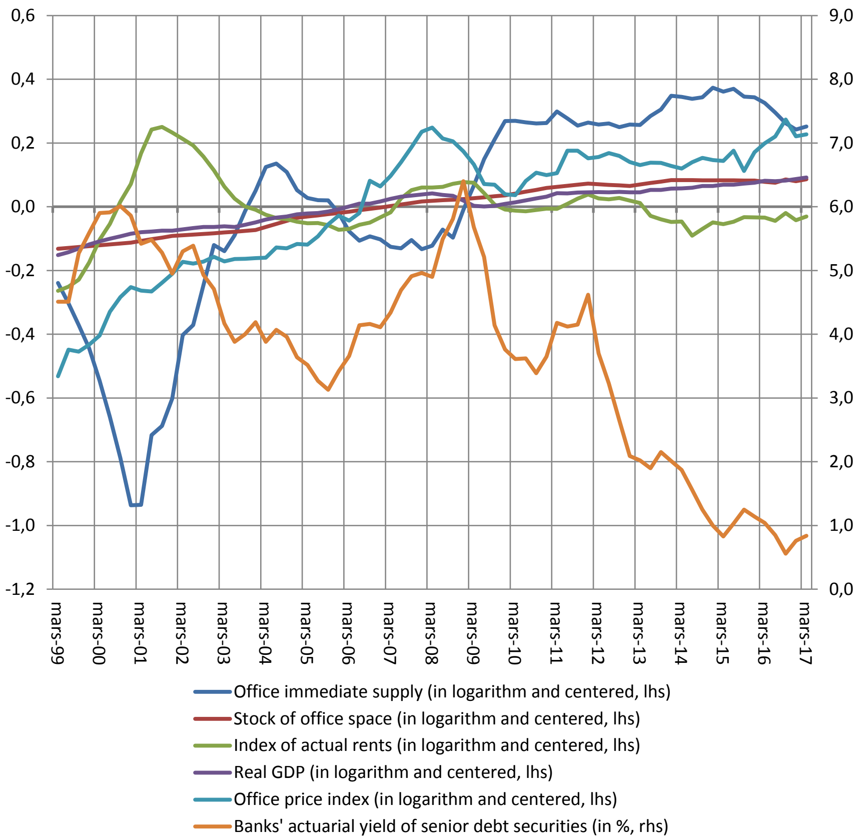
In the short run, stock of office space is inelastic; levels of rents strongly depend on general economic conditions such as the level of employment, companies' demand of office space and the office immediate supply measuring excess supply on the market. Property prices depend on the demand on the investment market which is strongly linked to the expected profitability of the office market. The profitability depends positively on future income flows relying mostly on the level of rents and the vacancy rate, and negatively on the level of yields on other markets such as debt securities market. Depending on the level of property prices, new constructions are initiated if projects are profitable; in the long run, new constructions drive down rents and prices on the long run.

Our empirical approach to describe these interactions

Previously described interactions between office prices and its key determinants can be well-described with a co-integrated vector autoregressive model. In this model, each variable, and especially the value of the office price index, is supposed to depend on its previous values and previous values of its key determinants. Besides, this model is also used in an innovative way to propose a measure of price overvaluation. For that purpose, we rely on the Granger's decomposition from which each variable considered in the model can be broken down into a "cycle" component and a "trend" component. The trend component is supposed to represent the long run equilibrium of the variable while the cycle component accounts for the temporary deviation from this equilibrium. This method has some comparative advantages compared to other well-known methods such as the Hodrick-Prescott filter, in our case, the decomposition will be less subject to revisions especially at the end of the period.

This model is estimated on a restricted time set from Q1 2003 to Q1 2017, even though we can build time series started not later than 1999. Considering the complete set would have significantly attenuated causal links between our variables, as the French market observed a crisis in the beginning of the 2000s. The evolutions of the logarithm of the office price index is explained by five determinants represented on figure 3: the logarithm of the real GDP, the logarithm of the index of actual rents in Paris region, the logarithm of the office immediate supply in Paris region, the logarithm of the stock of office space in Paris region and the banks' actuarial yield of senior debt securities. Index of actual rents is favoured to the detriment of index of facial rents: unlike actual rents, measures of facial rents are published every quarter; nevertheless, this measure does not include incentives reducing headline rents. We estimated the index of actual rents from the index of facial rents and incentive rate made available by real estate agencies. Furthermore, the measure of the stock of office space is estimated by the real estate observatory of the Paris region, but this information is not publicly made available. In practice, this indicator is approached by the ratio between the office immediate supply and the vacancy rate, both information are published on a quarterly basis by BNP Paribas Real Estate.

Figure 3. Evolutions of each dependent variables included in the model



Sources: Immostat (actual rents), BNP Paribas RE (Office immediate supply and estimations of stock office space), INSEE (Real GDP), ECB from MSCI/IPD (Office price index), Datastream (Actuarial yield).

Description of the model considered

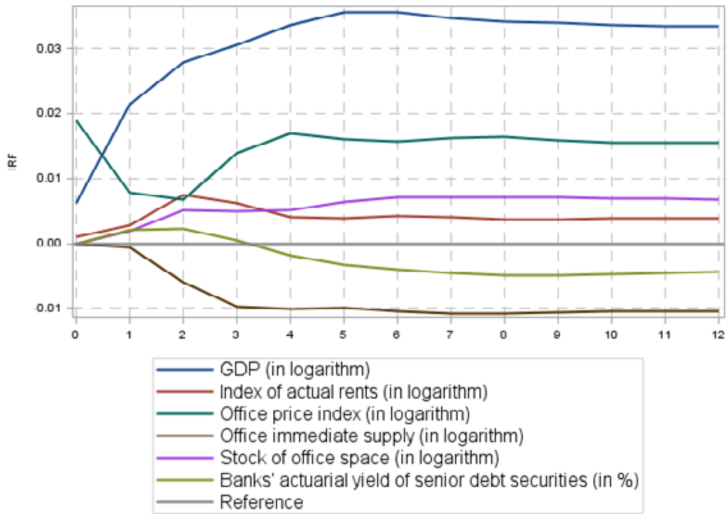
As all indicators considered in this model are non-stationary ones, a cointegrated vector autoregressive model is implemented. This type of model relies on variables in first differences while preserving the information carried by variables in level such as common trends between these variables. The estimated model is a cointegrated vector autoregressive model of order 2 with 2 cointegration relationships. The short-term equation of the model can be expressed as:

$$\Delta Y_t = c + \alpha\beta^T Y_{t-1} + \Phi_1 \Delta Y_{t-1} + u_t \quad (1)$$

Where Y_t accounts for the vector of dependent variables at time t: Y_t = (log_GDP$_t$, log_Rent$_t$, log_Price$_t$, log_Office_supply$_t$, log_Stock_Office_Space$_t$, Yield$_t$), ΔY_t its first differences, u_t the residual terms, and $\beta^T Y_{t-1}$ the co-integration relationships representing "the long run relationships of the model". A further hypothesis on a linear trend in level is added to the model implying a constant term c in the short-term equation of the model.

To analyse interactions between dependent variables identified by the model, orthogonalized impulse response functions, accounting for the impact of an orthogonalized shock of one variable on other variables, are calculated. Beforehand, dependent variables must be ordered by relying on Granger's causality tests. The order chosen is to consider first the logarithm of the real GDP followed by the logarithm of actual rents, the logarithm of office prices, the logarithm of office supply, the logarithm of stock office space and the banks' actuarial yield of senior debt securities as the last variable. This structure implies that a shock on yield does not have an immediate impact on any other variables, while a shock on GDP immediately impacts all other variables.

Figure 4. Variations in percentages over quarters of office prices after a shock at quarter 0 of one standard deviation of each variable



Amplitude of the standard deviation of the shock on each variable — Table 1

Variable	Value of the standard deviation
GDP	0.3%
Index of actual rents	1.1%
Office price index	1.9%
Office immediate supply	2.5%
Stock of office space	0.2%
Bank's actuarial yield of senior debt securities	0.25%

As expected, a positive orthogonalized shock on the GDP or on the index of actual rents positively impact office prices, while a positive shock on office immediate supply or on the actuarial yield negatively impact office prices. Nevertheless, a positive shock on the stock of office supply positively impact office prices; this last result is hardly interpretable.

The overvaluation measure of office prices

Co-integrated autoregressive models split the estimation into short term equations and long terms ones. The Granger's representation consists in rewriting a co-integrated auto-regressive process such as the one described by the formula (1) in a synthetic way gathering both short and long term impacts of other variables on the variable of interest. This representation was demonstrated by Engle & Granger (1987) and Johansen (1991) while the exact formula was obtained by Hansen (2005). Levels of dependent variables are expressed as the sum of a trend components and a cycle component:

$$Y_t = C\sum_{s=1}^{t} u_s + C(L)u_t + \tau(t) + \widetilde{Y_0} \ (2)$$

Where $\widetilde{Y_0}$ the initial component, $C\sum_{s=1}^{t} u_s$ the stochastic trend, $\tau(t)$ the deterministic trend accounts for the trend component and $C(L)u_t$ is the cycle component. The matrix C is computed from the matrices α and β defined in the formula (1) and $C(L)$ is a lag polynomial depending on the parameters of equation (1). All formulas can be retrieved from Hansen (2005).

The overvaluation measure of office prices can be approached by the cycle component of the office prices equation, i.e. the difference between the observations and the trend component extracted from the model.

In order to assess the robustness of estimated parameters, we run stability tests, in particular the Ploberger's stability test[5]. Estimated parameters appear to be unstable; a breaking point on the parameters of the long-run relationships can be observed in 2013. This instability raises an additional difficulty; which set of parameters should be chosen to model the relationships between dependent variables and estimate the overvaluation measure.

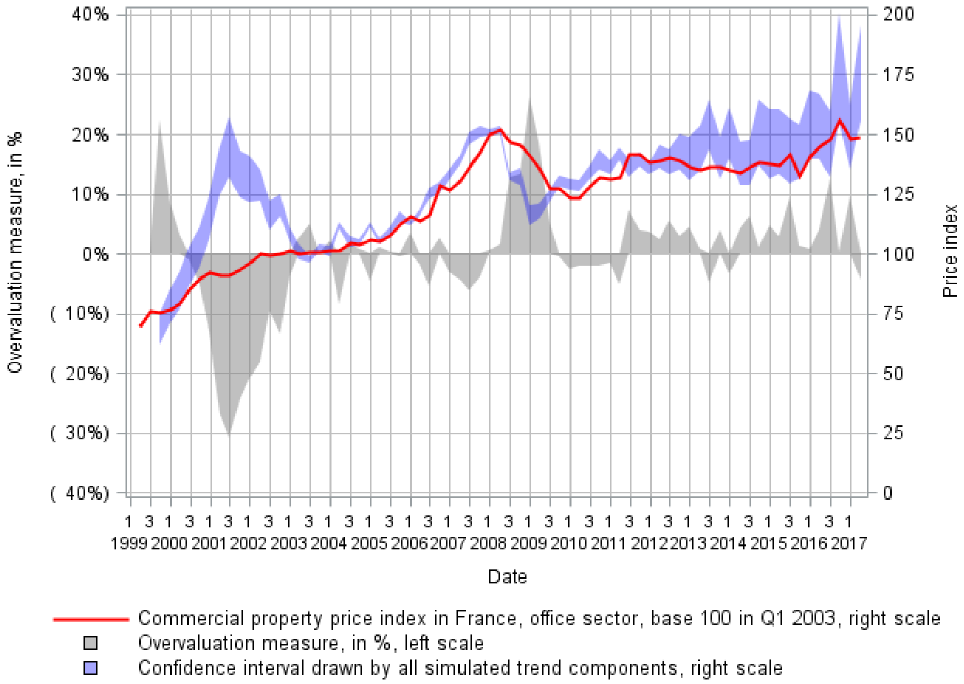
To circumvent this instability issue, we estimate an upper bound of the overvaluation measure. For this purpose, we estimate our model on different samples, firstly on the sample gathering observations from Q1 2003 to Q2 2009, and on the following samples obtained by increasing by an increment of one quarter at the end of the sample, up to Q4 2011, therefore on the samples from Q1 2003-Q2 2009, Q1 2003-Q3 2009, Q1 2003-Q4 2009, ..., to Q1 2003-Q4 2011. We stop at the end of 2011 instead of taking the result from the stability tests at granted by taking the end of 2012. Indeed, the diverging trends between the end-user and investment markets have been observed since 2012.

From each set of estimated parameters, a trend component is simulated over the complete set of observations, i.e. from Q1 1999 to Q1 2017. A confidence interval surrounding all simulated trend components can be derived. The lower bound of the confidence interval, i.e. the lowest values taken by the simulated trend components over time, is used to define an upper bound of the overvaluation measure. This last metric is defined as the difference between the observed values of the office price index and the lower bound of the confidence interval.

Considering the evolutions of its key determinants, office prices appear to be undervalued from 2000 to 2003 (Figure 5). In fact, during the dot-com crisis, the end-user market may have been overvalued: office rents increased significantly while office prices remained flat. During the subprime mortgage crisis, office prices adjusted lately compared to its key determinants, office prices were overvalued by more than 25% at the end of 2008. Since 2011, office prices may have been overvalued but only to a limited extent. The overvaluation measure increased slightly in Q2 2016 reaching 12%, but decreased after this quarter.

[5] Hansen & Johansen (1999)

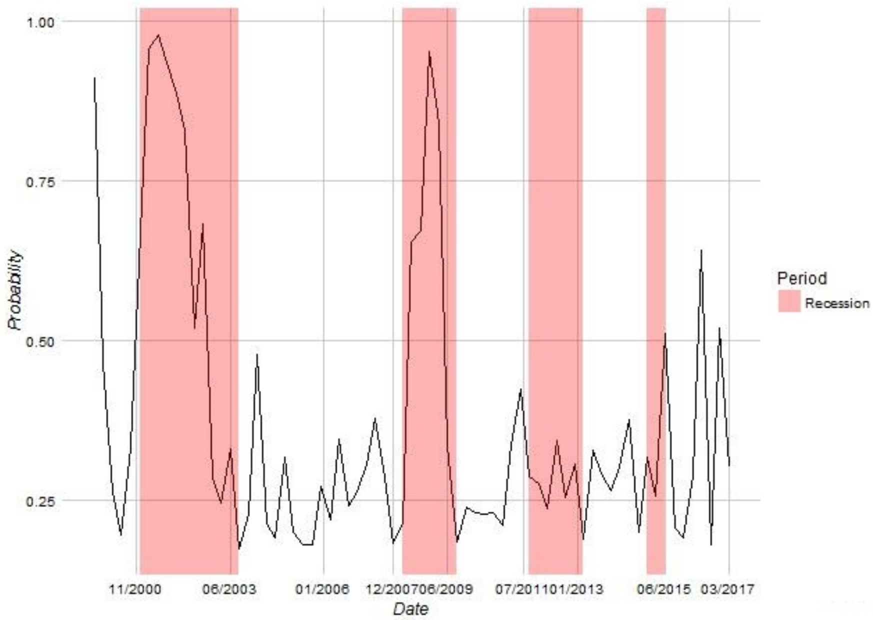
Figure 5. Evolutions of the IPD office price index, the overvaluation measure and the confidence interval estimated from all the simulated trend components.



Finally, in order to assess the value-added of this indicator, the overvaluation measure is used to predict French recession periods identified by the OECD. The OECD used a list of leading indicators, such as car registrations, consumer confidence indicators, production survey, or export order books. Bry & Boschan methodology is used to detect peaks and troughs. At the time of this estimation, from January 1999 to March 2017, the OCDE have identified 4 periods of recession: from December 2000 to June 2003, from January 2008 to June 2009, from July 2011 to January 2013, and from October 2014 to June 2015.

To compute a recession indicator for France, the absolute value of the overvaluation measure is used as an explanatory variable in a logistic regression of the OECD recession periods. In practice, the estimated recession indicator succeeds to identify the dotcom crisis and the subprime mortgage crisis, while the sovereign debt crisis did not affect commercial property markets. The probability to be in a recession period slightly increased in 2015 and 2016 but is under 50% in Q1 2017.

Figure 6. A recession indicator for France estimated from the estimated overvaluation measure of office prices



Sources: OECD for the recession periods

Concluding remarks

From this stocktaking exercise to gather information on commercial real estate, it appears that, as the ESRB highlighted in its latest report on commercial real estate, some indicators are already made available but cover only partially markets to be monitored. For the French end-user market, key indicators made available by commercial real estate agencies focus mainly on the office sector and the Paris region. The investment market is better covered; in particular, French semi-hedonic price indexes estimated by MSCI/IPD and delivered to the ECB cover relatively well the French area and the different sectors.

From this exercise, a reasonable set of data on the office sector give us the opportunity to estimate monitoring indicators. For this purpose, we rely on an econometric approach, a co-integrated vector autoregressive model, to estimate an overvaluation measure of office prices. From this approach, office prices appear to be overvalued at the end of 2008 by more than 25 %, and since 2011, but only to a limited extent. To assess the predictive power of this indicator, a recession indicator is estimated by modeling OECD recession periods with the overvaluation measure. This measure appears to capture relatively well the dotcom crisis and the subprime mortgage crisis, while the sovereign debt crisis did not stand out.

This encouraging work needs to be carried on. Firstly, successive revisions on MSCI/IPD property price indexes observed in the past have significantly modified the results obtained and the resulting analysis. For these reasons, monitoring revisions of data provided by private entities appears crucial. Besides, to enlarge our information set, we need to assess the value added of granular sources of information already collected, such as transaction prices and characteristics stored in notarial databases. This type of dataset show several advantages, firstly as a tool to evaluate the quality of private sources. Secondly, this dataset cover all sectors, especially the retail one which also rose concerned recently. Finally, precise geographic localization of exchanged property is made available; geographic areas boosting prices could be properly identified.

References

Devaney, S & Martinez Diaz, R (2010). Transaction based indices for the UK commercial property market: exploration and evaluation using IPD data. University of Aberdeen Business School Working Paper Series, vol. 02, University of Aberdeen Business School, Aberdeen, pp. 1-18

DiPasquale, D. & Wheaton, W. C. (1992). The Markets for Real Estate Assets and Space: A Conceptual Framework, *Real Estate Economics*, **20**, issue 2, p. 181-198.

Engle, R. F. & Granger, C. W. J. (1987). Co-integration and Error Correction: Representation, Estimation, and Testing, Econometrica, Econometric Society, vol. 55(2), pages 251-276, March.

Hansen, H. & Johansen, S. (1999). Some tests for parameter constancy in cointegrated VAR-models, *Econometrics Journal*, **2**, issue 2, p. 306-333.

Hansen, P. (2005). Granger's representation theorem: A closed-form expression for I(1) processes. *The Econometrics Journal, 8*(1), 23-38.

Johansen, S. (1991).Estimation and Hypothesis Testing of Cointegration Vectors in Gaussian Vector Autoregressive Models, Econometrica, Econometric Society, vol. 59(6), pages 1551-1580, November.

Wheaton, W. C., Torto, R. G. & Evans, P. (1997). The Cyclic Behavior of the Greater London Office Market, The Journal of Real Estate Finance and Economics, Springer, vol. 15(1), pages 77-92, July.

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BANK FOR INTERNATIONAL SETTLEMENTS

IFC-National Bank of Belgium Workshop on "*Data needs and Statistics compilation for macroprudential analysis*"

Brussels, Belgium, 18-19 May 2017

Evaluating risks in the French office market with new sources of data on commercial property prices[1]

Edwige Burdeau,
Bank of France

[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.

Evaluating risks in the French office market with new sources of data on commercial property prices

May 18th, 2017

Edwige Burdeau

Banque de France, Directorate General Statistics
Engineering and Statistics Project Management Division

Motivations

- Financial risks of commercial property markets
  - ➢ The commercial real estate market is highly capital intensive and dependant on external financing
- Recommendation 19 of the G20 Data Gaps Initiative and Recommendation 2016/14 of the ESRB on closing real estate data gaps
  - ➢ Need of comprehensive and timely data on both residential and commercial property prices

In France

- Quarterly *residential property price index* recognized for its high quality, timeliness and historical depth, but some reluctance to apply the same methodology on commercial property prices:
  - ➢ Commercial markets are heterogenous and illiquid.

- Some statistics made available by French public institutions:
  - ➢ Monthly building permits,
  - ➢ Construction starts breakdown by sector.

A strong need to improve our statistical knowledge of commercial property markets !

Regular collection of information from websites of commercial real estate agencies (BNP Paribas RE, CBRE, JLL, Immostat) and books of commercial real estate professionals (IEIF)

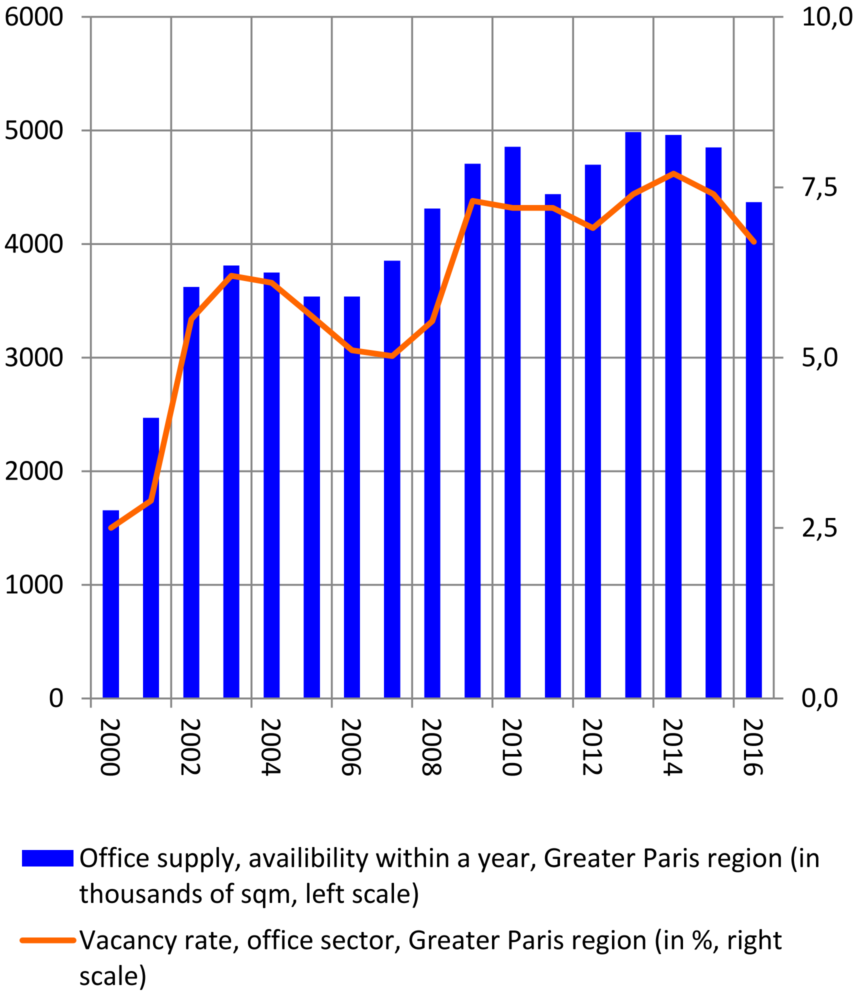
End-user market, focus generally on Greater Paris region and office sector:

- "Volume measure": office take-up in square meters,
- "Price measure": average rent,
- Measures of occupancy such as vacancy rates.

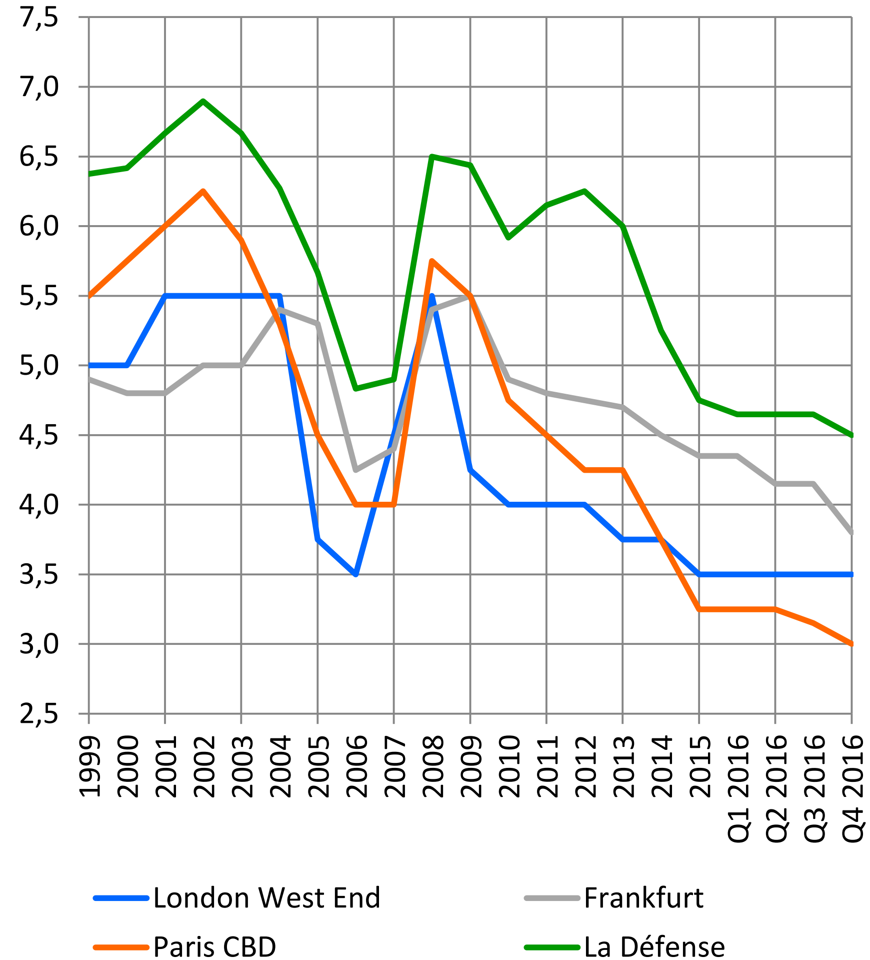
Investment market:

- "Volume measure": Aggregate volume of investments, breakdown by sector,
- Measures of profitability such as commercial property yield index, breakdown by sector and specific areas,
- "Price measures":
  - Directly, recently made available for offices in Greater Paris, the average price of investments,
  - Indirectly, the ratio between the rent and the yield index, especially for the prime sector.

Office supply available within a year and vacancy rate, Greater Paris region



Commercial property rental yield index in %, prime transactions, office sector



Sources: IEIF, BNP Paribas RE, CBRE, JLL

An Eurosystem working group (WGGES) launched in 2010 a stock-taking exercise on commercial property markets:

- To identify potential sources of commercial property prices in each member state,
- To design a commercial property price index for the euro area.

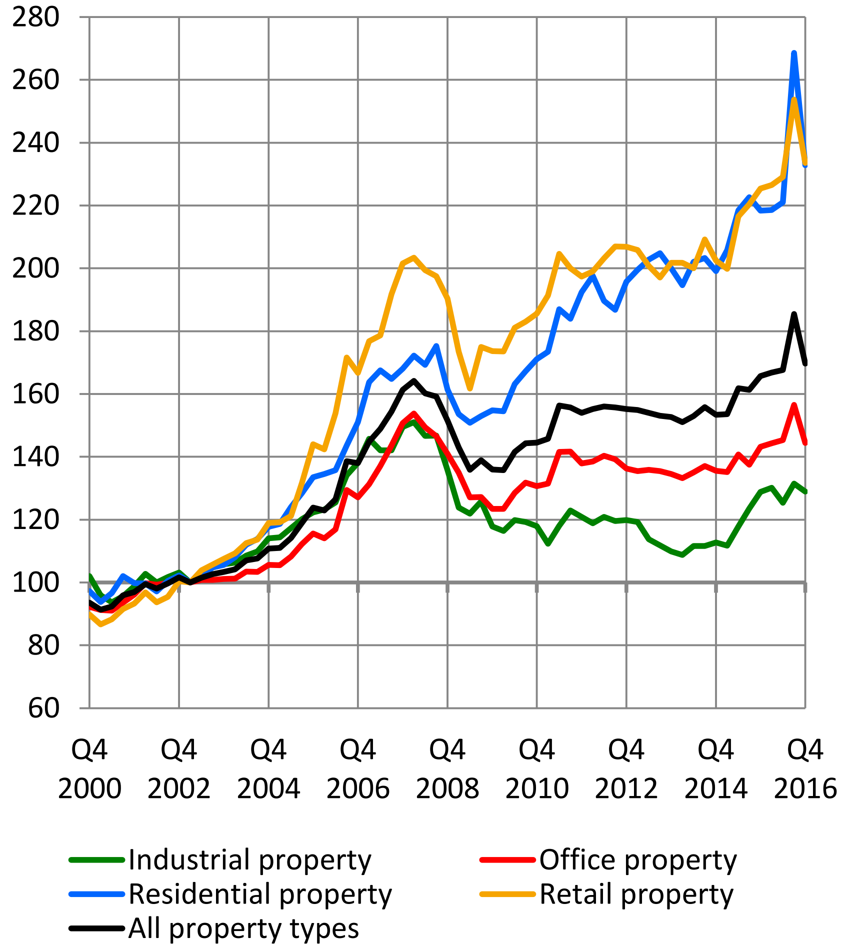
A partnership with MSCI/IPD was set up to obtain price indicators for member states like France, for which no price index was available.

For France, several indexes are indeed made available by MSCI/IPD each quarter:

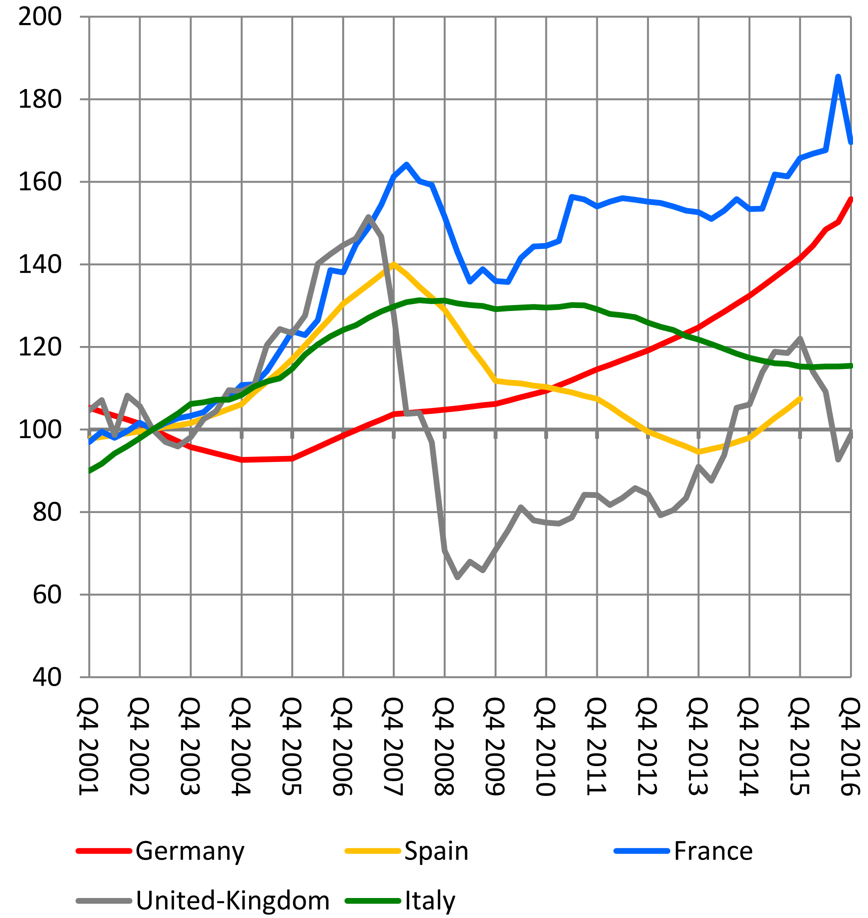
- **Appraisal values** breakdown by sector, also available from other data providers,
- And a **semi-hedonic price index for each sector** relying on both transaction prices and appraisal values,
- With a relatively good coverage of the market : IPD sample covered around 40% of the market in 2011.

According to IPD data, the French market remains bullish during the crisis

French commercial property price indicators, by sector, index base 100 = 2003



Commercial property price indicators, by country, index base 100 = 2003



Sources: ECB from IPD, Bulwiengesa and vdp for Germany, Banca d'Italia for Italy

Strong expectations to assess whether commercial property prices were overvalued:

In France, evolutions of commercial property market raised concerns, especially since 2010:

- The end-user market remains sluggish,
- While the investment market has recovered since 2010, boosting commercial property prices.

How to measure price overvaluation ?

- Theoretically (DiPasquale & Wheaton 1992),
  - **In the short run**, property prices depend positively on rents and negatively on interest rates. While rents depend negatively on vacancy rates and positively on economic growth.
  - **In the long run**, new construction should drive down rents.
- Empirically,
  - **A cointegrated vector autoregressive model** can be used to model interactions between the property price index and its economic determinants,
  - The "equilibrium" commercial property price index is defined as **the trend component explained by its economic determinants** (Hansen, 2005) and "overvaluation" is defined as the deviation from this equilibrium price index.

In practice, we focused on the office market,

Some variables were selected to explain the IPD semi-hedonic office price index,

- Market-specific variables: index of actual rents, office immediate supply, stock of office space,
- and other macroeconomic variables: GDP, banks' actuarial yield of senior debt securities.

But because of breaks in time series,

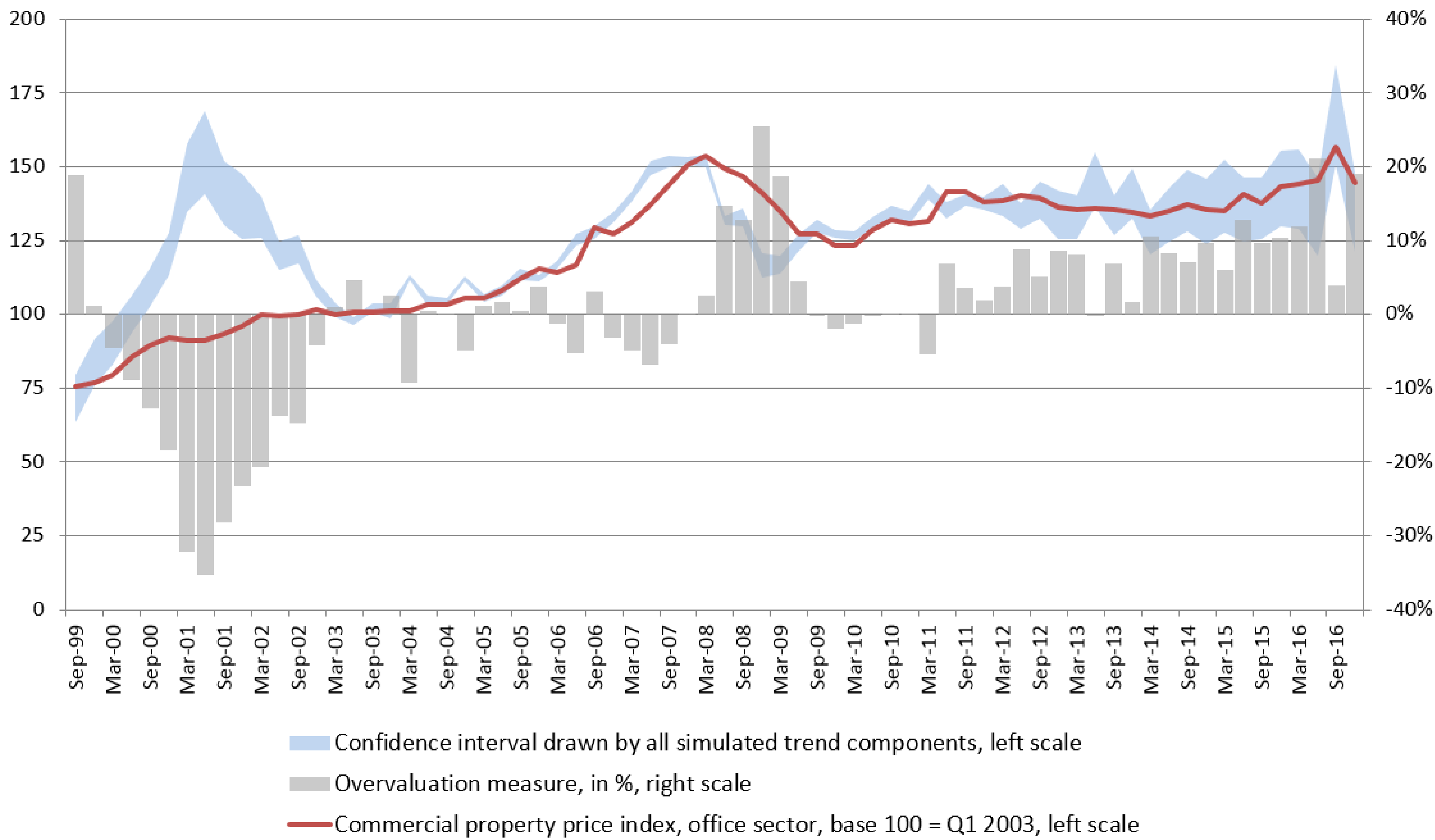
- some points were initially withdrawn for the estimation part,
- and the model was estimated on several subsamples from 2003Q1 - 2009Q2 to 2003Q1 - 2011Q4

From these multiples estimations, several trend components are **simulated dynamically over 1999Q1 to 2016Q4.**

The trend component is defined as the minimum within the set of simulated trend components.

The overvaluation is the deviation of this trend component from the observed series.

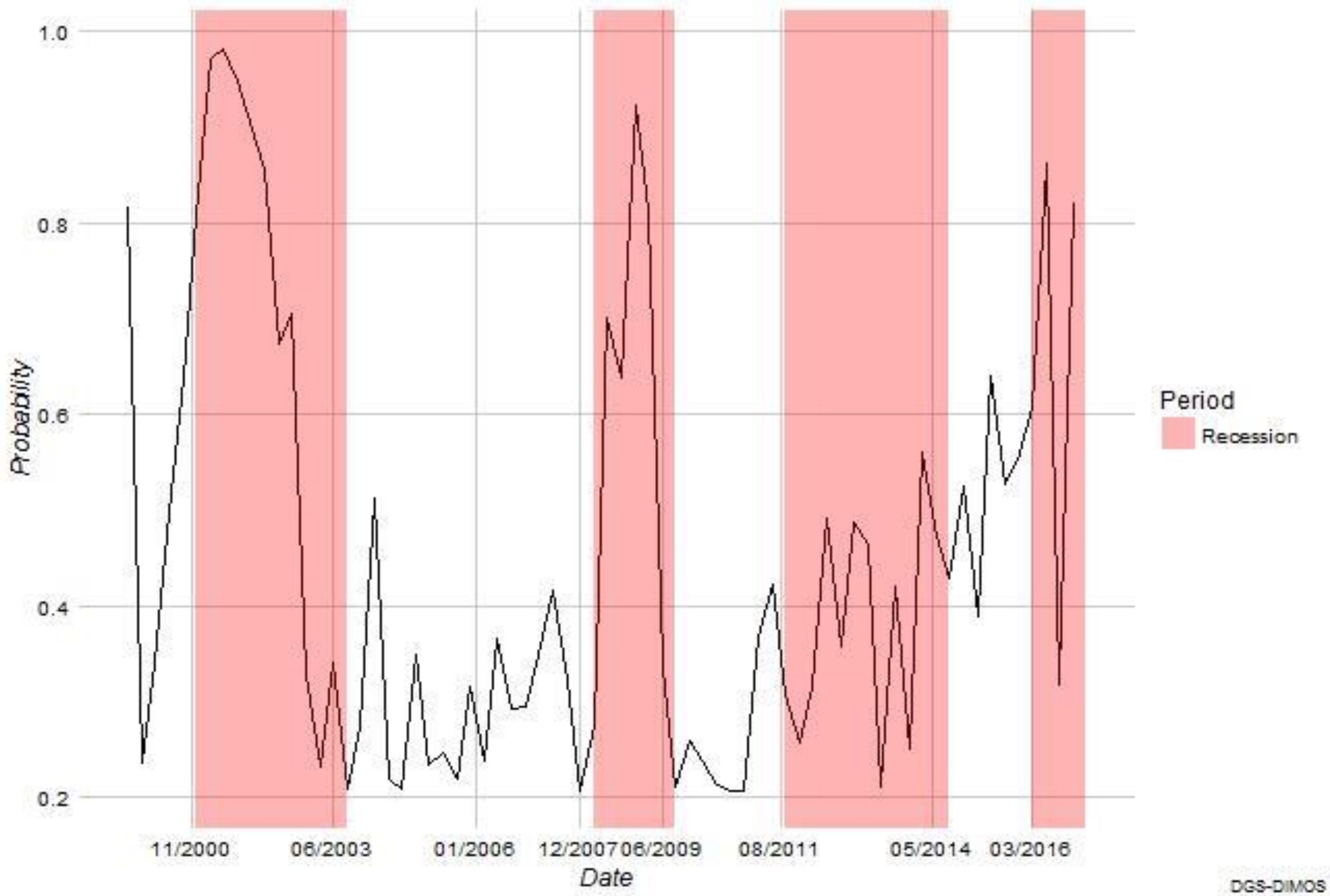
Evolutions of the IPD office price index, the overvaluation measure, and the confidence interval drawn by the simulated trajectories



Our recession indicator clearly identifies the Dot-com crisis and the subprime mortgage crisis

The estimated measure of price overvaluation is used to compute a recession indicator for France

This indicator is estimated by calibration of the absolute value of the overvaluation measure on recession periods identified by the OECD.



*According to the OECD, France entered in recession in 2016, but other publications such as the composite leading indicators indicate a recovery as of 2016 Q3.

- The quality of the IPD index must be better assessed:
    - for some quarters, the magnitude of revisions can be higher than the standard deviation of the time series.

- We are working on granular data such as transaction prices and characteristics stored in notarial databases, in order to identify properly geographic areas boosting prices.

- Strong need to evaluate an overvaluation measure for other sectors (retail in particular)
    - But we do not have enough data on that sector,
    - Hardly possible to set up good indicators for this sector as this market is highly heterogeneous.

Thank you for your attention

Any question ?

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Pockets of risk in the Belgian mortgage market - Evidence from the Household Finance and Consumption survey[1]

Philip Du Caju,
National Bank of Belgium

[1] This paper 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.

Pockets of risk in the Belgian mortgage market

Evidence from the Household Finance and Consumption Survey (HFCS)

Philip Du Caju[1]

Abstract

This article complements macroeconomic indicators for macroprudential policy with information from microeconomic survey data from the Household Finance and Consumption Survey (HFCS), to identify pockets of risk in the Belgian mortgage market. It takes into account distributional aspects of debt and assets, with a special focus on the coverage of households' mortgage debt by (liquid) financial assets. It identifies the share of outstanding mortgage debt that is possibly at risk, and the parts of the population most affected, on the basis of income and assets-related debt indicators. The first finding is that some groups of households have problems servicing their debt out of their income and some lack the financial resources to cope with income loss. The second finding is that Belgian households' considerable financial wealth is (very) unequally distributed, and that therefore this wealth covers their outstanding mortgage debt only to a limited extent. As a consequence, a severe unemployment shock could hurt many mortgage-indebted households, involving a significant part of total outstanding mortgage debt in Belgium. All in all, this article shows that survey data can complement macro data for macroprudential policy purposes, but that there is still room for improvement.

Keywords: Household finance, Financial Fragility, Mortgage markets, Survey, HFCS

JEL classification: D14, D91, G21, G28, K35

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1. Introduction

Risks in the mortgage market are related to households' capacity to pay back mortgage loans. Households can default on their mortgage loan if their flow of income is not sufficient to pay the (monthly) debt-service payments and if their (liquid) financial assets are not sufficient to finance the service payments or to pay back (part of) the outstanding debt. If, on top of that, the asset that covers the mortgage loan is not worth considerably more than the outstanding debt, the lender faces a risk of loss. In this respect, micro data can shed a light on these risks in a way that is not possible with macro data alone, if debt and assets are unequally distributed between households.

To capture the different aspects of mortgage-debt burden for households, we look at ratios relating mortgage debt (service) to income, liquid financial assets and real-estate value. We define a mortgage-debt-to-income ratio MDtI, a mortgage-debt-service-to-income ratio MDStI, a liquid-assets-to-mortgage-debt-service ratio LAtMDS, a liquid-assets-to-mortgage-debt ratio LAtMD and a mortgage-loan-to-value ratio MLtV.

High financial wealth, as registered by macroeconomic financial accounts, is generally seen as contributing to the sustainability of the mortgage indebtedness of Belgian households. However, our analysis of survey data shows that mortgage-indebted households in Belgium on average hold less (liquid) financial assets than households without mortgage debt. One of the findings of this analysis is that, of the total amount of outstanding mortgage debt of Belgian households, almost a third is held by households that could service their mortgage debt out of liquid financial assets for less than six months. Almost half is held by households owning liquid financial assets that are worth less than 10 % of their outstanding mortgage debt. Therefore, for a significant part of the population, the high stock of financial wealth in Belgium does not enhance the sustainability of mortgage debt.

The share of outstanding mortgage debt in Belgium that is at risk because of high debt ratios is broadly comparable to that share in the euro area. This result confirms the vulnerability of Belgian households to income loss. It implies that a severe unemployment shock with income loss could hurt many mortgage-indebted households involving a significant part of total outstanding mortgage debt in Belgium.

The analyses in this article are based on the data from the Household Finance and Consumption Survey (HFCS). In 2008, the Governing Council of the European Central Bank (ECB) decided to conduct a survey on the financial behaviour of households in the euro area. A specific research network, called the Household Finance and Consumption Network (HFCN), was set up for this purpose, comprising researchers, statisticians and survey specialists from the ECB, national central banks, some national statistical institutes and external consultants. The National Bank of Belgium is responsible for Belgium's HFCS.

The network aims to supplement existing macroeconomic financial accounts data with microeconomic information at individual household level, to conduct specific scientific research and policy-relevant analyses, and to learn about aspects related to the distribution of assets and liabilities. The HFCS was designed to support the Bank's and the Eurosystem's analyses of monetary and macroprudential policies. Data which reflect the heterogeneity of the household sector, such as those collected by the HFCS, can usefully supplement macroeconomic and financial statistics by adding information on distribution (notably on the asymmetric distribution of wealth). HFCS data permit analysis of specific groups of households key to policymaking, e.g. the lowest and highest income and wealth deciles, excessively indebted households and households facing credit constraints. In Belgium, the survey is conducted by the Bank. The fieldwork, i.e. the actual collection of information through face-to-face-interviews of households, is outsourced to an external agency by public tender and then followed up by the Bank.

The HFCS provides detailed data at household level about a range of aspects, covering households' wealth (real and financial assets and liabilities) as well as related variables, including their income and demographic characteristics. The actual HFCS questionnaire is fairly comprehensive and the questions are answered by the person best informed about the household's financial situation. It should be noted that the HFCS records the value of the assets and liabilities as estimated by the households themselves. Where useful and possible, the interviewers encourage respondents to consult relevant documents such as bank statements, tax returns etc. This is not possible for all types of assets, of course, residential property being a case in point, and estimated values will not necessarily always match real market values.

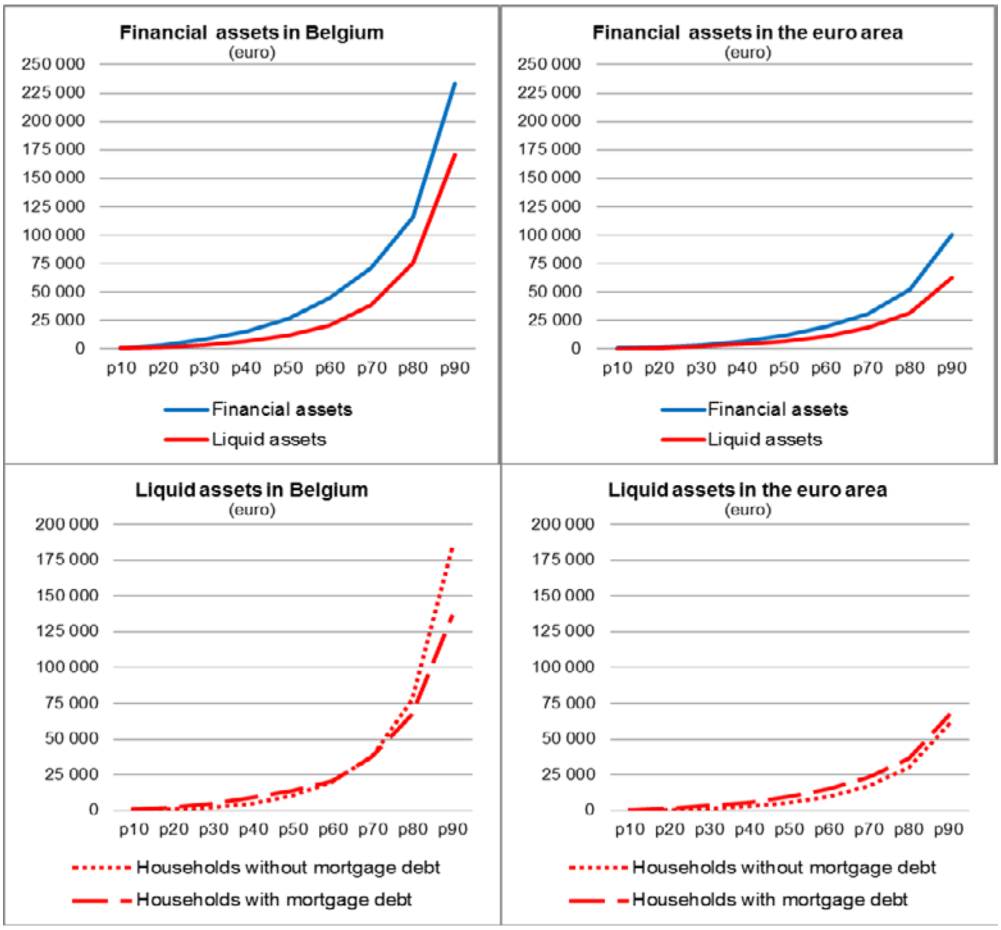
HFCS data for two waves (2010 and 2014) are now available. Next waves of the survey are ongoing or planned (2017, 2020, ...). From the second wave, the survey covers all euro area (and some other) countries, sampling more than 80 000 households, of which around 2 300 in Belgium). The data collection fieldwork and post-fieldwork statistical processing are time consuming. Therefore, these survey data are published with a considerable time lag. More information on the survey can be found in HFCN (2013a, 2013b; 2016a, 2016b).

2. Households' financial and liquid assets

Data from the Household Finance and Consumption Survey (HFCS) show that the high financial wealth of Belgian households is unequally distributed (Du Caju, 2013 and 2016). The median household in the middle of the distribution holds financial assets worth 26 000 euro, which is at least 36 times more than a household in the lowest decile and at least 9 times less than a household in the highest decile (see the top left panel of Graph 1). Together, Belgian households have much more financial wealth than euro area households. The median household in the euro area owns 11 000 euro in financial assets, which is at least 28 times more than a household in the lowest decile and at least 9 times less than a household in the highest decile (see the top right panel of Graph 1).

The distribution of households' financial and liquid assets[1]

Graph 1



Source: HFCS.

1 A household's liquid assets are composed of its money holdings in deposits, mutual funds, bonds and listed shares.

To investigate the extent to which household debt is covered by financial assets, we can limit the scope to liquid financial assets. Liquid assets allow a household to immediately pay back debt if income falls. Liquid assets are defined as the sum of money holdings in deposits, mutual funds, bonds and listed shares, thus excluding not-quoted private business wealth, pension wealth and other financial wealth. As such, the median household in Belgium owns 12 000 euro of liquid assets, at least 47 times more than a lowest-decile household and at least 15 times less than a highest-decile household (see the top left panel of Graph 1). In the euro area as a whole, the median household has 7 000 euro in liquid assets, at least 79 times more than a lowest-decile household and at least 9 times less than a top-decile household (see the bottom left panel of Graph 1).

Liquid financial assets are not equally distributed between mortgage-indebted households and households without mortgage debt. Moreover, liquid assets are distributed more equally among mortgage-indebted households than among the other households in Belgium (see the bottom left panel of Graph 1). This reflects the high values of not-quoted private business wealth that some wealthy households hold. In the euro area, mortgage-indebted households hold more liquid financial assets throughout the whole distribution (see the bottom right panel of Graph 1).

Distribution of financial assets between mortgaged-indebted and other households

Table 1

	Share in the population (%)	Share in financial assets (%)	Share in liquid assets (%)	Median financial assets (euro)	Median liquid assets (euro)
Belgium (69.7% homeowners)					
Households with mortgage debt	30,5%	25,5%	21,9%	36 000	14 000
Households without mortgage debt	69,5%	74,7%	78,3%	22 000	11 000
Euro area (60.1% homeowners)					
Households with mortgage debt	23,1%	31,7%	27,5%	18 000	10 000
Households without mortgage debt	76,9%	69,2%	72,6%	10 000	6 000

Source: HFCS.

[1] A household's liquid assets are composed of its money holdings in deposits, mutual funds, bonds and listed shares.

Three out of ten Belgian households have mortgage debt, four out of ten households are outright homeowners without mortgage debt and another three out of ten households do not own any real estate. While the group of mortgage-indebted households represent 30.5 % of the population, they only hold 25.5 % of all the households' financial assets in Belgium and 21.9 % of all the liquid financial assets. The median mortgage-indebted household owns (14 000 euro) 36 000 euro of (liquid) financial assets, whereas the median household without mortgage debt owns (11 000 euro) 22 000 euro (see Table 1). In comparison, in the euro area as a whole, relatively fewer households (60.1 % of all households compared to 69.7 % in Belgium) are homeowners. In relation to this, fewer euro area households carry mortgage debt: 23.1 % (or 38.5 % of all homeowners) compared to 30.5 % (or 43.8 % of all homeowners) in Belgium. Belgian households possess more financial wealth than their euro area counterparts. This holds for liquid as well as for total financial assets and for mortgage-indebted households as well as for households without mortgage debt. However, in the euro area these (liquid) financial assets are relatively more concentrated with mortgage-indebted households: their share in total financial assets (31.7 %) and in total liquid assets (27.5 %) is greater than their share in the population (23.1 %). This is the opposite in Belgium, where mortgage-indebted households hold a smaller share of (liquid) financial assets compared to their share in the population (see Table 1).

Summing up: although in Belgium they own less financial assets on average, a typical (median) mortgage-indebted household owns more than a typical (median) household without mortgage debt. This is because financial assets are more equally distributed within the group of mortgage-indebted households than within the other group[2]. However, that does not imply that all mortgage-indebted Belgian households have sufficient financial assets to cover their debt. Compared to the euro area, they hold a smaller share of total financial wealth in the economy. The next section digs deeper into the distribution of debt and financial assets between mortgage-indebted households.

[2] The other group contains (relatively more wealthy) outright homeowners as well as (relatively less wealthy) households that do not own any real estate.

3. Mortgage debt and liquid financial assets

Households can default on their mortgage loan if their flow of income is not sufficient to pay the (monthly) debt-service payments and if their (liquid) financial assets are not sufficient to finance the service payments or to pay back (part of) the outstanding debt, in case income sources would suddenly run dry. If, in case of default, the asset that covers the mortgage loan is not worth significantly more than the outstanding debt, the lending bank faces a risk of loss. We therefore look at debt ratios that relate mortgage debt (payments) to income, liquid financial assets and real-estate value:

- The mortgage-debt-to-income ratio (MDtI) divides the outstanding amount of a household's mortgage debt by the flow of its yearly gross income. This ratio indicates the number of years of total income a household would need to repay its outstanding mortgage debt.
- The mortgage-debt-service-to-income ratio (MDStI) divides the flow of monthly mortgage-debt service payments by the flow of monthly gross household income. This ratio indicates which part of its income a household needs to periodically service its mortgage debt.
- The liquid-assets-to-mortgage-debt-service ratio (LAtMDS) divides the stock of a household's liquid assets by the flow of monthly mortgage-debt service payments. This ratio indicates how many months a household could service its mortgage debt out of liquid assets, e.g. when income suddenly falls away.
- The liquid-assets-to-mortgage-debt ratio (LAtMD) divides the stock of a household's liquid assets by the outstanding amount of mortgage debt. This ratio indicates the part (percentage) of a household's outstanding mortgage debt that could immediately be repaid with liquid assets.
- The mortgage-loan-to-value ratio (MLtV) divides a household's outstanding mortgage debt by the (self-assessed) value of its real estate.

If debt ratios related to income or to liquid financial assets exceed critical values, households could run a greater risk to default on their mortgage debt (see also Du Caju et al., 2016 and De Backer et al., 2015). We look at the share of mortgage-indebted households that face mortgage-debt ratios exceeding certain values, at the share of total outstanding mortgage debt in Belgium that these households represent and the part of that share that is high compared to the value of the underlying real estate covering the debt (see Table 2). In general, 20.2 % of Belgian households' outstanding mortgage debt consists of loans with a mortgage-loan-to-value ratio above 80 %. By not only looking at the number of households at risk but also at the amount of outstanding debt they represent, we get a clearer picture of the risks for the financial sector.

Looking at the capacity to repay mortgage debt out of current income, according to the data of the 2010 wave of the HFCS, 30.5 % of Belgian households have a mortgage debt. In the group of mortgage-indebted households, 12.8% spend more than 30 % of their income to pay their periodical debt service. Together they hold 24.9 % of all outstanding household mortgage debt in Belgium, of which 6.7 ppt is debt with an MLtV ratio above 80 %. Moreover, 6.3 % of mortgage-indebted households pay more than 50 % of their income for debt service. They represent 12.7 % of total outstanding mortgage debt, of which 3.0 ppt with an MLtV ratio above 80 %. Similar pictures can be made looking at other threshold values of the MDStI ratio or alternatively looking at different values of the mortgage-debt-to-income ratio MDtI.

With respect to the coverage of mortgage debt by liquid financial assets, it appears that 26.3 % of mortgage-indebted households do not own enough liquid assets to pay more than six months debt service on their mortgage. This group of households together holds 30.8 % of total outstanding household mortgage debt in Belgium, of which 7.7 ppt with an MLtV ratio above 80 %. A 54.2 % of this total debt is held by households that could pay less than two years of mortgage-debt service out of their liquid financial assets. Looked at differently, 35.4 % of mortgage-indebted households could repay less than 10 % of their mortgage debt out of liquid financial assets. Together they hold 46.0 % of the total amount of outstanding mortgage debt.

Households' mortgage debt at risk in Belgium

Table 2

	Share in the population of mortgage-indebted households (%)	Share in total outstanding mortgage debt (%)	of which is mortgage debt with MLtV>80% (ppt)	Cumulative share in the population of mortgage-indebted households (%)	Cumulative share in total outstanding mortgage debt (%)	of which is mortgage debt with MLtV>80% (ppt)
Mortgage-debt-to-income ratio (MDtI)[1]:						
more than 5 years	5,9%	18,3%	6,8%	5,9%	18,3%	6,8%
between 4 and 5 years	5,7%	8,8%	4,5%	11,7%	27,2%	11,3%
between 3 and 4 years	7,3%	8,9%	3,4%	18,9%	36,1%	14,7%
between 2 and 3 years	13,3%	18,8%	2,2%	32,2%	54,9%	16,8%
2 years or less	67,8%	45,1%	3,4%	100,0%	100,0%	20,2%
Mortgage-debt-service-to-income ratio (MDStI)[2]:						
more than 50 %	6,3%	12,7%	3,0%	6,3%	12,7%	3,0%
between 40 and 50 %	2,0%	5,5%	0,9%	8,3%	18,2%	3,9%
between 30 and 40 %	4,5%	6,7%	2,9%	12,8%	24,9%	6,7%
between 20 and 30 %	19,3%	23,9%	8,5%	32,1%	48,9%	15,2%
20 % or less	67,9%	51,1%	5,0%	100,0%	100,0%	20,2%
Liquid-assets-to-mortgage-debt-service ratio (LAtMDS)[3]:						
less than 2 months	14,5%	16,0%	5,9%	14,5%	16,0%	5,9%
between 2 and 6 months	11,8%	14,7%	1,7%	26,3%	30,8%	7,7%
between 6 and 12 months	12,5%	12,4%	3,3%	38,8%	43,2%	10,9%
between 12 and 24 months	15,4%	16,2%	3,3%	54,2%	59,4%	14,2%
24 months or more	45,8%	40,6%	6,1%	100,0%	100,0%	20,2%
Liquid-assets-to-mortgage-debt ratio (LAtMD)[4]:						
less than 5 %	25,7%	35,1%	9,9%	25,7%	35,1%	9,9%
between 5 and 10 %	9,7%	11,0%	2,1%	35,4%	46,0%	12,0%
between 10 and 25 %	18,6%	19,8%	5,9%	54,0%	65,8%	17,8%
between 25 and 50 %	10,5%	12,8%	1,3%	64,5%	78,6%	19,1%
50 % or more	35,5%	21,4%	1,0%	100,0%	100,0%	20,2%
Mortgage-loan-to-value ratio (MLtV)[5]:						
more than 90 %	3,6%	10,0%	10,0%	3,6%	10,0%	10,0%
between 80 and 90 %	6,6%	10,2%	10,2%	10,2%	20,2%	20,2%
between 70 and 80 %	3,8%	8,2%	0,0%	14,0%	28,4%	20,2%
between 60 and 70 %	5,1%	8,5%	0,0%	19,1%	36,8%	20,2%
60 % or less	80,9%	63,2%	0,0%	100,0%	100,0%	20,2%

Source: HFCS.

1 The outstanding amount of a household's mortgage debt divided by the flow of its yearly gross income. Indicates the number of years of total income a household would need to repay its outstanding mortgage debt.

2 The flow of monthly mortgage-debt service payments divided by the flow of monthly gross household income. Indicates which part of its income a household needs to periodically service its mortgage debt.

3 The stock of a household's liquid assets (the sum of a household's money holdings in deposits, mutual funds, bonds and listed shares) divided by the flow of monthly mortgage debt service payments. Indicates how many months a household could service its mortgage debt out of liquid assets.

4 The stock of a household's liquid assets divided by the outstanding amount of mortgage debt. Indicates the part (percentage) of a household's outstanding mortgage debt that could immediately be repaid with liquid assets.

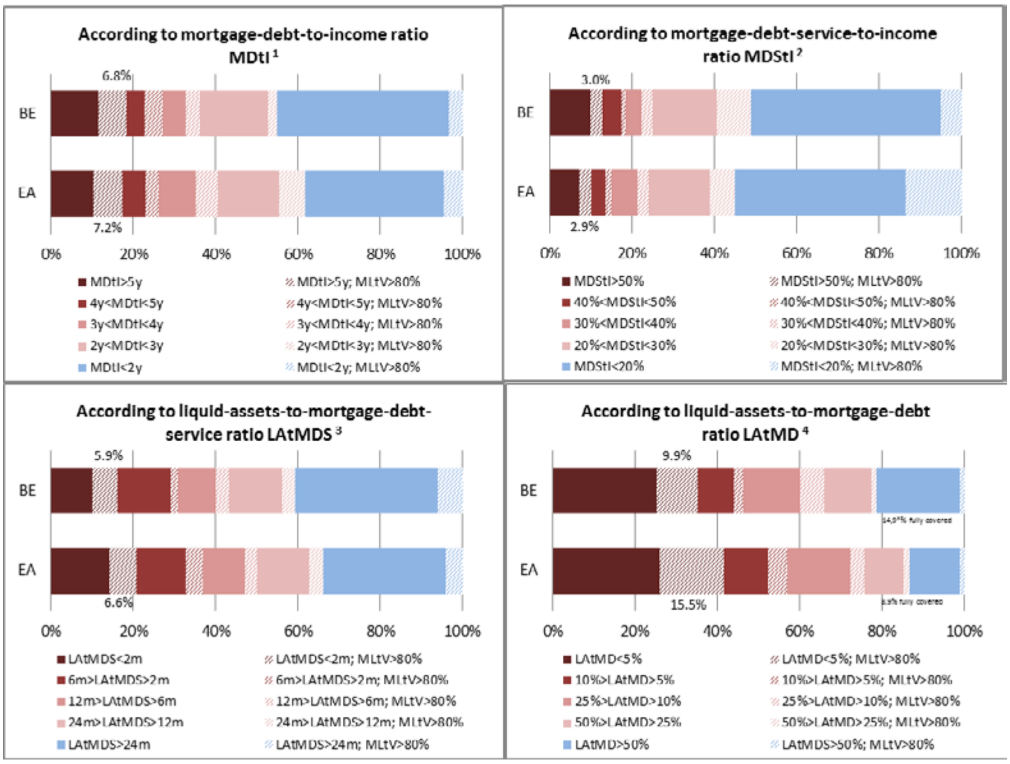
5 A household's outstanding mortgage debt divided by the (self-assessed) value of its real estate.

All in all, the share of total outstanding mortgage debt that is carried by households with a high mortgage-debt-service-to-income ratio or by households with only limited liquid financial assets to cover their mortgage debt in Belgium is comparable to that share in the euro area (see Graph 2). In the euro area as a whole, 27.2 % (12.9 %) of all households' mortgage debt is in the hands of households that need more than 30 % (50 %) for their periodical debt repayments.

As to the coverage of mortgage debt by liquid financial assets, 34.0 % of all households' mortgage debt in the euro area is held by households that could not serve more than six months of debt payments; 53.5 % of mortgage debt lies with households owning liquid financial assets worth less than 10 % of their outstanding mortgage debt.

Distribution of mortgage debt according to risk

(Percentages of outstanding mortgage debt) Graph 2



Source: HFCS.

1 The outstanding amount of a household's mortgage debt divided by the flow of its yearly gross income. Indicates the number of years of total income a household would need to repay its outstanding mortgage debt.

2 The flow of monthly mortgage-debt service payments divided by the flow of monthly gross household income. Indicates which part of its income a household needs to periodically service its mortgage debt.

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4 The stock of a household's liquid assets divided by the outstanding amount of mortgage debt. Indicates the part (percentage) of a household's outstanding mortgage debt that could immediately be repaid with liquid assets.

5 A household's outstanding mortgage debt divided by the (self-assessed) value of its real estate.

Combining the 80 %-threshold of mortgage-loan-to-value with the most problematic thresholds for the other debt ratios, we get the following picture. In Belgium, 3.0 % of mortgage debt is held by households that pay more than 50 % of their income to debt service and have a MLtV above 80 %, similar to 2.9 % of households in the euro area. Comparing outstanding debt with income, for 6.8 % of Belgian households the outstanding mortgage debt ways more than five years of income and the MLtV is above 80 %, compared to 7.2 % of households in the euro area. Turning to the liquid-assets-related indicators, 5.9 % of Belgian households have a MLtV above 80 % and not enough liquid assets to serve more than two months of debt payments, against 6.6 % of all households in the euro area. Moreover, for 9.9 % of Belgian households the mortgage debt represents more than 80 % of the value of their real estate and is covered for less than 5 % by liquid financial assets, compared to 15.5 % of households in the euro area. On the other side of the picture, 14.9 % of total outstanding mortgage debt in Belgium is fully covered by households' liquid assets, against 8.9 % in the euro area.

All in all, the results confirm the debt vulnerability of Belgian households to severe income loss, as could be the case when an unemployment shock hits the economy, which is documented by De Backer et al. (2015), Du Caju et al. (2014) and by Du Caju et al. (2016).

Therefore, for a significant part of the population, financial wealth does not guarantee the sustainability of mortgage debt in the case of income loss. As such, the share of outstanding mortgage debt in Belgium that could be regarded as being at risk because of low coverage by households' liquid financial assets (or equivalently by household income or by real-estate value) is broadly comparable to that share in the euro area.

4. Households with mortgage-debt at risk in Belgium

To see how many and which households are homeowners carrying mortgage debt at risk, we divide households according to the labour status of the reference person into working (employee or independent), unemployed and inactive (retired and other inactive)[3], and into income and age categories.

We can then identify "vulnerable" households based on debt ratios exceeding a certain threshold. As an example, we look at mortgage-indebted homeowners with a mortgage-debt-to-income ratio (MDtI) of more than 3 years, mortgage-debt-service-to-income ratio (MDStI) above 30 %, a liquid-assets-to-mortgage-debt-service ratio (LAtMDS) less than 6 months and a liquid-assets-to-mortgage-debt ratio (LAtMD) below 10 %.

4.1. Households at risk according to labour status

According to the HFCS, 69.7 % of all households in Belgium are homeowners. Among the households with a working reference person, 71.3 % are homeowners. Also, 33.5 % of the unemployed and 74.7 % of the inactive households own a home. The vast majority of inactive (mostly retired) households are outright homeowners with no mortgage, while most working households have mortgage debt (see Graph 3).

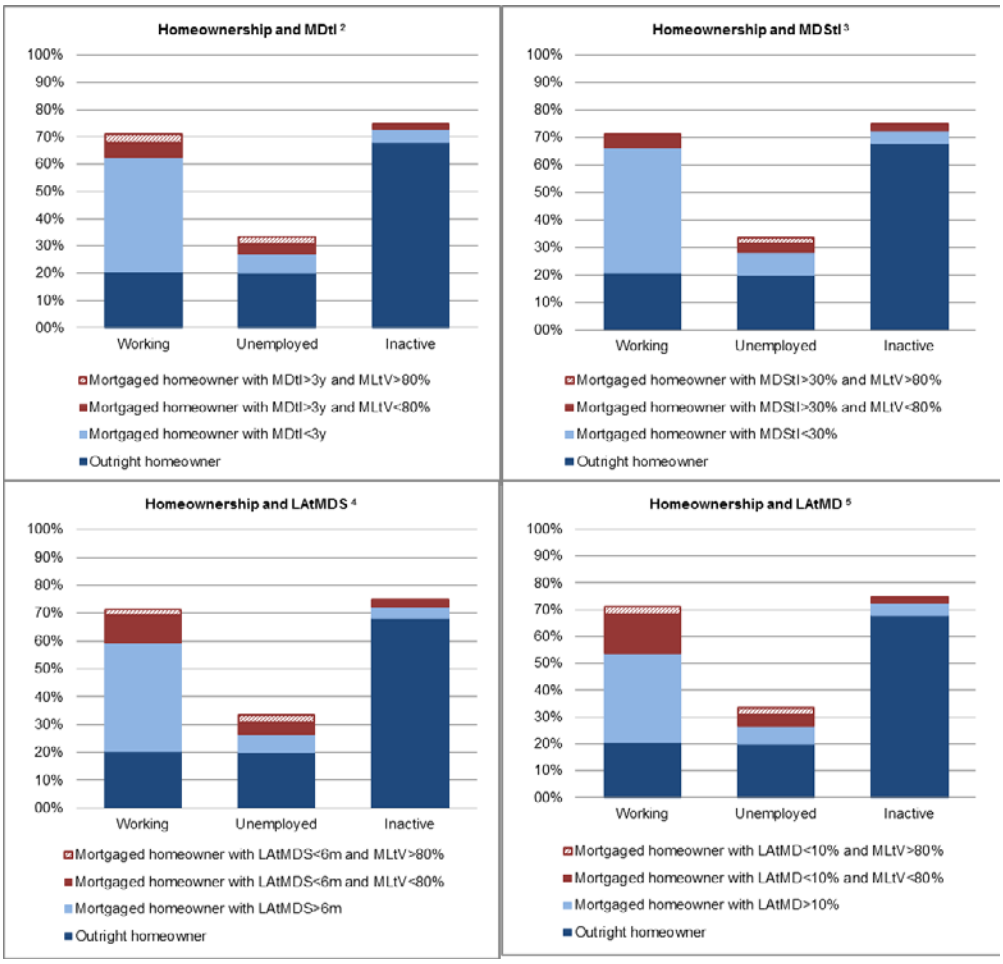
Parts of the mortgage-indebted households have "problematic" debt ratios in the way defined above. This part is bigger among the unemployed.

Looking at the income-related debt ratios, it appears that 9.3 % of mortgage-indebted working households spend more than 30 % of their income on mortgage-debt service (one out of six of them has a MLtV ratio above 80 %), while 37.0 % of the unemployed and 29.9 % of the inactive do so. Further, it appears that 17.2 % of mortgage-indebted working households have an outstanding mortgage debt of more than three years of gross household income; almost two thirds of them have an MLtV above 80 %.

The other two indicators, relating mortgage debt (service) to liquid financial assets, show broadly similar shares of vulnerable households for the unemployed and the inactive. However, these two indicators show a bigger vulnerable share for the working households, compared to the income-related indicator: 23.7 % of mortgage-indebted working households could pay less than six months debt service out of liquid assets; 34.2 % of mortgage-indebted working households could not repay more than 10 % of their outstanding mortgage debt with liquid assets; one out of five households in these groups has a mortgage-loan-to-value ratio of more than 80 %. This reflects the fact that working households are still in the phase of accumulating financial assets, but it also shows their vulnerability in case of severe income loss.

[3] For a more in-depth analysis of the distribution of debt in general across households in euro area countries, see Bover et al. (2016).

Homeownership and mortgage-debt burden by labour status of Belgian households[1]
Graph 3



Source: HFCS.

1 Households are categorised according to the labour status of the reference person into working (employee or independent), unemployed and inactive (retired and other inactive).

2 The outstanding amount of a household's mortgage debt divided by the flow of its yearly gross income. Indicates the number of years of total income a household would need to repay its outstanding mortgage debt.

3 The flow of monthly mortgage-debt service payments divided by the flow of monthly gross household income. Indicates which part of its income a household needs to periodically service its mortgage debt.

4 The stock of a household's liquid assets (the sum of a household's money holdings in deposits, mutual funds, bonds and listed shares) divided by the flow of monthly mortgage debt service payments. Indicates how many months a household could service its mortgage debt out of liquid assets.

5 The stock of a household's liquid assets divided by the outstanding amount of mortgage debt. Indicates the part (percentage) of a household's outstanding mortgage debt that could immediately be repaid with liquid assets.

This analysis shows that, although only few working households have problems servicing their debt out of their income, a significant part of these households lack the liquid financial resources to cope with severe income loss. If they lose their job, they could get in difficulty to service the mortgage debt on their home.

4.2. Mortgage debt at risk according to household income and age

Turning to income and age groups, based on total household income and on the age of the reference person in the household, the HFCS data show that most of the outstanding mortgage debt in Belgium is held by middle-aged high-income households. This reflects the life cycle and paying capacity. Broadly the same households also hold most of the debt at risk that is only moderately covered by liquid financial assets. However, their share in this debt at risk is smaller than their share in total debt. It is the young and low-income households who hold relatively larger shares in mortgage debt at risk, compared to their shares in total mortgage debt (see Graph 4). This analysis shows that young low-income households are relatively more at risk when an unemployment shock hits the economy.

Distribution of mortgage debt (at risk) between income and age groups[1] in Belgium

Graph 4

Concentration (%) of outstanding mortgage debt

	-34	35-44	45-54	55-64	65+	
I	1.7%	1.1%	0.9%	0.6%	0.3%	4.6%
II	1.3%	0.9%	1.5%	1.0%	0.5%	5.2%
III	6.6%	4.5%	3.7%	1.4%	0.3%	16.5%
IV	8.0%	10.8%	6.5%	1.4%	0.4%	27.1%
V	6.9%	22.8%	13.3%	3.7%	0.0%	46.7%
	24.4%	40.0%	25.9%	8.1%	1.6%	100.0%

Concentration (%) of outstanding mortgage debt with MLtV[2] > 80%

	-34	35-44	45-54	55-64	65+	
I	1.2%	0.5%	0.9%	0.0%	0.0%	2.6%
II	3.3%	2.5%	0.0%	0.0%	0.9%	6.6%
III	15.8%	2.2%	3.9%	2.2%	0.3%	24.4%
IV	12.5%	8.0%	6.5%	0.0%	0.3%	27.3%
V	12.1%	18.5%	7.0%	1.5%	0.0%	39.1%
	44.9%	31.7%	18.3%	3.6%	1.5%	100.0%

Concentration (%) of outstanding mortgage debt with MDtI[3] > 3 years

	-34	35-44	45-54	55-64	65+	
I	4.6%	2.8%	2.1%	1.6%	0.6%	11.7%
II	3.1%	2.3%	3.2%	1.5%	1.1%	11.3%
III	15.7%	4.9%	5.1%	1.9%	0.2%	27.8%
IV	9.8%	8.2%	6.2%	0.9%	1.0%	26.0%
V	1.9%	17.8%	3.6%	0.0%	0.0%	23.2%
	35.1%	36.0%	20.2%	5.9%	2.8%	100.0%

Concentration (%) of outstanding mortgage debt with MDStI[4] > 30%

	-34	35-44	45-54	55-64	65+	
I	6.8%	4.0%	3.5%	2.3%	0.6%	17.2%
II	3.4%	2.9%	4.3%	2.9%	1.1%	14.6%
III	13.1%	2.8%	5.2%	0.2%	0.1%	21.4%
IV	7.0%	6.6%	7.1%	0.2%	0.1%	20.9%
V	0.0%	21.1%	4.7%	0.0%	0.0%	25.8%
	30.3%	37.4%	24.8%	5.5%	2.0%	100.0%

Concentration (%) of outstanding mortgage debt with LAtMDS[5] < 6 months

	-34	35-44	45-54	55-64	65+	
I	3.1%	1.0%	1.4%	1.2%	0.6%	7.3%
II	2.0%	1.8%	2.6%	1.3%	1.1%	8.8%
III	8.2%	6.9%	4.0%	1.3%	0.3%	20.8%
IV	9.2%	12.7%	6.8%	0.9%	0.0%	29.6%
V	6.6%	17.0%	7.2%	2.8%	0.0%	33.5%
	29.1%	39.5%	21.9%	7.5%	2.0%	100.0%

Concentration (%) of outstanding mortgage debt with LAMtD[6] < 10%

	-34	35-44	45-54	55-64	65+	
I	4.2%	1.5%	2.0%	1.8%	0.9%	10.4%
II	2.8%	2.6%	3.8%	1.9%	0.3%	11.4%
III	6.4%	6.1%	4.9%	2.1%	0.4%	19.8%
IV	6.4%	13.5%	9.0%	1.4%	0.0%	30.3%
V	6.0%	15.3%	5.4%	1.3%	0.0%	28.1%
	25.8%	39.0%	25.1%	8.5%	1.7%	100.0%

Source: HFCS.

1 Households are categorised according to the age of the reference person.

2 A household's outstanding mortgage debt divided by the (self-assessed) value of its real estate.

3 The outstanding amount of a household's mortgage debt divided by the flow of its yearly gross income. Indicates the number of years of total income a household would need to repay its outstanding mortgage debt.

4 The flow of monthly mortgage-debt service payments divided by the flow of monthly gross household income. Indicates which part of its income a household needs to periodically service its mortgage debt.

5 The stock of a household's liquid assets (the sum of a household's money holdings in deposits, mutual funds, bonds and listed shares) divided by the flow of monthly mortgage debt service payments. Indicates how many months a household could service its mortgage debt out of liquid assets.

6 The stock of a household's liquid assets divided by the outstanding amount of mortgage debt. Indicates the part (percentage) of a household's outstanding mortgage debt that could immediately be repaid with liquid assets.

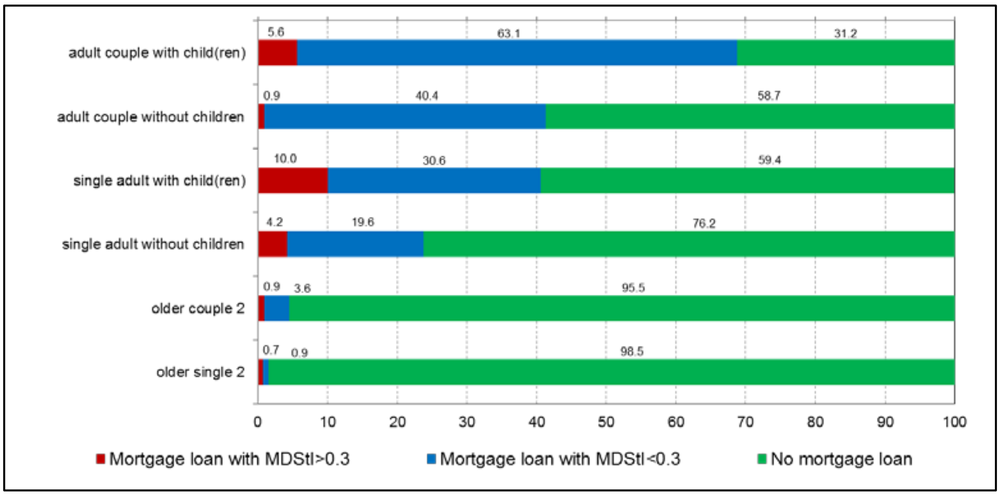
4.3. Households at risk according to family status

Mortgage debt is not equally easy to shoulder for all types of households. Here, too, HFCS findings prove enlightening, as households can be divided into families with and without children. This distinction to a large extent determines housing requirements and spending patterns. Division by age is another possibility – i.e. whether or not the adult(s) in the household have or have not reached the age of 65, as this influences income perspectives and savings behaviour, and whether or not they are a couple, which helps to determine their potential financial resources. Six groups of households emerge: adult couples with children, adult couples without children, lone parent families, single-person households, older couples (at least one of whom is 65 years or older) and older people living alone. Debt positions can be described for each of these types of family: no mortgage loan, a mortgage loan at an MDStI of < 0.3 or a mortgage loan at an MDStI of > 0.3.

Breaking down households by household type and by debt position is highly revealing, allowing identification of potential pockets of risk in the mortgage market in the shape of steep MDStI ratios, particularly for lone parent families and to a lesser extent also single-person households. The survey shows that one in ten lone parent families need over 30% of their household income to pay their mortgage, i.e. one in four households with this level of debt in this category.

Mortgage debt and MDStI ratio[1], by household type

(Percentages of the total number of households) Graph 5



Source: HFCS.

1 The flow of monthly mortgage-debt service payments divided by the flow of monthly gross household income. Indicates which part of its income a household needs to periodically service its mortgage debt.

2 At least one person is over the age of 65.

The illustrations above are based on simple bivariate descriptions. More (multivariate) econometric evidence on socio-demographic (age, income, labour or family status) profiles of household indebtedness (holding, amount, interest rate), related to institutions and credit market characteristics, can be found in Bover et al. (2016). Du Caju et al. (2016) provide (multivariate) econometric evidence on the role of labour status and demographics, as well as on the impact of unemployment shocks on (changes in) household over-indebtedness. In relation to this, Du Caju et al. (2014) show that loan defaults and payment arrears in Belgium are correlated with the unemployment rate, especially for the youngest borrowers.

Main findings

In Belgium, mortgage-indebted households on average hold less (liquid) financial assets than households without mortgage debt. Of the total amount of outstanding mortgage debt of Belgian households, almost a third (29.8 %) is held by households that could service their mortgage debt out of liquid financial assets for less than six months. Almost half (44.6 %) is held by households owning liquid financial assets that are worth less than 10 % of their outstanding mortgage debt. The share of outstanding mortgage debt in Belgium that is at risk because of low coverage by households' liquid financial assets is not much lower than that share in the euro area. This implies that pockets of risk exist in the Belgian mortgage market, due to households facing high (income or asset related) debt ratios, and that these risky pockets are similar to the ones in the euro area.

Although only few working households have problems servicing their debt out of their income, a significant part of them lacks the financial resources to cope with severe income loss. Most of the debt at risk (and of the debt in general) in Belgium is held by middle-aged high-income households, but young low-income households, and especially single parents, are relatively more at risk when an unemployment shock hits the economy.

This analysis puts into perspective the general idea that high financial wealth, as registered by macroeconomic financial accounts, contributes to the sustainability of the mortgage indebtedness of Belgian households. It implies that, because financial wealth is (very) unequally distributed, a severe unemployment shock with income loss could hurt many mortgage-indebted households involving a significant part of total outstanding mortgage debt in Belgium.

Conclusion regarding data needs for macroprudential policy

Distribution matters for macroprudential policy and micro data are needed to identify pockets of risk in the mortgage market, thus complementing standard (macro) indicators. Survey data like the Household Finance and Consumption Survey (HFCS) can shed a light on these pockets of risk, because they collect debt, real assets, financial assets and income, for the same individual observation unit (i.e. the household).

However, survey data take time to collect and process. Therefore, the Household Finance and Consumption Network (HFCN) tries to shorten the time gap between collection and publication of data, and to better synchronise the collection in different countries. Moreover, survey data are based on a sample of households and are never exhaustive. Their results can therefore differ from macro statistics. In this field, an Expert Group on Linking Macro and Micro Data (EG-LMM) explores the possibilities for improvement.

References

Bover O., J.M. Casado, S. Costa, Ph. Du Caju, Y. McCarthy, E. Sierminska, P. Tzamourani, E. Villanueva and T. Zavadil (2016), "The distribution of debt across euro area countries : the role of individual characteristics, institutions and credit conditions", *International Journal of Central Banking,* 12(2), pp. 71-128.

De Backer B., Ph. Du Caju, M. Emiris and Ch. Van Nieuwenhuyze (2015), "Macroeconomic determinants of non-performing loans", NBB, *Economic Review*, December, pp. 47-67.

Du Caju Ph. (2016), "The distribution of household wealth in Belgium: initial findings of the second wave of the Household Finance and Consumption Survey (HFCS)", NBB, *Economic Review*, September, pp. 27-43.

Du Caju Ph. (2013), "Structure and distribution of household wealth: An analysis based on the HFCS", NBB, *Economic Review*, September, pp. 41-63.

Du Caju Ph., Th. Roelandt, Ch. Van Nieuwenhuyze and M.-D. Zachary (2014), "Household indebtedness: evolution and distribution", NBB, *Economic Review*, September, pp. 65-85.

Du Caju Ph., F. Rycx and I. Tojerow (2016), *Unemployment risk and over-indebtedness: a microeconometric perspective,* ECB, Working Paper 1908.

Household Finance and Consumption Network (2013a), *The Eurosystem Finance and Consumption Survey: Methodological Report for the First Wave*, ECB Statistical Paper Series 1, April.

Household Finance and Consumption Network (2013b), *The Eurosystem Finance and Consumption Survey: Results from the First Wave*, ECB Statistical Paper Series 2, April.

Household Finance and Consumption Network (2016a), *The Eurosystem Finance and Consumption Survey: Methodological Report for the Second Wave*, ECB Statistical Paper Series 17, April.

Household Finance and Consumption Network (2016b), *The Eurosystem Finance and Consumption Survey: Results from the Second Wave*, ECB Statistical Paper Series 18, December.

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Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

IFC-National Bank of Belgium Workshop on "*Data needs and Statistics compilation for macroprudential analysis*"

Brussels, Belgium, 18-19 May 2017

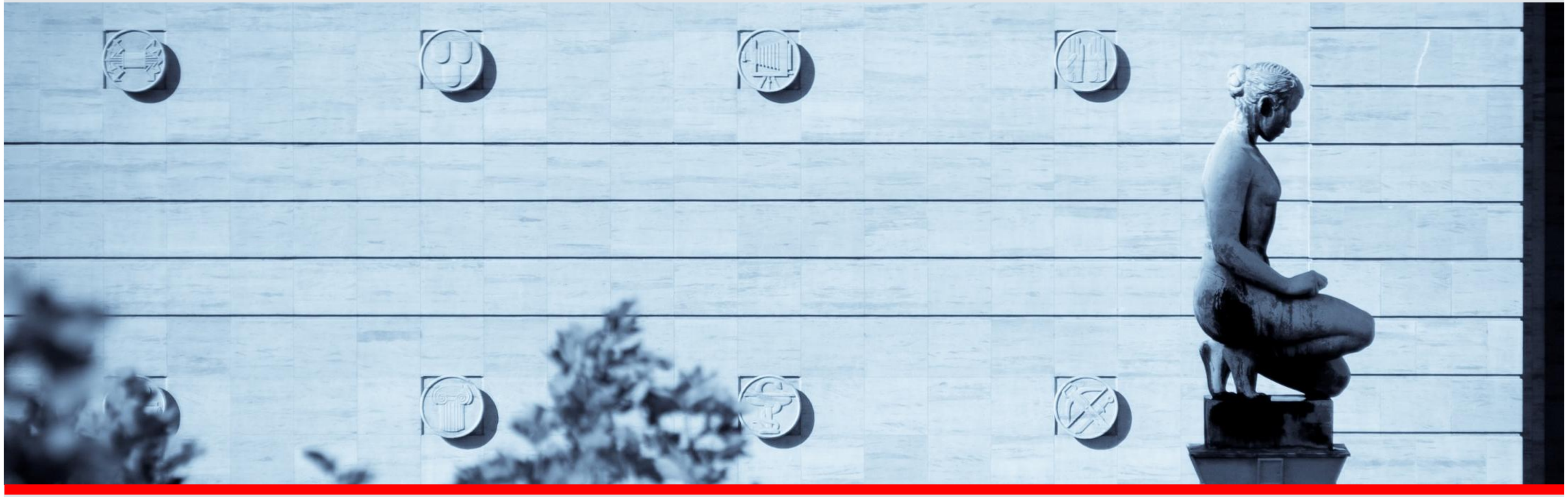
Pockets of risk in the Belgian mortgage market: Evidence from the Household Finance and Consumption Survey[1]

Philip Du Caju,
National Bank of Belgium

[1] This paper 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.

Pockets of risk in the Belgian mortgage market:
Evidence from the Household Finance and Consumption Survey

IFC/NBB Workshop, 18-19 May 2017



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Eurosystem

This presentation

- Complements (macro) indicators with information from micro survey data (Household Finance and Consumption Survey: HFCS),

  to identify pockets of risk in the Belgian mortgage market:

  - takes into account distributional aspects of debt and assets, with a special focus on the coverage of households' mortgage debt by (liquid) financial assets;
  - identifies the share of outstanding mortgage debt that is possibly at risk,

    and the parts of the population most affected,

    on the basis of income and assets-related debt indicators.

- Finds that:

  - some groups of households have problems servicing their debt out of their income and some lack the financial resources to cope with income loss;
  - households' financial wealth is (very) unequally distributed,

    and covers their outstanding mortgage debt only to a limited extent;
  - a severe unemployment shock could hurt many mortgage-indebted households, involving a significant part of total outstanding mortgage debt in Belgium;
  - survey data can complement macro data (but still room for improvement).

The Household Finance and Consumption Survey (HFCS)

- Harmonised survey covering assets (financial and real), debt (secured and non-secured), income (labour and other), demographics, … at the household level.

- ESCB network now covering all euro area (and some other) countries, > 80 000 households (+/- 2 300 in Belgium).

- Data for two waves (2010 and 2014) are available, next waves ongoing or planned (2017, 2020, …), data collection and processing is time consuming.

- Income- and assets-related debt ratios at the time of the interview:
  - Mortgage-loan-to-value ratio (MLtV);
  - Mortgage-debt-(service-)to-income ratio (MDtI and MDStI);
  - Liquid-assets-to-mortgage-debt-(service) ratio (LAtMD and LAtMDS):

    divides the stock of a household’s liquid assets (incl. deposits, mutual funds, bonds and listed shares; excl. non-listed business and pension wealth) by the outstanding amount of mortgage debt, or by the flow of monthly mortgage-debt service payments, at the time of interview.

Pockets of risk in mortgage debt of Belgian households, due to high mortgage-debt-service-to-income MDStI[1] and mortgage-loan-to-value MLtV[2] ratios

	Share in the population of mortgage-indebted households (%)	**Share in total out-standing mortgage debt** (%)	***of which is mortgage debt with MLtV>80%*** *(ppt)*	**Cumulative share in the population of mortgage-indebted households** (%)	**Cumulative share in total out-standing mortgage debt** (%)	***of which is mortgage debt with MLtV>80%*** *(ppt)*
Mortgage-debt-service-to-income ratio (MDStI):						
more than 50 %	6.3	12.7	*3.0*	6.3	12.7	*3.0*
between 40 and 50 %	2.0	5.5	*0.9*	8.3	18.2	*3.9*
between 30 and 40 %	4.5	6.7	*2.9*	12.8	24.9	*6.7*
between 20 and 30 %	19.3	23.9	*8.5*	32.1	48.9	*15.2*
20 % or less	67.9	51.1	*5.0*	100.0	100.0	*20.2*

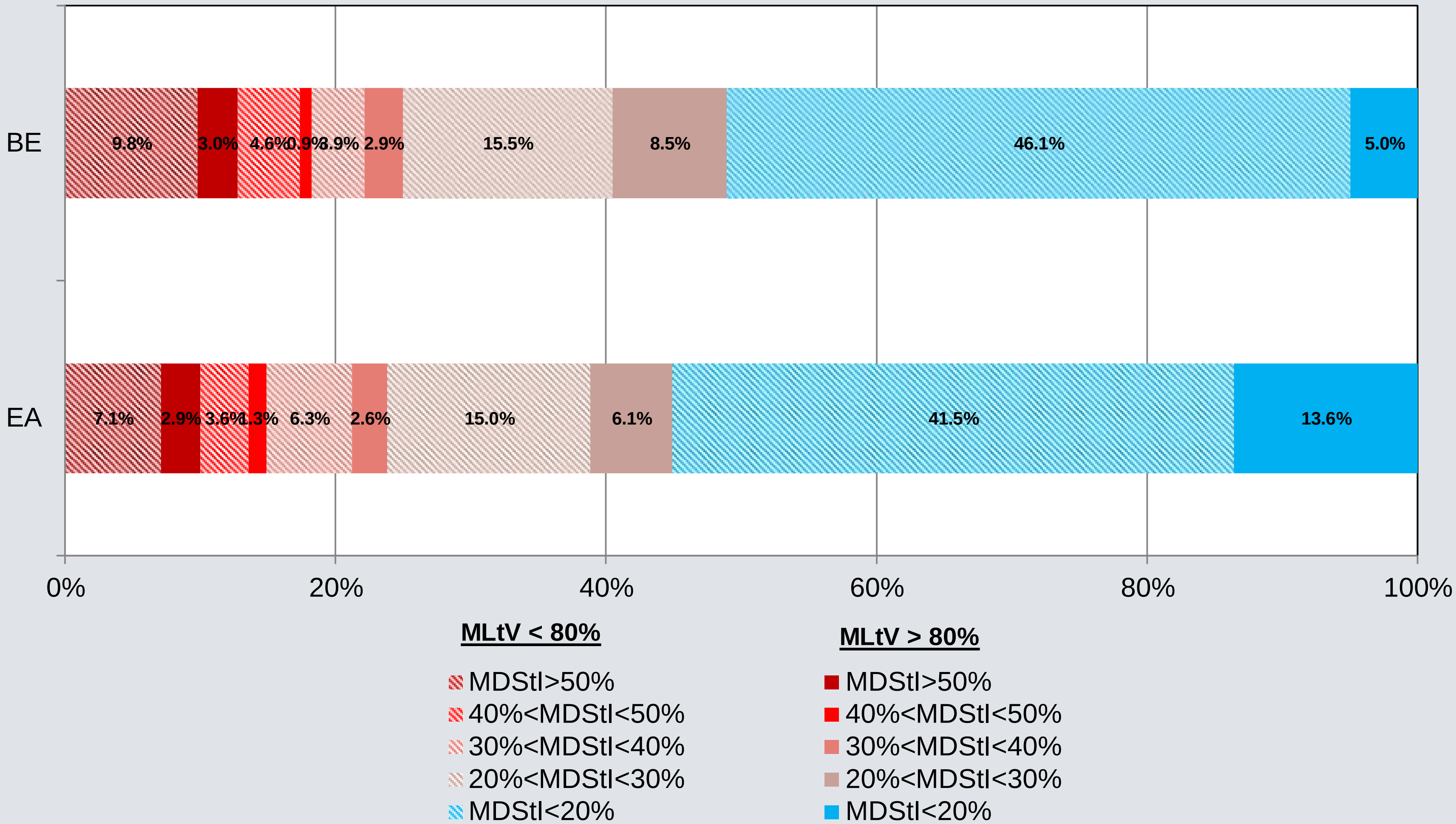
Source: HFCS.

[1] The flow of monthly mortgage-debt service payments divided by the flow of total monthly gross household income, at the time of interview. Indicates which part of its income a household needs to periodically service its mortgage debt.

[2] A household's outstanding mortgage debt divided by the (self-assessed) value of its real estate, at the time of interview.

Similar pockets of risk in the euro area

Percentages of outstanding mortgage debt in Belgium and in the euro area, according to mortgage-debt-service-to-income MDStI[1] and mortgage-loan-to-value MLtV[2] ratios



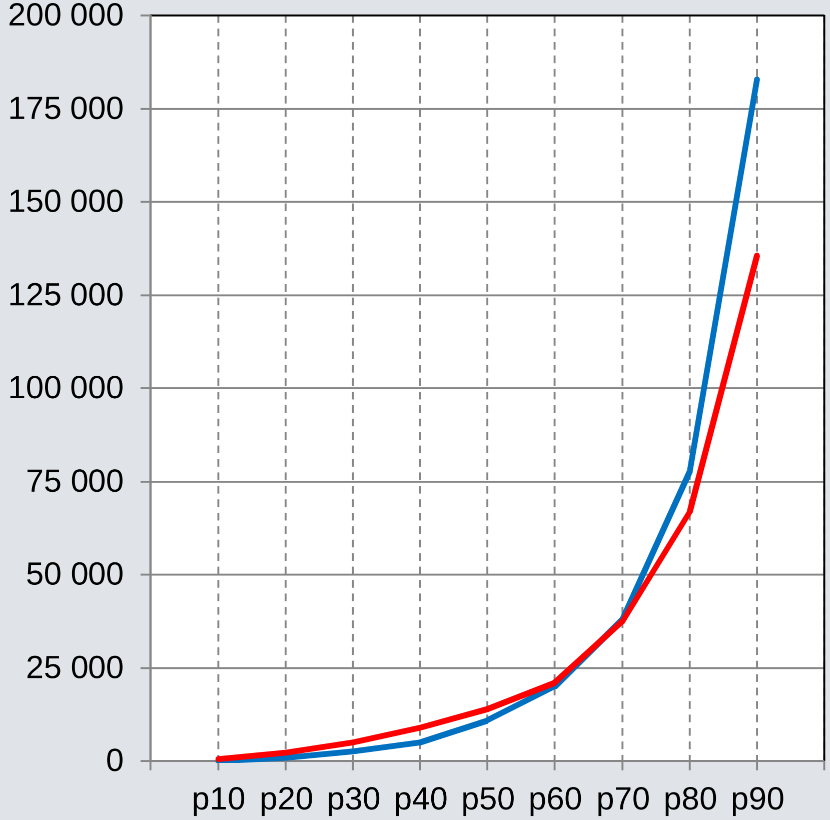
Source: HFCS.

[1] The flow of monthly mortgage-debt service payments divided by the flow of total monthly gross household income, at the time of interview. Indicates which part of its income a household needs to periodically service its mortgage debt.

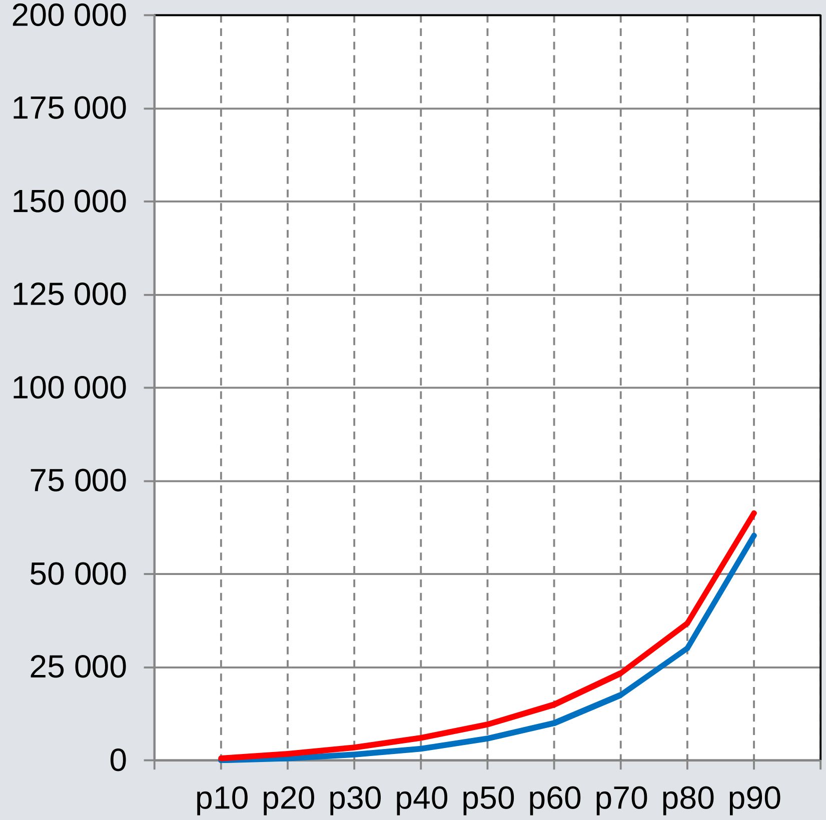
[2] A household's outstanding mortgage debt divided by the (self-assessed) value of its real estate, at the time of interview.

Households' liquid financial assets[1] are unequally distributed

Liquid assets in Belgium (>150 %GDP)
(percentiles in euro)



Liquid assets in the euro area (>100 %GDP)
(percentiles in euro)



Households without mortgage debt — Households with mortgage debt

Source: HFCS.
[1] A household's liquid assets are composed of its money holdings in deposits, mutual funds, bonds and listed shares.

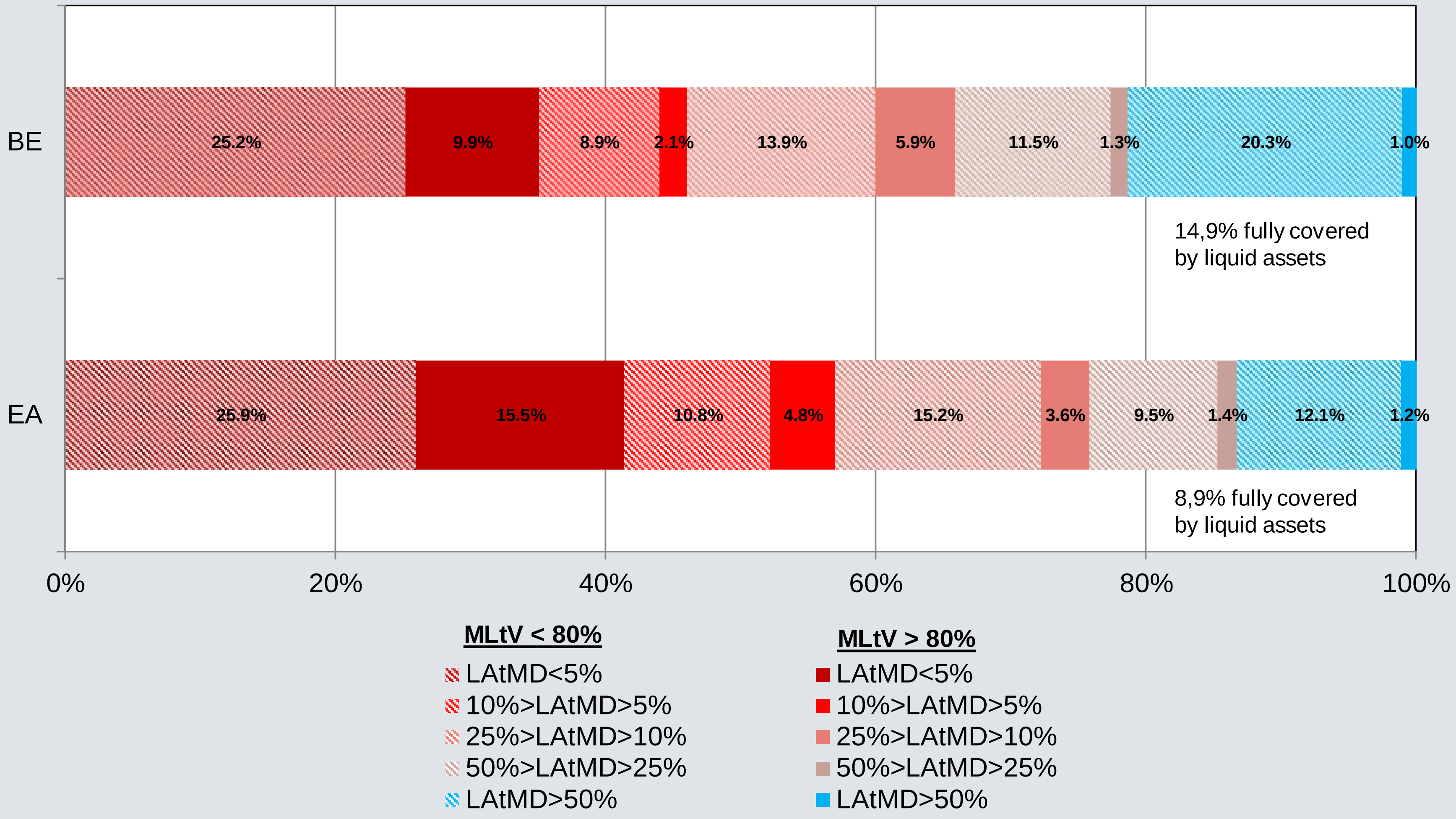
Asymmetric distribution of financial assets between mortgaged-indebted and other households

	Share in the population (%)	**Share in liquid[1] assets** (%)	**Median liquid assets** (euro)
Belgium (+/- 70% homeowners)			
Households with mortgage debt	30.5	21.9	14 000
Households without mortgage debt	69.5	78.3	11 000
Euro area (+/- 60% homeowners)			
Households with mortgage debt	23.1	27.5	10 000
Households without mortgage debt	76.9	72.6	6 000

Source: HFCS.
[1] A household's liquid assets are composed of its money holdings in deposits, mutual funds, bonds and listed shares.

Households' liquid assets cover part of their outstanding mortgage debt, but only to a limited extent

Percentages of outstanding mortgage debt in Belgium and in the euro area, according to liquid-assets-to-mortgage-debt LAtMD[1] and mortgage-loan-to-value MLtV[2] ratios



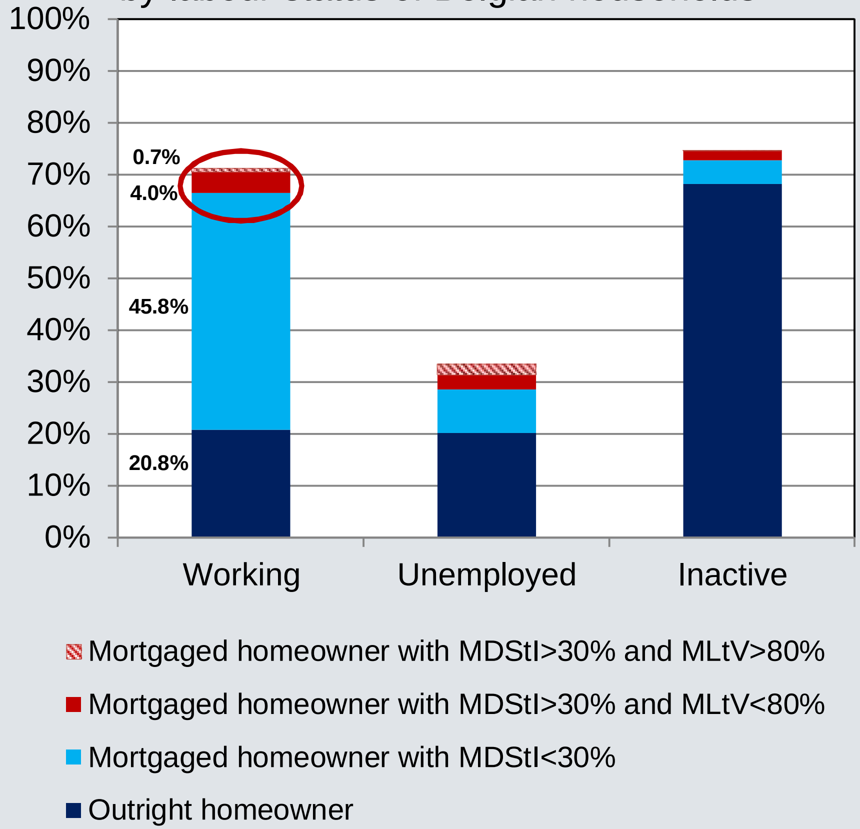
Source: HFCS.

[1] The stock of a household's liquid assets divided by the outstanding amount of mortgage debt, at the time of interview. Indicates the part (percentage) of a household's outstanding mortgage debt that could immediately be repaid with liquid assets.

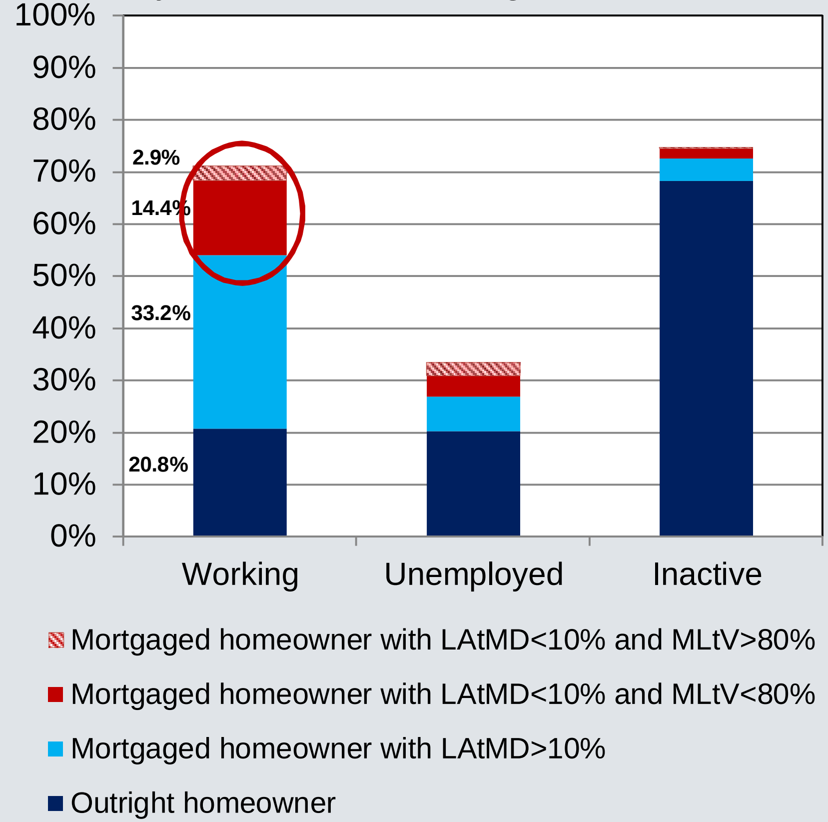
[2] A household's outstanding mortgage debt divided by the (self-assessed) value of its real estate, at the time of interview.

The unemployed[1] have more problems repaying their debt, but pockets of working households are also at risk

Homeownership and MDStl[2]
by labour status of Belgian households



Homeownership and LAtMD[3]
by labour status of Belgian households



Source: HFCS.

[1] Households are categorised according to the labour status of the reference person into working (employee or independent), unemployed and inactive (retired and other inactive).

[2] The flow of monthly mortgage-debt service payments divided by the flow of total monthly gross household income, at the time of interview. Indicates which part of its income a household needs to periodically service its mortgage debt.

[3] The stock of a household's liquid assets divided by the outstanding amount of mortgage debt, at the time of interview. Indicates the part (percentage) of a household's outstanding mortgage debt that could immediately be repaid with liquid assets.

Mortgage debt at risk is relatively concentrated with young and low-income households

Concentration (%) of mortgage debt according to households' income quintile and age group[1] in Belgium

Outstanding mortgage debt

	-34	35-44	45-54	55-64	65+	
I	1.7%	1.1%	0.9%	0.6%	0.3%	4.6%
II	1.3%	0.9%	1.5%	1.0%	0.5%	5.2%
III	6.6%	4.5%	3.7%	1.4%	0.3%	16.5%
IV	8.0%	10.8%	6.5%	1.4%	0.4%	27.1%
V	6.9%	22.8%	13.3%	3.7%	0.0%	46.7%
	24.4%	40.0%	25.9%	8.1%	1.6%	100.0%

Outstanding mortgage debt with **MDStI[2] > 30%**

	-34	35-44	45-54	55-64	65+	
I	6.8%	4.0%	3.5%	2.3%	0.6%	17.2%
II	3.4%	2.9%	4.3%	2.9%	1.1%	14.6%
III	13.1%	2.8%	5.2%	0.2%	0.1%	21.4%
IV	7.0%	6.6%	7.1%	0.2%	0.1%	20.9%
V	0.0%	21.1%	4.7%	0.0%	0.0%	25.8%
	30.3%	37.4%	24.8%	5.5%	2.0%	100.0%

Outstanding mortgage debt with **LAMtD[3] < 10%**

	-34	35-44	45-54	55-64	65+	
I	4.2%	1.5%	2.0%	1.8%	0.9%	10.4%
II	2.8%	2.6%	3.8%	1.9%	0.3%	11.4%
III	6.4%	6.1%	4.9%	2.1%	0.4%	19.8%
IV	6.4%	13.5%	9.0%	1.4%	0.0%	30.3%
V	6.0%	15.3%	5.4%	1.3%	0.0%	28.1%
	25.8%	39.0%	25.1%	8.5%	1.7%	100.0%

Source: HFCS.

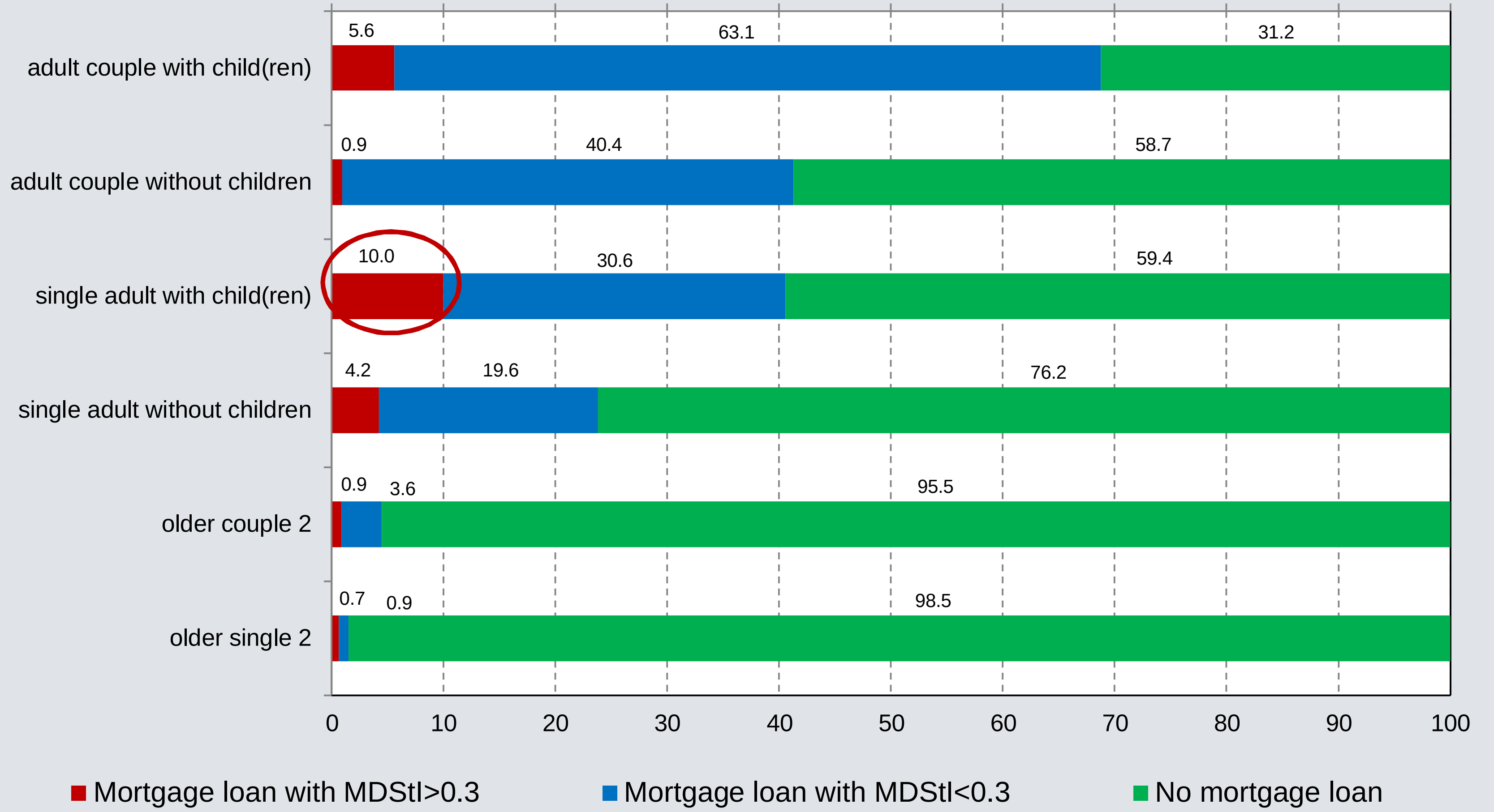
1 Households are categorised according to the age of the reference person.

2 The flow of monthly mortgage-debt service payments divided by the flow of total monthly gross household income, at the time of interview. Indicates which part of its income a household needs to periodically service its mortgage debt.

3 The stock of a household's liquid assets divided by the outstanding amount of mortgage debt, at the time of interview. Indicates the part (percentage) of a household's outstanding mortgage debt that could immediately be repaid with liquid assets.

Especially single parents are vulnerable

(Mortgage-debt burden (MDStI[1]) for different types of households, % of total households per type)



Source: HFCS.

1 The flow of monthly mortgage-debt service payments divided by the flow of total monthly gross household income, at the time of interview. Indicates which part of its income a household needs to periodically service its mortgage debt.

2 At least one person is 65 years or older.

More (multivariate) econometric evidence on:

- Socio-demographic (age, income, labour or family status, …) profiles of household indebtedness (holding, amount, interest rate), related to institutions and credit market characteristics:

  International Journal of Central Banking, June 2016.

- The role of labour status and demographics, and the impact of unemployment shocks on (changes in) household over-indebtedness:

  European Central Bank Working Paper N°1908, May 2016.

Main findings

- Pockets of risk exist in the Belgian mortgage market, due to households facing high (income or asset related) debt ratios,

  similar to the euro area.

- Part of households' outstanding mortgage debt is covered by financial assets,

  but because financial wealth is (very) unequally distributed,

  it covers outstanding mortgage debt only to a limited extent, even in Belgium.

- Although only few working households in Belgium have problems servicing their debt out of their income,

  a significant part of them lacks the financial resources to cope with severe income loss.

  Single parents, young and low-income households are relatively more vulnerable.

- A severe unemployment shock with income loss could hurt many mortgage-indebted households,

  involving a significant part of total outstanding mortgage debt in Belgium.

Data needs

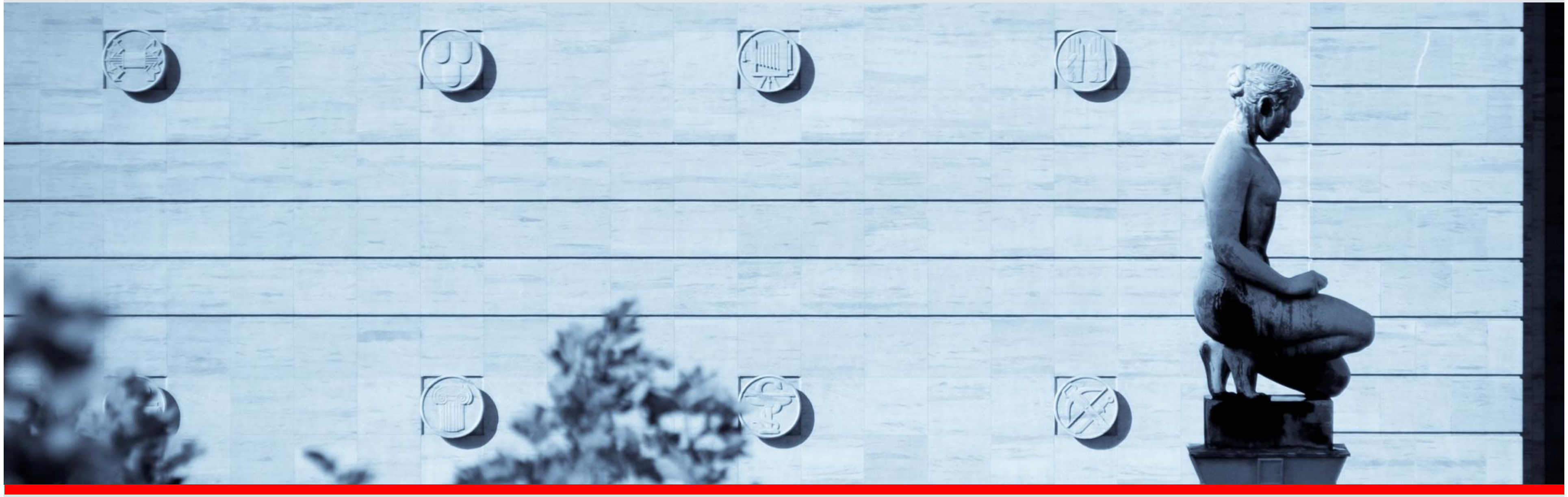
- Distribution matters for macroprudential policy, and micro data are needed to identify pockets of risk in the mortgage market, thus complementing standard (macro) indicators.

- Survey data (e.g. HFCS) can shed a light on these pockets of risk, because they collect debt, real assets, financial assets and income, for the same individual observation unit (i.e. the household).

- Survey data take time to collect and process: HFCN tries to shorten the time gap between collection and publication of data, and to better synchronise the collection in different countries.

- Survey data are based on a sample of households and are never exhaustive, their results can therefore differ from macro statistics: an Expert Group on Linking Macro and Micro Data (EG-LMM) explores the possibilities for improvement.

Thank you!



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BANK FOR INTERNATIONAL SETTLEMENTS

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Brussels, Belgium, 18-19 May 2017

Simulating impacts of borrower based macroprudential policies on mortgages and the real estate sector in Austria – evidence from the Household Finance and Consumption Survey 2014[1]

Peter Lindner and Nicolás Albacete,
Central Bank of the Republic of Austria

[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.

Simulating the impact of borrower-based macroprudential policies on mortgages and the real estate sector in Austria – evidence from the Household Finance and Consumption Survey 2014

Nicolás Albacete, Peter Lindner[1]

Abstract

In this paper we simulate the impact on house prices and credit available of different macroprudential restrictions on household mortgages in Austria. We apply the methodology developed in the literature for credit register-based information and extend it to the use of survey data. This allows us to make use of the most recent wave of the Household Finance and Consumption Survey (HFCS) in Austria to investigate the linkages between macroprudential policy and credit supply. We find that of the three standard credit ratio-based criteria – loan to value (LTV), debt to income (DTI) and debt service to income (DSTI) – for most households, the income based criteria (DTI followed by DSTI) are the binding ones, while the role of the LTV is limited. The relationship between credit supply and house prices is found to be positive, but weak. We simulate various macroprudential scenarios and find that macroprudential measures may potentially have sizeable effects on the credit available to households for financing real estate. Furthermore, it can be seen that – as expected – macroprudential policy tends to affect less affluent mortgage holders (although at the median, mortgage holders are more affluent than the general household population). The results also show that the simulated macroprudential policy measures trigger smaller changes of house prices.

Keywords: Macroprudential policy, house price development, mortgage market, HFCS

JEL classification: D12, D14, G21, G28, R21, R31

[1] Oesterreichische Nationalbank, Economic Analysis Division, Nicolas.Albacete@oenb.at (Nicolás Albacete) and Peter.Lindner@oenb.at (Peter Lindner). This paper was prepared for the IFC-NBB Workshop on "Data needs and statistics compilation for macroprudential analysis". The original work is published in the Financial Stability Report 33 of the Oesterreichsiche Nationalbank. The views expressed in this paper are exclusively those of the authors and do not necessarily reflect those of the OeNB or the Eurosystem. The authors would like to thank the referee for helpful comments and valuable suggestions.

Contents

Introduction - motivation

Real estate prices as well as household mortgage debt levels increased in Austria. In fact, the strongest increase in residential property prices of the whole euro area was measured in Austria between 2007 and 2016. According to the indices available in the Statistical Data Warehouse, nominal prices rose by 60% between the first quarter in 2007 and the third quarter in 2016, while they stagnated in the rest of the Euro Area. Albacete et al. (2016a) find that strong increases in available house price indices in Austria are likely to be driven by the upper part of the house price distribution. Although, a number of studies have put forward reasons arguing that the mortgage debt of households in Austria are sustainable (see e.g. the analyses in Albacete and Fessler 2010, Albacete et al. 2012, Albacete and Lindner 2013, Albacete et al. 2014, Albacete and Lindner 2015), in October 20106 the European Systemic Risk Board (ESRB) issued an official warning concerning vulnerabilities in the Austrian real estate sector. Following a discussion of real estate developments and debt sustainability, the Financial Market Stability Board (FMSB) in Austria issued a statement particularly focusing on vulnerability indicators of households in Austria.

So far all the analyses in Austria about household mortgage market and vulnerability focused on the identification of potential weaknesses of the sector (e.g. stress testing or the investigations concerning foreign currency loans of households). At least since the official statement of the FMSB in Austria, however, there is a need to assess the potential impact of macroprudential policy measures on households and the real estate market. Macroprudential policy is complementary to monetary policy and can play an important role in limiting the build-up of risks, e.g. in a situation of strong debt-driven house price increases, as, for instance, the Irish experience has shown. Furthermore, macroprudential policies also aim to limit contagion effects in the financial sector and to create the right set of incentives for market participants. Until now there has been a lack of information on the potential impact of macroprudential policy measures. Understanding the role which macroprudential policy could play in limiting the build-up of risks like e.g. strong debt-driven house price increases is an essential task. Thus, this study intends to shed some first light in this direction. As recommended by the ESRB handbook (ESRB, 2014) the paper takes the borrowers perspective. We perform an impact analysis of macroprudential intervention in Austria, setting constraints to the loan to value (LTV), debt to income (DTI) and debt service to income (DSTI) ratio, with a focus on measuring the effects of such interventions on the real estate sector, i.e. mortgage supply and on house prices. We adapt the approach developed by Kelly et al. (2015) and use the best and most recent source of information available, i.e. data from the second wave of Household Finance and Consumption Survey (HFCS 2014) for Austria. The methodology applied in this study basically consists of four main steps: identifying the market conditions, estimating the maximum credit available to consumers, running house price regressions, and simulating various scenarios of macroprudential policy. We find potentially sizeable impacts on credit available whereas the impact on house prices is smaller. Additionally, we are able to identify and discuss the group characteristics of the affected households.

The study underlying this presentation at the IFC-NBB Workshop on "Data needs and statistics compilation for macroprudential analysis" is published in the Financial Stability Report 33 of the Oesterreichsiche Nationalbank (OeNB). The paper can be downloaded (free of charge) from the website of the OeNB and is thus not repeated here again. Instead, this article provides a short overview of the presentation, which is put into the appendix, and some more details on the analysis. The text refers to the presentation where appropriate. The interested reader is referred to the original work (see Albacete and Lindner, 2017). The article is structured as follows. The next section introduces the methodology followed by the data used for the exercise. Results and their discussion are provided in the main part following the description of the data. Concluding remarks round up the article.

Methodology

We make use of the methodology proposed by Robert Kelly, Fergal McCann and Conor O'Toole (Kelly et al., 2015) from the Central Bank of Ireland. It basically consists of four main steps laid out below. It has to be stressed, that due to data differences (see the section on data below) our approach is not completely identical to Kelly et al. (2015), but we tried to follow the proposed methodology as closely as possible.

Credit available (first two steps)

As a first step we need to identify the prevailing market conditions in Austria. We infer these credit market conditions by studying the distribution of ratios on credit standards at the time of the origination of the mortgage. We consider three ratios: the loan to value (LTV), debt to income (DTI) and debt service to income (DSTI) ratio.

Considering the distribution of these debt burden ratios, it seems obvious that the prevailing market condition with respect to the most extreme values that are financed by the banking sector are given by relatively high percentiles. Although, we do not directly consider the maximum observed value, for the sake of simplicity we refer to these parameters as maximum DTI (DTI_{Max}), maximum LTV (LTV_{Max}), or maximum DSTI ($DSTI_{Max}$) in the remainder of the paper.

Having identified the prevailing market conditions for the maximum ratios banks are willing to provide, it is possible to calculate the amount of credit each individual household might obtain along each channel, i.e. LTV, DTI, DSTI, based on some relevant characteristics of each household (e.g. wealth and income levels).

We can thus compute the maximum credit amount satisfying these constraints, for each borrower household, denoted CA_i in slide 8. Calculating the down-payment available to the borrower and denoting it with $deposit_i$ we calculate the maximum credit along the LTV channel (see slide 8 in the appendix). Based on (initial) income we can calculate the maximum credit over the DTI channel by the second formula in slide 8, stating the product between income and market based maximum DTI. The last channel (see third formula in slide 8) is a bit more complicated since we need to specify the term of the loan in the market, denoted by TERM, as well as the interest rate. Based on a household's income and the prevailing conditions ($DSTI_{Max}$) a maximum repayment per year can be defined, denoted as $RepayMax_i$, which can be used, together with the compound interest formula, to calculate the maximum credit available along this channel. The concrete specifications chosen for the above formulas are outlined in the section on the data. For the complete details, the reader is referred to the paper (Albacete and Lindner, 2017).

Obviously, a bank in the market will consider all three channels together as well as additional information available about the mortgage taker. Here we provide the channels one by one in order to be clear and transparent. Thus, putting all the channels together and taking the minimum, we are able to estimate the credit available for each household. It is calculated as specified in the last formula in slide 8 in the appendix. The measure of available credit represents the amount of funds the bank (the market) is willing to supply to a household after considering the three credit ratio criteria together. Importantly, it is not the realized amount of credit given to the household. There might be many reasons why a households may be able to purchase the desired property without taking out the entire available credit, e.g. the availability of sufficient funds from other sources.

House price regression and simulation (last two steps)

Once we have computed the amount of credit available at the level of each borrower, we can estimate the relationship between house prices and available credit by performing a regression of houses prices on available credit. We can include borrower characteristics and hedonic characteristics of the house as variables of control in this regression. The matrix X_i (see slide 9 in the appendix) contains an extensive set of real estate and borrower characteristics in order to control for price differences that are due to other factors than the credit available.

For the simulation exercise we look at various different scenarios (see the list in slide 9 in the appendix). First, in line with international efforts and in order to ensure comparability, we look at the impact of each of the three channels separately identified by the market condition. In particular, we look at a 5 percentage point reduction of the prevailing maximum LTV ratio, a 1 year decrease of the prevailing maximum DTI ratio, and a 5 percentage point decrease of the prevailing maximum DSTI. Looking at each channel separately allows us to inspect the impact of each measure. As all three measures are often implemented together and the FMSB also discussed all three policy rates, we additionally combine the three scenarios. For each scenario, we compute a new value of available credit for each borrower by using the method described above. We compare the new value of available credit (offered by the bank [market]) with the observed credit (actually given to the household) to describe the borrowers who have to exit the market due to the new constraint (if available credit is smaller than observed credit and one cannot fully finance the desired demand).

Additionally, we approach the simulation from a different angle (last scenario in the slide). Here we perform a grid search of policy measures that lead to a decrease of average credit available of 30%. In contrast to the assumptions on debt burden indicators this part is more backward looking in the sense that it assumes a particular outcome (decrease of average credit available of 30%) and looks for the policies needed to achieve it. As we are interested in the impact of tighter credit conditions on the market we only investigate a decrease of this figure.

We use this new measure for credit available together with the estimates of the house price equation to simulate the counterfactual house price dynamics under the assumed macroprudential intervention. Hence, while the effect on the price dynamics depends on the house price equation, the change in maximum credit available to households only depends on the observed market conditions.

Data

We use data from the Household Finance and Consumption Survey (HFCS) as the basis of the investigation. In the analysis the second wave of the Austrian HFCS, which was conducted in 2014 and 2015, is taken. The HFCS is a euro area-wide project coordinated by the European Central Bank (ECB). The OeNB is responsible for conducting the survey in Austria. HFCS data provide detailed information on the entire balance sheet as well as several socioeconomic and sociodemographic characteristics of households in the euro area. In particular, the survey provides information on the wealth held in a household's main residence (HMR) and other real estate. In addition to the estimated market price of a particular property at the time of the interview, the survey also collects information about the value of each property at the time when the household acquired (or built) this property. Furthermore, information of potentially multiple loans to finance the HMR of each household are collected as well as outstanding and initial loan amounts and there is also information on interest rates and loan terms. All this information is used in the analysis at hand. We additionally use some specific variables for Austria which are not publicly available, such as, the information on payments into the repayment vehicles of bullet loan holders, which are not part of the core variables of the HFCS; these data are additionally collected in Austria due to the relatively high prevalence and thus importance of this type of credit. We include such payments into the definition of debt service. We also include Austria-specific information on net income (see below) or the region where the household is located to estimate the house price equation. The results reported in this study apply to households in Austria only. All estimates are calculated using the final household weights and the survey's multiple imputations (see Albacete et al., 2016b, for a detailed description of the survey methodology in Austria). The net sample of the HFCS 2014 in Austria contains 2,997 households. Of these households, about half own their main residence and about 400 (i.e. 15.5% of the household population) have outstanding mortgage debt for their main residence. Overall, the methodology of the second HFCS wave 2014 follows – with some improvements – that of the first HFCS wave (2010) and is documented in Albacete et al. (2016b). Thus, for the specifics of the survey the interested reader is referred to the documentation.

For our present analysis, we need to construct three ratios: LTV, DTI and DSTI. For simplicity reasons, we restrict the analysis to mortgages taken out to finance a household's main residence only. As we are interested in these ratios at the time of the origination of the mortgage, we approximate them by using some retrospective information available in the HFCS. We estimate the LTV by dividing the sum of a household's main residence mortgages at origination by the value of the household's main residence at acquisition. This ratio is called initial LTV and used throughout the analysis. The initial DTI is estimated by dividing the sum of a household's main residence mortgages at origination by the yearly net household income at the time of loan origination.[2] The DSTI is estimated by dividing the sum of all annual mortgage payments (including savings for bullet loans) for the household's main residence (at the time of the interview) by the household's net annual income (at the time of loan origination). Furthermore, the maximum credit ratios reflecting the prevailing market condition with respect to the highest ratios that are financed by the banking sector

[2] For more details on the construction of household net income the interested reader is referred to Albacete and Lindner 2017.

should be given by relatively high percentiles of their distribution. Kelly et al. (2015) propose to use the 98th percentile from the credit register. Because of the structure of the survey and the relatively small number of observations we take the 75th percentile for LTV and the 95th percentile for the other two ratios.

Finally, for the calculation of available credit as laid out above we also need to construct the following additional variables: the household's down-payment, which is defined as the difference between the value of the main residence at the time it was acquired and the initial amount borrowed at the time the loan was granted; the interest rate, which is measured by the current interest rate paid by the borrower; and the maximum loan term allowed by banks in order to repay mortgages (TERM), which is measured by the 50th percentile of the maximum loan term distribution across borrowers.

Results

This part provides the results based on the empirical exercise described above.

Market conditions

First, we need to look at the general market conditions for the HMR mortgage market in Austria as found in the HFCS. Table 1 in slide 11 in the appendix provides the prevailing market conditions based on the percentiles specified above, the resulting maximum credit available along each channel and the share of households for which the specific channel is binding. It does not only provide the overall structure but also allows to inspect the trend over the last years.

The median volume that banks are willing to supply to a borrower applying the LTV criterion (middle panel in table 1) is given by about 924,000 euros. This relatively large amount is due to the relatively high prevailing maximum LTV that the market allows a household, as can be seen in the 75th percentile of the LTV distribution in the bottom panel in table 1 (see slide 11), i.e. the maximum LTV is estimated to 90,5%. At the median the maximum credit along the DTI and DSTI channel is given by 370 and 380 thousand euro respectively. One has to keep in mind that these results are medians and are based on a complete distribution based on household individual wealth and income levels (as well as term and interest rate levels for the DSTI channel). The total credit available for each household is given by the minimum of the three figures in the middle panel of table 1. Thus, at the median overall credit available to a HMR mortgage borrower is about 370 thousand Euros. Obviously, this figure is well above the median level of initial loan amount at the time of loan origination since not all households need to take out the maximum amount available. Additionally, we see that for most households that binding channel is given by DTI followed by DSTI. This points towards a bigger impact of a policy focusing on these measures compared to the LTV channel.

The table in slide 11 additionally presents the development of indicators over time in order to inspect potential changes in the impact discussed below. We find that although income-based borrowing conditions tightened slightly over time, the maximum credit available in absolute terms increased and the share of binding conditions remained stable, and thus the underlying structure seems to be relatively stable as well. As the HFCS collects only data on outstanding loans and households pay back their mortgages over time, the number of observations is low early on (i.e. about 25 in the time bracket 1990-1994) but increases over time (i.e. about 120 in 2005-2009).

Simulation

Before discussing the results from the simulation, we need some information on the estimation of the house price model for Austria using HFCS data. We restrict the estimation sample to homeowners with an outstanding mortgage taken out to acquire their main residence, so that the estimation sample includes about 400 observations. We do this because the measure of credit available based on all three channels is only available for households holding an outstanding mortgage – at the time of the interview. As control variables we use a broad set of household and real estate characteristics. The former include age (linear and quadratic), income, down payment, and obviously credit available to the households. The latter are region, size of the households' main residence, time since loan origination, time of living in the household, and paradata about the real estate such as type and rating of dwelling, as well as rating of the surrounding area and also outward appearance of the real estate as recorded by the interviewer. The estimates of the house price equation are used for the simulation.[3] Overall, we find in general a positive but small (and partly statistically insignificant) correlation between credit available and house prices. Results from the regression can be inspected in slide 23 in the appendix.

The first column in table 3a (see slide 12 in the appendix) shows the starting point of the simulation in the baseline scenario with the market conditions found in the HFCS (see also table 1 in slide 11). Then we first simulate a 5ppts decrease of the maximum LTV, followed by a 1-year reduction of the DTI and a 5ppts decrease of the maximum DSTI. The last column provides the results of the combined scenarios where all the three previously separately analyzed reductions are put into one simulation.

The top panel again (as in table 1) shows the share of the binding constraint in each simulation whereas the second panel shows the maximum credit available along each channel in each scenario. The last panel is reserved for the results on the average changes in house prices as well as the maximum credit available due to the change in policy rates.

Table 3a shows that a reduction of the maximum LTV reduces the median maximum credit available along this channel to around 550,000 Euros – quite a substantial reduction. Also, the share of households for which this channel is binding increases substantially. However, the impact on the overall house price level and the maximum credit available is limited. This general picture is similar also for the other two channels, with the DTI channel having the larger impact on credit available and house prices. Combining all three measures results in a larger impact since now households are affected along all channels at the same time. Thus, a particular household may, for example, have an income high enough to accommodate a change in the maximum DSTI, but at the same time may well be affected by the change in the maximum LTV. The same may hold for other households the other way round. Overall, the modelled changes imply that the share of households for which the maximum LTV is binding increases whilst the share for which the maximum DTI and

[3] Results from these regressions are provided in Albacete and Lindner (2017).

DSTI is binding decreases. In summary, all results point toward a relatively modest impact of the modelled changes.

As mentioned above we also simulate an average decrease of credit available of 30% (a more restrictive case in terms of reduction of credit available), the results of which are shown in table 3b (see slide 13 in the appendix). The idea behind this discussion is to evaluate the size of a policy change needed in order to generate a certain result.

Thus, we see in the last line of the table that the change of credit available always amounts to -30%. This would be associated with lower house prices of about 3%. Columns 2 to 4 show the change needed in each of the three policy measures. A grid search yielded this result. We find that along the LTV channel a reduction of 21 percentage points (starting from the around 90% in the base line market condition) would make this threshold binding for close to 60% of borrower households in the HFCS and the median maximum credit is reduced to about EUR 210,000. The same impact in terms of the average change of credit available would be reached over a reduction of the DTI ceiling by 4.3 years or a reduction of the DSTI ratio of almost 25 percentage points. In each case the respective policy rate would be binding for almost all households. In the case of the combined scenario we can see that much smaller reductions in each channel together result in the same decrease in credit available. Note, that for the combined scenario we report only one possibility. There are many alternative policy mixes (as example columns 2 to 4 can be inspected) that might yield the same simulation results.

Affected households

In the last step, we provide some first information regarding borrowers that are potentially affected by macroprudential measrures. We do that by identifying households that under the combined scenario would no longer be able to finance the full amount actually observed. Since the prevailing market conditions are based not on the maximum observed values but some smaller percentiles, there are a few households (1.5%) that are affected in the baseline scenario. We define a household as being affected by the above introduced combined scenario if the newly derived maximum credit available is below the initial amount of loan taken out.

In table 4 (see slide 14 in the appendix) we report some general descriptive statistics of the overall household population, the mortgage holders for the households' main residence and the group affected by the combined scenario.

We see that households with HMR mortgages are more affluent than the overall population both in terms of wealth as well as current annual gross income and that the ones affected by macroprudential policies are likely to be households that are more affluent than the overall population as well. Within the group of mortgage holders, however, they are the less affluent households in terms of both wealth and income levels. We also check several other socio-demographic characteristics not displayed in the table in slide 14, but it turns out that the group of affected households seems – with the exception of income and wealth – not to be much different from the average mortgage holder (in terms of, e.g., age). It can also be confirmed that among the affected households in the scenarios there is a substantial share of households that is identified as potentially vulnerable according to several standard vulnerability measures (e.g. DTA>100%, DTI>300%, DSTI>40%).

Concluding remarks

In this paper, we adapted the approach developed by Kelly et al. (2015) to the Austrian case and to household level survey data. Instead of credit register data we use data from the second wave of the Austrian HFCS for 2014/15, which allows us to characterize in detail the households affected by the simulated macroprudential policy measures.

In a first step, we estimate the credit supply of banks to households on the basis of the three standard credit ratio criteria LTV, DTI and DSTI. We find that the income-based criteria (DTI and DSTI) are the ones which are most often binding for Austrian households. Hence, a policy focusing on the LTV ratio is expected to be less effective than limiting the DTI or DSTI.

In a second step, we estimated the house price model and show that the amount of credit that is available to each borrower has a positive but small impact on the value of the main residence that is purchased. In other words, mean main residence prices do not seem to be strongly credit driven in Austria. However, it could well be that certain quantiles of the main residence price distribution or main residence prices of certain borrower groups (e.g. foreign currency borrowers) or house prices of other properties than the main residence would still change under such scenarios. This is left for future research.

In a third step, we simulate the impact of macroprudential policy interventions on the Austrian housing market. We consider several scenarios that involve restrictions on each of the following ratios: LTV, DTI and DSTI. According to our findings, in Austria, macroprudential policy interventions would be effective in reducing credit supply to households, but less so in slowing down a rapid increase of house prices. Moreover, the impact on house prices is found to depend on the levels at which LTV, DTI and DSTI limits are set. The analysis just simulates the impact on credit supply and does not simulate the impact on the credit actually given to the household or newly granted credit by banks (which would also depend on credit demand and is beyond the scope of this paper).

It is left for future research to analyze what the impact of macroprudential policies would be on rental prices. In Ireland, for example, rental prices have strongly increased since the implementation of macroprudential policies (see RTB, 2016). Furthermore, future analyses of this kind for Austria could be further extended if credit register data covering the whole universe or at least a large part of Austrian households' mortgage loans in their entirety or at least to a large extent, including appropriate information on the mortgage holders, would be available. This would provide a much larger sample and more precise information on the origination of the loans and could help inform the process.

References

Albacete, N. and K. Wagner. 2009. Housing Finance of Austrian Households. Monetary Policy & The Economy Q3/09, 62–92.

Albacete, N. and P. Fessler. 2010. Stress Testing Austrian Households. In: Financial Stability Report 19. 72–91.

Albacete, N., P. Fessler and M. Schürz. 2012. Risk Buffer Profiles of Foreign Currency Mortgage Holders, In: Financial Stability Report 23. 58–71.

Albacete, N. and P. Lindner. 2013. Household Vulnerability in Austria – A Microeconomic Analysis Based on the Household Finance and Consumption Survey. In: Financial Stability Report 25. 57–73.

Albacete, N., J. Eidenberger, G. Krenn, P. Lindner and M. Sigmund. 2014. Risk-Bearing Capacity of Households – Linking Micro-Level Data to the Macroprudential Toolkit. In: Financial Stability Report 27. 95–110.

Albacete, N., P. Fessler, and P. Lindner. 2016a. The distribution of residential property price changes across homeowners and its implications for financial stability in Austria. In: Financial Stability Report 31. 62-81.

Albacete, N., P. Lindner and K. Wagner. 2016b. Eurosystem Finance and Consumption Survey 2014: Methodological Notes for the second wave in Austria. Addendum to Monetary Policy and the Economy Q2/16.

Albacete, N. and P. Lindner. 2017. Simulating impacts of borrower based macroprudential policies on mortgages and the real estate sector in Austria) – evidence from the Household Finance and Consumption Survey 2014. In: Financial Stability Report 33.

Chatterjee, S., and A. S. Hadi. 2012. Regression Analysis by Example. 5th ed. New York: Hoboken, NJ.

ESRB 2014. The ESRB Handbook on Operationalising Macro-prudential Policy in the Banking Sector. European System of Financial Supervision.

Fessler, P., P. Lindner and M. Schürz. 2016. Household Finance and Consumption Survey des Eurosystems 2014: First results of the second wave for Austria. In: Monetary Policy and the Economy Q2/2016.

Kelly R., McCann F. and C. O'Toole. 2015. Credit conditions, macroprudential policy and house prices. Central Bank of Ireland Research Technical Paper, 6/RT/15.

RTB. 2016. Residential Tenancies Board Rent Index Quarter 3 2016. http://www.rtb.ie/docs/default-source/default-document-library/rtb-rent-index-report-q3-2016-final.pdf?sfvrsn=2

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Simulating impacts of borrower based macroprudential policies on mortgages and the real estate sector in Austria – evidence from the Household Finance and Consumption Survey 2014[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.

Simulating impacts of borrower based macroprudential policies on mortgages and the real estate sector in Austria

Evidence from the Household Finance and Consumption Survey 2014

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IFC – National Bank of Belgium Workshop on "Data needs and Statistics compilation for macroprudential analysis"

18.05.2017

[1] Additional to the usual disclaimer, the opinions expressed in this paper solely represent those of the authors and do not necessarily reflect the official viewpoint of the Oesterreichische Nationalbank or of the Eurosystem.

Outline

1. Motivation
2. Methodology
3. Results
4. Conclusion

Motivation

Motivation ↪ Discussion on macroprudential policy

- On November 28, 2016: ESRB warning on medium-term vulnerabilities in the residential real estate sector for Austria and seven other EU countries:
  - Rapid rise in (residential) real estate prices, robust mortgage credit growth and risk of a (further) loosening of lending standards
- Response of the Austrian finance ministry, which had been agreed with the Financial Market Authority (FMA) and the Oesterreichische Nationalbank:
  - Mitigating factors not been considered adequately in the ESRB's analysis (low share of mortgage lending, low default and loss ratios, high significance of social and rental housing)
  - Recent measures taken are considered to be adequate in view of the current house price cycle and the current credit cycle:
    - ⋆ Initiative to preventively create a legal basis for additional macroprudential instruments to enable the FMA to impose limits on loans granted by commercial lenders
    - ⋆ Communication on three criteria for sustainable real estate lending: LTV, DTI and DSTI ratios ("on the basis of improved reporting, [we] may specify in more detail the criteria [...] and issue recommendations if the need arises")

Literatur

Motivation ↪ Aim of the study

- So far, all the analyses in Austria about household mortgage market and vulnerability focused on the identification of potential weaknesses (e.g. stress testing or FX loans) of this sector
- At least since the FMSB statement there is a need to assess the potential impact of policy measures on households and the real estate market
- Until now there has been a lack of information on this topic. This study intends to shed some first light in this direction.
- The aim of our study: perform an impact analysis of macroprudential intervention in Austria setting constraints to the LTV, DTI and DSTI with a focus on measuring the effects of such interventions on the real estate sector, i.e. mortgage supply and on house prices.
- Approach developed by Robert Kelly, Fergal McCann and Conor O'Toole (2015) **"Credit conditions, macroprudential policy and house prices"** in Research Technical Papers 06/RT/15, Central Bank of Ireland
- Results planned to be published in the Financial Stability Report 33 of the OeNB

Methodology

METHODOLOGY ↪ Main steps

- For this analysis we will use the best source of information available, i.e. the second wave of Household Finance and Consumption Survey (2014) for Austria (whole balance sheet of about 3.000 households)

  ▸ More on the data

- The methodology consists basically in four main steps:
  - identifying the market conditions,
  - estimating the maximum credit available to consumers,
  - running house price regressions, and
  - simulating various scenarios of macroprudential policy

Methodology $\hookrightarrow$ Available credit

- LTV-channel

$$Loan_{LTV_i} = \frac{deposit_i}{1 - LTV_{Max}} - deposit_i$$

- LTI-channel

$$Loan_{DTI_i} = income_i * DTI_{Max}$$

- DSTI-channel

$$Loan_{DSTI_i} = RepayMax_i * \frac{1 - (1 + r_i)^{-TERM}}{r_i}$$

- Credit available

$$CA_i = Min(Loan_{DTI_i}, Loan_{DSTI_i}, Loan_{DSTI_i})$$

Methodology $\hookrightarrow$ House price regression and simulation

- House price regression

$$HousePrice_i = \beta CA_i + \gamma' X_i + \varepsilon_i$$

Simulation scenarios:

- LTV_{Max} minus 5 ppts
- DTI_{Max} minus 1 year
- $DSTI_{Max}$ minus 5 ppts
- Combined
- What does it take to reduce CA by 30% at the mean?

More on model specification

Results

Results ↪ Market conditions

Table 1: Descriptive statistics of the components of credit avaliable and the binding condition

	All	1990 to 1994	1995 to 1999	2000 to 2004	2005 to 2009	2010 and younger (2015)
Share of households for which the binding binding condition is						
LTV	13,6%	11,1%	12,6%	14,0%	16,8%	14,7%
DTI	49,8%	43,7%	46,2%	44,8%	51,0%	52,6%
DSTI	36,6%	45,2%	41,2%	41,2%	32,2%	32,7%
Conditional Median of Maximum Credit given by (in 1.000€)						
LTV[1]	924,4	768,5	1.069,5	902,0	1.046,0	1.126,5
DTI	367,8	182,3	327,5	374,4	427,5	492,0
DSTI	379,7	180,5	328,9	395,8	431,6	496,9
Market condition of thresholds						
LTV (P75)	90,5	68,5	79,8	100,5	85,4	102,4
DTI (P95)	12,4	9,3	12,5	12,5	11,8	8,6
DSTI (P95)	66,5	60,3	70,4	63,6	60,3	51,4

Source: HFCS Austria 2014, OeNB.

Note: The time line refers to the year when the highest household main residence mortgage was taken out.

▸ House price regression

Table 3a: Simulation results

	Base Line	LTV - 5ppts	DTI - 1 year	DSTI - 5ppts	Combined I
Share of households for which the binding condition is					
LTV	13,6%	23,0%	12,9%	13,0%	20,9%
DTI	49,8%	43,9%	66,2%	33,2%	46,5%
DSTI	36,6%	33,2%	20,9%	53,8%	32,6%
Conditional Median of Maximum Credit given by (in 1.000€)					
LTV[1]	924,4	548,8	924,4	924,4	548,8
DTI	367,8	367,8	338,2	367,8	338,2
DSTI	379,7	379,7	379,7	351,1	351,1
Changes with respect to					
House prices	.	-0,6%	-0,6%	-0,3%	-1,3%
Credit available	.	-5,8%	-5,5%	-3,2%	-12,1%

Source: HFCS Austria 2014, OeNB.

Results ↪ Simulation II

Table 3b: Simulating a reduction of available credit of 30%

	LTV - scenario	DTI - scenario	DSTI - scenario	Example of a combined scenario II
Change of				
LTV (in ppts)	-21	0	0	-10
DTI (in years)	0	-4,3	0	-2,8
DSTI (in ppts)	0	0	-24,5	-18,0
Share of households for which the binding condition is				
LTV	57,2%	8,5%	8,5%	24,8%
DTI	22,9%	89,4%	0,0%	32,3%
DSTI	20,0%	2,1%	91,5%	42,9%
Conditional Median of Maximum Credit given by (in 1.000€)				
LTV[1]	208,1	924,4	924,4	379,9
DTI	367,8	240,5	367,8	284,9
DSTI	379,7	379,7	239,8	276,9
Changes with respect to				
House prices	-3,2%	-3,1%	-3,2%	-3,2%
Credit available	-30%	-30%	-30%	-30%

Source: HFCS Austria 2014, OeNB.

Results ↪ Affected households I

Table 4: Characteristics of the households affected by macroprudential policy

	All	HMR Mortgage Holders	Affected households in combined scenario
Share of affected households	100,0%	15,5%	2,2%
Household Wealth (in 1.000€)			
Gross Wealth Mean	275,7	644,8	487,1
Gross Wealth Median	100,4	340,6	318,5
Household Income (in 1.000€)			
Gross Current Income Mean	43,3	60,5	46,3
Gross Current Income Median	35,7	54,5	41,0
Household financial knowledgable person - socio-demographics			
Mean Age	53	48	48
Median Age	54	46	47
Household debt structure			
Median current outstanding debt (in 1.000€)	.	63,1	108,2
Share of vulnerable - DTA>100%	6,3%	1,4%	3,3%
Share of vulnerable - DTI>300%	6,2%	36,0%	62,7%
Share of vulnerable - DSTI>40%	2,6%	15,1%	37,2%
Share of vulnerable - expenses above income	6,9%	12,8%	11,1%

Source: HFCS Austria 2014, OeNB.

More

Conclusion

Conclusion ↪ Discussion

- Income based criteria (LTI and DSTI) are the ones which are most often binding for Austrian households
- Mean main residence prices do not seem to be strongly credit driven in Austria
- Macroprudential policy interventions effective in reducing credit supply to households, but less so in calming a rapid increase in the housing market (impact depends on the levels at which LTV, DTI and DSTI limits are set)
- Data aspects
  - Use of survey data important
  - Additional information form credit register desirable
  - Information needs to include complete balance sheet (partial information often of little use)

Thank you very much for your attention!

Appendix

Appendix ↪ Literature

- Strong increases in available house price indices in Austria are likely to be driven by the upper part of the house price distribution:
  - Albacete, N., Fessler, P. and Lindner, P. (2016) **"The Distribution of Residential Property Price Changes across Homeowners and its Implications for Financial Stability in Austria"** in Financial Stability Report 31/2016, pp. 62–81. OeNB.
- There are various reasons for debt sustainability of the mortgage market for households in Austria; see e.g.
  - Albacete, N. and Fessler, P. (2010) **"Stress Testing Private Households in Austria"** in Financial Stability Report 19/2010, pp. 72–91. OeNB,
  - Albacete, N. Fessler, P. and Schürz, M. (2012) **"Risk Buffer Profiles of Foreign Currency Mortgage Holders"** in Financial Stability Report 23/2012, pp. 58–71. OeNB,
  - Albacete, N. and Lindner, P. (2013) **"Household Vulnerability in Austria - A Microeconomic Analysis Based on the Household Finance and Consumption Survey"** in Financial Stability Report 25/2013, pp. 57–73. OeNB,
  - Albacete, N., Eidenberger, J., Krenn, G., Lindner, P. and Sigmund, M. (2014) **"Risk Bearing Capacity of Households – Linking Microlevel Data to the Macroprudential Toolkit"** in Financial Stability Report 27/2014, pp. 95–110. OeNB,
  - Albacete, N. and Lindner, P. (2015) **"Foreign currency borrowers in Austria evidence from the Household Finance and Consumption Survey"** in Financial Stability Report 29/2015, pp. 93–109. OeNB.

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- Euro area wide effort to collect micro data on household finances
- Data on the whole balance sheet
- 2^{nd} wave 2014/2015 with 20 countries (1^{st} wave 2010/11 with 15 countries)
- Ongoing project with intention to collect data every 3 years
- Ex-ante harmonization not only of the questionnaire but the whole data production process
- Computer Assisted Personal Interviews (CAPI)
- Harmonized Bayesian-based multiple Imputation procedure
- ECB coordinates project and checks the quality
- Variance estimation based on 1.000 replicate weights (bootstrap procedure)
- Second wave net sample more than 84 thousand households, about 3.000 in Austria (SCF in the USA: 6.500)

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Appendix $\hookrightarrow$ Model specification and robustness checks I

- Income based specification
  - HFCS in AT collects gross (net) yearly income for calendar year preceding interview $\rightarrow$ use trend of average disposable income to estimate income at the time of loan origination (income structure constant)
  - Use initial net income to be in line with general discussion
  - 95^{th} Percentile of DTI and DSTI
- LTV
  - Initial LTV collected in the HFCS in terms of both value of HMR at the time of ownership transfer and loan at origination
  - Abstract from specifics of ownership transfer and building
  - 75^{th} Percentile initial LTV
- Term length
  - Median maximum (if a household holds more than one HMR mortgage) term length of mortgage loan
  - Reflects 25 years common in Austria

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Appendix $\hookrightarrow$ Model specification and robustness checks II

- Interest
  - Median of potentially multiple interest rates for HMR mortgage of a single household
- Robustness checks
  - House price regression:
    - various specifications
    - levels as well as logs (inverse hyperbolic sine transformation)
  - Market conditions:
    - LTV of 90%
    - LTV of close to 100%
  - Income:
    - net and gross income
    - initial and current income

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Results ↪ House price regression

Table 2: House price regression

	Full Sample		*Restricted Sample*		*Unweighted Regression*	
	Level initial house value	Logarithm initial house value	Level initial house value	Logarithm initial house value	Level initial house value	Logarithm initial house value
	I	II	III	IV	V	VI
Credit available (CA)	0.062	0.332***	0.110	0.339***	0.061	0.351***
	(0.074)	(0.101)	(0.082)	(0.108)	(0.067)	(0.108)
Total household initial net income	-0.137	-0.149	-0.263	-0.139	-0.158	-0.176
	(0.898)	(0.130)	(0.840)	(0.124)	(0.965)	(0.137)
Value of put down deposit (equity capital, down payment)	0.835***	0.040***	0.652***	0.027***	0.880***	0.043***
	(0.186)	(0.007)	(0.218)	(0.006)	(0.116)	(0.006)
Age	-4,200.853	-0.013	-1,455.621	-0.007	-5,445.458	-0.021
	(5,891.842)	(0.026)	(4,164.130)	(0.022)	(4,791.668)	(0.020)
Age squared	33836	0.000	13071	0.000	43119	0.000
	-57930	(0.000)	-41382	(0.000)	-48594	(0.000)
Controlled for [1]						
Region	X	X	X	X	X	X
Time brackets of loan originiation	X	X	X	X	X	X
Size of HMR	X	X	X	X	X	X
Duration of living in the HRM	X	X	X	X	X	X
Type of dwelling (paradata)	X	X	X	X	X	X
Dwelling rating (paradata)	X	X	X	X	X	X
Dwelling location (paradata)	X	X	X	X	X	X
Outward appearance of dwelling (paradata)	X	X	X	X	X	X

Source: HFCS Austria 2014, OeNB.

Notes:

1) Every regression includes a constant.

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Results ↪ Affected households II

Table 5: Share of aggregate debt held by households affected by macroprudential policy

	Base Line	Combined Scenario I
Conditional share of affected households	9,7%	14,0%
Conditional current share of aggregate HMR mortgage	16,6%	23,4%
Conditional initial share of aggregate HMR mortgage	8,3%	11,1%

Source: HFCS Austria 2014, OeNB.

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Brussels, Belgium, 18-19 May 2017

Countercyclical capital regulation in a small open economy DSGE model[1]

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Matija Lozej and Ansgar Rannenberg, 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.

Countercyclical Capital Regulation in a Small Open Economy DSGE Model*

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January 2017

Abstract

We assess the macroeconomic performance of different countercyclical capital buffer rules, where regulatory capital responds to deviation from a long-run trend in the credit-to-GDP ratio (the credit gap), in a medium scale DSGE model of the Irish economy. We find that rules based on the credit gap create a trade-off between the stabilisation of fluctuations originating in the housing market (which are attenuated) and stabilisation of fluctuations caused by foreign demand shocks (which are amplified) because the credit gap is not always procyclical. The trade-off disappears if the regulator follows a rule based on house prices instead of the credit gap.

JEL classification: F41, G21, G28, E32, E44,
Keywords: Bank capital, Countercyclical capital regulation, Housing bubbles, boom-and-bust.

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1 Introduction

Since the financial crisis, regulation of the financial sector has undergone several changes in advanced economies. Several financial regulators have implemented macroprudential policy frameworks that envisage systematic variations of regulatory capital ratios of banks in response to changes in cyclical variations of aggregate variables. In the European Union, the European Systemic Risk Board (ESRB) has recommended that macroprudential authorities must pay particular attention to the so-called credit gap (the deviation of the credit-to-GDP-ratio from a long run trend) when setting regulatory capital buffers (ESRB, 2014).

In this paper, we investigate the merits of linking countercyclical capital buffers (CCyB) to the credit gap, the house price gap, and also compare the effects of CCyB-type rules to those of imposing a substantially higher constant capital requirement. Following Beneš and Kumhof (2014) and Jakab and Kumhof (2015), banks in our model are subject idiosyncratic shocks to their net return on assets, which may reduce their capital ratio below the regulatory minimum in the next quarter, in which case they face a penalty. An increase in the regulatory capital requirement therefore induces banks to restrict their lending, thus raising the cost of credit for the non-financial sector and providing regulators with a means to affect real activity. Furthermore, the model features spillovers from the housing market to domestic demand due to risky household borrowing from banks, similar to Clancy and Merola (2014). We embed these features in the model developed for the Irish economy by Clancy and Merola (2016). We take our model to the data by matching the impulse response functions of the DSGE model with those of an estimated structural VAR model of the Irish economy.

Contrary to most of the literature, we look at the CCyB rates based on a credit gap rule and find that such rules are not always optimal. On the positive side, rules based on the credit gap dampen fluctuations originating from the housing market. As the credit gap moves strongly pro-cyclically in response to these shocks, regulatory capital and thus credit are tightened during the boom, dampening the increase in GDP. Limiting the excesses of the boom makes a bust following a boom less painful as the economy enters the downturn with smaller debt and physical capital overhang and better capitalised banks, allowing some capital to be released. On the other hand, CCyB rates based on the credit gap may amplify the response of the economy to adverse export demand and producer markup shocks, as these shocks cause the credit gap to increase, implying an increase in the minimum capital requirement. Hence targeting the credit gap helps stabilising the economy's response to housing demand shocks, but is destabilising in the presence of export demand or supply shocks. By contrast, we find that a rule based on house prices instead of the credit gap is always stabilising, as house prices always move procyclically for all shocks considered here. Finally, we find that imposing substantially higher level of constant capital requirements makes the economy marginally more resilient in response to the shocks we consider, but the cost associated with the transition to the higher level of bank capital is substantial.

Our analysis contributes to the evolving literature in several ways. First, we consider regulation affecting bank capital requirements, thus complementing Carrasco-Gallego and Rubio (2015), who investigate the introduction of rules for loan-to-value ratios, or Chadha et al. (2015), who focus on the merits of a response of the central bank interest rates to stock prices. Second, we consider CCyB rules featuring the credit gap, which is considered a good predictor of financial crises and their costs (e.g. Schularick and Taylor (2012) and Jorda et al. (2012)), and therefore features in the ESRB Recommendation. Third, we consider rules featuring deviations of house prices from their long run value, which is one of the alternative indicator variables considered in Drehmann et al. (2010). By contrast, Angelini et al. (2012) and Angeloni and Faia (2013) consider only a response of the CCyB to GDP. Moreover, the model of Angeloni and Faia (2013) is also stylised in that they assume that banks own the physical capital stock and are thus directly affected by fluctuations in its value. Christensen et al. (2011), following the empirical investigation of Drehmann et al. (2010), consider a rule for regulatory capital involving the credit gap, but not house prices, as their model does not feature a housing market. Fourth, we investigate the case of a small open economy, which as far as we are aware is considered only by Clancy and Merola (2014), who however consider a more restricted set of both shocks and policy rules. To account for the membership in the monetary union, the policymaker in our model has no control over monetary policy as the economy studied is part of a monetary union, which renders our contribution distinct from Angelini and Neri (2014), Lewis and Villa (2016) and who study the optimal interaction of monetary and macroprudential policy.

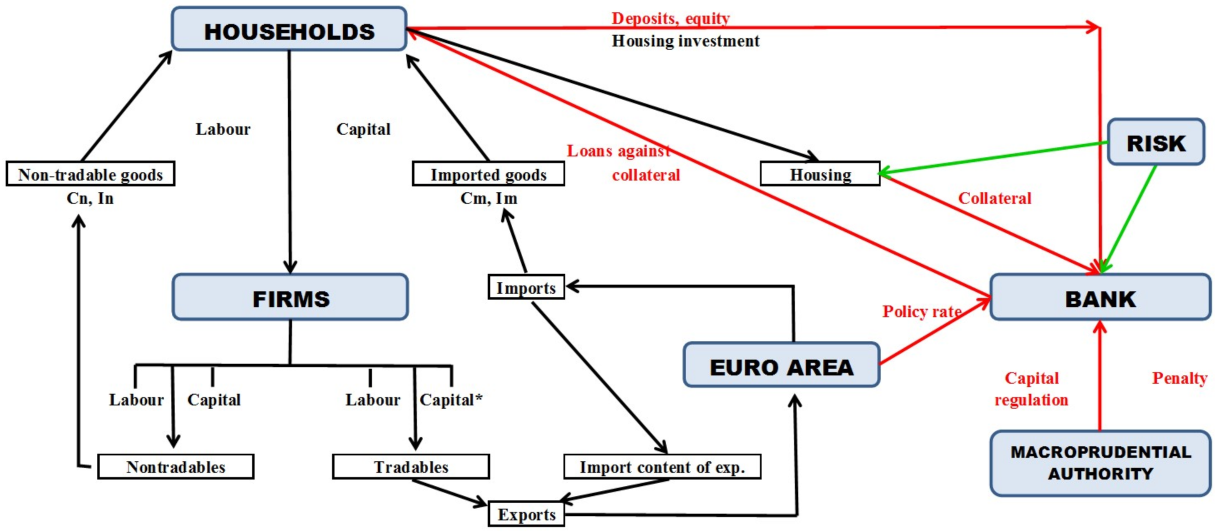
Fifth, our model features an explicit characterisation of the banking system and of its optimal behaviour. As in Clancy and Merola (2014), in our model banks serve two functions, namely channeling savings from borrowers to lenders and providing funds for transaction purposes, which makes credit more volatile compared to GDP. By contrast, the contributions cited above feature only the intermediation function of banking, like most DSGE models with financial frictions (see Jakab and Kumhof (2015) for a discussion of these two alternatives of modeling banks). Finally, unlike most of the contributions listed above, we fit the model to the data by matching the model impulse responses to those of an estimated structural VAR model.

The remainder of paper is structured as follows: Section 2 develops the model, Section 3 describes the parameterisation, Section 4 introduces the macroprudential rules whose performance we want to evaluate. Section 5 contains our main simulation results and Section 6 concludes.

2 The model

Figure 1 gives an overview of the linkages between various sectors in the model. The non-financial sector consists of firms producing consumption and investment goods for the domestic market (non-tradable goods sector) and a tradable goods sector producing export goods, as well as a household sector, and is close to Clancy and Merola (2016). The tradable goods sector uses intermediate imported goods as an input, a feature of many small open economies. Banks extend loans to, and collect deposits from, the domestic household sector, as well as the rest of the world. All foreign capital inflows are intermediated by the banking sector. Banks are subject to regulation in the form of a minimum capital requirement, which may be time varying. The economy is part of a currency union.

FIGURE 1. Structure of the model



2.1 Banks

Our formalisation of the banking sector largely follows Beneš and Kumhof (2014) and Jakab and Kumhof (2015). Banks extend loans to households, L_t, which they fund by domestic deposits, D_t, foreign deposits, B_t, and equity, $E_{b,t}$. Hence

$$L_t = D_t + B_t + E_{b,t}. \tag{1}$$

The capital adequacy ratio, el_t, is defined as the ratio of equity to loans,

$$el_t = \frac{E_{b,t}}{L_t}. \tag{2}$$

Banks raise equity from retained earnings. Bank equity therefore evolves according to

$$E_{b,t} = E_{b,t-1} R_{E,t} (1 - \theta_b), \tag{3}$$

where $R_{E,t}$ is the return on bank equity and θ_b is the share of dividends distributed to households, who own banks. This assumption ensures that banks never become fully self-financing.

The banks' net return on assets is subject to idiosyncratic shocks, which may be thought of as above average exposure to bad loans, or losses from trading activities not explicitly modeled. Their individual $t+1$ return on assets may therefore be written as $\widetilde{R_t}\omega_{b,t+1}$, where $\widetilde{R_t}$ denotes the average return on assets in the banking sector net of any costs associated with borrower bankruptcy, while $\omega_{b,t+1}$ denotes a lognormally distributed random variable with unit mean and $var(log(\omega_{b,t+1})) = \sigma_b^2$. The density and cumulative density functions are denoted as $\phi(\omega_{b,t+1})$ and $\Phi(\omega_{b,t+1})$, respectively.

The bank regulator sets a minimum capital requirement g_t. If as a consequence of a negative shock a bank's capital ratio falls below g_t, the bank has to pay a penalty equal to a fraction χ_b of its loans. This penalty represents all costs of "being caught" by regulators as badly capitalised, including regulatory penalties, the damage to the brand and the dilution of shareholder value associated with being forced to recapitalise at depressed share prices. More formally, banks have to pay a penalty if

$$\omega_{b,t}\widetilde{R_t}L_{t-1} - R_{t-1}(B_{t-1} + D_{t-1}) < \omega_{b,t} g_{t-1}\widetilde{R_t}L_{t-1}, \tag{4}$$

where R_t denotes the deposit rate. We can thus define the threshold $\overline{\omega_{b,t}}$

$$\overline{\omega_{b,t}} \equiv \frac{R_{t-1}(B_{t-1} + D_{t-1})}{(1 - g_{t-1})\widetilde{R_t}L_{t-1}}. \tag{5}$$

Banks have to pay a penalty if $\omega_{b,t} < \overline{\omega_{b,t}}$. The banks optimisation problem is thus given by

$$\max_{L_t, E_{b,t}} \quad E_t \beta \tfrac{\Lambda_{t+1}}{\Lambda_t} \left[\widetilde{R_{t+1}} L_t \omega_{b,t+1} - R_t(B_t + D_t) - \chi_b L_t \Phi(\omega_{b,t+1}) \right],$$

where $\beta \frac{\Lambda_{t+1}}{\Lambda_t}$ denotes the households' marginal discount factor. A bank's first-order condition with respect to loans states that the interest rate they charge in new loans is

$$\widetilde{R_{t+1}} - R_t = \chi_b \left(\Phi(\omega_{b,t+1}) + \phi(\omega_{b,t+1}) \frac{R_t}{(1 - g_t)\widetilde{R_{t+1}}} \right). \tag{6}$$

Furthermore, the average net return on assets must compensate the bank for any losses associated with bankruptcy, so that the actual lending rate $R_{L,t}$ is

$$\widetilde{R_t} = R_{L,t-1}\left(1 - \lambda\left(J_t\right)\right), \tag{7}$$

where J_t and λ denote the share of defaulting loans, to be determined in the next subsection, and and the loss given default (LGD), respectively. Equations 6 and 7 imply that in order to increase its lending by one unit and thus becoming more leveraged, the expected net return on assets $\widetilde{R_{t+1}}$ has to compensate the bank for its cost of funds R_t and the expected increase in the risk of ending up undercapitalised in period $t+1$ that is associated with higher leverage. Hence the lending rate has to be such that after deducting all costs associated with bankruptcy, the bank expects to earn $\widetilde{R_{t+1}}$. The bank capital ratio at the end of the period will therefore typically exceed the regulatory minimum. Furthermore, the regulator can increase the costs of funds of the non-financial sector by raising g_t and thus increasing the expected penalty associated with a given leverage. Unless otherwise mentioned, we assume $g_t = gmin$, with $gmin > 0$.

The return on equity, $R_{E,t}$, is defined as:

$$R_{E,t} \equiv R_{t-1} + (\widetilde{R_{t+1}} - R_{t-1})\frac{1}{el_{t-1}} - \chi_b \frac{1}{el_{t-1}}\Phi(\omega_{b,t}). \tag{8}$$

The first term in equation 8 is the riskless rate, the second term is the spread earned on the loan portfolio (scaled by the bank leverage), and the last term is the penalty paid in case minimum capital requirements are breached.

2.2 Households

Utility and budget constraints. We assume a continuum of optimising households indexed by j. Household j derives utility from consumption $C_{j,t}$, real saving deposits $D_{S,j,t}/P_t$ and housing $H_{j,t}$, and disutility from labour $N_{j,t}$

$$\mathbb{E}_t \sum_{i=0}^{\infty} \beta^i \left[\frac{\left(C_{j,t+i} - \chi C_{t+i-1}\right)^{1-\sigma}}{\left(1-\chi\right)^{-\sigma}\left(1-\sigma\right)} - \phi_N \frac{N_{j,t+i}^{1+\eta}}{1-\eta} + \varepsilon_{H,t}\frac{\zeta_H H_{j,t}^{1-\nu}}{1-\nu} + \zeta_D \frac{\left(\frac{D_{S,j,t+i}}{P_{t+i}}\right)^{1-\iota}}{1-\iota} \right],$$

where β and χ denote the household discount factor and the degree of habit formation, σ, η, ν and ι are curvature parameters and P_t denotes the price level of the consumption basket $C_{j,t}$. Households also hold deposits for transaction purposes $D_{T,j,t}$ due to a cash-in-advance constraint associated with consumption, investment and housing related transactions:

$$D_{T,j,t} = \gamma_C \left(P_t C_{j,t} + P_{I,t} I_t \right) + \gamma_H P_{H,t} H_{j,t}, \tag{9}$$

where γ_C and γ_H denote the shares of consumption and investment purchases funded by transaction deposits, respectively. $P_{I,t}$ and $P_{H,t}$ denote investment good prices and house prices. Total deposits are the sum of transaction deposits and saving deposits:

$$D_{j,t} = D_{T,j,t} + D_{S,j,t}. \tag{10}$$

In addition to deposits, households hold physical capital $K_{j,t}$, bank equity, $E_{b,j,t}$, and receive income in the form of wages W_t, rental income from the ownership of the capital stock $R_{K,t}$, and profits from the ownership of firms in the economy, $\Pi_{j,t}$. They have to pay lump sum taxes, $\Theta_{j,t}$. Their budget constraint is thus given by

$$\begin{aligned} P_t C_{j,t} + P_{I,t} I_{j,t} + P_{H,t} H_{j,t} + E_{b,j,t} - L_{j,t} + D_{j,t} \left[1 + \frac{1}{2} \xi_D \Omega_{D,t} \right] = \\ = W_t N_{j,t} \left[1 - \frac{1}{2} \xi_W \Omega_{W,t} \right] + R_{K,t} K_{j,t-1} + P_{H,t} H_{j,t-1} + R_{E,t} E_{b,j,t-1} - R_{L,t} L_{j,t-1} \\ + R_t D_{j,t-1} + \Pi_{j,t} - \Omega_{N,t} - \Omega_{M,t} - \Omega_{E,t} - \Theta_{j,t}. \end{aligned} \tag{11}$$

where I_t denotes real investment in physical capital. The introduction of the banking sector adds several elements to the household's budget constraint. L_t denotes loans from banks, on which households pay the interest rate $R_{L,t}$, while they receive the interest rate R_t on deposits D_t. Households own bank equity, $E_{b,t}$, on which they receive a return of $R_{E,t}$. As the aggregate housing stock is fixed, it holds that $P_{H,t} \int_0^1 H_{j,t} dj = P_{H,t} H$. Terms denoted by Ω are quadratic adjustment costs.[1]

Total capital, K_t, is the sum of capital in the tradable sector, $K_{X,t}$, and in the non-tradable sector, $K_{N,t}$. Capital in the tradable sector is assumed to be exogenous.[2] Capital accumulation in the non-tradable sector is subject to investment adjustment costs:

$$K_{N,t} = (1 - \delta) K_{N,t-1} + I_t \left(1 - \frac{1}{2} \xi_I \Omega_{I,t} \right), \tag{12}$$

where $\Omega_{I,t} \equiv (\log(I_t / I_{t-1})^2$ and $\xi_I \geq 0$ denotes the curvature of the capital adjustment cost function.

Household default. Housing wealth of households is subject to idiosyncratic shocks $\omega_{h,j,t}$. We assume that households default if their housing wealth declines below the value of their debt $R_{L,t-1} L_{j,t-1}$, i.e. if

[1] For instance, deposit-adjustment costs are defined as $\Omega_{D,t} \equiv (\log(D_{j,t}/D_{j,t-1}))^2$. Exact definitions of adjustment costs are provided in the appendix.

[2] See subsection 2.3 for details.

$$\exp\left(\omega_{h,j,t}\right) H_{j,t-1} P_{H,t} < L_{j,t-1} R_{L,t-1}, \tag{13}$$

and $\omega_{h,j,t} \sim N\left(0, \sigma_h\right)$. The default threshold for $\omega_{j,t}$ and the default probability J_t are thus given by

$$\overline{\omega_{h,j,t}} = \log(L_{j,t-1} R_{L,t-1} / (H_{j,t-1} P_{H,t})), \tag{14}$$

$$J_t = \Phi\left(\frac{\log(L_{j,t-1} R_{L,t-1} / (H_{j,t-1} P_{H,t}))}{\sigma_h}\right), \tag{15}$$

where $\Phi\left(\bullet\right)$ is the standard normal cumulative distribution function and σ_h measures the idiosyncratic risk of households. We also assume that in case of default, households face a cost $(1-\lambda) R_{L,t-1} L_{j,t-1}$. This cost can be thought of as the social stigma or the legal costs associated with default, and implies that the household does not incur a net gain from defaulting.[3] After $\omega_{h,j,t}$ has been revealed and some households default, resources are redistributed between households such that their housing wealth is again identical before they make their consumption and saving decisions. We therefore drop the j subscript from now on.

When choosing their optimal amount of borrowing, households take into account the impact of their loan-to-value ratio, LTV, defined as $(LTV_t \equiv L_{t-1} R_{L,t-1} / (H_{t-1} P_{H,t}))$, on the lending rate they are charged by banks due to the positive relationship between their LTV and the risk of default. The lending rate has to be sufficiently high for the banks' expected net return on assets to satisfy:

$$\widetilde{R_{t+1}} = R_{L,t}\left(1 - \lambda \mathbb{E}_t\left(J_{t+1}\right)\right). \tag{16}$$

First order conditions. We denote the Lagrange multiplier associated with the budget constraint (equation 11) with Λ_t, the Lagrange multiplier associated with the interest rate faced by the borrowing households (equation 16) as $\Lambda_{R_L,t}$, and the Lagrange multiplier associated with transaction deposits as $\Lambda_{T,t}$. The first order conditions with respect to C_t, L_t, $R_{L,t}$, $D_{T,t}$, $D_{S,t}$, $H_{j,t}$, I_t, and $K_{N,t}$ are

$$\Lambda_t P_t\left(1 + \gamma_C \frac{\Lambda_{T,t}}{\Lambda_t}\right) = (1-\chi)^{\sigma}\left(C_t - \chi C_{t-1}\right)^{-\sigma}, \tag{17}$$

$$\Lambda_t = \beta \Lambda_{t+1} R_{L,t} + \Lambda_{R_L,t} \lambda \frac{\phi(\overline{\omega_{h,t+1}})}{\sigma_h L_t}, \tag{18}$$

[3] This assumption is necessary to ensure that a change in the lending rate caused by an increase in the expected probability of default (J_{t+1}) has an effect on household behavior.

$$\frac{\Lambda_{R_L,t}}{\Lambda_t L_t}\left(1-\lambda J_{t+1}-\lambda\frac{\phi(\overline{\omega_{h,t+1}})}{\sigma_h}\right)=\beta\frac{\Lambda_{t+1}}{\Lambda_t}, \tag{19}$$

$$\frac{\Lambda_{T,t}}{\Lambda_t}=1-\beta\frac{\Lambda_{t+1}}{\Lambda_t}R_t, \tag{20}$$

$$D_{S,t}^{-\iota}P_t^{\iota-1}\zeta_D\frac{1}{\Lambda_t}=1-\beta R_t\frac{\Lambda_{t+1}}{\Lambda_t}+\xi_D\Omega'_{D,t}, \tag{21}$$

$$P_{H,t}\left(1+\gamma_H\frac{\Lambda_{T,t}}{\Lambda_t}\right) = \varepsilon_{H,t}\zeta_H\frac{H_{j,t}^{-\nu}}{\Lambda_t} + \beta\frac{\Lambda_{t+1}}{\Lambda_t}P_{H,t+1} + \frac{\Lambda_{R_L,t}}{\Lambda_t}\lambda\frac{\phi(\overline{\omega_{h,t+1}})}{\sigma_h H_t}, \tag{22}$$

$$P_{I,t}\left(1+\gamma_C\frac{\Lambda_{T,t}}{\Lambda_t}\right) = P_{K,t}\left[1-\frac{\xi_I}{2}\Omega_{I,t}-\xi_I\Omega'_{I,t}\right] + \beta\frac{\Lambda_{t+1}}{\Lambda_t}P_{K,t+1}\xi_I\Omega'_{I,t}\frac{I_{t+1}}{I_t}, \tag{23}$$

$$P_{K,t}=\beta\frac{\Lambda_{t+1}}{\Lambda_t}\left(\left(1-\delta\right)P_{K,t+1}+R_{K,t+1}\right). \tag{24}$$

In the equations above, $\phi(\bullet)$ denotes the probability density function of household default.[4] It is through this term and through the associated terms in equation 19 that households take into account that their borrowing decisions will affect the probability of repaying the loan, and therefore the lending rate of the bank. The remaining first order conditions are fairly standard. The only exception is equation 20, which shows how the constraint on transactions drives a wedge, represented by Λ_T, into otherwise standard first order conditions for consumption, investment, and housing (standard equations are obtained by setting $\Lambda_T = 0$ for all t). Note that in equilibrium, $H_{j,t} = H$. Households also set wages under standard assumptions regarding monopolistic competition and wage adjustment costs. The details of wage setting are reported in Appendix B.

2.3 Firms

There are four sectors in the model, as in Clancy and Merola (2016). The final goods sector combines non-tradable and imported goods to produce consumption and investment goods bought by domestic households. The non-tradable sector produces its output using domestic capital and labor. Importers sell imported goods to final goods firms at a markup over the world price. The export sector generates output using domestic capital and labor, as well as imported intermediate goods. The latter feature accounts for the fact that small open economies typically have substantially higher import content than domestic

[4] This is the derivative of $\Phi(\bullet)$ in equation 15.

demand. We also assume that capital in the tradable sector is exogenous, a feature intended to reflect that a large part of exporters in the Irish economy are foreign-owned multinationals, whose investment decisions are largely independent of domestic conditions. We therefore also assume that a share of profits of the non-tradable sector are transferred abroad, which allows the model economy to match the Irish export surplus. The non-tradable, tradable and import sectors all operate under monopolistic competition, while the non-tradable sector also faces nominal rigidities in the form of price adjustment costs. We refer the reader to Appendix C for details.

2.4 International capital flows

The bank deposit rate is linked to the euro area interest rate $R_{W,t}$ by

$$R_t = e_t R_{W,t} \tag{25}$$

$$e_t = \theta_B \left(\frac{B_t}{Y_t} - \zeta \right) \tag{26}$$

where e_t denotes a country risk premium which depends positively on the deviation of the foreign-debt-to-GDP ratio from its steady state value $\zeta \equiv \overline{B}/\overline{Y}$, with a sensitivity θ_B. This assumption ensures the stationarity of foreign deposits B_t that evolve according to

$$B_t = R_{t-1}B_{t-1} - TB_t + \Gamma_t, \tag{27}$$

where TB_t and Γ_t denote the trade balance and profits transferred abroad by foreign-owned exports, respectively. The trade balance is given by

$$TB_t = P_{X,t}X_t - P_{M,t}M_t, \tag{28}$$

where $P_{X,t}$, $P_{M,t}$, X_t and M_t denote the prices of exports and imports as well as the quantity of exports and imports, respectively.

3 Calibration

We estimate the model using the Limited information approach of Altig et al. (2005) using data over the 1999Q1-2014Q4 period. We divide the parameters in three groups. The first group is calibrated directly, based on typical values from the literature and standard assumptions. The second group of parameters is calibrated to match the steady-state values of a number of model variables. The third group has been calibrated by matching model impulse-responses to the responses obtained from an estimated structural VAR model.

In the first group, we set the inverse of the Frisch elasticity of labour supply, η, to 2, assume log utility ($\sigma = 1$), and the curvature of the utility function with respect to housing services, ν, to 1.[5] We assume Cobb-Douglas preferences over imported and domestically produced consumption and investment goods, and we set the minimum capital requirement, $gmin$, to 8%, in line with the Basel II rules.[6] We calibrate the demand elasticities of the individual varieties in the labor, non-tradable, tradable and import CES baskets to 11, implying a steady state markup of 1.1. Consumption and investment purchases are made using deposits and therefore $\gamma_C = 1$. For transactions in housing stock we set $\gamma_H = 0.014$, based on the fact that over the 2001-2014 period, the median fraction of the housing stock transacted each year equaled 4.1% (Coates et al., 2016). The price elasticity of exports, η_X, reflects the average of available micro and macro evidence on this parameter for Ireland (see Corbo and Osbat (2013) and Bredin et al. (2003)), while we set the price elasticity of imports equal to one. The depreciation rate of capital equals $\delta = 0.04\%$. Finally, we set the elasticity of the risk premium on domestic deposits over the world interest rate, which depends on the foreign-debt-to-GDP ratio, $\theta_B = 0.0001$. Unfortunately, the only existing evidence for loss given default, λ, covers 2014 and 2015, and is based on the EBA stress test. We set λ equal to the 2014 value for mortgages.[7]

The second set of parameters, and in particular those pertaining to the various financial frictions and household preferences over asset holdings, were calibrated by first specifying targets for the steady state values of a number of model variables. This approach follows e.g. Bernanke et al. (1999), Nolan and Thoenissen (2009), Christiano et al. (2014) and Rannenberg (2016). The targets include deposit and loan interest rates faced by the non-financial sector, information on the source of bank funding, as well as the ratio of non-financial sector loans and the value of the housing stock to GDP. Without loss of generality, we first assume $P_N = P_M$.[8] Most of the other targets were calculated from multi-year averages of the relevant empirical counterparts of these variables, while some are econometric estimates.

All values in Table 1 are computed based on annual levels and model values are reported on annual levels.[9] Parameter values implied by calibration targets in Table 1 are listed in Table 2 and marked by asterisks accompanying the names of parameters.

[5] As the housing stock is assumed to be fixed at 1, the value of ν has no effect on our results.

[6] We also set the steady-state values of productivities in the tradable and non-tradable sectors.

[7] The estimated loss-given default (LGD) on Irish mortgages equals 42.7% and 34.8% for 2014 and 2015, respectively. The estimated LGD on all Irish exposures would be even higher, namely 73.7% and 52.1%.

[8] Setting a target for P_N allows a recursive analytical calibration of the steady state of the model, while setting $P_N = P_M$ conveniently implies that ω_C and ω_M are the shares of imports in final consumption and investment goods, respectively. See Appendix H for details.

[9] As the model is on quarterly frequency, ratios involving a division of stock with a (quarterly) flow (e.g., housing stock-to-GDP ratio) in the model have to be multiplied by 4.

Parameters not used to match targets are without asterisks. Appendix G provides more detail on how the ratios in Table 1 were obtained.

The third group of model parameters (see Table 3) affects the dynamics, but not the steady state of the model, and include the curvature of wage, price and investment adjustment costs, the degree of price indexations in the non-tradable sector, and the persistence and standard deviations of the exogenous driving processes. We estimate these parameters by matching the impulse-responses (IRFs) of the model with the impulse-responses of an identified VAR model, using a variation of the approach of Altig et al. (2005) and Bilbiie et al. (2013). The variables included in the VAR are real GDP, the GDP deflator, real house prices (deflated with the GDP deflator), real exports and the EONIA, and the sample period is 1999Q1-2014Q4. We identify four shocks by placing the minimum set of sign restrictions necessary to achieve theoretically meaningful responses.[10] The sign restrictions are listed in Table 4, where each row refers to a shock and each column to a variable.[11]

We collect all model parameters to be estimated in the vector ζ_{par}, whose values we choose in order to minimise the criterion function

$$(\hat{\Psi} - \Psi(\zeta_{par}))' V^{-1} (\hat{\Psi} - \Psi(\zeta_{par})),$$

where ζ_{par}, denotes the parameters of the model, $\hat{\Psi}$ the vector of IRFs from the VAR, $\Psi(\zeta_{par})$ the IRFs from the model., and V denotes the diagonal weighting matrix based on the average sample variances of each IRF. This matrix attaches a higher weight to the more precisely estimated IRFs during the calculation of the criterion.[12]

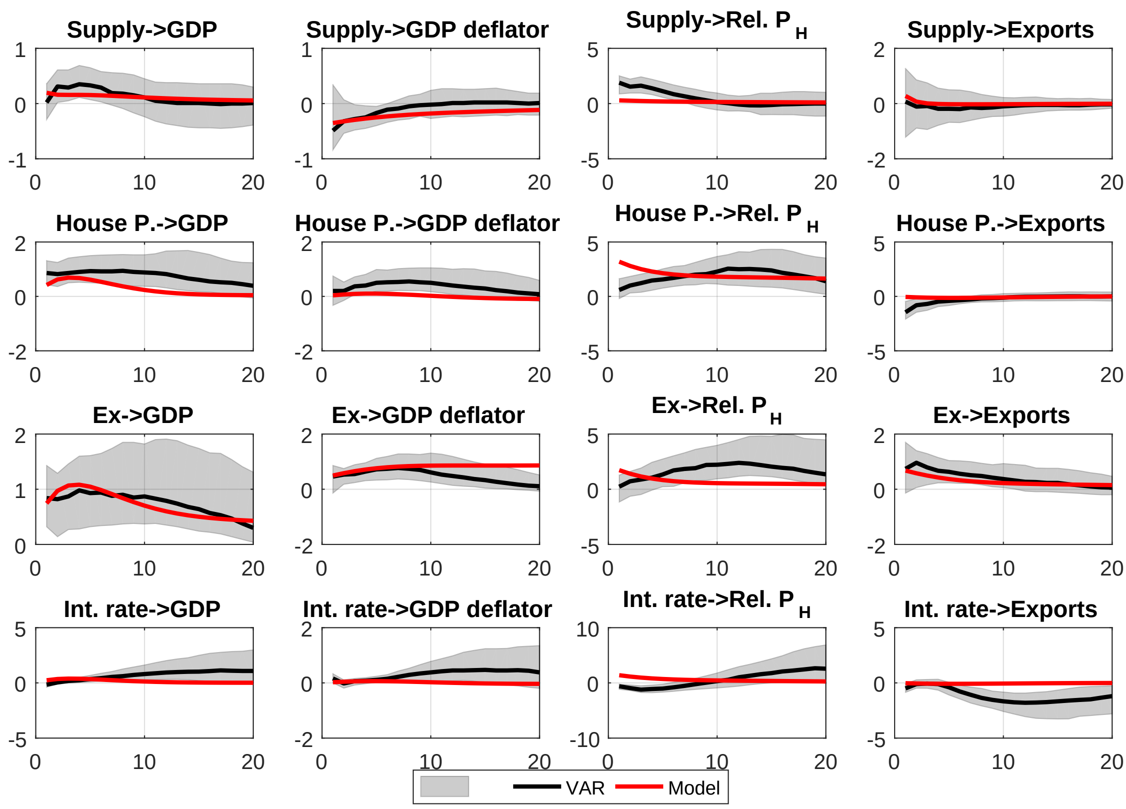
Figure 2 displays the response of the model and the VAR to the four identified shocks. The model matches the response of GDP, exports and the GDP deflator very well. The model also matches the order of magnitude of the house price response to various shocks, though not its hump shape. The reason for this is that the house price in the model is an asset price and thus purely forward looking, i.e. it depends only on the future discounted marginal utility of housing services. The failure of rational expectation models to generate hump shaped responses of house prices is well documented (e.g. Iacoviello and Neri (2010)).

[10] The only redundant restriction for identification purposes is the positive restriction on the response of the house price to the supply shock, which was placed for theoretical reasons.

[11] We leave one shock unidentified. Importantly, the responses of the variables to the unidentified shock do not correspond to the sign restrictions of any of the identified shocks. Moreover, they fluctuate around zero and are not statistically significant.

[12] Since we identify four shocks, we have 4x4xTx1 vector of IRFs stacked on top of each other, where T denoted the number of time periods from the IRF we attempt to match. Also, the first T nonzero elements of V are equal to the average variance of the first IRF in $\hat{\Psi}$, the second T elements are equal the average variance of the second IRF in $\hat{\Psi}$, etc. We set T=12.

FIGURE 2. VAR and model IRFs



Notes: Impulse response functions of the model and the impulse responses in the VAR to the identified shocks. Shaded areas denote 65% confidence intervals.

4 Capital Regulation

In the simulations below, we consider five alternative minimum capital rules. Equations (29) and (30) represent the case where the minimum capital requirement is kept constant over the business cycle, namely at the level mandated by the Basel regulations (equation 29) and the level that exceeds the Basel regulation by 8 percentage points (equation 30). The value of 8 percentage points was chosen in order to illustrate the degree of stabilisation achieved by a rather substantial increase in the minimum capital requirement.

$$g_t = gmin \tag{29}$$

$$g_t = gmin + 8 \; p.p., \tag{30}$$

Equations (31) to (34) represent cases where the macroprudential authority alters g_t depending on either the credit gap (equation 33) or the house price gap (equation 35).

Equation (31) is the rule based on the ESRB Recommendation (we refer to this as the ESRB rule), and says that g_t should respond to the credit gap in an asymmetric and piece-wise linear fashion.[13] In particular, g_t responds only to positive values of the credit gap exceeding 2 p.p., and the maximum increase of g_t is capped at 2.5 p.p.. Due to the rather complex nature of this rule, we also consider the case of a simple linear response to the credit gap (equation 32).

$$g_t = 8\% + \begin{cases} 0 & if \ gap_t \leq 2\% \\ 0.3125 \cdot gap_t - 0.625 & if \ 2\% < gap_t \leq 10\% \\ 2.5\% & if \ gap_t > 10\%, \end{cases} \tag{31}$$

$$g_t = 8\% + 0.43 \cdot gap_t, \tag{32}$$

where

$$gap_t = \left(\frac{L_t}{Y_t + Y_{t-1} + Y_{t-2} + Y_{t-3}} - \frac{\overline{L}}{4 \cdot \overline{Y}} \right), \tag{33}$$

Finally, as responding to the credit gap turns out to be destabilising in response to several shocks, we also consider a rule based on house prices, an indicator variable suggested by Drehmann et al. (2010):

$$g_t = 8\% + 0.85 \cdot price\ gap_t, \tag{34}$$

where

$$price\ gap_t = \frac{P_{H,t} - \overline{P_H}}{\overline{P_H}}. \tag{35}$$

Note that with the higher minimum capital requirement (equation 30), the structure of banks' balance sheets will be different. Accordingly, there will be a different steady state, with lower bank leverage, and different values for the other variables as well. Lower bank leverage implies that, on the one hand, a given absolute change in the portfolio return has less of an effect on the level of equity (percentage-wise), thus tending to make the economy more stable. On the other hand, the transition to the higher capital requirement will be associated with costs, which we examine in subsection 5.6.

[13] The ESRB defines the credit gap as the deviation of $\frac{L_t}{Y_t+Y_{t-1}+Y_{t-2}+Y_{t-3}}$ from a trend computed using a Hodrick-Prescott (HP) filter with a smoothing constant of 400,000. The resulting trend will be extremely smooth, implying that the steady state value represents a reasonable counterpart in the model.

5 Main results

This section discusses the response of the economy to two variants of a housing demand shock, an exogenous decline in export demand, a supply shock and an exogenous decrease in the cost of foreign borrowing, all for the five alternative rules described by equations (29) to (34). The magnitude of the shocks we assume in the simulations below exceeds the magnitude of the estimated standard deviations listed in Section 3.[14] When considering higher, but constant, regulatory capital ratio, we simulate transition from the current minimum capital requirement of 8% to the minimum capital requirement of 16% in subsection 5.6.

5.1 Positive housing demand shock

A positive housing demand shock is modeled as a temporary increase in household preferences for housing, which increases the house price on impact (Figure 3).[15] Our baseline is a constant bank capital requirement of 8% (dashed line below). With the supply of housing fixed, the increase in housing demand causes an increase in house prices, which is transmitted to domestic demand through lowering the households' loan-to-value ratios and thus the default rate. Lower expected losses from non-performing loans are passed on to households in the form of a lower loan rate, which stimulates consumption and investment. Lower interest rates and higher consumption induce house prices to increase even more, which can be interpreted as a financial accelerator mechanism. Wages and prices increase, worsening the country's competitiveness. Exports decrease and imports increase, implying that foreign borrowing in the form of foreign deposits rises, and is intermediated to the non-financial sector in the form of loans.

Total loans to households increase in response to the housing demand shocks for three reasons. First, the sudden increase in house prices and domestic demand increases households' demand for transaction deposits. Second, the decline in the loan rate increases the demand of households for saving deposits. Third, the increase in households' expenditure relative to their revenue requires an increase in borrowing. Bank equity increases due to the decline in the share of non-performing loans. The expansion in bank equity helps accommodate the increase in loans, implying that the bank capital ratio declines only marginally.

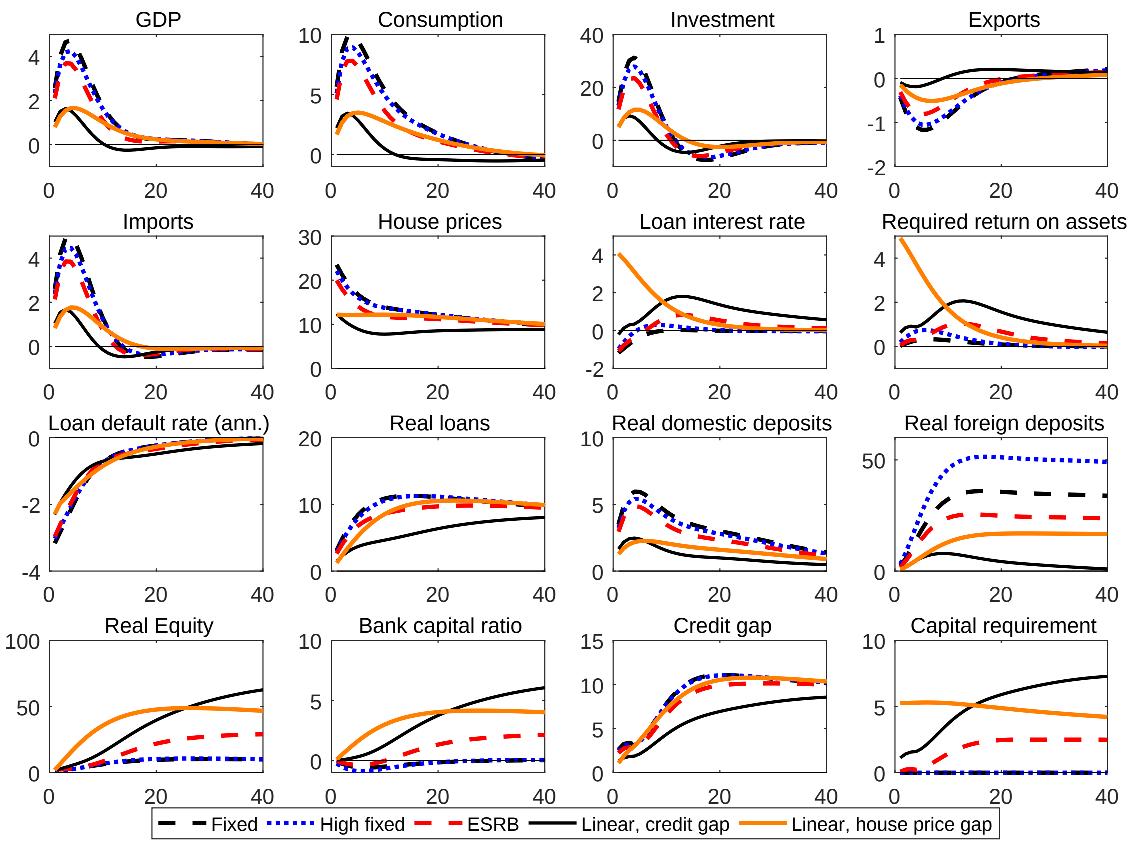
We now turn to the four alternative rules. When the rule recommended by the ESRB and the linear credit gap rule are in place instead of a fixed capital requirement, g_t increases

[14] We do so because for each of the exogenous driving process in our model, a shock of one standard deviation is too weak to cause an increase in the credit gap exceeding the two percent threshold, implying that g_t would always remain constant under the rule recommended by the ESRB. Larger shocks can also be justified by the magnitude of the recent crisis.

[15] Formally, this is a persistent shock to ε_H, which evolves as $ln(\varepsilon_{H,t}) = \rho_H ln(\varepsilon_{H,t-1}) + e_{H,t}$, where $e_{H,t}$ is the shock.

on impact under both rules (bottom-right panel in Figure 3) since the increase in lending immediately exceeds the 2 p.p. threshold in the ESRB Recommendation (equation 31). With a higher g_t, banks' capital buffer is smaller and the risk of ending up undercapitalised in period $t+1$ and having to pay a fine increases. This effect is reflected in a higher required expected return on assets, i.e. $\widetilde{R_{t+1}}$ increases. Banks pass this increase in their expected cost of lending on to households, requiring higher interest rates for loans. As a result, the responses of consumption, investment and house prices are all reduced compared to the case of a constant g_t. Under the ESRB rule, the peak of GDP is lowered by about 20%. Under our assumed linear credit gap rule, g_t increases substantially more than under the ESRB rule, as we calibrated it to achieve a two thirds reduction in the peak GDP response to the housing demand shock.

FIGURE 3. Housing demand shock



Notes: Impulse responses to a positive housing demand shock. All variables are in percentage deviations from the steady state, except interest rates, default rate, and marginal regulatory penalty, which are in annualised percentage-point deviations, and bank capital ratio, credit gap, and capital requirement, which are in percentage-point deviations.

By assumption, the peak of GDP under the linear house price rule is the same as under the linear credit gap rule. As the increase in the credit gap is more gradual than the increase in house prices, so is the increase in g_t. However, for both rules (house price gap and credit gap), g_t ultimately increases by more than twice as much than under the ESRB rule. Finally, fixing the minimum capital requirement at a higher level (dotted line in Figure 3) very slightly attenuates the response of the economy to the housing demand shock. Lower bank leverage reduces the impact of a lower default rate and thus a higher net return on assets on bank equity.

5.2 Boom and bust in the housing market

We model the boom-and-bust scenario on the housing market (a housing bubble) by assuming that the agents expect an increase in the demand for housing to occur in three years (i.e., in quarter 13).[16]

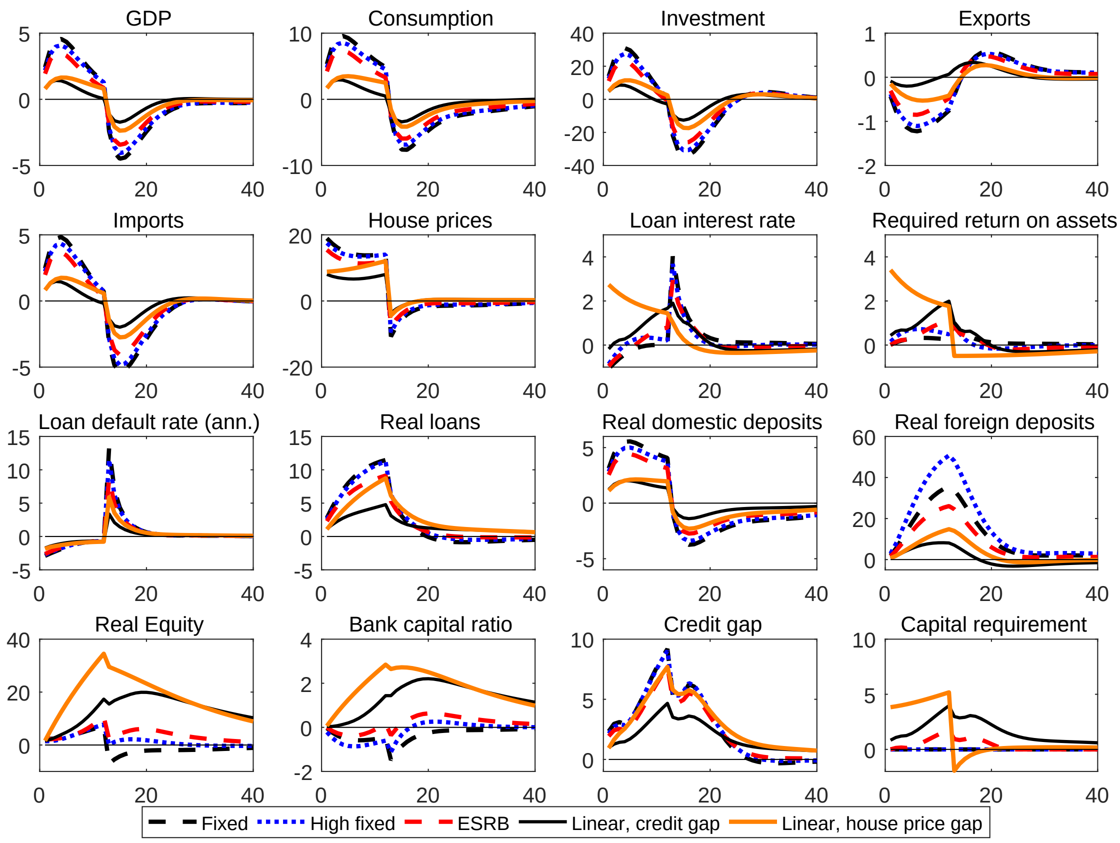
Expectations of a future increase in housing demand cause an immediate increase in house prices (see Figure 4), which transmit across the economy in a qualitatively similar manner as the housing demand shock. The main difference is that when quarter 13 arrives, the demand for housing *does not increase*. The disappointment causes a sharp drop in house prices and a substantial increase in the default rate, which leads to a recession because the economy now has a too high physical capital stock and too much (foreign) debt. Fixed capital requirements are not able to impede an increase in the loan interest rate (an increase in the default rate dominates the drop in the required expected return on assets due to deleveraging), which results in a sharp recession. High fixed minimum capital requirements do provide some stabilisation, but not enough.

All rule-based approaches to setting the CCyB stabilise the economy both during the boom and the bust. During the boom, the increase in the credit gap causes an increase in the regulatory capital ratio both under the ESRB rule and the linear rule based on the credit gap. Higher minimum capital requirements increase the risk of breaching the regulatory minimum capital and result in higher required return on assets. Higher lending rates dampen the the increase in domestic demand, while bank equity increases. CCyB rules are less effective during the bust. Because the drop in GDP partly offsets the sharp decline in borrowing, the credit gap does not close and the ESRB rule and the linear rule based on the credit gap still require banks to hold capital above the regulatory minimum (see the bottom-right panel of Figure 4). While there is some relief for the bank capital ratio from the swift decline in loans, the capital buffer of banks (the distance between their capital ratio and g_t) remains therefore depressed and thus the required expected return on loans remains above its steady state value for one to two years. Essentially,

[16] When this date arrives and the shock is expected to materialise, the demand increase does not happen. This should be viewed as a stylised representation of a housing bubble - a shock that has no "fundamental" basis, or a purely expectation-driven shock. Technically, we implement this scenario by simulating the model with the shock to housing demand expectations and then take the levels reached in quarter 13 as initial values for another simulation of the model, this time with no shocks.

rules based on the credit gap do not react sufficiently to release capital when the housing bubble bursts, and thus cannot counter the sharp increase in lending rates caused by the rising default rate. During the bust, the stabilisation of the economy under the credit gap rules therefore comes mainly from limiting the excesses of the boom in the form of capital overaccumulation and the run-up in domestic and foreign borrowing.

FIGURE 4. Stylised boom and bust in the housing market



Notes: Responses to an anticipated increase in housing demand in the future, which does not materialise. All variables are in percentage deviations from the steady state, except interest rates, default rate, and marginal regulatory penalty, which are in annualised percentage-point deviations, and bank capital ratio, credit gap, and capital requirement, which are in percentage-point deviations.

By contrast, the linear rule based on house prices reacts strongly during both boom and bust phases. Initially, it reacts strongly to the increase in house prices during the boom phase, pushing up lending rates and dampening the domestic expansion. Higher lending rates during the boom phase make bank lending more profitable and both bank equity and bank capital ratio improve substantially (see bottom-left panels of Figure 4). When the bubble bursts, the accumulated capital buffer is released, which undoes a large part of the lending rate increase. Moreover, the default rate does not increase as much during the bust because house prices fall by less (because they have also risen by less during the boom). Note that even though the rule based on house prices allows banks to decrease their capital below the regulatory minimum, this actually does not happen for the average bank. The reason is that banks have accumulated substantial capital buffer during the boom.[17]

Finally, it should be emphasised that the effectiveness of the ESRB rule in stabilising the cycle depends on the timing of the events (first boom, then bust), because the rule does not allow bank capital to decrease below the minimum. Linear rules are instead symmetric and perform better when the sequence of shocks is reversed.

5.3 Reduction in the foreign deposit interest rate

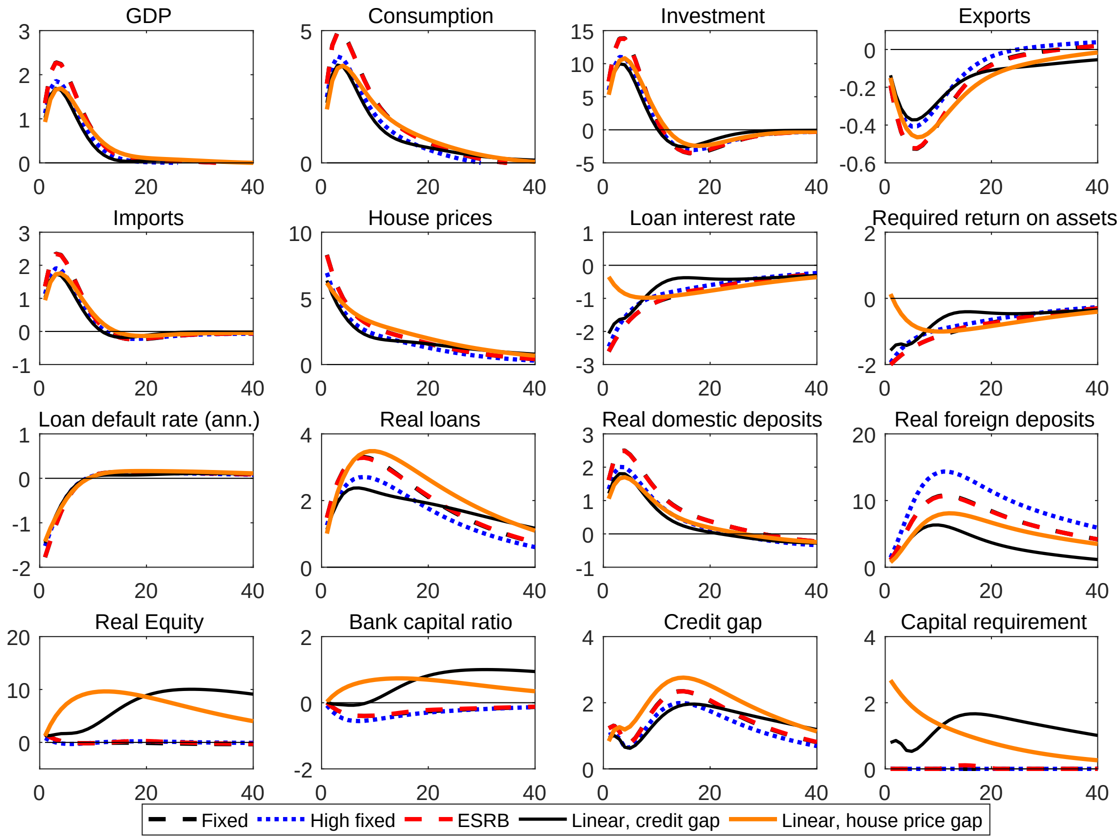
In this scenario, domestic bonds become more attractive to foreign investors, for instance due to lower risk perceptions.[18] We simulate this scenario as a decline in the foreign deposit rate. Banks pass the reduction in their borrowing costs to households through a lower lending rate (see Figure 5), which increases consumption, investment, and house prices. The associated decline in the default rate further lowers the lending rate. Higher domestic demand results in higher wages, prices and imports as well as lower exports, which increases the amount of foreign borrowing. Higher house prices and domestic activity increase the demand for transaction deposits.

The credit gap does not open much because of the simultaneous increase in GDP and loans. Because the 2 p.p. threshold is not breached, the ESRB rule does not react at all. By contrast, the two linear rules both lower the peak of GDP by about a fifth. Under a higher fixed level of g_t, a similar stabilisation gain is achieved.

[17]Note that by making the linear rule based on house prices more aggressive, one could achieve even greater degree of stabilisation without banks breaching the minimum capital requirement.

[18]Formally, this is a shock to the interest rate foreigners require for holding Irish assets, $R_{W,t}$. The shock is modelled as $R_{W,t} = (1 - \rho_{R_W})\overline{R_W} + \rho_{R_W} R_{W_{t-1}} + e_{R_{W,t}}$, where $e_{R_{W,t}}$ is the shock.

FIGURE 5. Reduction in the foreign deposit interest rate



Notes: Impulse responses to a decrease in the risk premium. All variables are in percentage deviations from the steady state, except interest rates, default rate, and marginal regulatory penalty, which are in annualised percentage-point deviations, and bank capital ratio, credit gap, and capital requirement, which are in percentage-point deviations.

5.4 Temporary decline in export demand

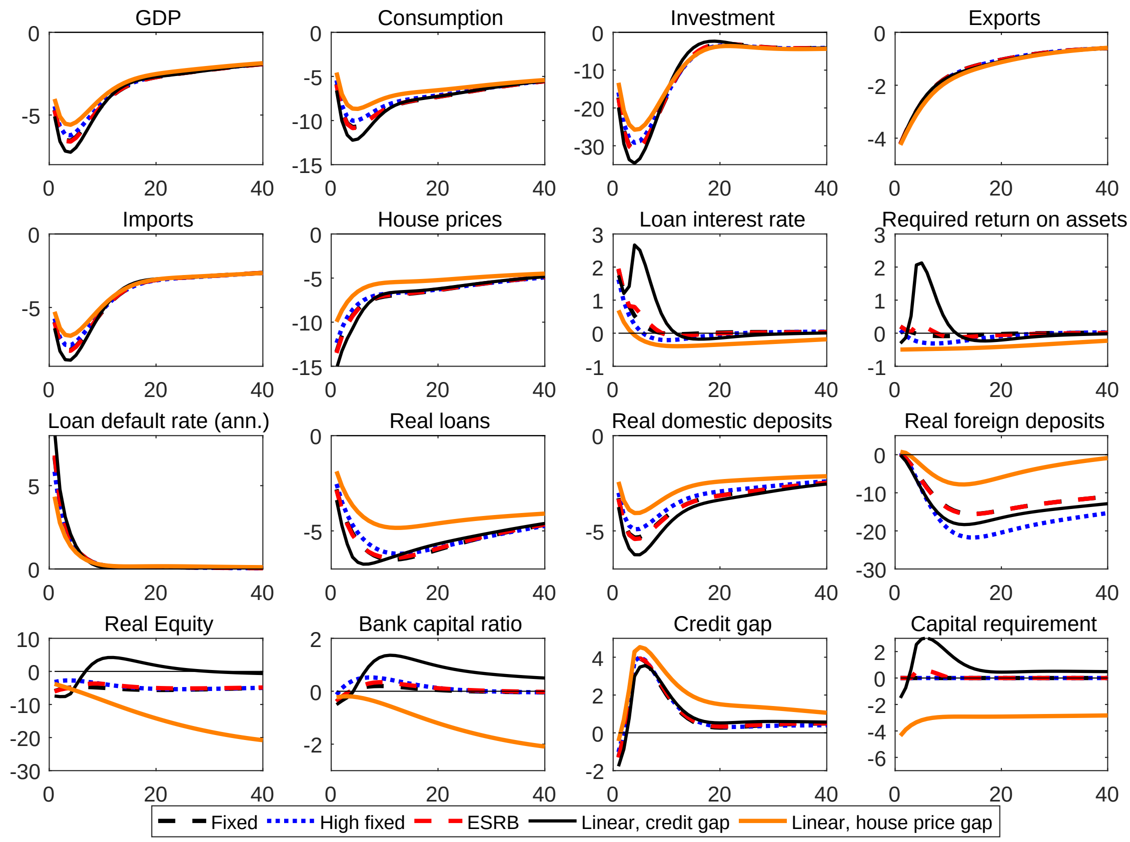
In this scenario, foreign demand for domestic export goods temporarily declines.[19] The decline in foreign demand depresses exports and therefore employment (Figure 6). The associated decline in wage pressure causes a decline in inflation and thus an increase in the real lending rate, which in turn further depresses consumption, investment and house prices. The decline in house prices substantially increases the default rate and thus the lending rate, regardless of the type of capital rule used. This interest rate increase further depresses house prices, consumption, investment, and GDP.

The decline in domestic spending and a reduced incentive to hold saving deposits leads to the decline in loans. However, because GDP declines by more than loans do,

[19] The shock is modelled as a temporary decrease in export demand. If XD_t is the shifter of the export quantity demanded and $\overline{T}$ is the steady-state level of the terms-of-trade, the shock process is $ln(XD_t) = (1 - \rho_X)ln(\overline{T}) + \rho_X ln(XD_{t-1}) + e_{XD,t}$, where $e_{XD,t}$ is the shock.

the credit gap opens. Part of the reason is that the loss in export revenue associated with these shocks tends to dampen the decline in non-financial sector borrowing relative to the decline in GDP. Under the linear credit gap rule, this causes a sufficiently large increase in the minimum capital requirement to worsen the downturn caused by the shock (bottom-right panel of Figure 6). The same happens under the ESRB rule, just that the increase in g_t is less pronounced.

FIGURE 6. Temporary decline in export demand



Notes: Impulse responses to a temporary decline in foreign demand. All variables are in percentage deviations from the steady state, except interest rates, default rate, and marginal regulatory penalty, which are in annualised percentage-point deviations, and bank capital ratio, credit gap, and capital requirement, which are in percentage-point deviations.

By contrast, under the rule based on the house price gap, the regulator quickly lowers the minimum capital requirements, because house prices decline. This reduces the likelihood that banks will have to pay the penalty for breaching the minimum capital requirement and banks can decrease the required return on their assets. The lending rate does not increase as much as under the alternative rules and it declines after a few quarters because the reduction in house prices is persistent. A less pronounced interest rate increase and their subsequent decline alleviate the decrease in consumption, investment and GDP.

For example, the drop in GDP under the house price rule is about 1 p.p. lower at the trough than under the ESRB rule or the linear rule based on the credit gap.

Note that the model may actually understate the increase in the credit gap and thus the tightening prescribed by rules featuring the credit gap. The model does not feature import content adjustment costs to be found, say, in the ECB's New Area Wide Model (Christoffel et al., 2008), implying that short and long-run price elasticities of are identical. A lower short run price elasticity would lower the decline in imports and strengthen the GDP decline. Furthermore, it would cause a higher path for foreign borrowing, which in our simulation actually decreases, and thus a higher path for domestic lending. Lower GDP and higher lending would imply a higher path for the credit gap and therefore even stronger tightening of capital requirements under the rules based on the credit gap.

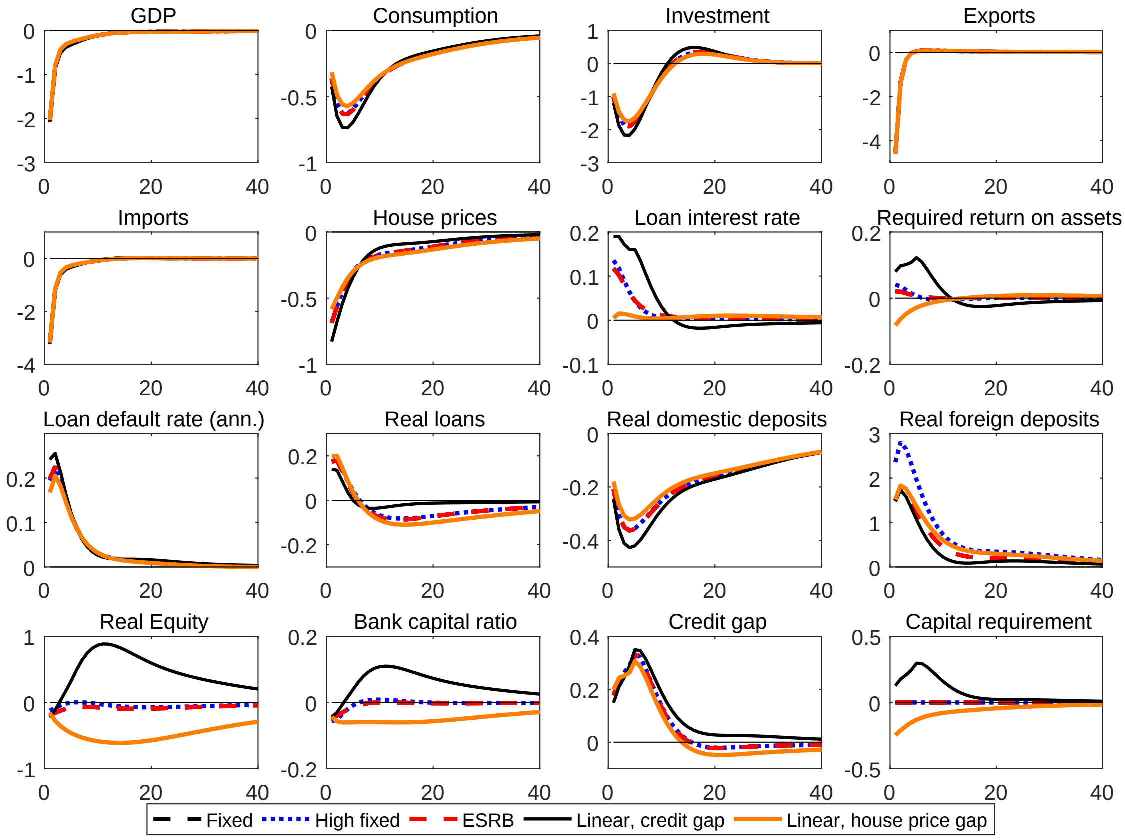
These results suggests that the credit gap may be a problematic indicator variable under a very common shock for small open economies. It prescribes tightening minimum capital requirements exactly at the time when foreign borrowing could be used to help smooth the adverse effects of a decline in foreign demand. The reason for such an adverse outcome is that the credit gap is countercyclical in this case. Furthermore, while the tightening of the capital requirement in recession is less pronounced under the ESRB rule than under linear the credit gap rule, the stabilisation gains achieved under the ESRB rule in the presence of house price shocks are also much more modest, especially so in the boom-bust scenario. Policy rules featuring the credit gap thus appear to create a trade-off between stabilising the economy's response to housing demand and export demand shocks. By contrast, this trade-off is absent when the capital requirement responds to house prices.

5.5 Supply shock

We model the supply shock as a temporary increase in the price markups in non-tradable goods and export sectors [20] The increase in price markups makes domestic goods less competitive, lowers exports and increases the import content of domestic consumption and investment goods (see Figure 7). The resulting current account deficit increases foreign borrowing (see also equations 60 and 59), and requires an increase in the deposit rate. The latter is passed on by the banks to the loan rate. Hence consumption, investment and house prices decline. The decline in house prices causes an increase in the share of non-performing loans and further increase in the loan rate, worsening the downturn.

[20] Formally, this is a simultaneous shock to μ_X and μ_N, where e.g. $\mu_X \equiv e^X/(e^X - 1)$. The shock process is $ln(\mu_{X,t}) = (1-\rho_\mu)ln(\overline{\mu_X}) + \rho_\mu \mu_{X,t-1} + e_{\mu_X,t}$, where $e_{\mu_X,t}$ is the shock.

FIGURE 7. Increase in non-tradable and export goods markup



Notes: Impulse responses to an increase in markup for non-tradable goods and for export goods. All variables are in percentage deviations from the steady state, except interest rates, default rate, and marginal regulatory penalty, which are in annualised percentage-point deviations, and bank capital ratio, credit gap, and capital requirement, which are in percentage-point deviations.

Just as in the case of a decline in export demand, the credit gap is countercyclical, as GDP declines and loans increase initially due to the increase in foreign borrowing caused by the temporary current account deficit. The increase in the credit gap is too small to trigger an increase in g_t under the ESRB rule, while the linear credit gap rule amplifies the decline in consumption and investment. By contrast, as house prices decline in response to the shock, the house price rule prescribes a small decline in the minimum capital requirement and attenuates the decline in consumption and investment.

5.6 Transition to higher capital requirement

The above results suggest that a higher minimum capital requirement makes a small contribution to stabilising the economy. However, the transition to double the level of minimum capital requirements will be associated with costs. In the following exercise, we simulate an increase in the minimum regulatory capital ratio from 8% to 16% (we emphasise that this scenario is for illustrative purposes only).[21]

An increase in the minimum capital requirement means that banks suddenly face a higher marginal regulatory penalty, as the distance between the level of equity they are supposed to hold and the amount they actually do hold has widened. As a consequence, the banks find themselves paying the cost of breaching the minimum capital requirements, cut their supply of loans, and increase lending rates (Figure 8).[22] The increase in the lending rate depresses domestic consumption and investment, causing a decline of GDP of 5.8% at the trough. The decline in domestic demand leads to an improvement of the current account, as imports decline and exports increase due to lower wage pressure. Furthermore, house prices decline as the current and future utility from owning a house is discounted more heavily. The resulting house price decline increases the share of nonperforming loans.

The decline in house prices and economic activity lower households' demand for transaction-related funds, which has an immediate negative effect on borrowing. Furthermore, the improvement in the current account is reflected both in lower borrowing of households from banks and in lower borrowing of banks from abroad. At the same time, the increase in the lending rate increases the revenues of banks and thus gradually raises their equity. The bank capital ratio slowly approaches the new higher regulatory ratio and the marginal cost of lending declines, allowing domestic demand and house prices to recover.

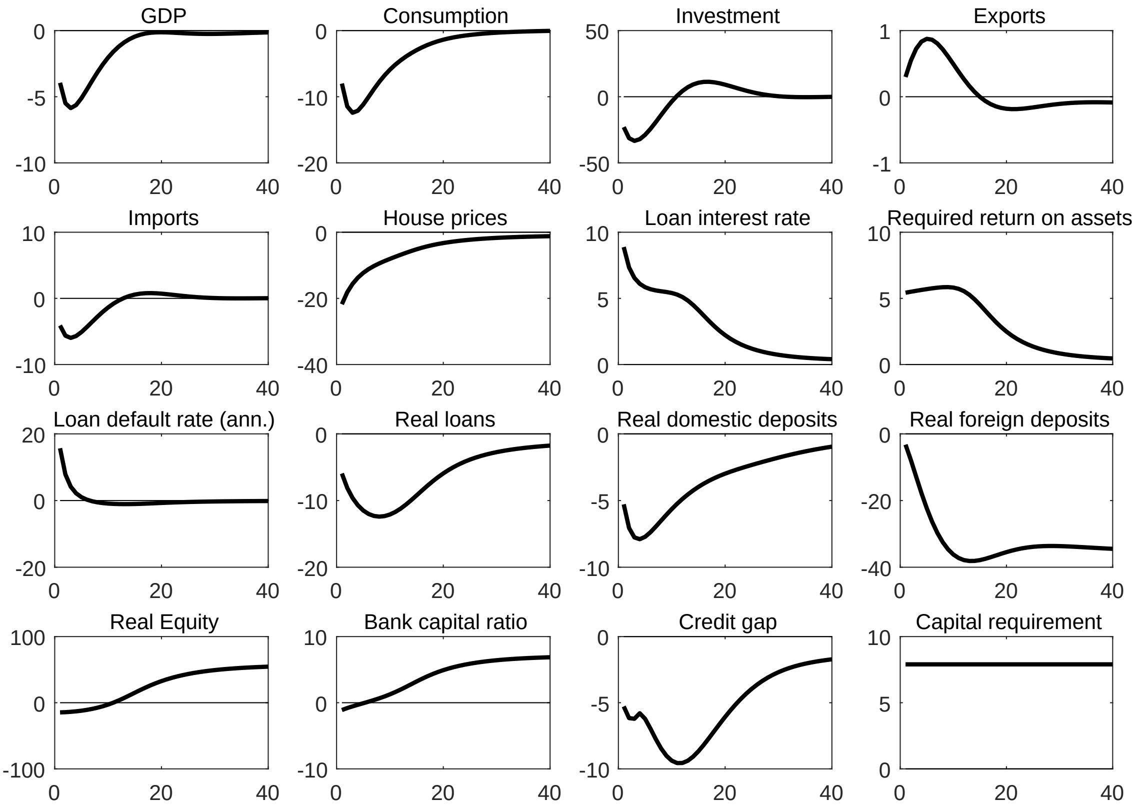
In the new steady state, the liability side of the bank balance sheet has changed. Banks rely more on equity and less on foreign deposits, while domestic deposits return to their pre-shock value. This implies that foreign debt of the economy as a whole is lower than before the increase in the capital requirement. Furthermore, the steady state of all other variables, including GDP and its components, lending and the lending rate are essentially unchanged.[23]

[21]The reason why we consider a substantial increase in bank capital is because such an increase is required to change bank leverage sufficiently in order to have a meaningful impact on dampening the fluctuations (which is what we consider in scenarios in the sections above).

[22]Note that in our model, banks can increase their capital only through retained earnings.

[23]An important caveat to the analysis that the model does not capture any effect of higher bank equity and lower bank leverage on the cost of equity and thus lending. A lower steady state level of bank leverage might reduce the cost of equity by lowering the risks associated with owning bank equity. But it might also increase the cost of equity if domestic households had preferences over the share of equity in their portfolio, requiring an increase in order to be willing to hold more equity. Furthermore, the analysis abstracts from the possible benign effects lower foreign debt might have on the costs of borrowing from abroad.

FIGURE 8. Increasing the minimum capital requirement



Notes: Transition to new, higher minimum capital requirements (from 8% to 16%). All variables are in percentage deviations from the initial steady state, except interest rates, default rate, and marginal regulatory penalty, which are in annualised percentage-point deviations, and bank capital ratio, credit gap, and capital requirement, which are in percentage-point deviations.

Our simulated GDP response to an increase in capital requirements is broadly in line with the literature. We compared the response of the model to an increase in capital requirements for a shock of similar magnitude as considered in the literature, i.e., 1 p.p. increase. The response of output in our model was of similar magnitude as that considered in Slovik and Cournède (2011), and well within the range of model responses considered in BCBS (2010).[24]

6 Conclusion

In this paper, we investigate the performance of several countercyclical capital buffer rules based on two different indicator variables, using a medium scale DSGE model of the Irish economy. First, we consider rules where the regulatory capital ratio is positively linked to the credit gap, including a rule recommended by the ESRB, as well as a simpler

[24]The comparison is with respect to a two-year gradual increase of capital requirement in BCBS (2010).

and more reactive linear policy rule. Second, we also consider specifications where the regulatory capital ratio is positively linked to house prices. Finally, we investigate a more conventional alternative (or complement) to the CCyB approach, namely substantially increasing acyclical regulatory capital requirements.

We obtain the following results. On the one hand, CCyB rules (simple linear rule and the ESRB rule) requiring that regulatory capital increases with the credit gap are able to dampen the response of the economy to housing demand shocks as well boom and bust cycles driven by expectations. The reason is that, in all these cases, the credit gap moves strongly procyclically, implying that regulatory capital is tightened when GDP increases. This limits physical capital overaccumulation and the development of a foreign borrowing overhang, and creates a bank capital cushion which is released once the economy and borrowing contract. The stabilisation is more modest under the ESRB rule because compared to the linear rule it caps the maximum increase in the minimum capital requirement during the boom, and that it is asymmetric, as it does not allow for a response to negative credit gap values.

Most importantly, CCyB rules based on the credit gap may fail to attenuate the response of the economy to other shocks, or even amplify their negative effects, if the shocks trigger an acyclical or countercyclical credit gap response. A relevant example, especially for small open economies, is a temporary decline in export demand, which lowers GDP more than domestic lending. Hence if the macroprudential authority responds aggressively to the credit gap, it worsens the export-induced downturn by effectively making borrowing more expensive. A similar effect occurs with the negative supply shock. Hence by targeting the credit gap, the macroprudential authority creates a trade-off between stabilising the response of the economy to housing demand shocks and destabilising the economy after export demand shocks. By contrast, such a trade-off does not arise if the regulator targets the house price gap, since house prices move procyclically in response to all shocks we consider. These results provide further justification for policymakers to consider a wider set of indicators, and particularly house prices, when setting CCyB rates. They also suggest that the prominence given to credit-gap-based thresholds for setting CCyB rates should be re-examined in the context of the ESRB recommendations on the conduct of macroprudential policy.

Finally, imposing a substantially higher constant capital requirement makes the economy only slightly more resilient in response to fluctuations. However, the costs associated with the transition to this higher regulatory capital ratio are substantial.

References

Altig, D., Christiano, L.J., Eichenbaum, M., Linde, J., 2005. Firm-specific capital, nominal rigidities and the business cycle. NBER Working Paper Series 11034.

Angelini, P., Neri, S. Panetta, F., 2014. The interaction between capital requirements and monetary policy. Journal of Money, Credit and Banking 46(6), 1073–1111.

Angelini, P., Neri, S., Panetta, F., 2012. Monetary and macroprudential policies. European Central Bank Working Paper 1449.

Angeloni, I., Faia, E., 2013. Capital regulation and monetary policy with fragile banks. Journal of Monetary Economics 60, 311–324.

BCBS, 2010. Assessing the macroeconomic impact of the transition to stronger capital and liquidity requirements. Interim Report, August. Bank for International Settlements, Basel.

Beneš, J., Kumhof, M., 2014. Risky bank lending and countercyclical capital buffers. Journal of Economic Dynamics and Control 58, 58–80.

Bernanke, B.S., Gertler, M., Gilchrist, S., 1999. The financial accelerator in a quantitative business cycle framework. Handbook of Macroeconomics I , 1341–1393.

Bilbiie, F.O., Meier, A., Mueller, G.J., 2013. What accounts for the changes in U.S. fiscal policy transmission? Journal of Monetary Economics 60, 311–324.

Bredin, D., Fountas, S., Murphy, E., 2003. An empirical analysis of short-run and long-run Irish export functions: does exchange rate volatility matter? International Review of Applied Economics 17(2), 193–208.

Carrasco-Gallego, J.A., Rubio, M., 2015. Macroprudential policy design in the euro area: The case of Spain. Mimeo.

Chadha, J.S., Corrado, G., Corrado, L., 2015. Consumption dynamics, housing collateral and stabilisation policy: A way forward for macro-prudential instruments. Mimeo.

Christensen, I., Meh, C., Moran, K., 2011. Monetary and macroprudential policies. Bank of Canada Working Paper 2011-32.

Christiano, L., Motto, R., Rostagno, M., 2014. Risk shocks. American Economic Review 104(2), 27–65.

Christoffel, K., Coenen, G., Warne, A., 2008. The New Area-Wide Model of the euro area: A micro-founded open-economy model for forecasting and policy analysis. Working Paper Series 944. European Central Bank. URL: http://ideas.repec.org/p/ecb/ecbwps/20080944.html.

Clancy, D., Merola, R., 2014. The effect of macroprudential policy on endogenous credit cycles. Research Technical Paper 15.

Clancy, D., Merola, R., 2016. Eire mod: A DSGE model for Ireland. The Economic and Social Review 47, 1–31.

Coates, D., McNeill, J., Williams, B., 2016. Estimating cash buyers and transaction volumes in the residential propery sector in Ireland 2000-2014. Central Bank of Ireland Quarterly Bulletin 03/2016.

Corbo, V., Osbat, C., 2013. Trade adjustment in the European Union. A structural estimation approach. European Central Bank Working Paper 1535.

Drehmann, M., Borio, C., Gambacorta, L., Jimenez, G., Trucharte, C., 2010. Countercyclical capital buffers: Exploring options. BIS Working Papers 317.

ESRB, 2014. Recommendation of the European systemic risk board. Official Journal of the European Union C239/01.

Gerlach, S., Stuart, R., 2013. Money demand in Ireland, 1933-2012. Journal of the Statistical and Social Inquiry Society of Ireland XLIII, 1–17.

Iacoviello, M., Neri, S., 2010. Housing market spillovers: Evidence from an estimated DSGE model. American Economic Review 2(2), 125–164.

Jakab, Z., Kumhof, M., 2015. Banks are not intermediaries of loanable funds - and why this matters. Bank of England Working paper 529.

Jorda, O., Schularick, M., Taylor, A.M., 2012. When credit bites back. Journal of Money, Credit and Banking 45(2), 3–28.

Kelly, R., O'Malley, T., 2015. The good, the bad and the impaired: A credit risk model of the Irish mortgage market. Journal of Financial Stability 22, 1–9.

Lewis, V., Villa, S., 2016. The interdependence of monetary and macroprudential policy under the zero lower bound. National Bank of Belgium Working paper 310.

McElligott, R., O'Brien, M., 2011. Irish money and banking statistics: A new approach. Central Bank of Ireland Quarterly Bulletin 11(01), 108–122.

Nolan, C., Thoenissen, C., 2009. Financial shocks and the U.S. business cycle. Journal of Monetary Economics 56, 596–604.

Rannenberg, A., 2016. Bank leverage cycles and the external finance premium. Journal of Money Credit and Banking 48(8), 1569–1613.

Schularick, M., Taylor, A.M., 2012. Credit booms gone bust: monetary policy, leverage cycles, and financial crises, 1870–2008. The American Economic Review 102, 1029–1061.

Slovik, P., Cournède, B., 2011. Macroeconomic impact of Basel III. OECD Economics Department Working Papers 844.

A Tables

Table 1. Steady state values of important variables and their counterparts in the data

Name	Model	Data	Sources
Consumption share, $\frac{PC}{Y}$	51.8	45.5	CSO NIE
Private inv. share, $\frac{P_I I}{Y}$	14.4	19.9	CSO NIE
Gov. exp. share*, $\frac{P_N G}{Y}$	20.6	20.6	CSO NIE
Export share, $\frac{P_X X}{Y}$	92.3	92.6	CSO NIE
Import share, $\frac{P_M M}{Y}$	79.2	78.3	CSO NIE
Export surplus* , $\frac{P_X X - P_M M}{Y}$	13.2	14.3	CSO NIE
Imp. share cons.* , $\frac{P_M C_M}{PC}$	45.0	45.0	CSO IO tables
Imp. share inv.* , $\frac{P_M I_M}{Y}$	50.0	50.0	CSO IO tables
Imp. share exports* , $\frac{P_M X_M}{P_X X}$	56.0	57.2	CSO IO tables
Labour share* , $\frac{WN}{Y}$	40.0	39.6	CSO IO tables
Non-fin. sec. loan rate* , R_L	4.0	4.0	CBI, OC
Deposit interest rate* , R	1.8	1.8	CBI, OC
Deposit interest semi-elast.*	1.5	1.5	Gerlach and Stuart (2013)
Deposit adjustment speed*	0.2	0.2	Gerlach and Stuart (2013)
Prob. of undercap.* , F_b	2.5	2.5	Jakab and Kumhof (2015)
Loan-to-GDP rat.* , $\frac{L}{Y}$	104.4	104	Internal CBI data
Foreign dep. share* , $\frac{B}{L}$	22.2	22.2	CBI, OC
Bank equity ratio* , $\frac{E}{L}$	12.1	12.1	CBI, OC
Housing stock ratio* , $\frac{P_H H}{Y}$	244.9	244.9	CBI, CSO NIE
Loan default rate* , F_h	0.8	0.8	CBI, OC, Kelly and O'Malley (2015)

Notes: All values are in %. CSO=Central Statistical Office; NIE=National Income and Expenditure, IO=Input-Output. OC = own calculations. Own calculations are detailed in Appendix G. An asterisk denotes a target value in the calibration.

Table 2. Calibrated Parameters

Symbol	**Name**	**Value**
Households		
β	Discount factor*	0.9855
ϕ_N	Utility weight of labour*	1.9282
ζ_D	Utility weight of deposits*	0.3526
ζ_H	Utility weight of housing*	0.1017
η	Labour supply elast.	2
ν	Elast. of housing demand	1
ι	Curvature of saving deposit utility*	5
ξ_D	Deposit adjustment cost*	2
γ_C	Share of consumption trans. dep.	0.2
γ_H	Share of housing trans. dep.	0.05
δ	Depreciation rate	0.04
σ_h	Idiosyncratic risk*	0.4721
μ_C	Final cons. demand elasticity	1.01
μ_I	Final inv. demand elasticity	1.01
e_N	Non-tradable goods varieties elasticity	11
e_M	Import varieties elasticity	11
e_X	Export varieties elasticity	11
$e_{X,W}$	Export basket demand elasticity	2
Banking sector		
λ	Loss given default	0.4217
σ_b	Idiosyncratic risk*	0.4721
ζ	Share of foreign debt in GDP*	1.0564
$gmin$	SS. minimum capital requirement	0.08
θ_b	Fraction retained equity*	0.9882
$\frac{B}{Y}$	SS. foreign-deposit-to-GDP*	23.2%
θ_B	Risk premium sensitivity	1e-8
R_W	World interest rate*	3%
Firms		
α	Share of imports in exports*	0.49
ω_C	Share of consumption imports*	0.2
ω_I	Share of investment imports*	0.3
γ^N	Share of labour (non-tradable)*	0.44
γ^X	Share of labour (tradable)*	0.44
e_W	Labour varieties elasticity	11
θ_Π	Tradable profits transferred abroad*	82.0%

Parameters denoted with an asterisk are implicitly calibrated in order to support targets listed in Table 1, as well as $P_N = 1$.

TABLE 3. Estimated parameters

Symbol	Name	Value
ξ_W	Wage adj. cost	1500
ξ_I	Investment adj. cost	2.55
ξ_N	Non-tradable price adj. cost	1500
χ	Habit formation	0.7
ω^{P_N}	Non-tradable price indexation	0.1
σ_μ	Sd. supply shock	0.05
σ_H	Sd. housing demand shock	0.14
σ_X	Sd. export demand	0.01
σ_R	Sd. monetary policy shock	0.005
ρ_μ	AR(1) supply shock	0.3
ρ_H	AR(1) housing demand shock	0.995
ρ_X	AR(1) export demand	0.993
ρ_{R_W}	AR(1) risk premium shock	0.957

TABLE 4. Matrix of sign restrictions

Shock in VAR (model)	GDP	GDP defl.	Real P_H	Exports	EONIA
Supply (markup)	+	-	+		0
Housing demand (prefer.)	+	+	+	-	0
Export demand (XD)	+	+		+	0
Monetary policy (R)	+	+			+

Note: In the estimation, the sign restriction is always applied to the fifth element of the IRF of the respective variable to the respective shock. An exception is the response of the EONIA, where restriction applies directly to the equation for the EONIA in the VAR.

B Wage setting

Wage and price adjustment costs are specified in terms of deviations from past growth rate of prices and wages.[25] However, we allow for a degree of indexation, which implies that only part of the deviation from previous-period price or wage inflation is subject to adjustment costs. E.g., for wages we have

$$\Pi_{t-1}^{W} = \left(\pi_{t-1}^{W}\right)^{\omega_W} (\pi)^{1-\omega_W}$$

where $0 \leq \omega_W \leq 1$ denotes the degree of indexation to past wage inflation.

Households set wages assuming monopolistic competition, where households are facing a downward sloping demand curve $N(\bullet)$ of the form

$$N\left(W_{i,t}\right) = \left(\frac{W_{i,t}}{W_t}\right)^{-e^W} N_t.$$

and wage adjustment costs

$$\Omega_{W,t} \equiv \frac{\xi_W}{2}\left(\log\left(\frac{W_{i,t}}{W_{i,t-1}}\frac{1}{\Pi_{t-1}^{W}}\right)\right)^2$$

The objective is given by

$$-\frac{1}{1+\eta}N_t^{1+\eta}\left(W_{i,t}\right) + \Lambda_t W_{i,t} N\left(W_{i,t}\right)\left[1-\Omega_{W,t}\right] + \beta\Lambda_{t+1}W_{i,t+1}N\left(W_{i,t+1}\right)\left[1-\Omega_{W,t+1}\right] \quad (36)$$

Substituting $N\left(W_{i,t}\right)$ and writing-out the adjustment costs gives

$$\begin{aligned} -\frac{1}{1+\eta}\left(\left(\frac{W_{i,t}}{W_t}\right)N_t\right)^{1+\eta} + \Lambda_t \frac{W_{i,t}}{W_t^{e^W}}^{1-e^W} N_t\left[1-\frac{\xi_W}{2}\left(\log\left(\frac{W_{i,t}}{W_{i,t-1}}\frac{1}{\Pi_{t-1}^{W}}\right)\right)^2\right] \\ +\beta\Lambda_{t+1}W_{i,t+1}N\left(W_{i,t+1}\right)\left[1-\frac{\xi_W}{2}\left(\log\left(\frac{W_{i,t+1}}{W_{i,t}}\frac{1}{\Pi_{t+1}^{W}}\right)\right)^2\right] \end{aligned}$$

Because $\frac{\partial N(W_{i,t}/W_t)}{\partial W_{i,t}} = -\frac{e^W}{e^W-1}\left(\frac{W_{i,t}}{W_t}\right)^{-\frac{e^W}{e^W-1}-1} N_t \frac{1}{W_t} = -\frac{e^W}{e^W-1}N_t\frac{1}{W_t}$, as all optimising households set the same wage in equilibrium. Hence the FOC w.r.t. $W_{i,t}$ is given by

$$\begin{aligned} \phi_N N_t^{\eta}\frac{e^W}{e^W-1}\frac{1}{W_t\Lambda_t} = 1-\frac{\xi_W}{2}\left(\log\left(\frac{\pi_t^W}{\Pi_t^W}\right)\right)^2 + \xi_W\left(\log\left(\frac{\pi_t^W}{\Pi_t^W}\right)\right)\frac{1}{e^W-1} \\ -\frac{1}{e^W-1}\beta\frac{\Lambda_{t+1}}{\Lambda_t}\pi_{t+1}^W\frac{N_{t+1}}{N_t}\xi_W\log\left(\frac{\pi_{t+1}^W}{\Pi_{t+1}^W}\right) \quad (37) \end{aligned}$$

[25] Note that steady-state inflation is calibrated to zero.

C Firms

There are five types of firms: Non-tradable goods firms, tradable goods firms, exporters, importers and final goods firms that aggregate intermediate goods into final goods.

C.1 Non-tradable goods firms

There is a continuum of non-tradable goods firms, indexed by i. Each non-tradable goods firm produces output using a Cobb-Douglas production function and face quadratic price adjustment costs. Its objective is given by

$$\sum_{j=0}^{\infty} \beta^j \Lambda_{t+j} \left[P_{N,i,t+j} Y_{N,i,t} \left[1 - \Omega_{P_N,t} \right] - W_{t+j} N_{t+j} - R_{K,t+j} K_{t+j-1} \right],$$

where

$$\Omega_{P_N,t} \equiv \frac{\xi_N}{2} \left(\log \left(\frac{P_{N,i,t+j}}{P_{N,i,t+j-1}} \frac{1}{\Pi_{N,t}} \right) \right)^2$$

are price-adjustment costs. Similarly as for wages, adjustment costs permit partial indexation that is costless. Variable Π_t^N denotes the indexation scheme for price changes in the non-tradable sector.

Each intermediate goods firm is a monopolistic supplier of its own variety and thus faces a downward-sloping demand curve, which it takes as a constraint in its optimisation problem:

$$Y_{N,i,t+j} = \left(\frac{P_{N,i,t+j}}{P_{N,t+j}} \right)^{-e^N} Y_{N,t+j}. \tag{38}$$

The other constraint it faces is its production function, which is assumed to be a standard Cobb-Douglas production function:

$$Y_{N,t+j} = A_{N,t+j} K_{N,t+j-1}^{1-\gamma_N} N_{N,t+j}^{\gamma_N} \tag{39}$$

Each firm chooses prices, capital, and labour, and both constraints bind. The first-order conditions w.r.t. $P_{N,i,t}$ is given by (note that in equilibrium, all non-tradable goods firms choose the same price and therefore $P_{N,i,t}/P_{N,i,t-1} = P_{N,t}/P_{N,t-1} \equiv \pi_t^N$

$$\begin{aligned} \frac{\xi_N}{e^N - 1} \log \left(\frac{\pi_t^N}{\Pi_t^N} \right) = \beta \frac{\Lambda_{t+1}}{\Lambda_t} \pi_{t+1}^N \frac{Y_{N,t+1}}{Y_{N,t}} \left[\frac{\xi_N}{e^N - 1} \log \left(\frac{\pi_{t+1}^N}{\Pi_{t+1}^N} \right) \right] + \\ + \frac{MC_{N,t}}{P_{N,t}} \frac{e^N}{e^N - 1} - \left[1 - \Omega_{P_N,t} \right] \end{aligned} \tag{40}$$

The optimality conditions w.r.t. capital and labour are given by:

$$(1 - \gamma_N) MC_{N,t} Y_{N,t} = R_{K,t} K_{t-1} \tag{41}$$

and

$$\gamma_N MC_{N,t} Y_{N,t} = W_t N_{N,t}. \tag{42}$$

C.2 Importers

Importers buy an import good at the (exogenous) world price $P^*_{M,t}$, which, converted into domestic units through the exchange rate S_t is their marginal cost:

$$MC_{M,t} = S_t P^*_{M,t} \tag{43}$$

Importers then use this good and transform it into varieties to be used in a CES basket. They thus face the following demand curve

$$M_{i,t+j} = \left(\frac{P_{M,i,t+j}}{P_{M,t+j}}\right)^{-e^M} M_{t+j}$$

and price adjustment costs $\Omega_{M,t} \equiv \frac{\xi_M}{2}\left(\log\left(\frac{P_{M,i,t+j}}{P_{M,i,t+j-1}}\frac{1}{\Pi_{N,t}}\right)\right)^2$. The objective is thus given by

$$\sum_{j=0}^{\infty} \beta^j \Lambda_{t+j}\left[P_{M,i,t+j}M_{i,t}\left[1-\Omega_{M,t}\right] - M_{i,t+j}MC_{M,t+j}\right],$$

implying that the FOC is analogous to the non-tradable sector:

$$\begin{aligned}\frac{\xi_M}{e^M-1}\log\left(\frac{\pi^M_t}{\Pi^M_t}\right) - \frac{MC_{M,t}}{P_{M,t}}\frac{e^M}{e^M-1} + \left[1-\Omega_{M,t}\right] = \\ = \beta\frac{\Lambda_{t+1}}{\Lambda_t}\pi^M_{t+1}\frac{M_{t+1}}{M_t}\left[\frac{\xi_M}{e^M-1}\log\left(\frac{\pi^M_{t+1}}{\Pi^M_{t+1}}\right)\right].\end{aligned} \tag{44}$$

C.3 Tradable goods producers

The competitive sector combines locally produced goods Z_t and imports $X_{M,t}$ to produce an export good using a Leontieff technology:

$$X_t = \min\left\{\frac{Z_t}{(1-\alpha)}, \frac{X_{M,t}}{\alpha}\right\}$$

where

$$Z_t = A_{X,t}\overline{K}^{1-\gamma_X}_{X,t-1}N^{\gamma_X}_{X,t}, \tag{45}$$

and $\overline{K}_{X,t-1}$, the capital used in the production of tradable goods, is exogenous.

Tradable goods producers sell their products to the final goods sector at price $P_{XI,t+j}$. Their objective is thus given by:

$$\sum_{j=0}^{\infty}\beta^j\Lambda_{t+j}\left[\begin{array}{c} P_{XI,t+j}X_{t+j}\left[1-\frac{1}{2}\xi_X\left(\log\left(\frac{X_{t+j}}{X_{t+j-1}}\right)\right)^2\right] - W_{t+j}N_{X,t+j} - R_{K,t+j}\overline{K}_{X,t-1+j} \\ -\alpha P^M_{t+j}X_{t+j} - MC_{Z,t}\left((1-\alpha)X_t - A_{X,t}\overline{K}^{1-\gamma_X}_{X,t-1+j}N^{\gamma_X}_{X,t+j}\right)\end{array}\right]$$

The FOC w.r.t. X_t is given by

$$\frac{MC_{X,t}}{P_{XI,t}} - \left[1 - \frac{1}{2}\xi_X \log\left(\frac{X_t}{X_{t-1}}\right)^2\right] + \xi_X \log\left(\frac{X_t}{X_{t-1}}\right) =$$

$$= \beta\frac{\Lambda_{t+1}}{\Lambda_t}\pi_{XI,t+1}\frac{X_{t+1}}{X_t}\xi_X \log\left(\frac{X_{t+1}}{X_t}\right), \quad (46)$$

$$MC_{X,t} = \alpha P_{M,t} + MC_{Z,t}\left(1-\alpha\right), \quad (47)$$

and $\pi_{XI,t+1} \equiv \frac{P_{XI,t+1}}{P_{XI,t}}$.

The FOC w.r.t. labor is given by

$$\gamma_X MC_{Z,t} = W_t N_{X,t} \quad (48)$$

Note that because of Leontief technology, the shares of domestic production in exports and the import-content of exports are:

$$Z_t = (1-\alpha)X_t \quad (49)$$

and

$$X_{M,t} = \alpha X_t \quad (50)$$

C.4 Final goods firms

Final goods firms combine intermediate and imported goods to create final goods used for consumption and investment. They use constant-elasticity-of-substitution (CES) technology, which is allowed to differ in consumption and investment sector.

$$C_t = \left((1-\omega_C)^{\frac{1}{\mu_C}}\left(C_{N,t}\right)^{\frac{\mu_C-1}{\mu_C}} + (\omega_C)^{\frac{1}{\mu_C}}\left(C_{M,t}\right)^{\frac{\mu_C-1}{\mu_C}}\right)^{\frac{\mu_C}{\mu_C-1}}$$

Consistent with the CES production, demand functions for imported consumption goods, $C_{M,t}$, and for non-tradable consumption goods $C_{N,t}$, are

$$C_{M,t} = \omega_C\left(\frac{P_{M,t}}{P_t}\right)^{-\mu_C} C_t \quad (51)$$

$$C_{N,t} = (1-\omega_C)\left(\frac{P_{N,t}}{P_t}\right)^{-\mu_C} C_t, \quad (52)$$

where ω_C is the bias towards imported consumption goods, μ_C governs the elasticity of substitution between imported and non-tradable consumption goods, $P_{M,t}$ is the import price, $P_{N,t}$ is the price of non-tradable goods, and P_t is the general price index. The latter is defined as

$$P_t = \left(\omega_C P_{M,t}^{1-\mu_C} + (1-\omega_C)P_{N,t}^{1-\mu_C}\right)^{\frac{1}{1-\mu_C}}. \quad (53)$$

The equations for investment goods are analogous.

C.5 Exporters of final goods

Intermediate goods are transformed into final exports goods by monopolistically competitive exporters subject to price rigidities:

$$\sum_{j=0}^{\infty} \beta^j \Lambda_{t+j} \left[P_{X,i,t+j} X_{i,t+j} \left[1 - \frac{\xi_X}{2} \left(\log \left(\frac{P_{X,i,t+j}}{P_{X,i,t+j-1}} \frac{1}{\Pi_t^X} \right) \right)^2 \right] - P_{XI,t+j} X_{i,t+j} \right]$$

with Π_t^X denoting possibly time varying reference (i.e. indexation scheme) for price changes in the non-tradable sector. Demand is given by

$$X_{i,t+j} = \left(\frac{P_{X,i,t+j}}{P_{X,t+j}} \right)^{-e^X} X_{t+j}$$

and the price setting is determined as

$$\frac{\xi_X}{e^X - 1} \log \left(\frac{\pi_t^X}{\Pi_t^X} \right) =$$

$$= \beta \frac{\Lambda_{t+1}}{\Lambda_t} \pi_{t+1}^X \frac{X_{t+1}}{X_t} \frac{\xi_X}{e^X - 1} \log \left(\frac{\pi_{t+1}^X}{\Pi_{t+1}^X} \right) + \frac{P_{XI,t}}{P_{X,t}} \frac{e^N}{e^N - 1} - \left[1 - \frac{\xi_X}{2} \left(\log \left(\frac{\pi_t^X}{\Pi_t^X} \right) \right)^2 \right] \quad (54)$$

Finally, we assume that the demand curve for the export basket X_t is:

$$X_t = X_{D,t} \left(\frac{P_{x,t}/S_t}{P_{W,t} T_t} \right)^{-e^{X,W}}, \quad (55)$$

where $X_{D,t}$ denotes the exogenous component of world demand, S_t denotes the exchange rate and $P_{W,t}$ and T_t are both exogenous. Note that we assume $S_t = 1$, implying that the numerator of the above equation is equal to the export price firms charge, $P_{X,t}$. This implies that, given $D_{D,t}$, exports will fall when exporters charge higher prices.

We allow that export demand depends negatively on interest rates. This is because we use a monetary union setup, where interest rates are determined exogenously for Ireland, but we do take into account that the demand for Irish exports to the rest of the Euro area will tend to decline when Euro area interest rates increase and reduce demand abroad.

$$log(X_{D,t}) = (1 - \rho_{XD}) log(\overline{X}) + \rho_{XD} log(X_{D,t-1}) - XD_{RW}(R_{W,t} - \overline{R}), \quad (56)$$

where ρ_{XD} measures persistence of foreign export demand, XD_{RW} determines the sensitivity of this demand to interest rates, $R_{W,t}$ is exogenous, and bars over variables denote their steady-state values.

D Net foreign asset position

The domestic interest rate is linked to the Euro Area one via

$$R_t = e_t R_{W,t} \frac{S_{t+1}}{S_t} \tag{57}$$

$$e_t = \theta_B \left(\frac{B_t}{Y_t} - \zeta \right), \tag{58}$$

where θ_B denotes the parameter that determines the sensitivity of the interest rate payable on domestic debt, depending on the deviation of the current indebtedness of the country from its steady-state value, $\zeta \equiv \overline{B}/\overline{Y}$.

Foreign debt B_t evolves according to

$$B_t = R_{t-1}B_{t-1} - TB_t + \theta_\Pi \left((P_{X,t} - \alpha P_{M,t})X_t - W_t N_{X,t} \right), \tag{59}$$

where θ_Π denotes the share of profits transferred abroad by foreign-owned firms.

$$TB_t = P_{X,t}X_t - P_{M,t}M_t, \tag{60}$$

E Policy authorities

The exchange rate is fixed, and government spending is funded by lump sum taxes on optimising households

$$S_t = 1 \tag{61}$$

$$P_{N,t}G_t = \Theta_t \tag{62}$$

F Market clearing conditions

$$P_t C_t = P_{N,t}C_{N,t} + P_{M,t}C_{M,t} \tag{63}$$

$$P_t I_t = P_{N,t}I_{N,t} + P_{M,t}I_{M,t} \tag{64}$$

$$Y_{N,t} = C_{N,t} + I_{N,t} + G_t \tag{65}$$

$$M_t = C_{M,t} + I_{M,t} + X_{M,t} \tag{66}$$

$$N_t = N_{N,t} + N_{X,t} \tag{67}$$

$$K_t = K_{N,t} + \overline{K}_{X,t} \tag{68}$$

$$Y_t = P_t C_t + P_{I,t}I_t + P_{N,t}G_t + P_{X,t}X_t - P_{M,t}M_t \tag{69}$$

G Computation of empirical values

In this section we discuss the calibration of values reported in Table 1.

Imports for consumption, investment and export purposes. The targets for the import content of private consumption, private investment and exports used to calibrate ω_C, ω_I and α are computed based on the CSO input output tables.

Share of private consumption, private investment, government expenditure, exports, imports, the export surplus and the compensation of employees in GDP.

- Private investment I=gross fixed capital formation - government gross physical capital formation.
- Government expenditure G = Government consumption (=final consumption expenditure of government+net expenditure by central and local government on current goods and services) + GGPCF.
- Compensation of employees $W * N$= wages and salaries + Employers contribution to social insurance.
- The average shares are computed over the 2001-2014 period.

Housing stock value and non-financial-sector loan to GDP ratios.

- L=Total notional non-financial private sector loans to Irish counterparts, see McElligott and O'Brien (2011).
- $P_H * H$: Internal CBI series.

Calculation of bank funding shares B/L and E/L. All data is taken from Table A.4.1 – Assets and A.4.1 – Liabilities. The data is monthly

- D = Deposits from Irish residents (private sector) + Debt securities issued (Irish residents) + Remaining liabilities (resident)
- B = Debt securities issued (Euro Area) + Debt securities issued (rest of the World) + Deposits from non-residents (Euro Area) + Deposits from non-residents (rest of the World) + Remaining liabilities (non-resident) - (Loans to non-residents (Euro Area) + Loans to non-residents (rest of the World) + Holdings of securities issued by non-residents (Euro Area) + Holdings of securities issued by non-residents (rest of the World) + Central bank balances (resident) + Remaining assets (non-resident)).
- E=Capital and reserves (resident)+ Capital and reserves (non-resident)

The share of D, B and E in total funding is thus given by $\frac{D}{D+B+E}$, $\frac{B}{D+B+E}$ and $\frac{E}{D+B+E}$.

Non financial sector loan and deposit rates R_L and R. These are based on the CBIs retail interest rate statistics, Table B.2.1 "Retail Interest Rates and Volumes - Loans and Deposits, New Business". For both loan and deposit rates, we compute volume-weighted interest rates over all the reported maturities.

Household default rate J_t. The only attempt to estimate transition-into-default rates for Irish mortgages is Kelly and O'Malley (2015), who cover the 2010-2014 period. They estimate an average annual transition-into-default probability of 3.1% and 6.1% for owner occupier and buy-to-let (BTL) mortgages respectively. We compute the the median share of BTL mortgages in total mortgages outstanding during this period from "According to the Residential Mortgage Arrears and Repossessions Statistics", which equals 22%. We can then estimate the average probability of default as 0.78*3.1%+0.22*6.1%=3.76%, implying a quarterly default probability of 0.96%.

Saving deposit demand long interest elasticity and speed of adjustment Gerlach and Stuart (2013) estimate an error correction model for M2 money demand on annual data over the 1934-2012 period, and find a long run interest rate semielasticity of 2 and 1 depending on whether they use the short or long term interest rate, respectively (see their Table 2). We thus set our target value for the long run annual semielasticity of the demand for saving deposits $\epsilon_{D_S,R}$ to1.5. Their estimated speed of adjustment equals 0.2 (see their Table 5), which we denote as $Speed_A$. Linearising equation 21 yields

$$(\hat{D}_{S,t} - \hat{D}_{S,t-1}) = \frac{\iota(1-\beta R)}{\xi_D}(\frac{1-\iota}{\iota}\hat{P}_t + \frac{-\hat{\lambda}_t + \beta R(\hat{R}_t + \hat{\lambda}_{t+1})}{\iota(1-\beta R)} - \hat{D}_{S,t}), \tag{70}$$

implying that the long-run quarterly interest semielasticity and speed of adjustment are given by $\frac{\beta R}{\iota(1-\beta R)}$ and $\frac{\iota(1-\beta R)}{\xi_D}$. We can thus determine ι and ξ_D as

$$\iota = \frac{\beta R}{4\epsilon_{D_S,R}(1-\beta R)}$$
$$\xi_D = \frac{4\iota(1-\beta R)}{Speed_A}$$

H Steady state

H.1 Financial variables: Rates of return and ratio targets

Note first that

$$R_L = \frac{1}{\beta} \text{ from (18)}$$

Hence

$$\begin{aligned}
\widetilde{R} &= R + Spread \\
R_{L1} &= R_L\left(1 - \lambda J\right) \text{ from (7)} \\
\overline{\omega_b} &= \frac{R\left(\frac{1}{E/L} - 1\right)}{\left(\frac{(1-g)\tilde{R}}{E/L}\right)} \\
f(\overline{\omega_b}) &= \phi\left(log(\overline{\omega_b}) + \frac{1}{2}\sigma_b^2)\right) \\
R_E &= R + \frac{R_{L1} - R}{E/L} - \chi_b\frac{\Phi(\overline{\omega_b})}{E/L} \text{ from (8)} \\
J &= \frac{\left(1 - \frac{\widetilde{R}}{R_L}\right)}{\lambda} \text{ from (15)} \\
\frac{D}{Y} &= \frac{L}{Y}\left(1 - \frac{E}{L}\right) - \zeta \text{ from (1)}
\end{aligned}$$

Spread is set to achieve the target return on equity of banks (set at 11%). Recall that ϕ denotes the standard normal density function, which is equivalent to the derivative of Φ in our notation. Note that the steady state value R_E enters equation (3) also as a parameter in order to ensure that bank equity is stationary in the long run.

H.2 Real variables

First, MC_M, P_M are calculated as

$$\begin{aligned} MC_M &= \frac{P_M}{\frac{\mu_M}{\mu_M - 1}} \\ P_M^* &= \frac{MC_M}{S} \end{aligned}$$

We then set $P_N = P_N$, which allows to compute (using equations 53, 23, 24 and 40

$$\begin{aligned} P_I &= P_N\,(1-\omega_I) + P_M\omega_I \\ P &= P_N\,(1-\omega_C) + P_M\omega_C \\ P_K &= P_I(1+\gamma_C(1-\beta R)) \\ R_K &= P_K(1-(1-\delta)\beta)/\beta \\ MC_N &= P_N(\mu_N - 1)/\mu_N \end{aligned}$$

This allows to rearrange (41) to get

$$k_N = \frac{K_N}{N_N} = \left((\frac{(1-\gamma_N)MC_N A_N)}{R_K} \right)^{\frac{1}{\gamma_N}}$$

which allows to calculate

$$\begin{aligned} y_N &= A_N\,(k_N)^{1-\gamma_N} \text{ from (38)} \\ W &= \gamma_N MC_N A_N\,(k_N)^{1-\gamma_N} \text{ from (42)} \end{aligned}$$

It is now necessary to turn to the export sector first, for which we can compute all variables given that we have determined the wage W in the economy and using the fact that the export sector capital stock K_X is exogenous.

$$\begin{aligned} T &= 1 \text{ from calibration} \\ P_{X\_} &= P_M^* T \\ P_X &= SP_{x\_} \\ MC_X &= \frac{P_X}{\mu_X} \text{ from (54) and (46)} \end{aligned}$$

Then

$$MC_Z = \frac{(MC_X - \alpha P^W S)}{(1-\alpha)} \text{ from (47)}$$

This allows to compute

$$
\begin{aligned}
k_X &= \frac{K_X}{N_X} = (W/(A_X\gamma_X MC_Z))^{\frac{1}{1-\gamma_X}} \text{ from (48)} \\
N_X &= \frac{K_X}{k_X} \\
Z &= A_X (K_X)^{1-\gamma_X} (N_X)^{\gamma_X} \text{ from (45)} \\
X &= \frac{Z}{1-\alpha} \text{ from (49)} \\
X_M &= \alpha X \text{ from (50)} \\
PTR &= \Theta_\Pi((P_X - \alpha P_M)X - WN_X),
\end{aligned}
$$

where PTR denotes profit repatriation from multinationals. Having determined the export sector variables, it is now possible to derive an expression for N_N based on the steady state level of foreign debt and the implied trade balance, which restrict the size of the domestic economy. We start by assuming a steady state fraction of foreign debt in nominal GDP ζ. Hence we have

$$B = \zeta Y$$

(from 57) Note that nominal GDP can be written as the sum of value added in both sectors:

$$Y = P_N Y_N + (P_X X - P_M X_M) = P_N Y_N + (P_X - \alpha P_M) X$$

Hence

$$B = \zeta (P_N Y_N + (P_X - \alpha P_M) X)$$

Furthermore, we define

$$L = Y * L2GDP$$

$$TB = [(R-1)\zeta + J\lambda R_C * L2GDP] (P_N Y_N + PTR) \text{ from (59)}$$

Furthermore, combining (60), the definition of imports and (50), it is possible to write

$$C_M + I_M = \frac{X(P_X - P_M^* S\alpha) - TB}{P_M^* S} \tag{71}$$

which can be written as

$$C_M + I_M = \frac{\begin{array}{c} X(P_X - P_M^* S\alpha - [(R-1)\zeta + J\lambda R_L * L2GDP](P_X - \alpha P_M)) - PTR \\ -[(R-1)\zeta + J\lambda R_C * L2GDP] P_N Y_N N_N \end{array}}{P_M^* S} \tag{72}$$

Note that on the r.h.s., the only unknown is N_N. We can also express the l.h.s. in terms of N_N alone using (51), (52) and the equivalent for investment goods, (66), (12) , $k_N = \frac{K_N}{N_N}$ and $y_N = \frac{Y_N}{N_N}$ as

$$C_M + I_M = N_N \left[\left(Y_N - \delta \left(1-\omega_I\right) k_N\right) \frac{\omega_C}{1-\omega_C} \left(\frac{P_M}{P_N}\right)^{-\mu_C} + \omega_I \left(\frac{P_M}{P_I}\right)^{-\mu_I} \delta k_N \right] - \frac{\omega_C}{1-\omega_C} \left(\frac{P_M}{P_N}\right)^{-\mu_C} G \tag{73}$$

We now express steady state government expenditure as $G = \frac{Y*govsh}{P_N}$

$$G = \frac{\left(P_N Y_N + \left(P_X - \alpha P_M\right) X\right) * govsh}{P_N} \tag{74}$$

Hence we can write

$$C_M + I_M = N_N \left[\left(y_N - \delta \left(1-\omega_I\right) k^n\right) \frac{\omega_C}{1-\omega_C} \left(\frac{P_M}{P_N}\right)^{-\mu_C} + \omega_I \left(\frac{P_M}{P_I}\right)^{-\mu_I} \delta k^n \right] - \frac{\omega_C}{1-\omega_C} \left(\frac{P_M}{P_N}\right)^{-\mu_C} \left[\frac{\left(P_N Y_N + \left(P_X - \alpha P_M\right) X\right) * govsh}{P_N}\right]$$

Combining (72) and (74) and defining

$$Denominator \equiv \frac{\left[\left(R-1\right)\zeta + J\lambda R_C * L2GDP\right] P_N Y_N}{P_M^* S} + + \left(y_N - \delta \left(\left(1-\omega_I\right)\left(\frac{P_N}{P_I}\right)^{-\mu_I}\right) k_N\right) \frac{\omega_C}{1-\omega_C} \left(\frac{P_M}{P_N}\right)^{-\mu_C} + \omega_I \left(\frac{P_M}{P_I}\right)^{-\mu_I} \delta k_N$$

allows to solve for N_N as

$$N_N = \frac{\frac{X\left(P_X - P^W S\alpha - \left[(R-1)\zeta + J\lambda R_C * L2GDP\right]\left(P_X - \alpha P_M\right)\right) - PTR}{P_M^* S} + \frac{\omega_C}{1-\omega_C}\left(\frac{P_M}{P_N}\right)^{-\mu_C}\left[\frac{\left(P_X - \alpha P_M\right) X * govsh}{P^n}\right]}{Denominator} \tag{75}$$

Now the remaining real variables can be calculated easily:

$$
\begin{aligned}
N &= N_N + N_X \text{ using (68)} \\
K_N &= k_N N_N \\
Y_N &= y_N N_N \\
Y &= P_N Y_N + (P_X - \alpha P_M) X \\
G &= govsh * Y/P_N \\
K &= K_X + K_N \text{ using (69)} \\
I &= \delta K_N \text{ using (12)} \\
I_N &= (1-\omega_I)\left(\frac{P_N}{P_I}\right)^{-\mu_I} I \text{ (using the equivalent of (52) for investment)} \\
I_M &= \omega_I \left(\frac{P_M}{P_I}\right)^{-\mu_I} I \text{ (using the equivalent of (51) for investment)} \\
C_N &= Y_N - I_N - G \text{ using (66)} \\
C &= \frac{C_N}{(1-\omega_C)\left(\frac{P_N}{P}\right)^{-\mu_C}} \text{ using (52)} \\
C_M &= C\omega_C \left(\frac{P_M}{P}\right)^{-\mu_C} \text{ using (51)} \\
M &= X_M + C_M + I_M \text{ using (67)} \\
B &= \zeta Y \\
TB &= [(R-1)\,B + J\lambda R_C * L] \text{ using (59)} \\
\Theta &= G \;\text{ using (62)} \\
L &= \left(\frac{L}{Y}\right) Y \\
\Lambda &= \frac{1}{PC^{\sigma}(1+(1-\beta R))} \text{ using (17)} \\
\Lambda_T &= \Lambda(1-\beta R).
\end{aligned}
$$

Using 37, we can back out ϕ_N as

$$
\phi_N = \frac{1}{\mu_W N^{\eta}/(W/\Lambda)}.
$$

H.3 Remaining financial variables

We can now compute the remaining financial variables and the missing Lagrange multiplier. To see this, recall that we calibrate the ratios $P_H H/Y$, D/Y and L/Y. We denote these calibrated ratios with bars in the equations below:

$$
\begin{aligned}
P_H &= \left(\frac{\overline{P_H H}}{\overline{Y}}\right)\frac{Y}{H} \\
D_T &= \gamma_C\left(P * C + P_I I\right) + \gamma_H P_H H \text{ (from 9)} \\
D_S &= \left(\frac{\overline{D}}{\overline{\overline{Y}}}\right) Y - D_T \\
D &= D_T + D_S \text{ (from 10)} \\
F &= P_H H \\
\overline{F} &= L R_L / \psi \text{ (using 13)}
\end{aligned}
$$

To support the calibrated ratios, we have to compute the consistent values of ζ_H, ζ_D and σ_h. We first compute ζ_D and σ_h as follows:

$$
\begin{aligned}
\zeta_D &= \frac{(1-\beta R)}{D^{-\iota}\left(P\right)^{\iota-1}}\Lambda \text{ (using 21)} \\
\sigma_h &= \frac{\left(\log\left(\overline{F}-F\right)\right)}{\Phi^{-1}\left(\frac{J-\pi}{1-\pi}\right)} \text{ (using 15)}
\end{aligned}
$$

with Φ^{-1} denoting the inverse of the standard normal distribution function. To back out the value od ζ_H, we require the value of the household's Lagrange multiplier on the bank's lending rate, Λ_{R_L}. To avoid congestion we define an auxilliary variable, Aux, as follows:

$$
Aux = (1-\lambda J) - (1-\pi)\phi\left(\frac{log\left(\frac{R_L\overline{L}/\overline{Y}}{\psi(\overline{P_H H}/\overline{Y})}\right)}{\sigma_h}\right)\frac{\lambda}{\sigma_h}
$$

The Lagrange multiplier on the bank's lending rate is then

$$
\Lambda_{R_L} = \frac{\Lambda L\beta}{Aux},
$$

which allows us to back out ζ_H as

$$
\zeta_H = \frac{\Lambda P_H(1-\beta+\gamma_C(1-\beta R)) - \Lambda_{R_L}\lambda(1-\pi)\frac{\phi\left(log\left(\frac{R_L\overline{L}/\overline{Y}}{\psi(\overline{P_H H}/\overline{Y})}\right)/\sigma_h\right)}{\sigma_H H}}{H^{-\nu}},
$$

where $\phi(\bullet)$ denotes the normal density function.

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BANK FOR INTERNATIONAL SETTLEMENTS

IFC-National Bank of Belgium Workshop on "*Data needs and Statistics compilation for macroprudential analysis*"

Brussels, Belgium, 18-19 May 2017

Countercyclical capital regulation in a small open economy DSGE model[1]

Luca Onorante, European Central Bank,

Matija Lozej and Ansgar Rannenberg, 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.

Countercyclical Capital Regulation in a Small Open Economy DSGE Model

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May 2017

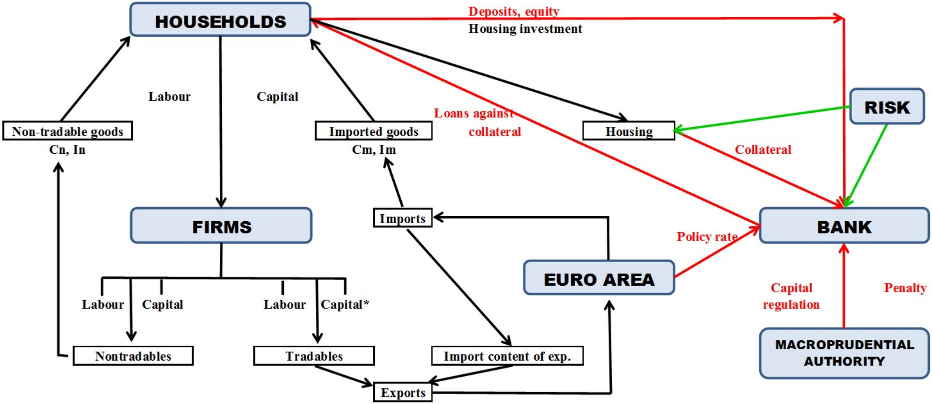
Disclaimer

THE VIEWS EXPRESSED HERE ARE THE VIEWS OF THE AUTHORS AND DO NOT NECESSARILY REFLECT THE VIEWS OF THE CENTRAL BANK OF IRELAND OR OF THE EUROSYSTEM.

Motivation

- ESRB has recommended national regulators to vary CCyB depending on the credit-to-GDP ratio, and *possibly* other variables
- The analysis of this rule has unconditional (based on cycles obtained from filtered data), but not conditional on shocks
- We look at the performance of the ESRB rule and other such rules for typical shocks affecting a small open economy using an extension of the model of Clancy and Merola (2014)
- Rules based on the credit-to-GDP ratio perform well in response to housing demand shocks, but worsen the response of the economy to export demand shocks
- Rules based on house prices appear to perform better since house prices tend to be procyclical after typical shocks affecting a small open economy

Graphical representation of the model



Capital rules

The credit gap and the house price gap are defined as:

$$gap_t = \left(\frac{L_t}{Y_t + Y_{t-1} + Y_{t-2} + Y_{t-3}} - \frac{L}{4 * Y} \right)$$

$$price\ gap_t = \frac{P_{H,t} - \overline{P_H}}{\overline{P_H}}$$

1. **ESRB rule:**

$$g_t = 8\% + \begin{cases} 0 & if\ gap_t \leq 2\% \\ 0.3125 * gap_t & if\ 2\% < gap_t \leq 8\% \\ 2.5\% & if\ gap_t > 8\% \end{cases}$$

2. **Linear rule:**

$$g_t = 8\% + \alpha * gap_t$$

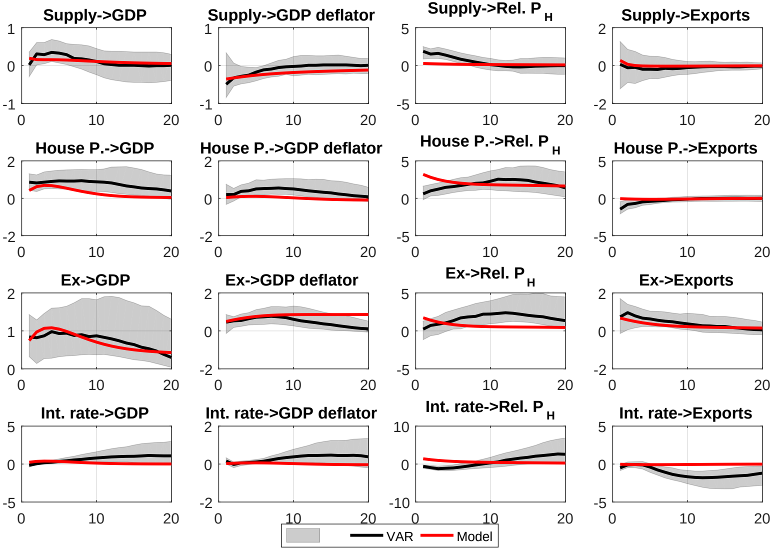
Constant capital: $\alpha = 0$; credit gap: $\alpha = 0.43$; house price gap $\alpha = 0.85$

Bringing the model to the data

To bring the model to the data, we use the following approach:

- Parameters that affect the steady state are set to match the Great Ratios (e.g., shares of imports, exports,...)
- Parameters that have clear counterparts in the literature are set to standard values (labour supply elasticity, markups,...)
- Parameters affecting model dynamics, and especially those without a clear counterpart in the literature, were calibrated by matching the model responses to the responses from a structural VAR

Impulse-response matching

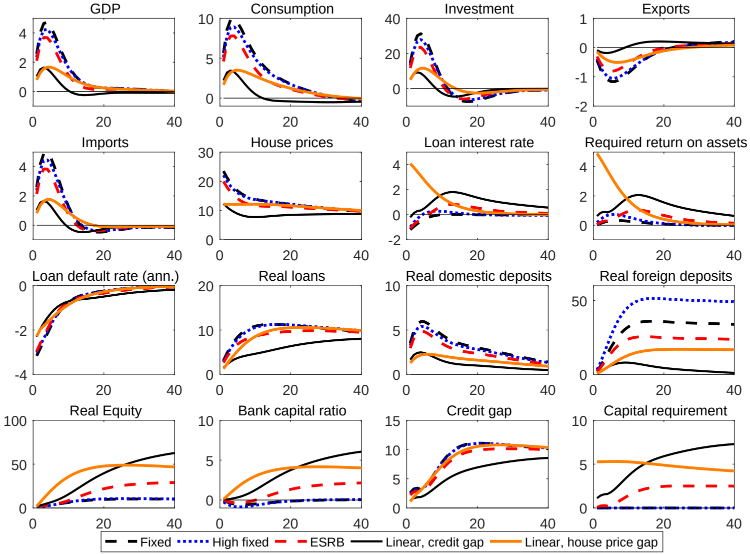


Overview of simulations

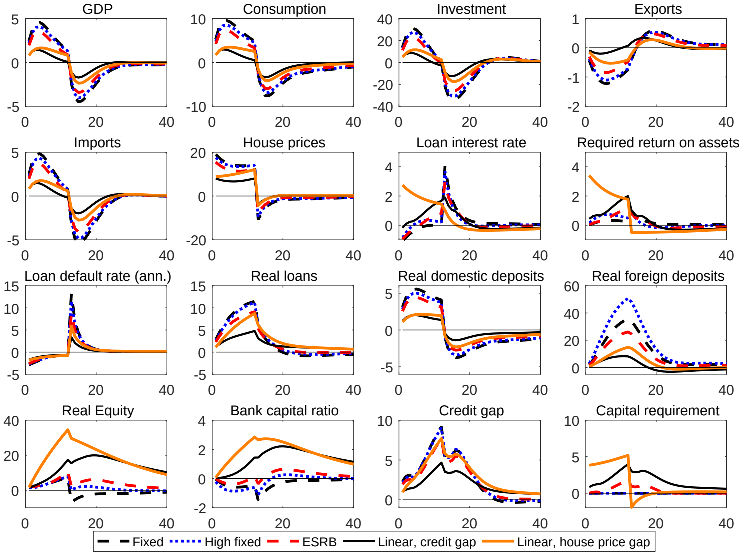
We perform the following simulations

- A positive housing demand shock
  - A one-time (but persistent) increase in households' preference for housing
- A bubble on the housing market
  - An expected increase in households' preference for housing in the future (news shock), expected in the beginning of year 3
  - When the increase in housing demand is supposed to materialise, it does not $\Rightarrow$ Households find themselves with too much housing, loans, foreign debt, and wish to deleverage immediately
- A negative foreign demand shock
  - A one-time (but persistent) decrease in foreigners' demand for imported goods

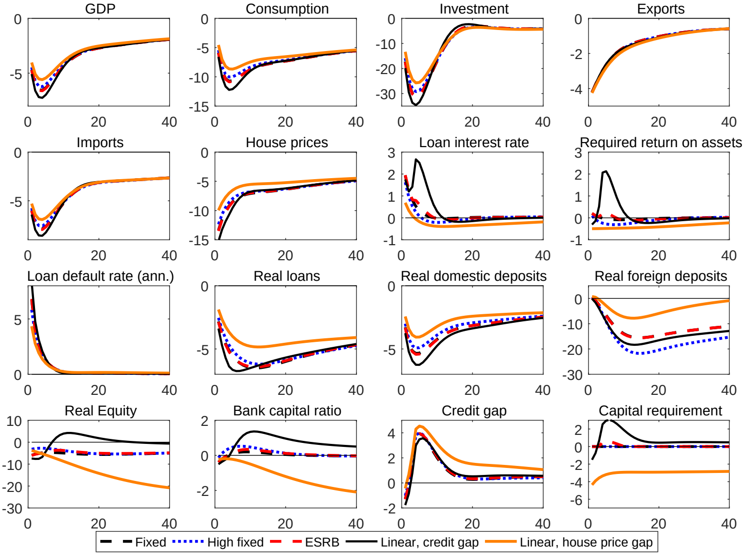
A positive housing demand shock



Boom and bust on the housing market



Negative foreign demand shock



Main messages

- CCyB rules based on the credit gap work well for some shocks
- Rules without floors or caps perform better
- The key mechanism for dampening boom-bust cycles is the build-up and subsequent release of the capital buffer
- For shocks to foreign demand (a highly relevant shock for small open economies), the rules based on the credit gap do not perform well because the credit gap is not procyclical after such shocks
- Because house prices react procyclically even after foreign demand shocks, more attention should be paid to them when setting CCyB in small open economies

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Stress testing the Czech household sector using microdata - practical applications in the policy-making process[1]

Simona Malovaná, Michal Hlaváček and Kamil Galuščák,
Czech National 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.

Stress Testing the Czech Household Sector Using Microdata[1]

Practical Applications in the Policy-Making Process

Simona Malovaná,[2] Michal Hlaváček[3] and Kamil Galuščák[4]

Abstract

We present a set of practical applications of the household sector stress testing approach used at the Czech National Bank. The CNB has been conducting stress tests of households once a year since 2011. The test results are published in its Financial Stability Reports. The aim is to test households' ability to repay their loans in the event of extremely adverse economic developments. Besides this, the household stress test has so far been used for two other purposes: (i) to construct a simple reverse stress test and explore the sensitivity of Czech households to a rise in loan interest rates and a decline in income, and (ii) to provide some supportive evidence for the calibration of debt service-to-income limits.

Keywords: financial surplus, household indebtedness, microdata, stress testing, DSTI calibration

JEL classification: D12, D31, E17

[1] We thank participants at the IFC-National Bank of Belgium Workshop in Brussels for helpful comments. This paper does not necessarily reflect the views of the Czech National Bank.

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1. Introduction

Household stress tests currently form an important complement to the standard macro stress tests, as they shed more light on the structure of the credit risks of the household sector. Unlike the standard top-down macro stress test,[5] which only uses semi-structured data on the main banks' credit portfolios, the household stress tests use micro data on individual households. Firstly, this allows us to analyse specific types of households (e.g. low-income households, young households with children) in order to fine-tune the quantification of household credit risk and the reaction of the household sector to macroeconomic shocks. It also allows us to discuss the social impacts of rising household indebtedness. Secondly, the micro nature of the household stress tests could open up further space for analysis of the feedback or second-round effects of macroeconomic shocks when the worsened financial situation of households in turn negatively influences the macro-economy and financial sector performance. These feedback effects could further improve the quality of the standard macro stress tests. Thirdly, the household stress tests could be important for calibrating the limits of macroprudential tools related to household indebtedness, especially tools pertaining to mortgage loans (LTV, LTI and DSTI ratios).[6]

In this article, we present the Czech National Bank's approach to household stress testing. Our results highlight the benefits of using micro-level datasets in the analysis of the incidence of household distress, as shocks have more pronounced effects among lower-income households. We also discuss the existing data gaps relating to household stress tests and suggest some solutions to them.

This article is structured as follows. After this introduction, we briefly present a review of literature relevant to the Czech case, with a special emphasis on existing data sources. In section 3, we describe the methodology of our stress testing approach, mainly considering labour market and interest rate shocks. The interpretation of the stress testing results, including a discussion of what debt burden is already excessive and simple reverse stress tests, follows in section 4. In section 5, we discuss the existing data gaps and suggest some further improvements to the stress testing setup. Section 6 then concludes.

2. Literature Review

The majority of the household stress tests applied by central banks (e.g. Galuščák et al, 2016, Albacete and Fessler, 2010, Johansson and Persson, 2006, Herrala and Kauko, 2007; see Table 1) use Household Budget Survey data. This data source offers relatively detailed micro data on households' income and expenditures and socio-economic characteristics, information on debt type and repayment size

5 For the results of the macroeconomic stress test in the Czech Republic, see the CNB's Financial Stability Reports. For the methodology, see Geršl et al. (2012).

6 For the setting of these ratios, see *Recommendation on the management of risks associated with the provision of retail loans secured by residential property* from the Official Information of the Czech National Bank of 13 June 2017.

for various types of loans, and information on housing type. These are mainly flow data and there is no information on the total stock of household indebtedness that needs to be estimated. This fact limits the types of analysis available. All the stress tests are based on some form of financial surplus calculated for each household as its net monthly income minus its monthly instalments and essential monthly expenditures. Distress is usually defined as a situation where the financial surplus is negative.

This surplus is usually used to simulate the probability of default (PD) and (if information on debt and collateral value is available) the loss given default (LGD) for each indebted household. Some studies (e.g. Messner and Zavadil, 2015) also use this surplus to simulate the incidence of debt.

Household stress tests in selected countries

Table 1

Country	Source	Data source	No. of HH covered	Stress scenarios			
				U	IR	ER	HP
Czech Republic	Galuščák et al. (2016)	HBS	2,900	Y	Y	N	N
Poland	Zajączkowski (2008)	HBS	35,000	Y	Y	Y	N
Austria	Albacete and Fessler (2010); Albacete et al. (2014)	HFCS, SILC	2,380	Y	Y	Y	Y
Lithuania	Central Bank of Lithuania (2015)	Extended HBS	N/A	Y	Y	N	Y
Australia	Bilston and Rodgers (2013); Bilston et al. (2015)	Own survey	9,180	Y	Y	N	Y
Croatia	Sugawara Zalduendo (2011)	HBS	3,108	Y	Y	Y	N
Finland	Herrala and Kauko (2007)	HBS	11,000	Y	Y	N	N

Note: U stands for unemployment, IR for interest rate, ER for exchange rate, HP for house price, HBS for Household Budget Survey, HSHW for Household Survey on Housing Wealth and HFCS for Household Finance and Consumption Survey.

The majority of the studies mentioned in Table 1 include an assessment of the impacts of unemployment shocks, shocks to household income, shocks to interest rates, shocks to essential expenditure, price shocks and combinations thereof. However, the financial surplus-based methodology only addresses shocks to income and debt repayment and does not usually take into account the volume of household debt and the value of households' assets. It is therefore relatively complicated to assess the impact of house price shocks and/or to interpret the impact of shocks on the standard LTV, LTI and DSTI measures. Central banks have therefore searched for alternative data sources to the HBS. In the Eurozone, the Household Finance and Consumption Survey (HFCS) project has helped to collect relevant data in many countries and given rise to numerous studies using this data source. For example, Messner and Zavadil (2015) analyse the impact of household indebtedness on household net wealth using Slovak data from the first wave of the HFCS. They use a three-step instrumental-variable approach, first modelling the incidence of debt, then predicting the value of the debt and finally estimating the net wealth of a household. Surprisingly, they find that income has no impact on household indebtedness in Slovakia. They also find a number of socio-economic and demographic factors influencing households' debt. They then find two effects of household indebtedness on household net wealth – a highly negative effect of non-mortgage debt and a neutral effect of mortgage debt.

Similarly, Albacete and Lindner (2013) refine the Austrian central bank's approach to household stress tests by incorporating new information from the HFCS, as they assess the debt burden of each household, simulate the DSTI ratio and estimate the LTV ratio. With the help of these ratios they identify potentially vulnerable households and search for the determinants of this vulnerability and potential risk channels.

Ampudia et al. (2014) do a similar exercise and propose a framework for stress-testing individual household balance sheets based on the HFCS data for the whole Eurozone. They put forward a metric of household distress which is constructed by combining the data on income, expenditure, assets, debt and collateral. This metric takes into consideration the household's liquidity and solvency situation. The authors use it to calculate credit risk indicators such as PD, exposure at default (EAD) and LGD and their distributions. The indicators are then shocked by hypothetical adverse macroeconomic scenarios comprising interest rate, employment and house price shocks. The authors also demonstrate how the framework could potentially be used for macroprudential purposes, for example, for the calibration of optimal LTV ratio caps.

Other studies using HFCS data include Costa and Farinha (2012) for Portugal, Adam and Tzamourani (2015) for Germany and D'Alessio and Iezzi (2015) for Italy, among many others (for a complete list see ECB, 2016). As for countries not participating in the HFCS, an interesting approach is used in Bierut et al. (2015), where the authors use micro data to assess the effects of the Polish regulation of LTV/LTI.

3. Methodology and Data

The CNB's household stress tests use the Household Budget Survey (HBS) as their main data source. The other data sources include publicly available macro-indicators and the Statistics on Income and Living Conditions (SILC). The HBS contains household-level data. This means that our methodology is microeconomic in nature, although it does allow us to make conclusions for the entire sector. However, we are limited by the data availability. In particular, the dataset does not contain household balance sheet data. The test is based on a sample of 2,929 households, of which 1,010 were servicing some sort of loan in 2015. Table 2 presents the average characteristics of households with and without debt. These numbers reveal that households with debt have a larger net monthly income, higher essential expenditure and a bigger financial surplus.

In what follows, we describe the methodology for stress testing the household sector using the available microdata. The methodology is based to a large extent on Galuščák, Hlaváč and Jakubík (2016). We therefore refer the reader to their paper for other details.

Average characteristics of households with and without debt

(average for 2015) Table 2

Indicator	Households	
	With debt	Without debt
Net income (CZK/month)	37,164	27,781
Instalments – all loans (CZK/month)	5,771	0
Instalments – mortgage (CZK/month)	7,236	0
DSTI – household with mortgage (%)	17.5	0
DSTI – household with other loan (%)	10.1	0
DSTI – household with mortgage and other loan (%)	18.8	0
Essential expenditure (CZK/month)	14,000	11,966
Financial surplus (CZK/month)	17,393	15,814
With loan (share in %)	34.5	0
With mortgage (share in %)	21.1	0
No. of households in HBS	1,010	1,919

Note: Financial surplus = Net income – Instalments (all loans) – Essential expenditure

Source: HBS 2015

Identification of Distressed Households

We define financial surplus (*FS*) as

$$FS = NI - INST - EE \tag{1}$$

where *NI* is household net monthly income, *INST* is monthly instalments and *EE* is monthly expenditure on essential goods (food, energy, health, rent). We identify a household as distressed if its financial surplus is negative.

In our simulations we consider several types of shocks affecting the financial surplus. Shocks to unemployment change net household income (*NI*), as work income is replaced by unemployment benefit or other social income. Interest rate shocks affect instalments (*INST*). We could potentially simulate shocks to consumer prices and the exchange rate (see Galuščák, Hlaváč and Jakubík, 2016), but these shocks are not essential for the applications presented in this paper.

Labour Market and Unemployment Shock

Previous studies (Johansson and Persson, 2006; Albacete and Fessler, 2010) consider an unemployment shock hitting employed persons. We extend their approach to account for transitions from employment to unemployment and also from unemployment to employment. We assume that individuals who are not active on the labour market remain inactive over the time period considered. Owing to data availability, we model the impact of the unemployment shock scenario on household heads and their spouses.

The key building block in the unemployment shock scenario is the probability that an individual is unemployed:

$$Prob(u_i = 1|x_i) = \emptyset(\alpha + \beta x_i) \quad (2)$$

where u_i indicates an unemployed person and x_i is a vector of socio-economic characteristics. $\emptyset(.)$ is the cumulative density function of the standard normal distribution. We use coefficient estimates to predict the probability of being unemployed for household heads and spouses.

Albacete and Fessler (2010) simulate the increased unemployment rate in the unemployment shock scenario by increasing the constant α in (2) until the aggregate rate of unemployment reaches the required level. Given the data availability, our estimation is based on pooled cross-section datasets. In this way, the individual's unobserved heterogeneity is neglected, leading to biased coefficient estimates. This raises the predicted probability of transitions between labour market states, particularly from unemployment to employment. Hence, we increase the constant term differently for unemployed and employed persons. Specifically, we increase the constant term for unemployed individuals until their average transition rate to unemployment matches the observed transition rate.[7] For employed individuals, we increase the constant term until the aggregate unemployment rate reaches the targeted value.

If an employed individual becomes unemployed, we assume his or her previous work income is replaced by unemployment benefit and that the income of other household members and other social income are unchanged. The amount of unemployment benefit is determined according to the eligibility rules. Unemployment benefit is collected depending on the individual's age. In the remaining period after the eligibility for unemployment benefit expires, we assume that net household income is increased to the level of the subsistence minimum amount if it is lower.[8]

While we simulate the non-work income of persons losing their job using the eligibility criteria, we have to determine the wage of non-workers upon finding a job. We predict the entry wage using the Heckman (1979) selection model. We estimate the wage equation:

$$\log(w_i) = \gamma x_i + u_{1i} \quad (3)$$

where w_i is the monthly net wage, x_i are observed characteristics and $u_{1i} \sim N(0, \sigma)$. The wage w_i is observed if

$$\delta x_i + u_{2i} > 0 \quad (4)$$

where $u_{2i} \sim N(0,1)$ and $corr(u_1, u_2) = \rho$. We estimate the wage and selection equations jointly by maximum likelihood. The identification of the model relies on nonlinearity in the selection equation. The predicted log of the wage is transformed into a level (the technique is described in Cameron and Trivedi, 2009).

The set of explanatory variables x_i in our Heckman selection model in (3) and (4) is the same as in the unemployment model in (2). Hence, we determine the probability of being unemployed as unity minus the predicted value from the selection equation. Applying the unemployment shock scenario, we assign to each

7 Unemployment to unemployment gross flows are largely insensitive to the business cycle.

8 We thus simulate net income under a hypothetical change in labour market status. For a detailed description of the Czech tax and benefit system and microsimulations, see Galuščák and Pavel (2012).

adult person in our sample a probability of being unemployed which is consistent with the targeted unemployment rate. For every possible combination of the employment and unemployment statuses of the household heads and spouses we compute the net household income and the financial surplus. The level of distress is calculated for each household as the weighted average of these binary outcomes.[9]

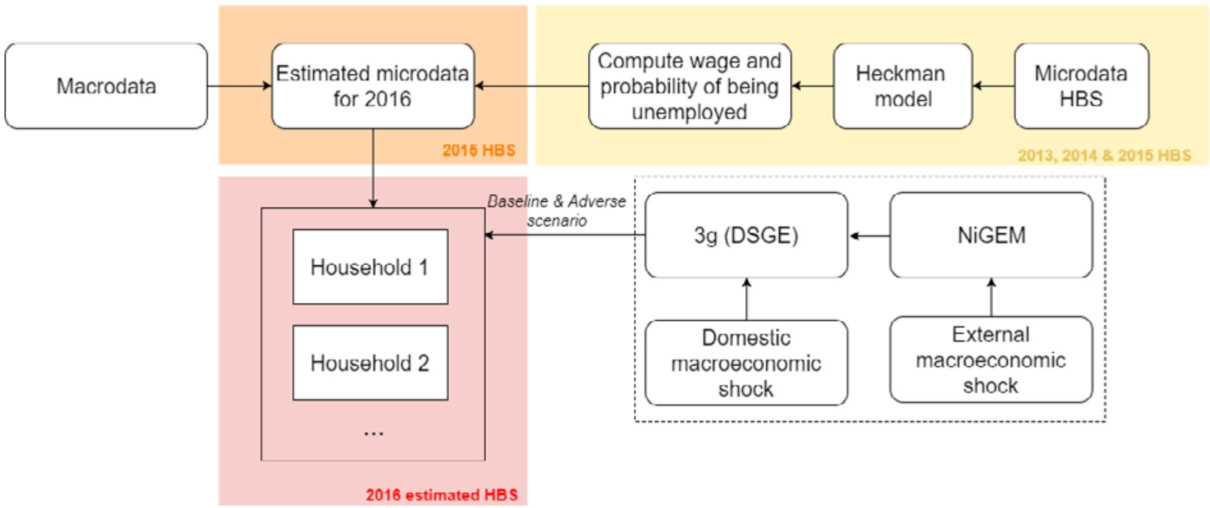
Interest Rate Shock

When applying the interest rate shock, we are limited by data availability. To be able to apply the interest rate shock properly we would need to know the maturities of, and interest rates on, each household's debt. This information, however, is not available in the HBS. Therefore, we have to approximate these statistics using aggregate CNB data.

4. Practical Applications for Policy Purposes

The CNB has been conducting stress tests of households once a year since 2011. The test results are published in its Financial Stability Reports. The aim is to test households' ability to repay their loans in the event of extremely adverse economic developments. These stress tests therefore focus mainly on the risk arising from financially distressed households, whose potential debt repayment difficulties transform into credit risk of the financial sector. The household stress test consists of several steps, which are described in Figure 1.

The CNB's household stress testing framework — Figure 1



[9] Our approach is equivalent to the Monte Carlo simulation used in Johansson and Persson (2006) and Albacete and Fessler (2010).

At the time of publication of the Financial Stability Report in June each year, the HBS had a lag of almost a year and a half, so for the stress tests in 2017 we use the HBS data for the end of 2015. Therefore, we need to consider changes in household distress that occurred between the end of 2015 and the end of 2016, to which the impacts of the scenarios for 2017 relate. To do so, we use publicly available macroeconomic data; for all households, prices of essential goods are increased by their rate of inflation, while interest rates on the individual loan types and the unemployment rate are changed according to the actual situation. The data ageing procedure is described in detail in Hlaváč et al. (2013; section 4).

The household stress tests are based on alternative macroeconomic scenarios. The scenarios are designed using the CNB's official prediction model. Adverse scenarios are constructed based on the identification of risks to the Czech economy in the near future. To compare the stress outcome with the most probable outcome, the stress tests use a Baseline Scenario, i.e. the current official macroeconomic prediction of the CNB. Both the Adverse Scenario and the Baseline Scenario serve as a starting point for many other stress tests conducted by the CNB and published in its Financial Stability Reports, e.g. macro stress tests of the solvency and liquidity of domestic banks, macro stress tests of the pension management companies sector and the review and evaluation of sovereign exposure concentration risk. In the household stress test, the Adverse Scenario was recently amplified by an increase in loan interest rates (Amplified Adverse Scenario; see CNB, 2017). The main reason is a growing amount of new mortgage loans provided by banks at historically low interest rates, which increases the sensitivity of households to a potential rise in loan interest rates not accompanied by growth in their income.

Key variables in the individual scenarios of the household stress tests

(end of period) Table 3

Indicator	2016	Baseline Scenario 2017	Amplified Adverse Scenario 2017
Unemployment rate (%)	3.8	3.6	5.5
Nominal wage growth (y-o-y, %)	4.7	5.4	-7.3
Inflation (y-o-y, %)	1.4	2.6	-0.6
Interest rate on mortgage loans (%)	2.7	2.7	5.7
Interest rate on consumer loans (%)	12.2	12.2	15.2
Interest rate on other loans (%)	3.8	3.8	6.8
Share of refixed mortgage loans (%)	40	40	40

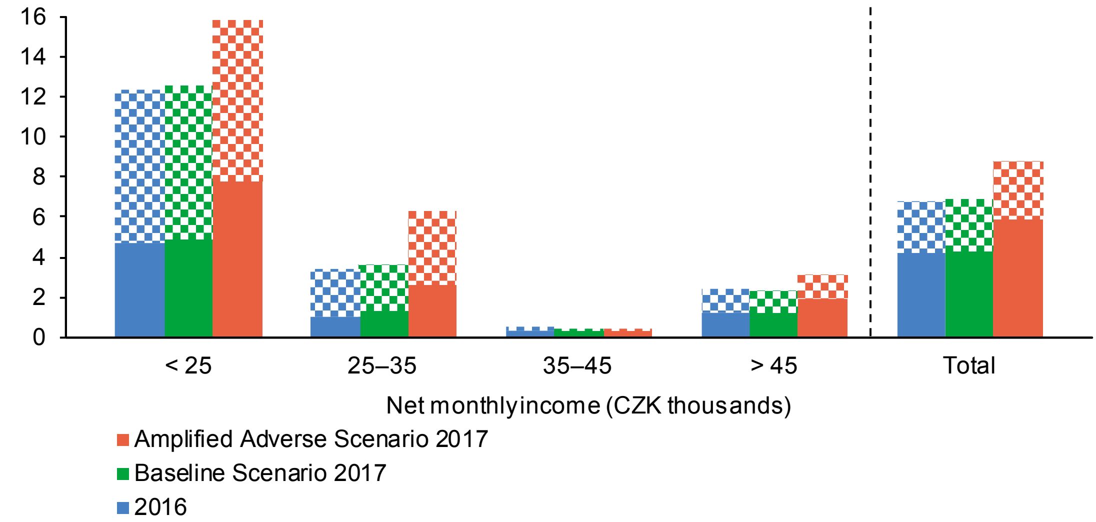
Source: CNB

Note: The 40% refixation rate corresponds approximately to the percentage of mortgage loans with a residual fixation period of up to and including one year.

The Amplified Adverse Scenario assumes that loan interest rates rise by 3 pp with a 40% mortgage refixation rate. The 40% refixation rate corresponds to the percentage of mortgages with a residual fixation period of up to and including one year. Table 3 presents the macroeconomic scenarios for the stress tests of the household sector. Both the Baseline Scenario and the Amplified Adverse Scenario correspond to the scenarios from the bank stress tests for 2017 (CNB, 2017). In the case of realisation of the Adverse Scenario and Baseline Scenario, the results are obtained by calculating the cumulative changes in the variables under study for the entire period from the end of 2015 to the end of 2017 in one step. The results for 2016 are thus not used as an input for the subsequent simulation.

Shares of overindebted households by income group

(%; averages in individual income groups) Figure 2



Source: CNB, CZSO

Note: Shares of households with loans. The solid part denotes the share of overindebted households with mortgages and the patterned part the share of overindebted households with loans other than mortgages. The average gross monthly nominal wage per FTE employee in the Czech economy was CZK 29,320 as of 2016 4Q; the median wage was CZK 25,061. The median net monthly income of households in HBS 2015 is CZK 28,487.

The impact of the shocks on households is assessed by comparing the percentage of distressed households before and after the simulation in the individual income groups (quintiles or specific ranges). Low-income households with mortgages are especially sensitive to financial stress. At the end of 2016, the pre-shock share of overindebted households with a net monthly income of less than CZK 25,000 was about 12%; households with mortgages accounted for about half of this figure (see Figure 2). After the Amplified Adverse Scenario was applied, the share of overindebted households with a monthly income of less than CZK 25,000 increased to about 16%. This was caused almost exclusively by a rise in the overindebtedness of households with mortgages. In other income groups, too, debt service problems in the event of adverse economic developments were encountered above all by households with mortgages. The increase in household overindebtedness is due to a combination of a fall in their net income and a rise in loan instalments. The significant growth in overindebtedness in the lowest income group is caused mainly by a low or zero pre-stress financial reserve.

Besides the regular assessment, the household stress test has so far been used for two other purposes: (i) to construct a simple reverse stress test and explore the sensitivity of Czech households to a rise in loan interest rates and a decline in income, and (ii) to provide some supportive evidence for the calibration of debt service-to-income (DSTI) limits. In the following we describe these two practical applications.

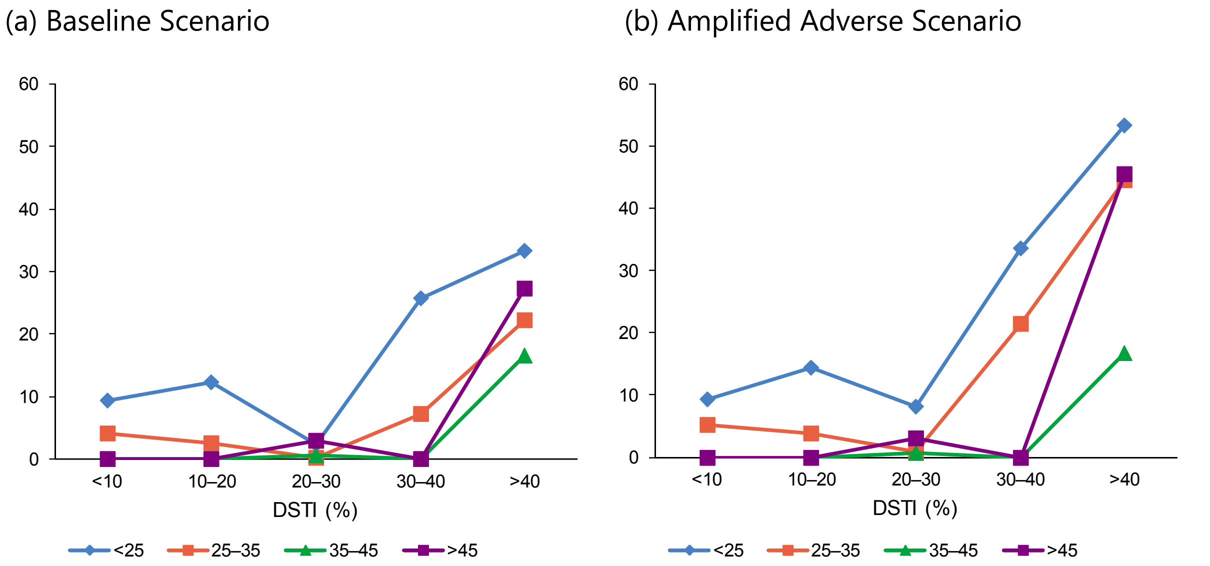
What level of debt burden is already excessive?

In its Financial Stability Reports, the CNB regularly assesses the ability of debt-burdened households to repay their obligations in the event of extremely adverse economic developments. These analyses focus among other things on the impact of the simulated stress on households' DSTI ratio. Previously, however, the analyses did not examine what debt burden can be considered excessive, or at what DSTI level Czech households become extremely sensitive to financial stress. For this reason, the stress test has been extended to include an analysis of the DSTI distribution of overindebted households. DSTI is defined as the monthly mortgage payment divided by the net disposable income of the household.

The results reveal that the share of overindebted households with a DSTI ratio of over 40% is relatively high even before the stress scenario is applied (see Figure 3, panel a). Their sensitivity to the simulated stress is significantly higher than that of households with lower DSTI ratios, regardless of their net monthly income (see Figure 3, panel b). Loans provided to borrowers with a DSTI ratio of over 40% can therefore be regarded as highly risky. This conclusion is in line with the analyses of other central banks and was used in the update of the *Recommendation on the management of risks associated with the provision of retail loans*.

Shares of overindebted households by DSTI ratio and income group

(%; averages in individual groups) Figure 3



Source: CNB, CZSO

Note: Shares of households with loans. The individual curves divide households into income groups according to the net monthly income of the entire household in CZK thousands.

Sensitivity of Czech Households to a Rise in Interest Rates and a Decline in Income: Simple Reverse Stress Tests

An assessment of the impact of a rise in interest rates is important for both monetary policy and financial stability. Monetary policy analyses focus mainly on estimating the effect of a change in interest rates on aggregate expenditure, while financial stability analyses focus rather on estimating the impact on growth in credit risk. However, the two types of impacts cannot be assessed separately. A decrease in aggregate expenditure due to a rise in interest rates can have an adverse effect on the financial sector, which, in turn, will pass through to the real economy and subsequently the monetary policy stance. Presented below is a sensitivity analysis of a rise in loan interest rates coupled with a change in the net income of households with mortgage loans. The analysis has the character of a reverse stress test. This test explores how interest rates and the net income of borrowers would have to change, ceteris paribus, for their debt service to increase to a level considered excessive. The debt burden is measured by means of the DSTI ratio. As concluded in the previous subsection households with a DSTI exceeding 40% are considered to be highly sensitive to financial stress.

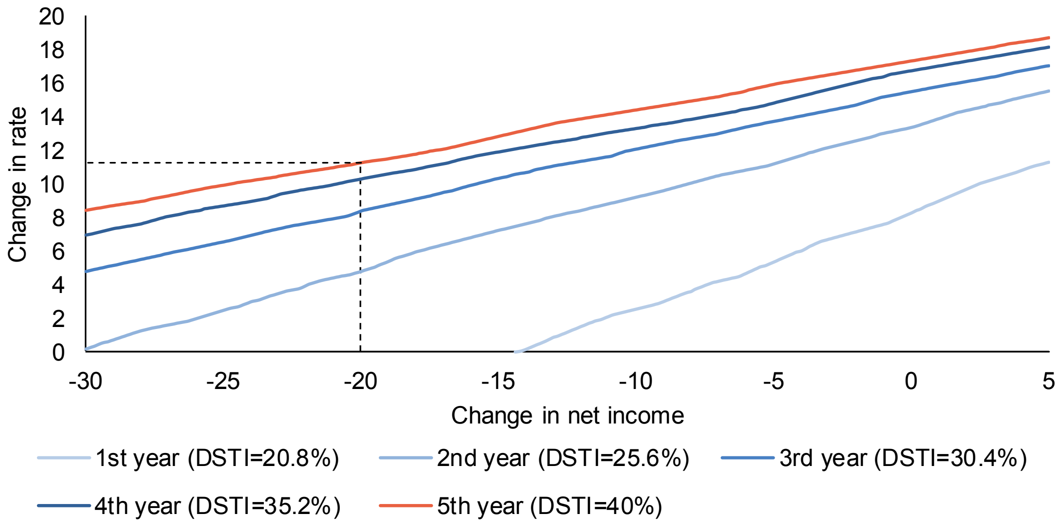
The speed of pass-through of an increase in rates to instalments depends, among other things, on the interest rate fixation period. Existing mortgage loans with floating rates or residual fixation periods of up to one year accounted for around 24% and mortgages with fixation periods of over one year and up to five years for another 57% at the end of 2015. Gradual refixation of 80% of the current portfolio over five years is thus considered.

Figure 4 shows the combinations of the total change in net income and the increase in loan interest rates which would lead, under the given assumptions, to a rise in the median DSTI to 40% at the five-year horizon. Some of these combinations are less likely, but they clearly illustrate the size of the shocks that would lead to the said DSTI being reached. If, for example, we consider the highly adverse scenario of a sizeable contraction in economic activity where income falls by 20% on average over five years (consistent with a decline of around 4.5% a year) due to growth in unemployment, rates on mortgage loans would have to go up by around 11 pp for the median DSTI of borrowers to reach 40%. However, this scenario is highly implausible, illustrating the current resilience of Czech household sector *as a whole* to an income and interest rate shock.

Reverse stress test: interest rate and income shock combinations over a five-year horizon

(x-axis: %, y-axis: pp)

Figure 4



Source: SILC, HBS 2015, CNB calculation

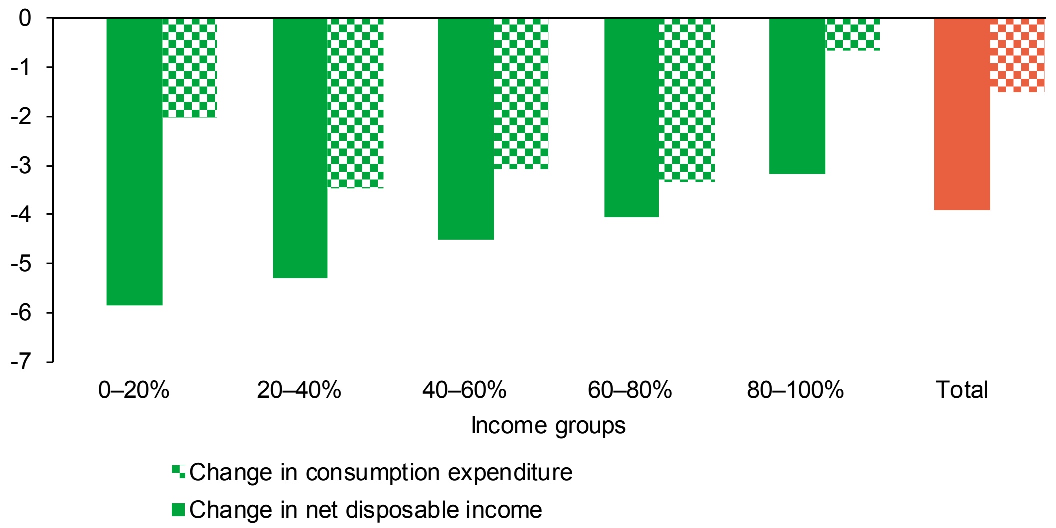
Note: The curves depict the combinations of changes in income and loan interest rates over a horizon of 1–5 years compared to the initial level which lead to a linear rise in the median DSTI ratio from its current level to a stress level of 40%. If, for example, we consider a 20% decrease in income over five years so that the median DSTI ratio rises to 40%, this shock would have to be accompanied by a gradual increase in rates by a total of around 11 pp (red curve).

The following analysis is based on a more moderate assumption of an increase in loan interest rates of 5 pp over three years (see Figure 5). Middle income groups cut back consumption expenditure the most in response to a rise in rates. In the case of net borrowers, a rise in loan rates results in an increase in debt servicing costs. This may be negatively reflected in their net disposable income and consumption expenditure. The analysis reveals that a rise in rates would have the greatest impact on the net disposable income of low-income households. The same does not apply to the change in consumption expenditure, where households in the lowest and highest income groups react the least to growth in instalments. In the case of high-income households, the explanation is simple – consumption expenditure accounts for around 65% of their net income. Even if their loan instalments increase, these households have a sufficient financial surplus and do not have to reduce their consumption significantly. In the case of low-income households, consumption expenditure accounts for around 90% of their net income, and most of it is essential expenditure, which cannot be reduced significantly.

Change in the net income and consumption of households with a mortgage loan in response to a rise in loan interest rates of 5 pp

(%)

Figure 5



Source: SILC, HBS 2015, CNB calculation

Note: The distribution into income groups (quintiles) is performed on the basis of the net income of all households.

5. Data Gaps

The approach to household stress testing described above is subject to several limitations and imperfections influenced mainly by the nature of the data used. In this section, we will discuss these limitations and solutions to them, and then we will discuss a possible extension of the underlying database to include other data sources.

The first problem with the household-level datasets is that they are only available with a significant delay.[10] Hence, it is necessary to rely on ageing the micro information in the datasets and to match it with up-to-date macroeconomic data, mainly the inflation rate, household loan rates and the unemployment rate.

A second complication arises from the fact that the underlying data only cover loan repayments and do not include information on the total stock of indebtedness. Therefore, the level of indebtedness can only be estimated. An increase in the accuracy of this estimate can be obtained thanks to newly available micro-data on mortgage-market characteristics within the SILC (monthly mortgage payment, initial

[10] The Household Budget Survey (HBS) data are available annually with a delay of approximately eight months. Data from the Eurozone Household Finance and Consumption Survey (HFCS) project are only available once every three years with a delay of around two years.

principal, maturity and year of negotiation) and thanks to data from the LTV/LTI survey performed by the CNB since 2015, which covers newly granted loans. Unfortunately, the data do not include information on default probabilities. We therefore have to proxy household debt repayment problems by the financial surplus of households after the shocks.

Thirdly, the HBS data do not include information on the value of the underlying property purchased using the mortgage loan. This makes it complicated to calculate the standard LTV measure (which is also subject to regulation by the CNB). The HBS data therefore have to be linked to some other housing prices. To do so, it is possible to follow Brůha et al. (2013), who combine (i) information from the HBS on housing type, the locality in which the household lives/owns property, the period of construction, equipment, floor area, the level of depreciation etc., and (ii) semi-structural data on property transaction prices published by the Czech Statistical Office, which are broken down by region, property type, municipality size and the extent of property depreciation. Thus, for each household the "shadow" value of the property it owns can be computed and used in further analysis. Another, more advanced technique for calculating shadow prices is to combine the HBS data on the property with the micro database of individual property transactions that is the source for the calculation of the (sub)aggregated property price indexes.[11] This estimation of the shadow value of the property should be much more precise than the simple method applied by Brůha et al. (2013).

With more precise information on the size of the loan, its interest rate and the value of the property, the household stress test methodology could be significantly extended, as it would be possible to calculate and stress the main debt-related indicators such as LTI, DSTI and LTV. Also, the incorporation of property prices allows one to study the effect of a shock to property prices (in addition to the current interest rate, unemployment and price shocks). The extended household stress tests could also be used to calibrate the limits for the LTV/LTI/DSTI regulations and to evaluate the effects of those regulations.

To sum up, household stress testing requires us to combine the primary data from the Household Budget Survey with numerous other data sources. The current stress testing approach already uses data from the labour statistics, macroeconomic data, data from the SILC database and others. The extended approach would require the use of new data from the SILC database on the volume of loans and data on residential property prices (preferably micro data on individual transactions). The quality of the household stress tests could be significantly improved if there were an integrated database available combining information on household income and expenditures with information on households' encumbrance by loans together with more precise data on the value of households' immovable property. Such a database could be obtained from the ad hoc central bank survey of banks, similar to the semi-annual surveys on new loans conducted by the CNB. International projects such as the HFCS[12] and the ECB's Anacredit project[13] also hold

[11] The Czech Statistical Offices uses data from property transfer tax returns; alternatively, it would be possible to use data from the Czech Cadastre.

[12] https://www.ecb.europa.eu/pub/economic-research/research-networks/html/researcher_hfcn.en.html

[13] https://www.ecb.europa.eu/stats/money_credit_banking/anacredit/html/index.en.html

promise in this respect. However, from the point of view of operational household stress tests they also have some drawbacks. For the HFCS data, these include a substantial publication lag together with only three-year frequency. Anacredit currently stresses the development of databases on corporate loans, whereas household data are not expected to be included in the Czech part of the project until later phases. Therefore, integration of different data from combined data sources is still necessary from the central bank perspective.

6. Concluding Remarks

This paper presented a methodology and a set of practical applications of the household sector stress testing approach used at the Czech National Bank. This framework allows us to simulate the effects of labour market, interest rate and consumer price shocks, which have a negative effect on indebted households, reducing their available financial surplus (net household income minus loan instalments and essential living costs). These factors lead to a rise in the percentage of distressed households, i.e. households with a negative financial surplus.

The CNB has been conducting stress tests of households once a year since 2011. The test results are published in its Financial Stability Reports. The main aim is to test households' ability to repay their loans in the event of extremely adverse economic developments. Besides this, the household stress test has so far been used for two other purposes: (i) to construct a simple reverse stress test and explore the sensitivity of Czech households to a rise in loan interest rates and a decline in income, and (ii) to provide some supportive evidence for the calibration of debt service-to-income limits. The results reveal that loans provided to borrowers with a DSTI ratio of over 40% can be regarded as highly risky, as their sensitivity to the simulated stress is significant. This conclusion is in line with the analyses of other central banks and was used in the update of the Czech National Bank's *Recommendation on the management of risks associated with the provision of retail loans*.

The approach to household stress testing is, however, subject to several limitations, connected especially with limited data availability. International projects such as the Household Finance and Consumption Survey and the ECB's Anacredit project (if extended in the Czech Republic to cover the household sector) may hold some promise with respect to improving this area in the future.

References

Adam, K and P Tzamourani (2015): "Distributional consequences of asset price inflation in the euro area," *Discussion Paper*, no 27, Deutsche Bundesbank.

Albacete, N, J Eidenberger, G Krenn, P Lindner and M Sigmund (2014): "Risk-bearing capacity of households – linking micro-level data to the macroprudential toolkit", *Financial Stability Report*, no 27, Österreichische Nationalbank, June.

Albacete, N. and P. Fessler (2010): “Stress Testing Austrian Households,” *Financial Stability Report*, no 19, Österreichische Nationalbank, June.

Albacete, N and P Lindner (2013): “Household vulnerability in Austria – a microeconomic analysis based on the household finance and consumption survey,” *Financial Stability Report*, no 25, Österreichische Nationalbank, June.

Ampudia, M, H Van Vlokhoven and D Żochowski (2014): “Financial fragility of euro area households,” *Working Paper*, no 1737, European Central Bank.

Bierut, B, T Chmielewski, A Głogowski, A Stopczyński and S Zajączkowski (2015): “Implementing loan-to-value and debt-to-income ratios: Learning from country experiences. The case of Poland,” *NBP Working Paper*, no 212.

Bilston, T, R Johnson and M Read (2015): “Stress testing the Australian household sector using the HILDA survey,” *Research Discussion Paper*, no 2015-1.

Bilston, T and D Rodgers (2013): “A model for stress testing household lending in Australia,” *Australia Central Bank Bulletin*, December 2013.

Brůha, J, M Hlaváček and L Komárek (2013): “Impacts of property prices on the financial condition of households,” Thematic Article, *Financial Stability Report 2012/2013*, Czech National Bank.

Cameron, A C and P K Trivedi (2009): “Microeconometrics using Stata,” *StataCorp*.

Central Bank of Lithuania (2015): “Stress testing of households,” https://www.lb.lt/stress_testing_of_households.

Czech National Bank (2017): *Financial Stability Report 2016/2017*.

Czech National Bank (2017): “Recommendation on the management of risks associated with the provision of retail loans secured by residential property,” 13 June 2017.

Costa, S and L Farinha (2012): “Households’ indebtedness: A microeconomic analysis based on the results of the Household Financial and Consumption Survey,” *Financial Stability Report 2012*, Banco de Portugal, May.

D’Alessio, G and S Iezzi (2015): “Over-indebtedness in Italy: How widespread and persistent is it?” Paper presented at the conference *The Bank of Italy’s Analysis of Household Finances*, Rome, 3–4 December 2015.

European Central Bank (2016): “Bibliography of the Household Finance and Consumption Survey,” 18 April 2016.

Galuščák, K, P Hlaváč and P Jakubík (2016): “Household resilience to adverse macroeconomic shocks: Evidence from Czech microdata,” *International Review of Applied Economics* 30(3), pp 377–402.

Galuščák, K and J Pavel (2012): "Taxes and benefits: Work incentive effects of policies," *Czech Journal of Economics and Finance* 62(1), pp 27–43.

Geršl, A, P Jakubík, T Konečný and J Seidler (2012): "Dynamic stress testing: The framework for testing banking sector resilience used by the Czech National Bank," *CNB Working Paper*, no 11/2012.

Heckman, J J (1979): "Sample selection bias as a specification error," *Econometrica* 47(1), pp 153–161.

Herrala, R and K Kauko (2007): "Household loan loss risk in Finland – estimations and simulations with micro data," *Bank of Finland Research Discussion Papers*, no 5/2007.

Hlaváč P, P Jakubík and K Galuščák (2013): "Household stress tests using microdata," Thematic Article, *Financial Stability Report 2012/2013*, Czech National Bank.

Johansson, M and M Persson (2006): "Swedish households' indebtedness and ability to pay – a household level study," *Penning – Ochvalutapolitik 3/2006*, pp 24–41.

Messner, T and T Zavadil (2015): "Are indebted households poorer? Evidence from Slovakia," *National Bank of Slovakia Working Paper*, no 2/2015, March 2015.

Sugawara, N and J Zalduendo (2011): "Stress-testing Croatian households with debt-implications for financial stability," *Policy Research Working Paper*, no 5906, World Bank.

Zajączkowski, S (2008): "Household sector stress tests on the basis of micro data," presentation at *National Bank of Romania Seminar*, 18–19 September 2008, https://www.imf.org/external/np/mcm/financialstability/fsconfrom.htm.

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BANK FOR INTERNATIONAL SETTLEMENTS

IFC-National Bank of Belgium Workshop on "*Data needs and Statistics compilation for macroprudential analysis*"

Brussels, Belgium, 18-19 May 2017

Stress testing the private household sector using microdata[1]

Kamil Galuscak,

Czech National Bank

[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.

Stress Testing the Private Household Sector Using Microdata

Kamil Galuščák

IFC – NBB workshop

Brussels, 18-19 May 2017

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Outline

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- Introduction
- Methodology
- Data
- Results
  - Impact of shocks
  - International comparison
  - CNB stress tests
- Planned extension of CNB stress tests
- Conclusions

Introduction

- Important to monitor and assess risks among households caused by accumulation of debts
- Analysis is limited to available datasets
- We consider effects of shocks to unemployment, interest rates and prices of essential expenditure on households’ ability to service their debts
  - We extend the approach of Johansson and Persson (2006) and Albacete and Fessler (2010)
- We illustrate the use of our methodology for CNB stress testing
  - Alternative way of calculating households’ probability of default in CNB’s credit risk model

Methodology - Overview

- We define financial surplus

$$FS = NI - INST - EE$$

  where NI is net household income, INST is monthly instalments, EE is monthly expenditure on essential costs
- A household is distressed if $FS < 0$
- We consider shocks caused by changes in unemployment rate, interest rate and prices
- Czech Household Budget Survey datasets
  - No information on assets and liabilities
  - Data ageing applied

Methodology – Unemployment rate shock

- Consider transitions between E and U
- Probability of being unemployed:

$$Prob(u_i = 1|x_i) = \emptyset(\alpha + \beta x_i)$$

- Increase the constant α until the unemployment rate meets the target
- Estimate the unemployment probit model using pooled cross sections
  - Neglecting unobserved heterogeneity increases predicted flows, particularly from U to E
- Eligibility rules are used to simulate the net household income while unemployed (Galuscak and Pavel, 2012)
- Entry wage is predicted using a Heckman selection model

Methodology – Unemployment rate shock

- Calculate the FS for every possible combination of E and U within a household
- The level of distress is the average of these binary variables weighted by their probability of occurrence
- The approach is equivalent to Monte Carlo simulations

- Both models are estimated for household heads and spouses using Czech Household Budget Survey data
- We consider shocks of the size of 1 to 3 standard deviations
  - Probability is 15.9, 2.3 and 0.1% respectively
  - Big shocks are extremely rare

Methodology – Interest rate shock

- Information on instalments by type of loan (housing, consumer, other loans)
- Interest rates are approximated, residual principal is estimated
- Short-term shock (one year): 51.1% of housing and other loans recalculated, consumer loans not affected
- Long-term shock: instalments in all loan types are renegotiated

Methodology – Price shock

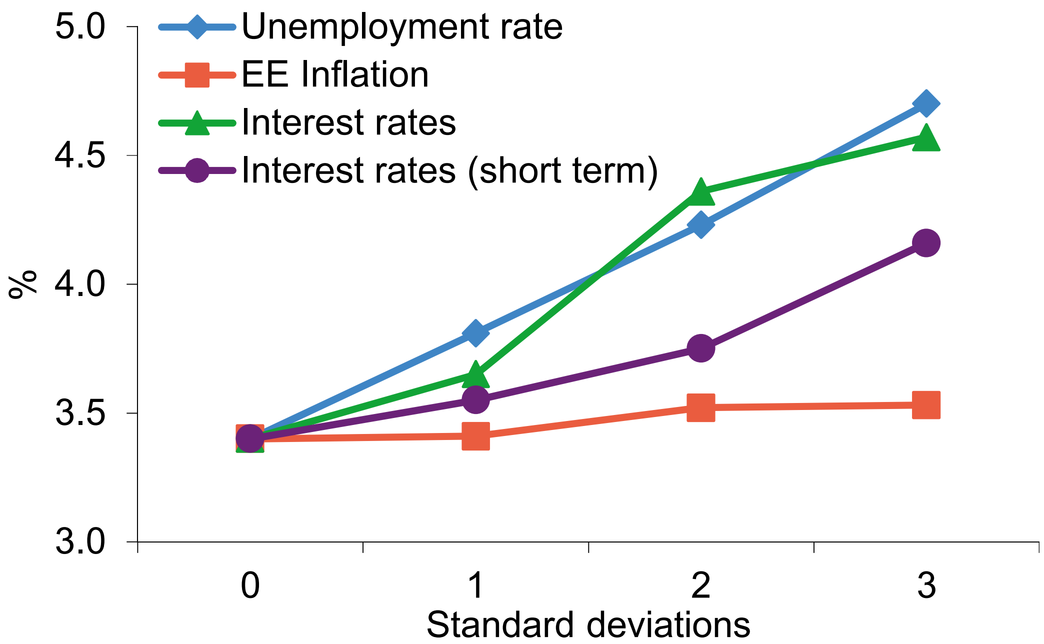
- Consider prices in groups typical for essential costs (food, energy, health, rent)
- Assume price and income elasticities from Dybczak et al. (2010)
- Consider the statutory subsistence minimum amount as an alternative definition of essential living costs

Data

- Czech Household Budget Survey (about 3,000 households in each year)
  - Survey of Income and Living Conditions as a complementary source of information
- Explanatory variables
  - Dummies for HH head, gender, education, spouse's education, spouse's labour market status
  - Age
  - Dummies for children (also interacted with gender), persons younger than 31 and older than 55
  - Net income of other household members, the amount of instalments
  - Dummies for region, ownership of durables (car, PC)

Results – Response to shocks

Percentage of distressed households in response to shocks
(% on y-axis; standard deviations on x-axis)



Source: Galuscak, Hlavac and Jakubik (2016)

- Unemployment rate shock has the largest impact
- Interest rate shock has smaller effects except for sizeable long-term shocks
- Effects due to price shocks are very small (mitigated due to non-zero demand elasticities)

Results – Response by income quintiles

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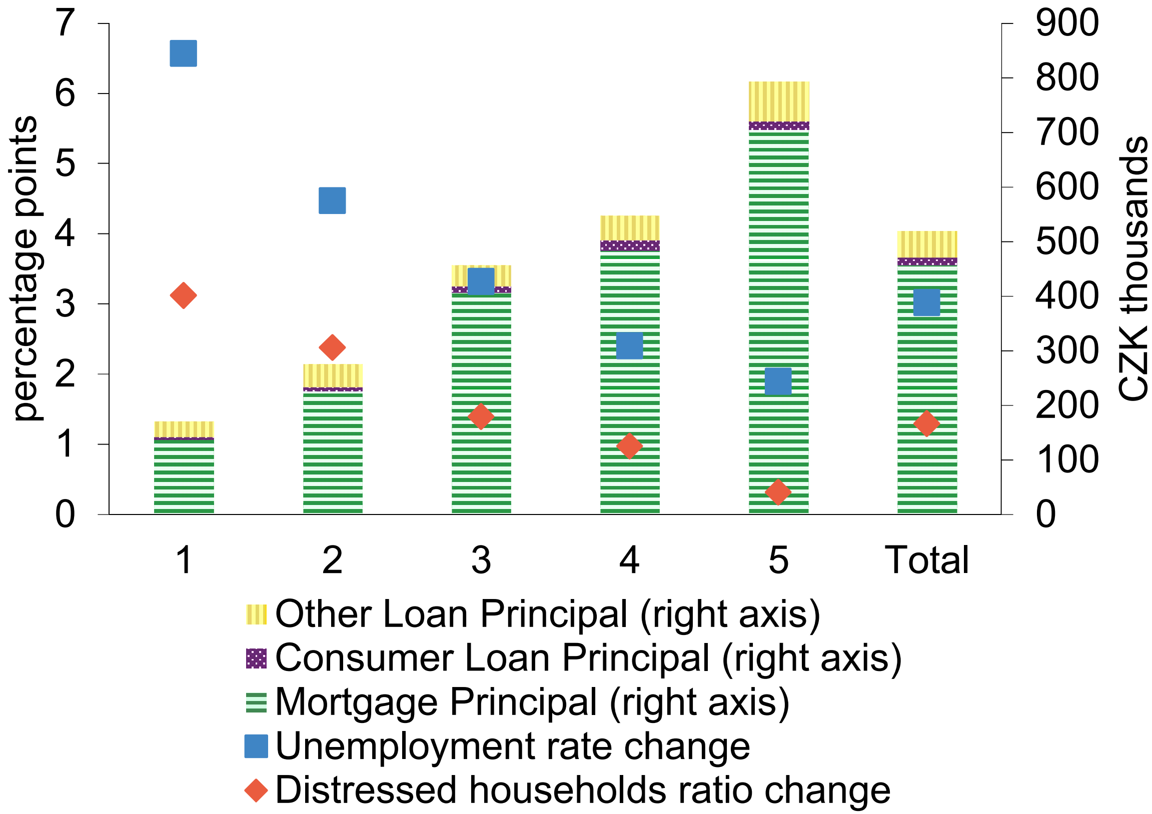
Response due to 3 standard deviation shock to unemployment rate, residual principal, by income quintiles (percentage points; CZK thousands)

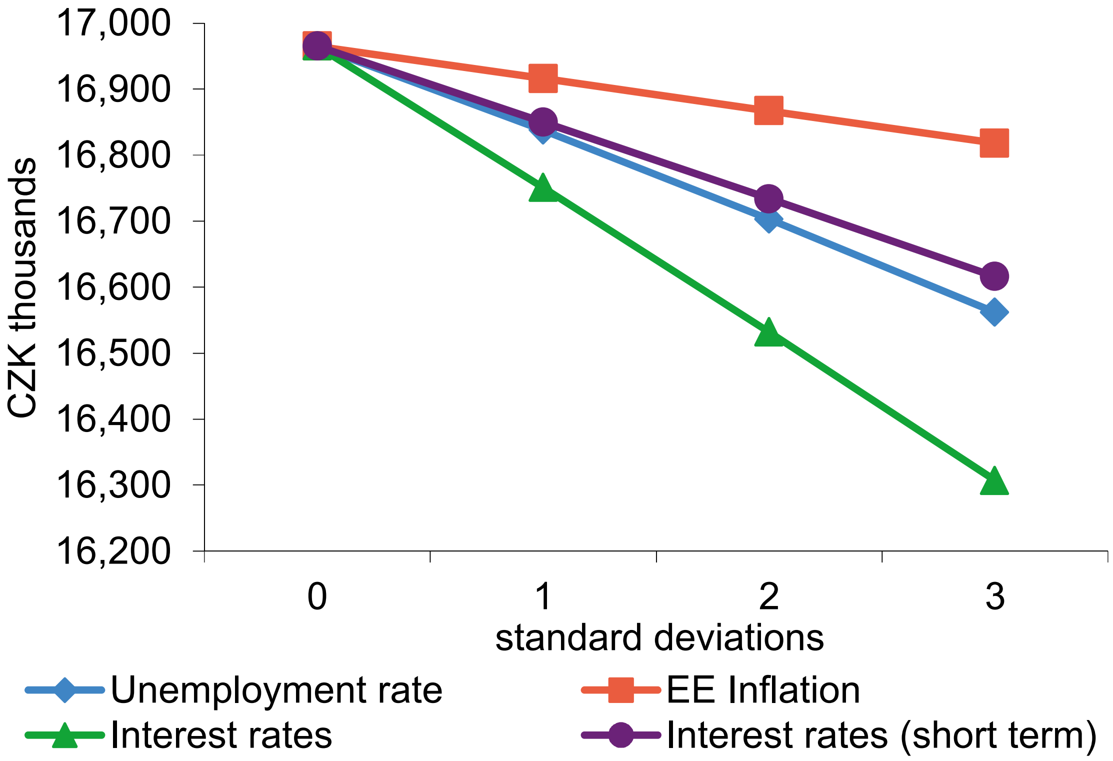


Source: Galuscak, Hlavac and Jakubik (2016)

- HHs in 1st and 2nd quintiles face the highest risk
- The highest debt burden is in mortgages

Results – Average financial surplus

Average financial surplus in response to shocks
(thousands CZK/month on y-axis; standard deviations on x-axis)



Source: Galuscak, Hlavac and Jakubik (2016)

- Long-term interest rate shock has the most pronounced impact on household budgets

Results – Combined shocks

Percentage of distressed households in response to combined shocks
(shocks of the size of standard deviations; zero shocks are the end of 2012)

Unemployment shock	Interest rate shock			
	0	1	2	3
0	3.4	3.6	3.8	4.2
1	3.8	4.0	4.2	4.6
2	4.2	4.4	4.6	5.0
3	4.7	4.8	5.1	5.5

Source: Galuscak, Hlavac and Jakubik (2016)

- Effects of the unemployment rate shocks combined with short-term interest rate shock
- The share of distressed households increases by up to 5.5 percentage points

Results – International comparison

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Impact of unemployment rate shock
(increase in the incidence of distressed households in p.p.; shock size in p.p.)

	1	2	3
Czech Republic	8.8	17.6	26.5
Sweden*	3.2	4.8	6.3
Austria**	1.1	1.1	2.2

Note: * Johansson and Persson (2006); ** Albacete and Fessler (2010)
Source: Galuscak, Hlavac and Jakubik (2016)

- The impact due to unemployment rate shock is much larger than in Sweden and Austria
- We include spouses (higher labour market flows)

Results – International comparison

Impact of interest rate shock (long-term effects in parentheses)
(increase in the incidence of distressed households in p.p.; shock size in p.p.)

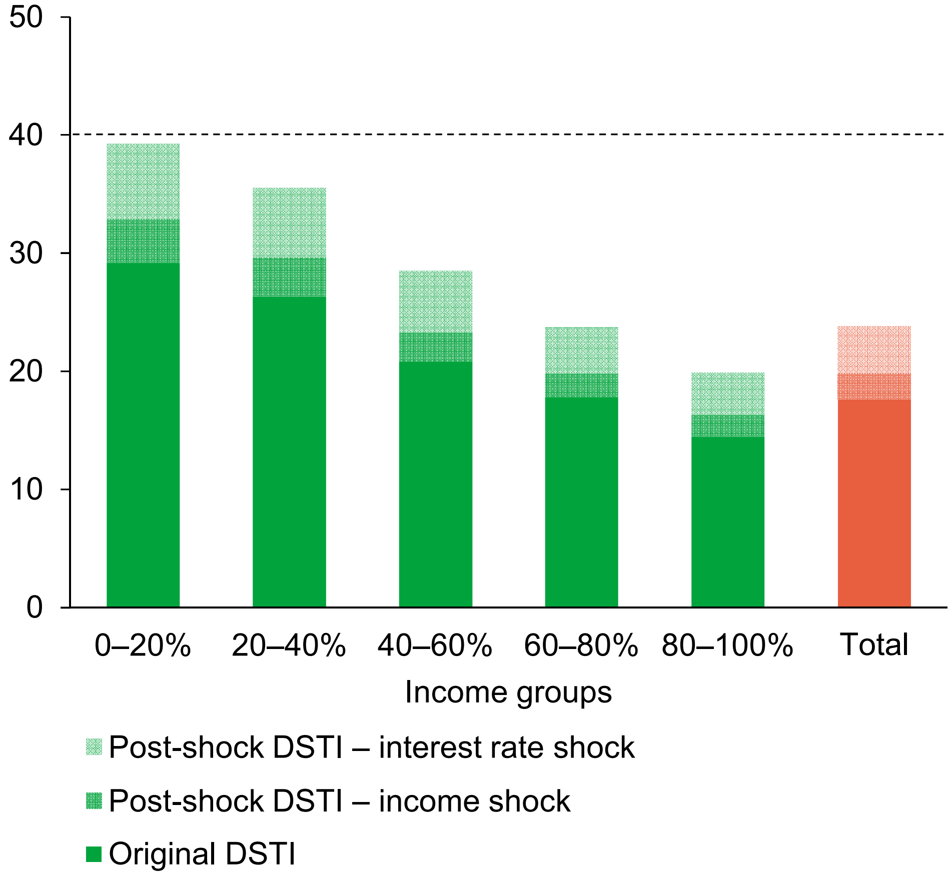
	1	2	3
Czech Republic	5.9 (8.8)	14.7 (38.2)	29.4 (47.1)
Sweden*	1.6 (4.8)	4.8 (12.7)	6.3 (15.9)
Austria**	6.5 (9.8)	20.7 (29.3)	30.4 (41.3)

Note: * Johansson and Persson (2006); ** Albacete and Fessler (2010)
Source: Galuscak, Hlavac and Jakubik (2016)

- Interest rate shocks have similar effects as in Austria, higher than in Sweden

Results – CNB stress tests

Sensitivity of the DSTI ratio of households with a mortgage loan by income group
(DSTI ratio in %)



Source: CNB Financial Stability Report 2015/2016
(SILC, HBS, CNB calculation)

Planned extension of CNB stress tests

- A new test to account for mortgages
- Use of additional data from SILC, CNB's LTV/LTI survey of new loans (since 2015), data on property prices from the Czech Statistical Office
- Housing prices shock will be newly integrated and its impact on LTV, LTI and DSTI studied (in combination with other shocks)
- Contribution of individual households to the overall impact of the shocks will be weighted with respect to the loan value

Conclusions

- Using available micro datasets, we identify financially distressed households
- We consider shocks to unemployment, interest rates and prices of essential expenditures
- We extend the previous approach by allowing for both E->U and U->E transitions
- Thanks to data availability, we consider HH heads as well as spouses

Conclusions

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- The highest impact is due to unemployment rate shock
- The impact on financial surplus is the most pronounced for the interest rate shock
- Effects of price shocks are very small
- We compare our results with Austria and Sweden
- We illustrate the use of our methodology in CNB stress tests, will be extended to account for mortgages
- We are limited to available datasets
    - New studies use HFCS data: Messner and Zavadil (2015) for SK, Albacete and Lindner (2013) for AT, Ampudia et al. (2014) for the euro area, etc.

Thank you for your attention

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Household vulnerability in the euro area[1]

Katarzyna Bańkowska, Juha Honkkila, Sébastien Pérez-Duarte
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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.

Household vulnerability in the euro area

Katarzyna Bańkowska, Juha Honkkila[1], Sébastien Pérez-Duarte and Lise Reynaert

Abstract

The distribution of income and wealth and the vulnerability of households have become important elements in the analysis of financial stability and the transmission of monetary policy. The economic and financial crisis has highlighted the significance of monitoring indebtedness and risk of debt default of households, not only at the macroeconomic level, but also at the individual level. However, while micro data are the key to understanding developments at the household level, there is a significant lag between data collection and data release. Particularly during times of rapid changes in the economy the timeliness of micro data is not sufficient for making relevant policy conclusions.

This paper addresses these issues in two steps. In the first one, it uses data from the European Household Finance and Consumption Survey (HFCS) to measure the vulnerability of households on various dimensions. These measures include information on household income, wealth and indebtedness, as well as debt burden indicators constructed from the monetary variables, such as debt-to-asset ratio and debt-service-to-income ratio, and combined measures. The vulnerability analysis is complemented with various subjective indicators collected in the HFCS. The impact of the recent economic crisis on household vulnerability is assessed by comparing the results of the two survey waves.

The second part of this paper evaluates different methodologies to combine information from timelier macro level sources with survey data to nowcast indicators on vulnerability. In a first approach we use observed distributions from survey data to break down macro level indicators. In a second approach we present the possible use of microsimulation techniques to estimate the impact of macro developments on individual households.

Keywords: household indebtedness, debt burden, vulnerability, survey, balance sheets

JEL classification: D140, D310

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Contents

Introduction

The economic and financial crisis has highlighted the significance of monitoring indebtedness and risk of debt default of households, not only at the macroeconomic level, but also at the individual level. With the use of the Household Finance and Consumption Survey (HFCS) microdata, we analyse whether the euro area households became more vulnerable during the financial crisis and present the main features of the potentially vulnerable households. In the first chapter, we analyse a set of measures used to assess the vulnerability of households. We find that in the euro area as a whole there was only a limited increase, from 11% in wave 1 to 13% in wave 2 in the share of potentially vulnerable households, while the heterogeneity across countries remains strong.

To address the issue of timeliness of the results available from HFCS, we present methodologies to draw distributional information from national accounts totals to get more up-to-date information from the developments of various types of households. In the second chapter, we analyse the ratio between debt and (adjusted) financial wealth. This indicator signals how well households can react to an income shock by amortising debt with liquid assets. The aim is to assess the impact of indebtedness on household vulnerability by combining national accounts data with HFCS data, making use of the strengths of both data sets. In the nowcasting exercise, we show how distributional national accounts data could be produced when new national accounts data are available, but distributional information is derived from the data from the previous survey wave. The main findings are that the exercise fails to capture important developments in the distribution of wealth and debt for some groups of households.

Another promising nowcasting technique is microsimulation. In chapter three, we review and analyse the empirical literature on the use of microdata to model the link between macroeconomic development and household distress. We also identify sources of up-to-date macro-level information that could be used at a European level and comment on the necessary adjustments to project HFCS micro-data to the latest period. Finally, in the last chapter, we conclude and present potential ways of improvement for future implementations.

1. Households vulnerability in the euro area

Despite the decreased share of indebted household in the euro area, the median debt burden (conditional on holding debt) has increased between the two waves of Household Finance and Consumption Survey (HFCS). With the use of the HFCS microdata we analyse whether the euro area households became more vulnerable during the financial crisis and what kind of households may be classified as potentially vulnerable. For that purpose in the first part of the paper we present the commonly used indebtedness indicators as a well as subjective indicators collected about income.

1.1 Data and overview of indicators

To investigate whether during the financial crisis the economic situation of households has changed and whether they have become more vulnerable this paper uses the microdata from both waves of the Household Finance and Consumption Survey (HFCS). The survey provides individual household data collected in a harmonised way. For the first wave the most common reference period was 2010 and for the second wave 2014, for more details sees HFCS (2016b). The data, with its rich information about the assets and liabilities of households, allows for the calculation of debt burden indicators and the analysis of the distribution of selected measures. Table 1.1 presents the definition of the selected measures of indebtedness and subjective measures of the overall income situation.

Definition of indicators on household debt burden and income situation

Table 1.1

Name of the indicators	Definition	Threshold
Debt service to income ratio (DSI)	The level of total monthly debt payments divided by gross monthly income, calculated for indebted households with debt payments	30%
Debt to income ratio (DI)	The level of outstanding total debt divided by the value of annual gross income	300%
Debt to asset ratio (DA)	The level of outstanding total debt divided by the value of household's total gross assets	90%
Low income	Income over the last 12 months was unusually low compared to an expected "normal" year income	NA
High expenses	Regular expenses over the last 12 months were higher than the income	NA

Notes: NA – not applicable

The burden of holding debt is analysed with the use of three commonly used indicators that focus on i) the financial burden of interest and loan repayments – debt service to income ratio (DSI) that reflects the burden of short-term commitments, ii) the level of outstanding debt compared to household income – debt to income ratio (DI) that informs about the debt sustainability in the medium to long term and iii) the level of outstanding debt compared to the value of household's assets – debt to asset ratio (DA) used to assess the ultimate capacity to pay back the debt. These indicators can be calculated for the indebted households, defined as those holding any type of mortgage or non-mortgage debt. While analysing the results the focus is given to the households that exceed a pre-defined threshold that in principle can point at possible difficulties to repay debt.

Another set of measures used to assess the vulnerability of households are the qualitative subjective indicators reported about their overall income situation. While (i) the first one identifies households whose income is defined as unusually low in the last 12 months compared to a "normal" year, ii) the second one reports on households whose expenses exceeded income over the last 12 months. In general, these indicators are reported for all the households, independently from the level of debt.

There are various combinations of measures that can reflect on the financial soundness of households or their economic situation, see for example D'Alessio and Iezzi (2015). Some of them may focus on the indebted households and their ability to pay back debt, while the others reflect more the availability of liquid assets, stability of income or households' ability to react to unpredictable negative shocks. In this paper we define the composite measure of vulnerability using the five indicators on debt burden and self-assessed income situation presented earlier. While the thresholds applied to the indicators for the indebted households are arbitrarily chosen, they are commonly used in the literature on households' indebtedness. The composite vulnerability measure proposed in this paper identifies a household as potentially vulnerable if the conditions for two or more of the indicators, as presented in Table 1.1, are met. These multiple indicators approach is sensitive to the shocks related to i) the interest rates ii) income and iii) accumulated assets thus not exclusively focusing on the ability to repay debt but also on the expenditure side of the low income households. Please see chapter 3 on how the impact of these shocks on financial vulnerability indicators can be modelled at household level.

1.2 Results

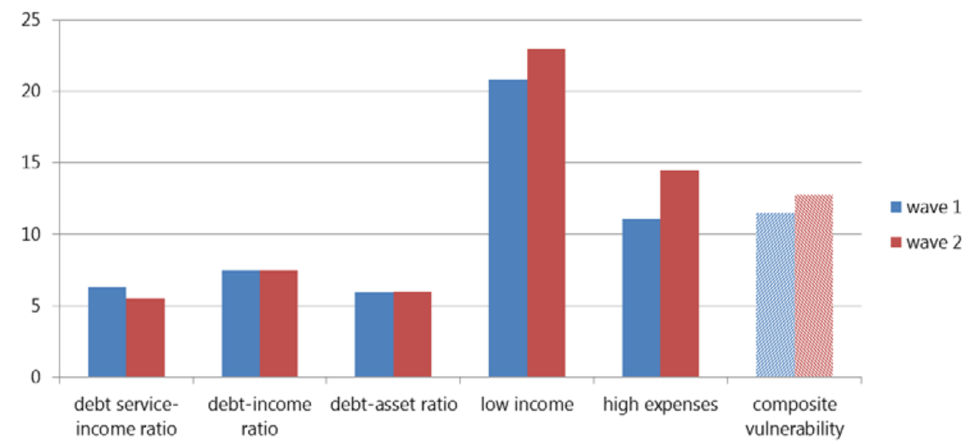
In this subsection we first present the results for each indicator of debt burden, self-assessed income situation and finally the composite vulnerability measure. We start with the share of households that fall into the predefined groups and comment on the overlaps of these indicators. In the next step we more closely look at households defined as potentially vulnerable to compare the cross country differences and changes over time. Finally, we present the main characteristics of the vulnerable groups and conclude.

When compared to wave 1, the share of indebted households in the euro area slightly declined in wave 2 (from 44.0% to 42.4%). The decrease was mainly driven by the lower debt participation rates of the upper part of the net wealth distribution, see HFCS (2016b). When looking however at the median outstanding amount of debt for the indebted households, it increased from EUR 24,000 to EUR 28,200 between the two waves. With the use of different measures we address the question of potential risk of households' unstable financial situation.

Figure 1.1 presents the shares of households that meet the criteria for a given indicator. The shares of the debt burden indicators above a certain threshold are in the range of 5% to 7% and stable across the two waves. These percentages are calculated out of all households not out of the indebted ones for the sake of calculating the composite vulnerability indicator that will apply also to all the households. When calculating the measures for households holding debt, the shares are between 13% and 18%. When looking at the subjective indicators reported about the overall income situation, 21% of households in wave 1 and 23% in wave 2 considered their income in the last 12 months as lower than average. At the same time 11% and 14% respectively reported that their regular expenses exceeded income.

Share of households in the euro area characterised by different measures, in %

Figure 1.1



Source: own calculations based on HFCS.

Note: euro area figures in wave 1 exclude FI, FR, IE, EE, LT, LV and in wave 2 exclude FI and LT. Thresholds for debt burden indicators as defined in Table 1.1.

Given various indicators of over-indebtedness and income situation, it is important to assess to what extent they overlap. The percentages presented in Table 1.2 show for each pair of indicators what the percentage of households is that meets both criteria (as defined by the column and the row of the table). Households who are identified as having large burden due to servicing debt (DSI) are in most of the cases also distinguished by high debt to income ratio (DI), which is not surprising. At the same time, only limited percentage of the households who assessed their income as low has been identified with a high debt burden indicator.

If we consider in general any combination of at least two indicators meeting the specific criteria, referred here as a composite vulnerability measure, we identify 11% and 13% of households in waves 1 and 2 respectively as potentially vulnerable, see Figure 1.1. Substantial differences across countries and time are presented in Figure 1.2. While the percentage of households defined as potentially vulnerable is below 10% in wave 2 in Italy, Austria, Malta, Germany and Belgium in strong contrast are countries affected mostly in the recent economic crisis. This measure increased substantially for Cyprus (from 28% to 40%) and Greece (from 13% to 25%) mainly due to high surge of the households with high debt to asset ratio and income identified as low in Cyprus. At the same time in Greece both low income and high expenses were reported by significantly higher share of households in wave 2. For Malta a severe drop was recorded (from 18% to 7%) because of the limited improvement in income in wave 2 compared to wave 1 that was however reflected well as a decrease of low income and high expenses measures.

Percentage of households in the euro area as defined by two indicators according to both the row and column criteria across waves

Table 1.2

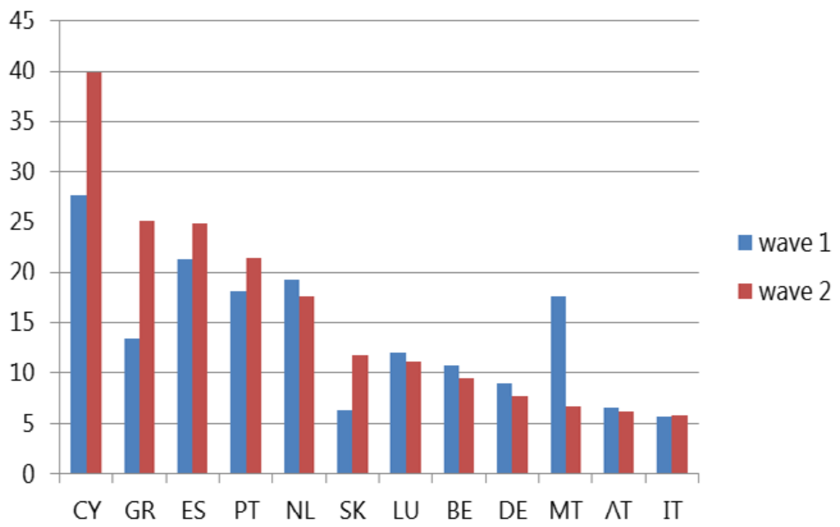
Wave 1	DSI	DI	DA	Low income	High expenses
DSI	6.3	4.2	1.2	2.4	1.5
DI	4.2	7.5	1.5	2.2	1.5
DA	1.2	1.5	5.9	1.6	1.6
Low income	2.4	2.2	1.6	20.8	4.6
High expenses	1.5	1.5	1.6	4.6	11.1
Wave 2					
DSI	5.5	3.6	1.0	2.2	1.5
DI	3.6	7.5	1.7	2.6	1.7
DA	1.0	1.7	6.0	1.5	1.7
Low income	2.2	2.6	1.5	23.0	6.1
High expenses	1.5	1.7	1.7	6.1	14.5

Source: own calculations based on HFCS.

Note: euro area figures in wave 1 exclude FI, FR, IE, EE, LT, LV and in wave 2 exclude FI and LT.

Share of vulnerable households by country and wave, in %

Figure 1.2



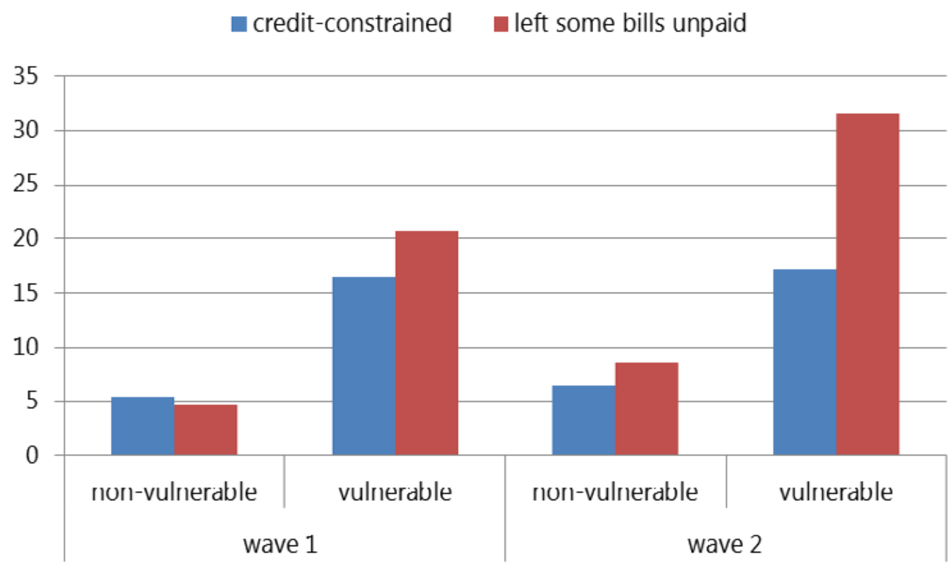
Source: own calculations based on HFCS.

Note: euro area figures in wave 1 exclude FI, FR, IE, EE, LT, LV and in wave 2 exclude FI and LT. Thresholds for debt burden indicators as defined in Table 1.1.

Focusing on the group of households classified as potentially vulnerable we identify some of their main features when compared to the other households. This group includes predominantly medium size households with 3-4 members with the mortgage on the household main residence (43% have the mortgage in the potentially vulnerable group compared to 16% in non-vulnerable one in wave 2). It also has substantially more households, as a proportion of the group that belong to the lowest income quintile and much less to the upper one. Taking the employment status of the reference person into consideration, there are more households for which that person is either self-employed or not working, but not retired. Other selected measures – the percentage of credit constrained households or those who left some bills unpaid point also at more financial difficulties for the potentially vulnerable households. As presented in Figure 1.3, these households are much more prone to be credit-constrained or not be able to pay all the bills. There were around 17% of households classified as credit-constrained in the vulnerable group while among the others there are only about 6%. These figures remained stable over the two waves considered. Substantial increase was reported however for the percentage of vulnerable households who left some bills unpaid. The indicator moved from 21% in wave 1 to 32% in wave 2 while the change for the non-vulnerable ones was much smaller (from 5% to 9% over the two waves).

Selected features by vulnerability groups in the euro area, in %

Figure 1.3



Source: own calculations based on HFCS.

Note: euro area figures in wave 1 exclude FI, FR, IE, EE, LT, LV and in wave 2 exclude FI and LT. Households are identified as potentially vulnerable if the conditions for two or more of the indicators, as presented in Table 1.1, are met.

While analysing different indicators reflecting the financial situation of households we conclude that there is a non-negligible share of households who can be classified as potentially vulnerable. Even if for the euro area as a whole there was only limited increase, from 11% in wave 1 to 13% in wave 2, the heterogeneity across countries remains strong. Furthermore, in case of the countries affected by the last economic crisis we also observe a substantial surge in the share of households defined as potentially vulnerable. With the HFCS data alone we are however not able to comment on any developments in the households financial situation in the most recent period, after 2014. For that reason in the next chapter of this paper we present a methodology to combine the information from the HFCS micro data with timelier macro aggregates from national accounts to address the issue of timeliness. Finally, in the third chapter we give an overview of microsimulation models used for nowcasting that are another way of computing the effect of recent macroeconomic changes on households.

2. Distributional information from National accounts

2.1 Motivation and literature

During the past decade, following the report by Stiglitz, Sen and Fitoussi (2009), substantial focus has been set on developing methodologies to derive distributional information from national accounts data on household sector income, consumption and wealth. The main motivation to produce distributional information from national accounts (NA) is timeliness. Usually there is a relatively large lag between the collection and release of survey data. Using methodologies to draw distributional information from NA totals could be used to get more up-to-date information from the developments of various types of households.

Most of the initiatives aiming to combine micro and macro data, such as the OECD Expert Group on disparities in a national accounts framework (see Zwijnenburg et al. 2016), have so far concentrated on income and consumption, since harmonised survey data on household wealth have not existed, unlike corresponding surveys on income and consumption. However, the Household Finance and Consumption Survey (HFCS), of which two waves have been conducted recently (HFCS 2016a), provide harmonised distributional information on household wealth for the euro area, Hungary and Poland. Outside Europe, household distribution tables combining micro and macro data have already been published by national statistical institutes of Canada and Australia (see van Rompaey, 2016 and Australian Bureau of Statistics, 2015).

This paper analyses the ratio between debt and (adjusted) financial wealth. This indicator signals, how well households can react to an income shock by amortising debt with liquid assets. The aim is to assess the impact of indebtedness on household vulnerability by combining NA data with HFCS data, making use of the strengths of both data sets. Empirical results are shown for the four biggest euro area countries, namely Germany, Spain, France and Italy. Although a limited set of countries and household breakdowns is shown, the methodology applied would allow calculating distributional indicators for any groups of households in any country conducting the HFCS or a corresponding wealth survey.

2.2 Methodology

The methodology applied in this paper to calculate distributional NA indicators follows broadly the one applied in the OECD Expert Group on disparities in a national accounts framework, where the estimation is done in five steps. In the first step, population adjustment is applied to national accounts figures. In the second step, relevant variables from both macro and micro sources are selected. In the third step, micro data are scaled to NA levels at the most detailed level possible. In the final steps households are clustered and relevant indicators are calculated.

The main difference to the OECD methodology is the procedure applied is in the second step. While the OECD expert group has decided to use the national accounts framework as the basis of estimation, this paper disregards wealth components that are not considered comparable across the two sources. A correspondence table presenting the comparability between various assets in HFCS and financial accounts is presented by Honkkila and Kavonius (2013), which indicates that some assets are available only in one of the two sources and for several types of financial wealth the comparability between the two sources is limited. Consequently, an adjusted concept of financial wealth is used in this paper, following the methodology of Kavonius and Honkkila (2016). This concept of adjusted financial wealth includes deposits, bonds, quoted shares, mutual funds and voluntary pension wealth.

In the measurement of distributional NA data, the level and structure of financial wealth is taken from NA and the distribution of each wealth component by household clusters (such as income quintile) is taken from the HFCS. Consequently, the sum of adjusted financial wealth (AFW), including *j=1 to y* wealth components, for household cluster *i*, where the household sector consists of *i=1 to x* clusters, is calculated as:

$$(1)\ AFW_i = \sum_{j=1}^{y}\left[\left(\frac{WH_{ij}}{\sum_{i=1}^{x} WH_{ij}}\right) * WN_j\right]$$

In equation (1), *WH* indicates wealth in the HFCS data and *WN* wealth in NA data.

Distributional NA data will be constructed in two different ways. First, data for the same period will be combined and the new indicators will reflect both the HFCS distribution and the NA structure of AFW at the same time *t* (first and second HFCS wave). Second, aiming to produce more timely indicators, the NA structure of wealth at time *t* (second HFCS wave) is broken down for household groups with HFCS distribution for time *t-1*, simulating a period where more recent distributional information is not available.

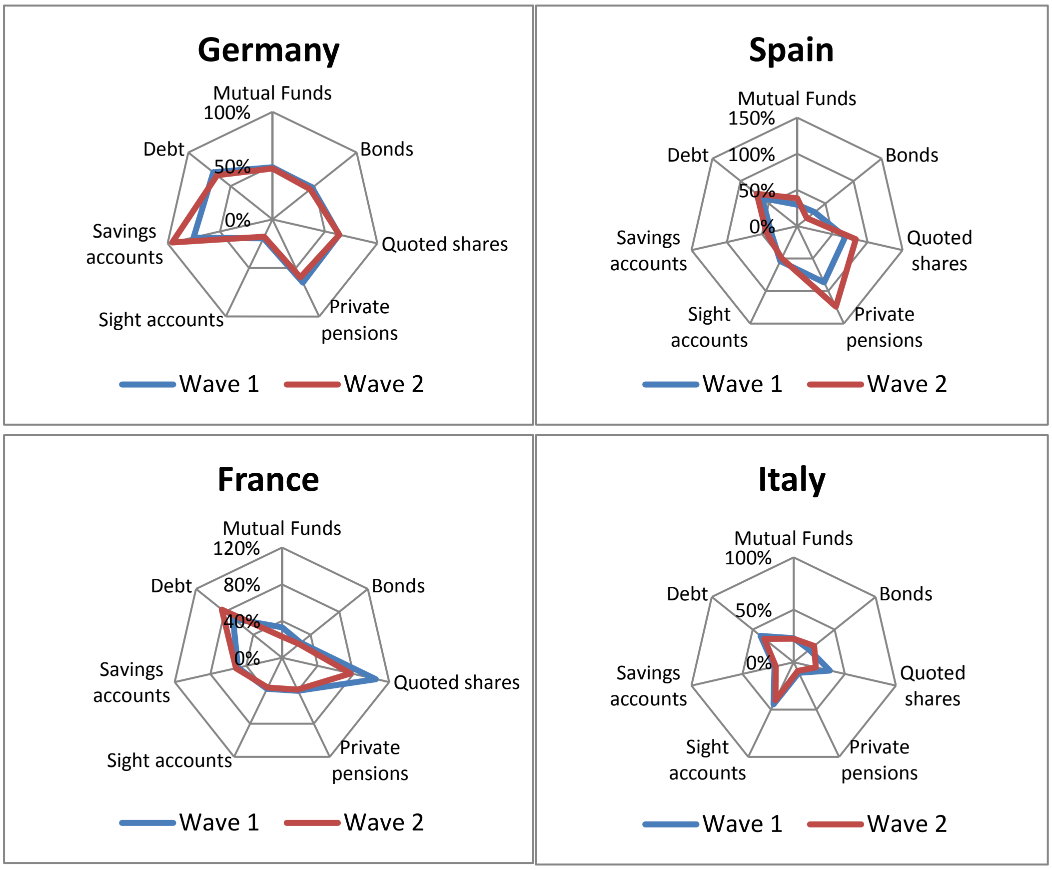
This methodology relies on two assumptions: i) reporting bias is not correlated with the indicator used to cluster the households (e.g. income) and ii) there is no sampling bias in the survey data, i.e. the distribution of the survey data reflects the true distribution. There are limited data available to assess the validity of the first assumption. Recent literature has tried to address the significance of the missing information from the upper tail of the wealth distribution (Vermeulen 2014). This paper does not intend to repeat these estimations, but recognises the need for further analysis on this topic.

2.3 Adjusting HFCS data on financial wealth to NA levels and structure

The first step in the calculation of distributional NA figures for adjusted financial wealth (AFW) is to multiply total sums of each individual wealth component with the inverse of the HFCS/NA coverage ratio. There are substantial differences between countries and between assets in the HFCS/NA coverage ratios (see Figure 2.1). The coverage ratios of adjusted financial wealth for the first / second HFCS wave are 55% (both waves) in Germany, 47% / 54% in Spain, 45% / 42% in France and 24% / 23% in Italy. For household debt, coverage ratios are higher in all countries, around 40% in Italy and between 62% and 84% in the three other countries. Except for a few individual cases the coverage ratios of individual assets in individual countries are relatively stable across the two survey waves. This indicates that the uncertainties in measurement are to a large extent systematic in individual countries and for individual wealth items. This observation is also a positive signal for the comparability between survey data across time in various countries.

HFCS/NA coverage ratio for selected assets and debt in Germany, Spain, France and Italy

Figure 2.1



Source: own calculations based on HFCS.

Note: Wave 1 refers to the year 2008 in Spain and the year 2010 in the other countries. Wave 2 refers to 2011 in Spain and 2014 in the other countries.

In the scaling up of HFCS data to NA totals, not only levels, but also distributions by different household clusters change. Because the adjusted financial wealth indicator is constructed from several components, the recalculated figures reflect the wealth structure of NA rather than the one of the HFCS. Reorganising equation (1), each wealth component will be multiplied by *WNj/WHj*. Consequently, if components that are more significant for wealthier household groups have lower coverage in the HFCS data, the distribution will become more unequal. For households' liabilities, the scaling of HFCS data up to NA levels has no impact on the distribution, since the concept of liabilities is consistent only at the aggregate level.

2.4 Empirical results

Figure 2.2 shows the differences of debt-to-adjusted financial wealth (DTAFW) ratios, i.e. sum of debt divided by sum of adjusted financial wealth for each gross income quintile, produced from HFCS and distributional NA data. There is a clear difference between the levels; the HFCS data provide higher levels of this indicator compared to NA. However, the differences between income quintiles are in most cases relatively small. There are several reasons for the difference between levels:

i) Underreporting of wealth by households

In a survey, wealth data are based on self-assessment of households. It is probable that households are not always able to provide accurate estimates of their financial wealth holdings. Underreporting has been observed to be more pronounced in the case of financial wealth than for liabilities. If we assume that underreporting is not correlated to the attributes used to group households, NA adjustment improves the measurements of DTAFW ratios by household groups.

ii) Sampling bias

Survey data are usually unable to capture information from the wealthiest households, who possess a significant share of total wealth, but probably a much smaller share of household debt. Adjusting wealth data to NA levels without capturing the missing tail of the wealth distribution will lead to an overestimation of financial wealth and underestimation of DTAFW ratios for the poorer household groups. In that sense the distributional NA data may provide biased results.

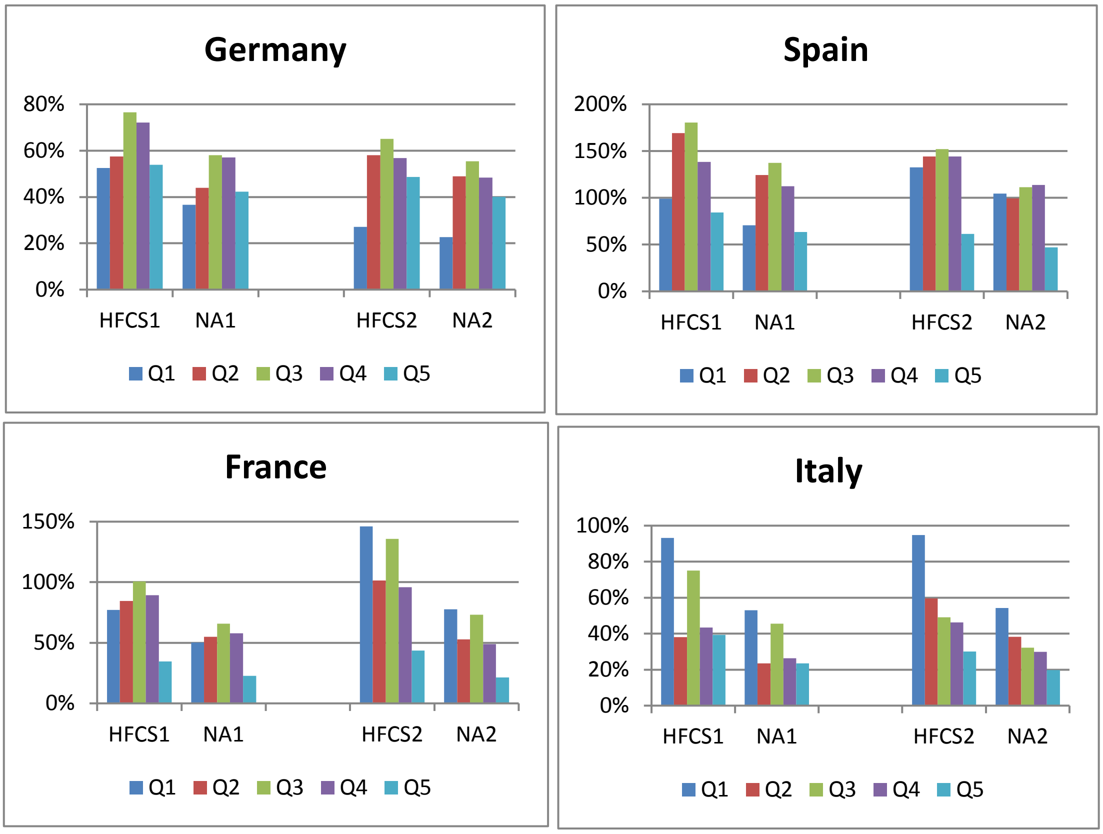
iii) Delineation between private and business wealth

Part of the missing wealth in the AFW concept can be included in the survey data under the variable "self-employment business wealth". This item is classified as real wealth in the HFCS. Small entrepreneurs who are not able to make a distinction between private and business wealth may report financial assets that NA classifies under the household sector, as business wealth. Similarly, NA data on household wealth are based on counterpart information. The delineation between households and small private businesses is not straight forward, and households' financial wealth in NA may include assets that are not classified as financial wealth of the household sector in the HFCS.

Nonetheless, both approaches of data collection serve very well the purposes of the corresponding statistics. The HFCS aims at providing distributional information of household wealth and indebtedness, and most valuable indicators are ones that describe events at certain points of distribution or ones that indicate the share of households owning certain assets or holding certain types of debt. Financial accounts aim at providing a comprehensive picture of wealth and indebtedness at the whole economy level. Due to the balancing adjustments some inaccuracy may need to be allowed for the household sector, and naturally NA data lacks any distributional information.

Debt-to-adjusted financial wealth ratios by income quintile in HFCS and distributional national accounts

Figure 2.2



Source: own calculations based on HFCS.

Note: Wave 1 refers to the year 2008 in Spain and the year 2010 in the other countries. Wave 2 refers to 2011 in Spain and 2014 in the other countries.

As a last step, we look at how changes in DTAFW and its components could be estimated for household groups in a timely manner, using distributional information from past surveys. The methodology used here is a simple one, combining two sets of indicators from publicly available statistical sources, with no intention to estimate the impact of the macro level changes on the distributions.

Figures 2.3 show the changes in AFW, debt and DTAFW for gross income quintiles in Germany, Spain, France and Italy. The first bars – called 'N' for nowcasting and marked with a pattern fill – show a simulation of how distributional NA data could be produced when new NA data are available, but distributional information is derived from the data from the previous survey wave. This approach takes into account the changes in the levels as well as in the structure of financial wealth by wealth components, but is unable to capture the changes in the distribution of wealth and indebtedness. Any changes in the distribution of wealth are caused by the change in the share of individual wealth components in the households' portfolios.

The second bars – called 'A' for actual – compare NA adjusted data from both waves, showing the results that can be acquired when the new survey data become available. This approach takes into account the changes in the levels and the structure of financial wealth by wealth components, as well as the differences in the distribution of individual wealth components and debt between different household groups.

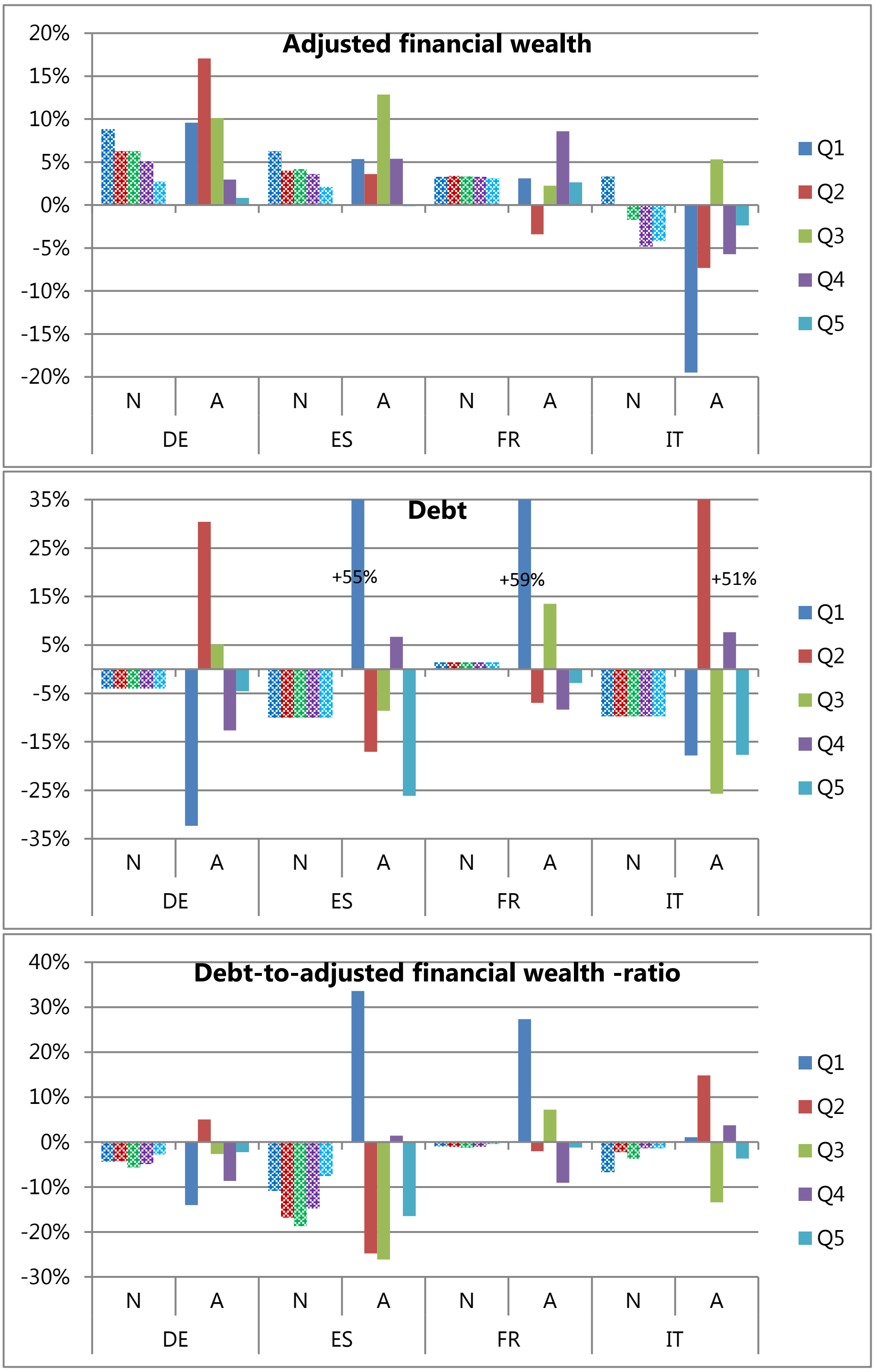
Both sets of calculations have the same denominator, and the difference between the changes show how much bias will be caused by assuming a stable distribution of financial wealth components and debt. Changes in adjusted financial wealth and debt are shown in percentages, changes in the debt to adjusted financial wealth ratio in percentage points.

For all indicators, this nowcasting exercise fails to capture important developments in the distribution of wealth and debt for some groups of households, particularly in the bottom part of the income distribution. In the case of adjusted financial wealth, the differences between nowcasting and actual data are still mostly within a manageable degree. More biased results are observed for changes in debt by income quintile at the bottom of the distribution. The bias in the estimation of debt is caused by two reasons: first of all, household indebtedness has declined during the crisis, and low income households are more frequently credit constrained (HFCS 2016b). On the other hand, many households who incurred debt before the crisis have experienced an income shock and fallen to the bottom of the income distribution, increasing the average debt in the bottom part of the distribution.

As a consequence of rapidly changing distributions of both financial wealth and debt, this nowcasting exercise fails also in providing reliable estimates of the debt-to-adjusted financial wealth –ratios for several parts of the distribution. While some changes more or less cancel each other out (increase in both wealth and debt for Q2 in Germany, decrease in both wealth and debt for Q1 in Italy), simply applying past distributions for relatively large clusters of households is not sufficient to get good estimates of household indebtedness and vulnerability, at least during times of financial crisis. A more promising solution would be to apply some types of microsimulation models to estimate the macro developments at the micro level.

Comparison of changes in AFW, debt and DTAFW ratio: nowcasting and actual distributional NA data

Figure 2.3



Source: own calculations based on HFCS.

3. The way forward: nowcasting with microsimulation models

Microsimulation constitutes another promising nowcasting technique. Instead of calibrating microdata to National Accounts, this technique consists in simulating the effect of recent macroeconomic changes on households, at a micro level, in order to draw conclusions that apply to higher levels of aggregation. These models are based on an analytical representation of specific financial, economic and institutional constraints faced by households (static or cross-sectional component), their behavioural response to the modification of these constraints (behavioural component) and - if possible - the way of adapting their behaviour overtime (dynamic or longitudinal component). Nowcasting microsimulation models depend on the availability and quality of microdata[2] and timely macro information, as well as micro-economic understanding of household behaviour. Although no microsimulation model - as fine-tuned as it could be - is an adequate substitute for a new collection of microdata, the method can preserve important layers of idiosyncrasy and provide reliable answer to questions where timeliness is important[3]. In addition, microsimulations are also widely used to stress test households under various hypothetical shock scenarios, even if no single model can provide a comprehensive account of all possible risk factors.

Several microsimulation studies originating mostly from NCBs already focused on household financial distress, with a view to better assess the risks to financial stability by looking into the accumulation of imbalances in the household sector. These studies quantify the impact on financial stability by simulating changes or shocks in household income, employment and balance sheet thanks to static microsimulation models. Overall, the impact of these changes depends on household heterogeneity, as holdings of different types of assets and liabilities differ according to economic and socio-demographic characteristics, as well as country specific institutional factor. For example, countries where mortgages have more adjustable-rate are more affected by an interest rate shock.

In this section, we aim at reviewing and analysing the empirical literature on the use of microdata to model the link between macroeconomic development and household distress. We first present an overview of the existing literature and identify sources of up-to-date macro-level information that could be used at a European level. We then describe in more detail the necessary adjustments to project HFCS micro-data forward to "now". Finally, we mention potential ways of improvement for future implementations.

3.1 An overview of empirical literature

So far, to our knowledge, only Ampudia et al. (2014a and 2014b) implemented a microsimulation framework using the HFCS at the euro area level, both to nowcast

[2] Administrative data, census data, household survey data, synthetic dataset, etc.

[3] This is worth noticing that some of the empirical literature (Sutherland, 2013), have concentrated on nowcasting income, poverty risk and inequality in a 2-3 years horizon using EU-SILC together with the European Union tax-benefit microsimulation model EUROMOD.

and stress test households' financial vulnerability. The six country specific studies that used the HFCS are Albacete and Fessler (2010) for Austria[4], IMF (2012) for Spain, IMF (2013), Michelangeli and Pietrunti (2014) and Bettocchi et al. (2016) for Italy, and Meriküll and Rõõm (2017) for Estonia.

Other European national studies used Household Budget Surveys, like Galuščák et al. (2014) for Czech Republic or Zajączkowski and Żochowski (2007) for Poland, or income surveys like Herrala and Kauko (2007) for Finland, or Danmarks Nationalbank Financial Stability Report (2007).

Outside Europe, Bank of Canada notably implemented a dynamic and flexible microsimulation framework (Peterson and Roberts, 2016[5]), extending the analysis to a multi-year horizon by allowing risks to evolve overtime. The Federal Reserve Bank of St. Louis (Krimmel et al., 2013) updated mechanically the Survey of Consumer Finances microdata using financial accounts and other macro data sources. Finally, the Reserve Bank of Australia also carried out a stress-test (Bilston et al., 2015) that shares many features with Albacete and Fessler (2010).

Please see Table A in annex for a non-exhaustive overview of empirical literature linking household financial vulnerability and macroeconomic developments.

A common structure

All of these studies display a common structure. First, a measure of financial distress and the macroeconomic changes or shocks are defined, and then the impact on the households' distress measure of the macroeconomic changes is quantified. Finally, the impact on the banks is analysed thanks to measures like exposure at default and losses given default[6].

The first step consists in choosing a measure to classify a household as financially vulnerable. Most studies used indicators relating to households' monthly cash flow position, i.e. either the financial margin[7] like Johansson and Persson (2006), Herrala and Kauko (2007), Zajączkowski and Żochowski (2007), Danmarks Nationalbank Financial Stability report (2007), Sveriges Riksbank Financial Stability Report (2009), Albacete and Fessler (2010), Galuščák et al. (2014), Bettocchi et al. (2016) or the debt-service-to-income-ratio like Djoudad (2010), IMF (2012) for Spain, IMF (2013) for Italy, Michelangeli and Pietrunti (2014). Ampudia et al. (2014b) put forward a comprehensive measure of financial distress that takes into account liquidity and

4 Apart from HFCS, Albacete and Fessler (2010) also used EU-SILC, the Austrian Consumption Survey to determine the minimum expense, and a Survey on Financial Household Wealth.

5 This report combines, updates, and expands on content from reports and discussion papers that have previously been published on this topic (Faruqui et al. (2012) and Djoudad (2010, 2012)) by the Bank of Canada.

6 Exposure at default represents the debt held by vulnerable households as a percentage of total debt. Losses given default represents the potential losses faced by the banking sector as a percentage of total debt.

7 The financial margin is defined as income net of debt service costs and essential living costs. The current empirical literature have taken different approaches to defining essential living costs: Bilston et al, (2015), Ampudia et al (2014) and Meriküll and Rõõm (2017) defined it as the poverty line, Albacete and Fessler (2010) as the household self-reported minimum subsistence level, and Galuščák et al. (2016) as the consumption of food, energy, health and rent.

solvency, since only if those two conditions are met the household is forced to default. Bettocchi et al. (2016) used this alternative measure of financial distress.

The macroeconomic changes or shocks, and their modelling are then determined. Risk factors that are frequently analysed in the literature are interest rates, asset prices, unemployment and income, while changes in debt, expenditures, inflation and exchange rates have been less often implemented. A stochastic component is introduced to incorporate household heterogeneity in the modelling of macroeconomic developments, mostly for income growth (Ampudia et al., 2014; Michelangeli and Pietrunti; 2014), unemployment (Djoudad 2010; Ampudia et al., 2014; Zajączkowski and Żochowski, 2007; Albacete and Fessler, 2010; Peterson and Roberts, 2016) and debt growth (Peterson and Roberts, 2016);

Finally, the impact on the households' distress measure of the macroeconomic changes is quantified, and the impact on the banks analysed. When the modelling includes a stochastic component, these steps were usually repeated in a Monte Carlo simulation from 50 to 1,000 times and the vulnerability indicators are calculated in each step, and the means are then computed over all the simulated draws (Johansson and Persson, 2006; Zajączkowski and Żochowski, 2007; Danmarks Nationalbank Financial Stability report, 2007; Albacete and Fessler, 2010; Michelangeli and Pietrunti, 2014). Monte Carlo simulations can then be used to assess statistical significance. Confidence intervals are only provided in Michelangeli and Pietrunti, (2014).

3.2 Macrodata availability

One of the main challenges in nowcasting is to identify sources of timely, comparable across countries and consistent macro-level information on the important dimensions with a sufficient level of details. In addition, when integrating micro and macro data sources in such a simulation exercise, an important issue consists in reconciling the economic concepts and measurement used in the two data sources.

Euro Area Accounts (EAA) provide a consistent and comprehensive information on recent[8] macroeconomic developments by institutional sectors, and therefore for the households. It covers the three dimensions of interest for household financial vulnerability: consumption, income and wealth. However, not all variables are comparable between the EAA and the HFCS and therefore some adjustments must be made. See Honkkila and Kavonius (2013) for a bridging table comparing various assets, income and liability in both sources.

Regarding labour market changes, we can resort on information from the EU Labour Force Survey (LFS). However, we need to take into account that labour market concepts do not align perfectly between the HFCS and LFS. The most up-to-date source of LFS information is the quarterly aggregate statistics published by Eurostat, which are made available three to four months after the end of the reference quarter. These provide estimates by three sets of characteristics: age group, gender and education level (a total of 18 strata).

[8] The EAA are published about four months after the end of the reference quarter.

In addition to EAA and LFS information, Ampudia et al. (2014 a) also resorted to house price indexes, and indexes of quoted and unquoted stocks, and bonds.

3.3 Components of the nowcasting process

Most studies have used microsimulation models to stress test households, while rather few[9] introduced a nowcasting part in a short to medium time horizon – i.e. one to three years - (Johansson and Persson, 2006; Djoudad 2010; IMF, 2012; Michelangeli and Pietrunti, 2014; Ampudia et al. Aug. 2014a; Bettocchi et al., 2016). Peterson and Roberts (2016) focused on a longer time horizon of three to five years.

The traditional adjustments necessary to project HFCS micro-data forward to "now" consist of three components:

1) Updating mechanically income, asset prices, and debt service from the reference income year or balance sheet year to the point in time corresponding to the latest published indexes, and possibly to macro-level forecasts or assumptions.

2) Accounting for labour market change and debt growth rate between the reference year and the most recently available information. These adjustments can incorporate household heterogeneity by allowing the labour market status or debt growth of each household to depend on its specific socioeconomic characteristics and certain empirical relationships.

3) Accounting for demographic and compositional change. In case of no major demographic or compositional shift during the time lag, this step could be avoided. However, it is possible that in time of rapid economic change, the effects of economic migration for example could have an impact on the results.

Updating wealth, income and debt service

To approximate the evolution of the distribution of wealth, income and debt service, Ampudia et al. (2014a) and Krimmel et al. (2013) updated the valuation of the different asset types, income components and rate of debt service with country-level aggregate data. These adjustments to asset values and income are only estimates, as each household will experience its own specific change. However, these indexes capture the average movement of asset values and income since the last wave of the HFCS.

Put into practice, Ampudia et al. (2014a) used the following external information to estimate changes in asset valuation: house price indexes, Harmonised Indices of Consumer Prices (HICP), and indexes of quoted and unquoted shares, and bonds. As for changes in income, an extension was also performed using wages per employee, gross operating surplus and mixed income, interests and HICP. In addition, the debt service was adjusted for the adjustable-rate mortgages, assuming a complete pass-through[10].

Modelling labour market changes

[9] Only one-third of the microsimulation papers introduced a nowcasting exercise.

[10] Assessing the pass-through of interest rates to lending rates is quite challenging, considering that that the microsimulation is at a Euro Area level and that each country has different financial products and banking practices.

Estimating the impact of changes in work status on household income and therefore on their financial margin consists in two steps: first, the work status for each individual is simulated and then, for those whose work status changed, the income is appropriately adjusted.

In addition, Peterson and Roberts (2016) introduced the duration of unemployment as another source of uncertainty.

Changes in work status

Regarding the first step, the simplest approaches assume equal unemployment risk across individuals (Johansson and Persson, 2006; Herrala and Kaukko, 2007), while more advanced approaches take into account the fact that individuals with different personal characteristics such as age, gender and education have a different propensity for becoming unemployed (Albacete and Fessler, 2010; Bilston et al., 2015; Meriküll and Rõõm (2017), Galuščák et al., 2016; Ampudia et al., 2014b, and Bańbuła et al., 2015). The three last studies also modelled transitions from unemployment to employment, in addition to the probability of becoming unemployed.

Albacete and Fessler (2010), Ampudia et al. (2014), Meriküll and Rõõm (2017) used a quite similar approach to simulate the change in work status. For each individual (or employed head), the probability of becoming unemployed is determined in relation to demographic and socio-economic characteristics. A rise in the unemployment rate is simulated by increasing this estimated probability by a shock. Ampudia et al. (2014a) introduced a sector-specific shock and accounts for the fact that unemployment exhibits different dynamics across economic sectors. If the increased probability of being unemployed is greater than a random number drawn from a uniform distribution, the person is assumed to be unemployed and receiving unemployment benefit.

Income adjustment

For the newly employed workers, the employment benefits are replaced with predicted labor income (Ampudia et al., 2014), while the labor income of the newly unemployed individual are replaced with unemployment benefits. These unemployment benefits are often computed roughly using the long term net replacement rates (Albacete and Fessler, 2010; IMF, 2012; Ampudia et al, 2014, Meriküll and Rõõm, 2017). Some national studies tried to simulate their national unemployment benefit system (Herrala and Kauko, 2007; Danmarks National bank Financial Stability report, 2007; Galuščák et al., 2014).

Modelling debt growth rate

The simplest approaches simply update debt growth rate (Johansson and Persson, 2006; Herrala and Kauko, 2007). A slightly more complex method by Michelangeli and Pietrunti (2014) for the Italian HFCS, distinguishes between existing debt and new originations. For new mortgage originations[11], they used pseudo-panel groups based on the last three waves to compute the number of new originations. For each group, the number of new mortgages is kept constant. To

[11] A new mortgage origination occurs when a household has a mortgage debt equal to zero at time t-1 and a positive mortgage debt at time t.

each household with a new mortgage, a debt amount is assigned and it equals the mean debt at origination for households belonging to the same group who had an origination between the last two waves. The amount of debt associated with new originations is then adjusted to match the macro data.

Ampudia et al. (2014a) and Peterson and Roberts (2017) incorporated household heterogeneity in debt growth dynamics by allowing the growth of each household's debt to depend on its specific socioeconomic characteristics and certain empirical relationship. Ampudia et al. uses the logic of life-cycle behaviour by trying to approximate life-cycle profile of debt holding, while Peterson and Roberts makes a specific distinction between first-time homebuyers, who have yet to contract mortgage debt, and all others. To be eligible to be a first-time homebuyer, a household must first satisfy certain demographic conditions and then be able to afford to purchase a starter home in the region in which it lives.

Accounting for demographic changes

So far, to our knowledge, all nowcasting microsimulation exercises regarding household financial distress kept constant the information on demographic characteristics of individuals. Except in exceptional circumstances this should not pose a problem when simulating policy changes within a short-term time frame, as major demographic or compositional shifts are unlikely. However, it is worth noticing that a lag longer than three year may be vulnerable to shifts in household characteristics.

In such cases the appropriate methodology would be re-weighting, as an explicit simulation would require the full power of a dynamic microsimulation model.

Re-weighting for this kind of change requires up-to-date information on the dimensions to be changed. Further work is required to establish whether such information exists, how up-to-date and comparable across countries it is and whether it is available in a form that is consistent with corresponding variables in the HFCS.

Multi-country microsimulation

The main methodological choice when implementing a multi-country microsimulation is whether to assemble together models built for the purpose of national analysis, or to build a model that covers many countries in a consistent way (like Ampudia et al., 2014b). In principle, microsimulation analysis could be carried out using side by side a set of pre-existing national models. However, in our case, it is highly unlikely that national models would be made available at the Euro Area level.

Model validation

It is important to validate the model in order to assess its reliability and the validity of its main mechanisms. For the nowcasting part, an ex post analysis or a cross-check with alternative data could be implemented. The ex post analysis consists in running the model forward from one wave of the survey to the next published one (e.g. from 2010 to 2014), the "nowcasted" results could be compared to what has actually happened. The cross-check analysis consists in comparing the results with an alternative data source. Michelangeli and Pietrunti (2014), and Peterson and Roberts (2016) performed an ex post analysis, while Ampudia et al.

(2014a) cross-checked with the preview of results of the 2011 wave of the Spanish Survey of Household Finances (EFF).

All of these three validation checks had positive conclusions about the validity of the models mechanisms. Michelangeli and Pietrunti (2014) found that they are able to replicate quite well the percentage of vulnerable households in 2010 and 2012 starting from the 2008 and 2010 waves. Peterson and Roberts (2016) also found that overall the backtesting exercise provides evidence of the validity of the main mechanism of their model. However, while their model can produce an increase in financial distress of a similar magnitude, this increase is delayed by a couple of quarters. Peterson and Roberts explained this delay by the fact that their model does not account for forward-looking behaviour, which might otherwise contribute to a certain extent to strategic default. Ampudia et al. (2014a) found that their approximation matches quite closely the income and net wealth medians.

4. Conclusion

In this paper, we aim at assessing whether euro area households became more vulnerable in the context of the financial crisis using HFCS microdata. We defined a household as vulnerable if the conditions for two or more indicators on debt burden and self-assessed income situation are met. This definition has the advantage not only to focus on the ability to repay debt, but also on the expenditure side of the low income households.

The share of households defined as vulnerable is non-negligible and increased slightly in the euro area between 2010 and 2014. However, the heterogeneity across countries remains strong. In particular, among countries affected by the last economic crisis, the share of potentially vulnerable households surged.

To nowcast the vulnerability indicators after 2014, timelier macro level sources were combined with HFCS data. The method we implemented consists in drawing distributional information from national accounts totals. However, the *ex post* analysis had negative conclusions about the validity of this method, due to the rapidly changing distributions of both financial wealth and debt.

In a second approach we present the possible and promising use of microsimulation modelling to nowcast vulnerability indicators through a review of literature.

Possible future direction

The microsimulation models that have been implemented so far take into account as much as possible household heterogeneity in terms of income, portfolio structure and age, and include a high degree of micro detail. All of these models except Peterson and Roberts (2016) are static, as they evaluate immediate distributional impact upon household of macroeconomic developments without reference to the time dimension. Peterson and Roberts extended the static models by allowing individuals to change their characteristics due to endogenous factors within the model and let households evolve overtime, in a three to five years horizon. Compared with static models, this dynamic simulation model comes with a cost: it is more complex to develop, to comprehend and control, and has more methodological challenges.

It is essential to properly validate this kind of static model before increasing its complexity by adding dynamic and behavioural components. This validation would help determine the validity and reliability of its mechanism, and whether further complexity would be desirable. Unfortunately, so far, only limited validation has been performed due notably to the unavailability of two consecutive waves of the HFCS at the time of the nowcasting exercise.

For future directions, a realistic strategy would be to implement a very detailed static microsimulation model based on what was already implemented. In addition to what was already done, the demographic changes and other changes in the structure of the population or asset ownership could also be taken into account with a re-weighting method. The model reliability should then be fully evaluated using ex post analysis, and the results would help determine whether further refinements are necessary. The first static version of the model could then be expanded into a more complex one.

As a possible refinement, Ampudia et al. (2014a) proposed to further improve household behavioural responses: one could consider life-cycle models, such as "consumption-saving choices under uncertainty, portfolio choice, borrowing for housing and durable consumption goods, saving for retirement". Ampudia et al. also suggested to better model income and social benefits in case of unemployment (e.g. see Rehder Harris, 2005).

References

Albacete, Nicolas and Peter Fessler (2010), Stress testing Austrian households, Financial Stability report 19, June, European Central Bank

Albacete, Nicolas and Peter Fessler (2013), Household vulnerability in Austria – a microeconomic analysis based on the household finance and consumption survey, Financial stability report 25 – June 2013

D'Alessio, Giovanni and Stefano Iezzi (2016), Over-Indebtedness in Italy: How Widespread and Persistent Is It? Bank of Italy Occasional Paper No. 319, March 2016

Ampudia, Miguel, Akmaral Pavlickov. Jiri Slacalek and Edgar Vogel (2014a), Household Heterogeneity in the Euro Area Since the Onset of the Great Recession, ECB Working Paper Series, No 1705

Ampudia, Miguel, Has van Vlokhoven, Dawid Żochowski (2014b), Financial fragility of Euro Area households, ECB Working Paper Series, No 1737

Australian Bureau of Statistics (2015): Australian National accounts: Distribution of household income, consumption and wealth, 2003-04 to 2014-15

Bettocchi, Alessandra, Cristiana Moriconi, Elena Giarda, Federica Orsini, Rita Romeo (2016), Assessing and Predicting Financial Vulnerability of Italian Households: A Micro-Macro Approach, Prometeia

Bilston, Tom, Robert Johnson and Matthew Read (2015), Stress Testing the Australian Household Sector Using the HILDA Survey, Research Discussion Paper, Reserve Bank of Australia

Danmarks Nationalbank (2007), Macro Stress Testing of Danish Households, Financial Stability Review, 2007

Djoudad, Ramdane (2010), The Bank of Canada's Analytic Framework for Assessing the Vulnerability of the Household Sector, Bank of Canada Financial Stability Review, June 2010

O'Donoghue, Cathal, Jason Loughrey (2014), Nowcasting in microsimulation models: a methodological survey, Journal of Artificial Societies and Social Simulation 17 (4) 12

Galuščák, Kamil, Petr Hlaváč, and Petr Jakubík (2014), Stress Testing the Private Household Sector Using Microdata, Working paper WP2/2014, Czech National Bank

Faruqui, Umar, Xuezhi Liu and Tom Roberts (2012), An Improved Framework for Assessing the Risks Arising from Elevated Household Debt, Bank of Canada Financial Stability Review, June 2012

Herrala, Risto and Karlo Kauko (2007), Household loan loss risk in Finland – estimations and simulations with micro data, Bank of Finland Research Discussion Papers 5 2007

Honkkila, Juha and Ilja Kristian Kavonius (2013), Micro and Macro Analysis on Household Income, Wealth and Saving in the Euro Area, ECB Working Paper Series No 1619, European Central Bank

Household Finance and Consumption Network (2016a): The Household Finance and Consumption Survey: methodological report for the second wave. ECB Statistics Paper Series No 17. December 2016. European Central Bank.

Household Finance and Consumption Network (2016b): The Household Finance and Consumption Survey: results from the second wave. ECB Statistics Paper Series No 18. December 2016. European Central Bank

IMF (2011), United Kingdom: vulnerabilities of private sector balance sheets and risks to the financial sector technical notes, IMF Country Report, No. 11/229, July 2011

IMF (2012), Spain: vulnerabilities of private sector balance sheets and risks to the financial sector technical notes, IMF Country Report, No. 12/140, June 2012

IMF (2013), Italy: The financial situation of Italian households and non-financial corporations and risks to the banking system technical notes, IMF Country Report, No. 13/348, December 2013

Jakubík, Petr (2010), Household Response to the Economic Crisis: Micro-simulation for the Czech Economy, IFC Working Papers, No. 6, Irving Fischer Committee on Central Bank Statistics, Bank for International Settlements, December.

Johansson, Martin and Mattias Persson (2006), Swedish households' indebtedness and ability to pay – a household level study, Penning – Ochvalutapolitik 3/2006

Karasulu Meral (2008), Stress Testing Household Debt in Korea, IMF Working Paper No WP/08/255

Kavonius, Ilja Kristian and Juha Honkkila (2016): Deriving household indebtedness indicators by linking micro and macro balance sheet data. Statistical Journal of the IAOS, Vol 32 (2016) pp. 693-708

Michelangeli, Valentina and Mario Pietrunti (2014), A microsimulation model to evaluate Italian households' financial vulnerability, International Journal of microsimulation (2014) 7(3) 53-79

Krimmel, Jacob, Kevin B. Moore, John Sabelhaus, and Paul Smith (2013), The Current State of U.S. Household balance sheets, Federal Reserve of Bank of Saint Louis Review, 95(5), 337-359

Navicke Jekaterina, Olga Rastrigina and Holly Sutherland (2013), Using EUROMOD to nowcast poverty risk in the European Union, Eurostat Methodologies and Working papers

Rehder Harris, Amy, John Sabelhaus, and Almudena Sevilla-Sanz (2005), Behavioral Effects of Social Security Reform in a Dynamic Micro-Simulation with Life-Cycle Agents, Working paper 6, Congressional Budget Office

Sveriges Riksbank (2009), Stress Test of Households' Debt Servicing Ability, Financial Stability report, 2009:1, pp 51–52.

Stiglitz, J. E., A. Sen, and J.-P. Fitoussi. 2009. Report by the Commission on the Measurement of Economic Performance and Social Progress, CMEPSP, September, 2009

Sugawara, Naotaka and Juan Zalduendo (2011), Stress-Testing Croatian Households with Debt: Implications for Financial Stability, World Bank Policy Research Working Paper No 5906

Van Rompaey, Catherine (2016): Wealth in Canada: Recent Developments in Micro and Macro Measurement. Paper prepared for the 34th IARIW General Conference

Vermeulen, Philip (2014): How Fat is the Top Tail of the Wealth Distribution? ECB Working Paper Series No 1692, European Central Bank

Zwijnenburg, Jorrit, Sophie Bournot and Federico Giovanelli (2016): Expert Group on Disparities in a National Accounts framework. Results from the 2015 exercise. OECD Statistics Working Papers 2016/10, OECD publishing, Paris.

Non exhaustive overview of current empirical literature linking household financial vulnerability and macroeconomic developments   Table A

	Country	Microdata source	Measure of financial vulnerability	Nowcasting?	Stress-testing?	Static/ Dynamic	Monte-carlo simulations?	Model validation?
Johansson and Persson (2006)	Sweden	Wealth and income data (HEK)	Negative financial margin (FM)	Yes: from 2004 to 2005	Yes	Static	Yes: 1000 iterations	No
Herrala and Kauko (2007)	Finland	Income data	Negative (FM + pledgeable amount of wealth)	Yes: from 2004 to 2005	Yes	Static	No	No
Zajączkowski and Żochowski (2007)	Poland	Household Budget Survey	Negative FM	No	Yes	Static	Yes: 1000 iterations	No
Danmarks Nationalbank Financial Stability report (2007)	Danmarks	Income data	Negative FM	No	Yes	Static	Yes: 500 iterations	No
Sveriges Riksbank Financial Stability Report (2009)	Sweden	Wealth and income data (HEK)	Negative FM	No	Yes	Static	No	No
Albacete and Fessler (2010)	Austria	Household Finance and Consumption Survey (HFCS)	Negative FM	No	Yes	Static	Yes: 1000 iterations	No
Djoudad (2010)	Canada	Canadian Financial Monitor survey	DSTI > 30%	Yes	Yes	Static	No	No
Sugawara and Zalduendo (2011)	Croatia	Household Budget Survey	1) Negative FM 2) DSTI > 35%	No	Yes	Static	No	No
IMF (2011)	UK	NMG Consulting survey	DSTI > 40%	No	Yes	Static	No	No
Faruqui et al. (2012)	Canada	Canadian Financial Monitor survey	DSTI > 40%	No	Yes	Dynamic	No	No
IMF (2012)	Spain	HFCS	DSTI > 40%	Yes: from 2008 to 2011	Yes	Static	No	No
IMF (2013)	Italy	HFCS	DSTI > 30%	No	Yes	Static	No	No
Michelangeli and Pietrunti (2014)	Italy	HFCS	DSTI > 30% and income below the median in population	Yes	Yes	Static	Yes: 50 iterations	Yes: ex post analysis
Galuščák et al. (2014)	Czech Republic	Household Budget Survey	Negative FM	No	Yes	Static	No	No
Ampudia et al. (2014a)	Euro Area	HFCS	-	Yes: from 2010 to 2013	No	Static	No	Yes: cross-check with alternative data
Ampudia et al. (2014b)	Euro Area	HFCS	Negative FM and negative cash flow > liquid assets for a certain timescale	No	Yes	Static	No	No
Bilston et al. (2015)	Australia	Household, Income and Labour Dynamics (HILDA)	Negative financial margin (FM)	No	Yes	Static	Yes: 1000 iterations	No
Bettocchi et al. (2016)	Italy	HFCS	Negative FM and negative cash flow > liquid assets for a certain timescale	Yes: from 2014 to 2017	Yes	Static	No	No
Peterson and Roberts (2016)	Canada	Canadian Financial Monitor survey	DSTI > 40%	Yes: 3 to 5 years	Yes	Dynamic	No	Yes: ex post analysis
Meriküll and Rõõm (2017)	Estonia	HFCS	Negative FM and negative cash flow > liquid assets for a certain timescale	No	Yes	Static	Yes: 1000 iterations	No

Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

IFC-National Bank of Belgium Workshop on "*Data needs and Statistics compilation for macroprudential analysis*"

Brussels, Belgium, 18-19 May 2017

Household vulnerability in the euro area[1]

Katarzyna Bańkowska, Juha Honkkila, Sébastien Pérez-Duarte and Lise Reynaert Lefebvre,
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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Household vulnerability in the euro area

IFC-NBB Workshop

Data needs and statistics compilation for macroprudential analysis

19 May 2017, Brussels

Overview

- **Motivation:**

Households asset-liability matching → Behaviour of sub-population → Financial stability analysis

- **Dataset:**

HFCS

Household Finance and Consumption Survey

- Data mostly for 2010 and 2014
- Available every 3 years
- Euro area countries (without LT), Hungary and Poland
- Cross-country comparable micro data on assets and liabilities, income, consumption and credit constraints

Measures of vulnerability

A. Focused on debt burden for indebted households (from the perspective of repaying debt):

- Debt service to income ratio (threshold: > 30%) – financial burden of interest and loan repayments;
- Debt to income ratio (threshold: > 300%) – level of outstanding debt compared to household income;
- Debt to asset ratio (threshold > 90%) – level of outstanding debt compared to the values of household's assets.

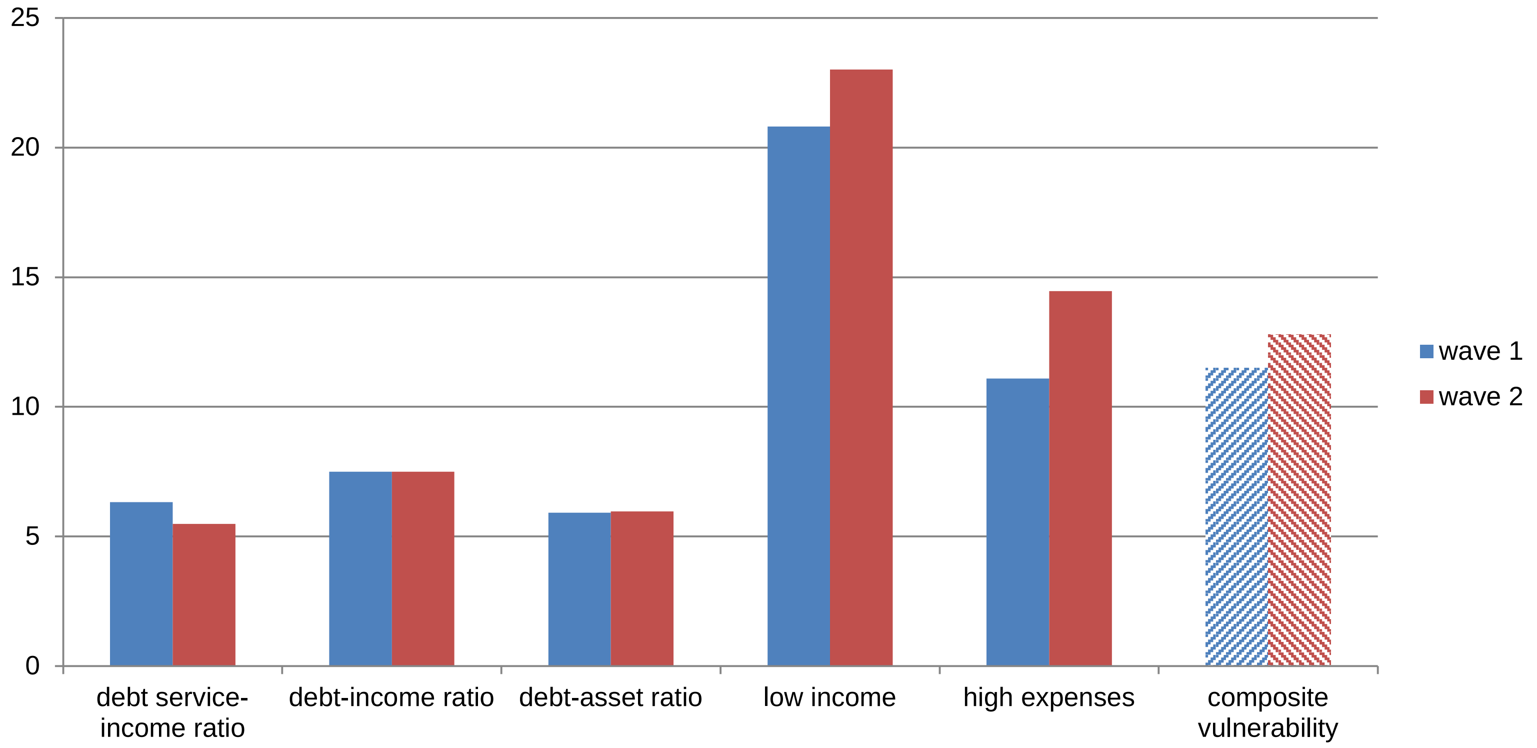
B. Focused on the overall income situation (from the perspective of affecting consumption), qualitative self-assessment:

- Income defined as "low" in the reference period of 12 months;
- Expenses exceed income in the last 12 month.

Composite measures of vulnerability

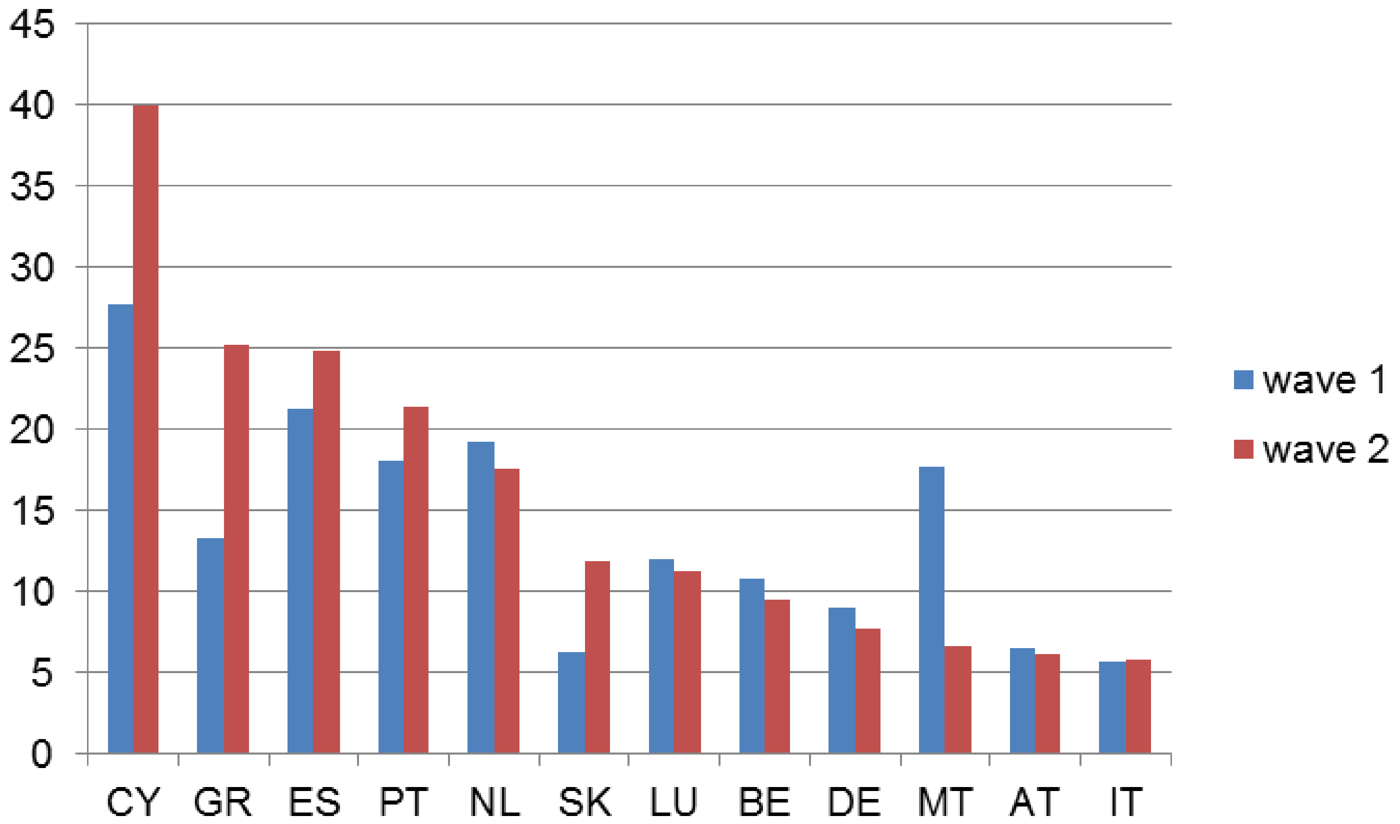
- It defines households as potentially vulnerable if the conditions for two or more of the debt burden or income indicators are met
- It is sensitive to the shocks related to i) the interest rates ii) income and iii) accumulated assets thus not exclusively focusing on the ability to repay debt but also on the expenditure site of the low income households

Share of households characterised by different measures, in %



Note: euro area figures in wave 1 exclude FI, FR, IE, EE, LT, LV and in wave 2 exclude FI and LT.
Source: HFCS and own calculations.

Share of vulnerable households by country and wave, in %



Note: data for IE, EE, LV are available only for wave 2. Data for FI and FR are excluded due to missing indicators for some of the measures.

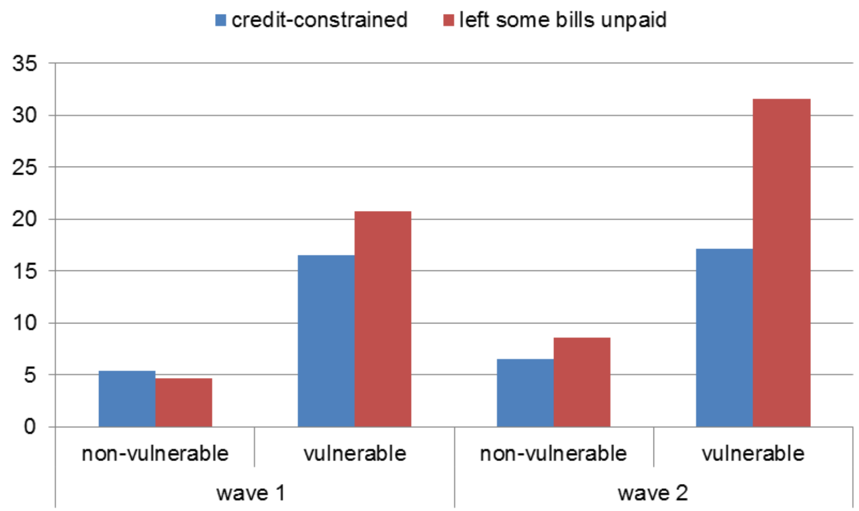
Source: HFCS and own calculations.

Main characteristics of vulnerable households

The group of households defined as vulnerable in wave 2 compared to non-vulnerable ones includes more:

- Middle size HHs of 3-4 members
- HHs with mortgage on the household main residence
- HHs from bottom income quintile
- self-employed and not working
- credit-constrained
- prone to have bills left unpaid

Selected features by vulnerability groups, in %



Note: euro area figures in wave 1 exclude FI, FR, IE, EE, LT, LV and in wave 2 exclude FI and LT.
Source: HFCS and own calculations.

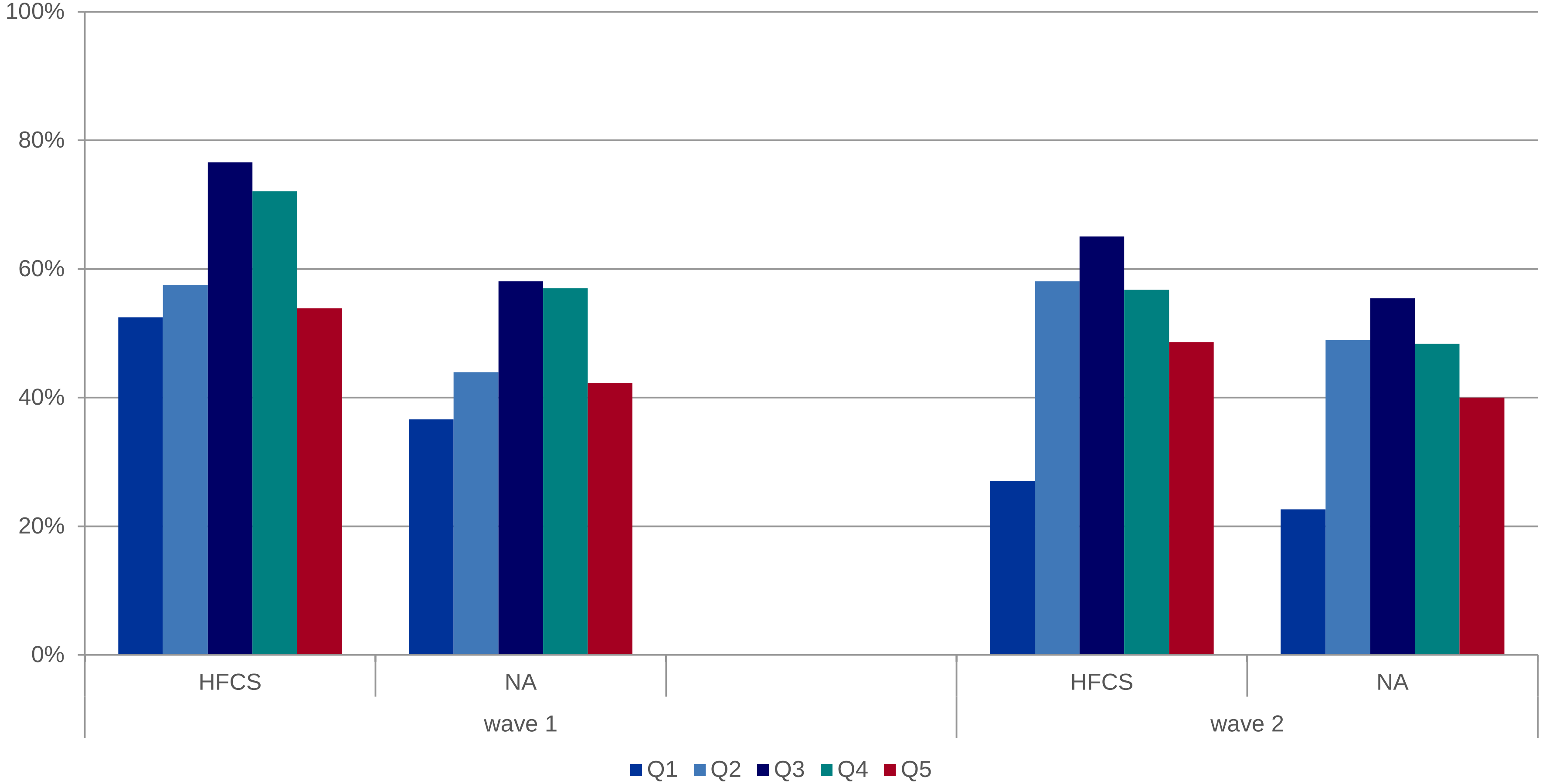
Distributional information from National accounts

- Combining macro aggregates and household surveys to get **timely indicators** on the distribution of income, wealth and indebtedness consistent with **NA levels**
  - Population adjustments
  - Select comparable variables
  - Scale micro data to NA levels at the most detailed level possible
  - Cluster households
  - Calculate indicators

Debt-to-(adjusted)-financial wealth ratio (DTAFW)

T of macro with T of micro

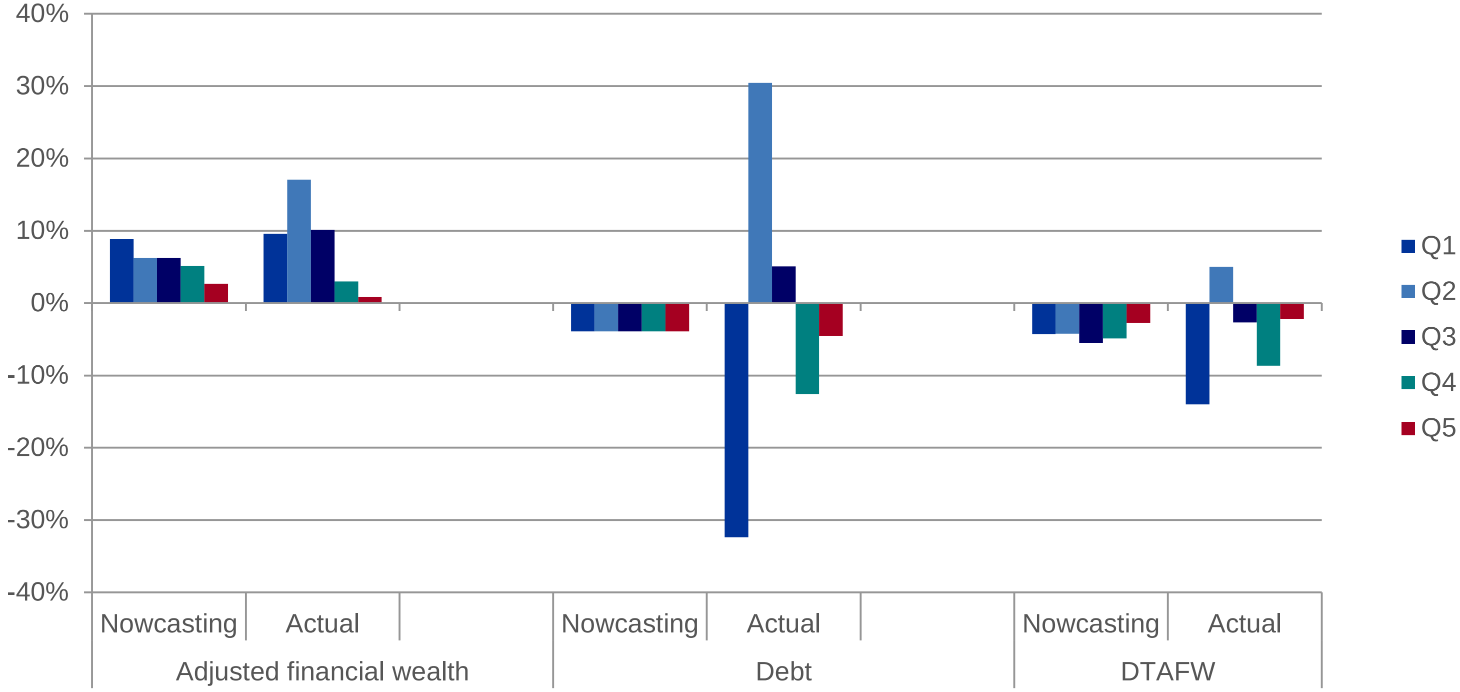
DTAFW ratio by income quintile - Germany, in %



Source: HFCS, ESA2010 and own calculations.

Nowcasting exercise: T-1 of micro with T of macro

Change in AFW, debt and DTAFW by income quintile in Germany, in % and pp



Source: HFCS, ESA2010 and own calculations.

Overview of microsimulation modelling

- Simulating the effects of macro changes on households, at a micro level
- Based on an analytical representation of:
  - the constraints faced by households (static component);
  - their behavioural response to the modification of these constraints (behavioural component);
  - the way of adapting their behaviour overtime (dynamic component).
- Microsimulation can be used for nowcasting and stress-testing under various hypothetical scenarios
- The quality of the nowcasted results will eventually depend on:
  - The quality of the microdata source;
  - The availability of timely, comparable and consistent macro-level information;
  - Micro-economic understandings and modelling of household behaviours.

Review of literature

- Several studies quantified the impact of household vulnerability on financial stability, by simulating changes in income, employment, interest rates and balance sheet at a micro level

- Microsimulation studies with the HFCS:

	Albacete & Fessler (2010)	IMF (2012)	IMF (2013)	Michelangeli & Pietrunti (2014)	Ampudia *et al.* (2014a)	Ampudia *et al.* (2014b)	Bettocchi *et al.* (2016)	Meriküll & Rõõm (2017)
Countries covered	Austria	Spain	Italy	Italy	Euro area	Euro area	Italy	Estonia
Static or dynamic	Static	Static	Static	Static	Static	Static	Static	Static
Nowcasting	×	✓	×	✓	✓	×	✓	×
Time horizon		3 years		3 years	3 years		3 years	
Stress-testing	✓	✓	✓	✓	×	✓	✓	✓

Review of literature: features of the modelling

- Macro-level information at the EA-level: EAA, LFS, House Price Index, HICP and other indices (Ampudia *et. al*, 2014)

- Possible components of the nowcasting process:
  - Update income, asset prices and debt service
  - Accounting for labour market change and debt growth rate
  - Accounting for demographic and compositional change

- E*x post* analysis or cross-check are limited: only Michelangeli and Pietrunti (2014) for Italy, and Ampudia *et al.* (2014) for Spain
  - Overall positive conclusions about model reliability
  - Further validation should be performed to determine if further refinements are desirable

Conclusion

- The HFCS captures the heterogeneity in household finances
- It is useful to detect group of households that displays various form of financial vulnerability
- However the data is available with a long time lag
- Timelier macro information can be used to nowcast vulnerability

Two nowcasting techniques:

- Adjusting HFCS data to NA levels and structure
    - *It fails to capture important developments in the distribution of households' balance sheet*
- Microsimulation modelling
    - *Several static models have already been implemented to nowcast using HFCS (only one at the EA-level)*
    - *Validation procedures are limited and should be further developed to determine the need for complex and costly refinements (Peterson and Roberts, 2016)*

Thank you for your attention

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Household debt burden and financial vulnerability in Luxembourg[1]

Gaston Giordana and Michael Ziegelmeyer,
Central Bank of Luxembourg

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.

Household debt burden and financial vulnerability in Luxembourg[1]

Gaston Giordana[2] and Michael Ziegelmeyer[3]

Abstract

We construct debt burden indicators at the level of individual households and calculate the share of households that are financially vulnerable using Luxembourg survey data collected in 2010 and 2014. The share of households that were indebted declined from 58.3% in 2010 to 54.6% in 2014, but the median level of debt (among indebted households) increased by 22% to reach €89,800. This suggests that indebted households in 2014 carried a heavier burden than indebted households in 2010. However, among several debt burden indicators considered, only the debt-to-income ratio and the loan-to-value ratio of the outstanding stock registered a statistically significant increase. The median debt service-to-income ratio actually declined, mainly reflecting lower costs on non-mortgage debt. Using conventional thresholds to identify financially vulnerable households, we find that their share in the population of indebted households increased, although the change was only statistically significant when measured by the debt-to-income ratio. The different indicators of debt burden and financial vulnerability are highly correlated with several socio-economic characteristics, including age, gross income and net wealth. In particular, low income households have lower leverage and disadvantaged socio-economic groups (in terms of education, employment status and home-ownership status) tend to be less financially vulnerable. However, after controlling for other factors, low income or low wealth increase the probability of being identified as vulnerable.

Keywords: Household debt; Household financial vulnerability; Financial stability; HFCS; Household finance

JEL classification: D10, D14, G21

1 This paper should not be reported as representing the views of the Banque centrale du Luxembourg (BCL) or the Eurosystem. The views expressed are those of the authors and may not be shared by other research staff or policymakers in the BCL, the Eurosystem or the Eurosystem Household Finance and Consumption Network. We give special thanks to Paolo Guarda. In addition, we would like to thank Anastasia Girshina, Abdelaziz Rouabah, Jean-Pierre Schoder, Cindy Veiga, and participants at a seminar at the BCL for useful comments.

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Contents

1 Introduction

Despite their relative wealth, Luxembourg households are generally more indebted than households in other European countries (HFCN, 2013). This emphasises the need for a detailed assessment of household debt sustainability in Luxembourg. During the global financial crisis mortgage defaults had consequences for financial stability around the world. Unsustainable household debt also contributed to deepening the economic consequences of systemic banking crises in certain European countries following the global financial crisis. More recently, in responding to the low inflation environment, the European Central Bank (ECB) took unprecedented monetary policy measures, which cut household borrowing costs in the euro area (EA).

More recently, the Luxembourg central bank drew attention to concerns regarding household financial vulnerability (BCL 2015, 2016, 2017).[4,5] In particular, the latest financial stability reviews noted the substantial share of loans with a short mortgage rate fixation period, which are vulnerable to unexpected interest rate increases. They also noted that household debt was growing faster than the value of household assets, implying higher bank losses in case of default. However, this analysis is limited by its reliance on aggregate data and population averages. The picture drawn from the analysis of time series data can be enriched using detailed cross-sectional balance sheet data at the individual household level. In spite of that, our cross-sectional balance sheet data refers to 2010 and 2014 and is less timely than aggregate data.

This paper calculates household-level indicators of debt burden and identifies financially vulnerable households using the 1st and 2nd wave of the Luxembourg Household Finance and Consumption Survey (LU-HFCS). Our analysis extends work reported in BCL (2013) to include the 2nd wave of the LU-HFCS conducted in 2014, and aims to complement the BCL (2017) assessment of household financial vulnerability by studying survey data. In particular, we provide a detailed description of the distribution of debt burden indicators by household socio-economic characteristics. In addition, we investigate which characteristics are more closely linked to household financial vulnerability. In future research we plan to implement a household stress test using micro-simulation methods.

The evidence we provide draws a mixed picture on the changes of household indebtedness and financial vulnerability in Luxembourg across the two waves. In 2014, 54.6% of all resident households were indebted. These households are the reference population for the analysis in this paper. The share of indebted households actually fell by 3.8 percentage points (ppt) since 2010, but the level of debt in the typical household increased. The conditional mean of household total debt increased by 27% to reach € 178,400 (the conditional median increased by 22% to reach € 89,800). Among the debt burden indicators we study, there were increases in the median debt-to-asset ratio, the median loan-to-value ratio (of the outstanding stock) and the median debt-to-income ratio. However, these changes

4 See the Section 3 in the first chapter of Revue de Stabilité Financière 2015 (pages 17-25) and Box 1.1 in Revue de Stabilité Financière 2016 (pages 21-23).

5 The European Systemic Risk Board also addressed a warning to Luxembourg about residential real estate developments and their financial stability consequences (ESRB/2016/09).

are only statistically significant for the debt-to-income ratio and the loan-to-value ratio (of the outstanding stock). In contrast, the debt service-to-income ratio declined due to the low interest rate environment. This was mostly driven by lower debt service on non-mortgage debt.

Financially vulnerable households are identified following two alternative approaches. The first approach considers one debt burden indicator at a time. This approach does not indicate a uniform significant increase in the share of financially vulnerable households between 2010 and 2014. The second approach combines information from several debt burden indicators and shows a larger (in relative terms) but still not statistically significant increase. The share of financially vulnerable households is 2.2% of the indebted population and 2.6% of the population with mortgages on their main residence in 2014.

Finally, we analyse the household socio-economic characteristics most closely associated with a higher probability of being financially vulnerable. We find that age, gross income and net wealth are highly correlated with various debt burden indicators and the share of financially vulnerable households. Disadvantaged socio-economic groups (in terms of education, employment and home-ownership status) tend be less often financially vulnerable. Conversely, low income and low wealth increase the probability of being identified as vulnerable. However, the analysis of the median debt burden indicators suggests that low income households are those with the lowest median leverage (debt-to-asset ratio and loan-to-value ratio of the outstanding stock).

The paper is organized as follows. In section 2, debt burden indicators are defined and the different approaches to identify vulnerable households are explained. The dataset used is briefly presented. Section 3 compares household debt burden indicators and the share of financially vulnerable households in 2010 and 2014. The distribution by demographic characteristics is also described. In addition, we use multivariate regression techniques to identify which household characteristics are more closely correlated with the probability of having a high median debt burden or being financially vulnerable. Section 4 concludes.

2 Methodology and data

To investigate different dimensions of the household debt burden, we consider several possible indicators (HFCN, 2013). These indicators are calculated for every indebted household. We identify indebted households as those with outstanding loans from financial institutions (mortgage, consumer, personal, instalment, etc.) and/or from relatives, friends, employers, etc. Households with credit lines/overdraft debt or credit card debt are also considered indebted. Overall debt is divided into non-mortgage debt and mortgage debt. Unless indicated differently, the indicators below are all calculated over the entire population of indebted households.

Financially vulnerable households are identified as those for which the debt burden indicators exceed certain thresholds. We adopt both single indicator and multiple indicator approaches for this purpose as detailed below.

Table 1 below reports the definitions of the different debt burden indicators. Three of them refer to the level of household leverage. The debt-to-asset (DA) ratio is the most traditional of these leverage measures. The debt-to-income (DI) ratio captures households' ability to service their debt from income streams rather than by selling their assets. The outstanding loan-to-value (LTV) ratio captures the current leverage position of the household in relation to the current self-assessed selling price of their household main residence (HMR). The outstanding LTV should not be confused with the LTV ratio at mortgage origination. The former contains the current stock of all HMR mortgages taken out. The outstanding LTV (stock) is the preferred measure to assess the current debt burden of households. The initial LTV (flow) is of additional interest as it can be the object of macro-prudential regulation.

Household debt burden indicators and financial vulnerability thresholds

Table 1

Debt burden indicator	Definition	Vulnerability threshold	Number of observations[6]
Debt-to-assets ratio (DA)	Total outstanding debt divided by household assets.	≥ 75%	2010: 580 2014: 952
Debt-to-income ratio (DI)	Total outstanding debt divided by annual household gross income.	≥ 3	2010: 580 2014: 952
Debt service-to-income ratio (DSI)	Monthly debt payments divided by monthly gross income. No debt service information is collected in the HFCS for credit lines/overdraft liabilities (set to zero). Debt service includes interest and principal repayment but excludes taxes, insurance and any other related fees. Payments for leasing contracts are also excluded.	≥ 40%	2010: 580 2014: 952
Mortgage debt service-to-income ratio (MDSI)	Total monthly mortgage debt payments (mortgages on the HMR and other properties) divided by household gross monthly income. Only defined for households with mortgage debt.	≥ 40%	2010: 405 2014: 664
Outstanding loan-to-value ratio of HMR (LTV) - stock	Outstanding stock of HMR mortgages divided by the current value of the HMR. Only defined for households with HMR mortgage debt.	≥ 75%	2010: 328 2014: 547

Complementary indicator	Definition	Threshold	Number of observations
Net liquid assets to income ratio (NLAI)	Net liquid assets divided by gross annual income. Net liquid assets include deposits, mutual funds, debt securities, non-self-employment business wealth, (publicly traded) shares and managed accounts, net of credit line/overdraft debt, credit card debt and other non-mortgage debt.	< 2 months of income	2010: 580 2014: 952

We also consider two indicators based on the flow of payments servicing the debt. The debt-service-to-income (DSI) ratio focuses on short-term requirements by measuring the drain on current income from payments of interest and principal. The mortgage debt service-to-income (MDSI) ratio provides similar information but only considers debt with real estate collateral. Since these ratios compare flows, they can vary with changes in the interest rate.

Finally, we calculate the net liquid assets to income (NLAI) ratio. This does not really measure the debt burden, but rather a household's ability to continue

[6] We report the unweighted numbers of observations. The weighted numbers of observations would be smaller as we oversample high income households, which are also more likely to hold debt.

servicing debt (by selling its liquid assets) when faced with a sudden temporary drop in income. Unlike the debt burden indicators introduced above, NLAI focuses on the liquidity of household balance sheets. Specifically, it represents the number of months that a household can replace its usual sources of income by selling its liquid assets.

We classify a household as vulnerable if its debt burden indicator exceeds the associated threshold reported in the last column of Table 1. These are conventional thresholds common across the existing literature on household financial vulnerability and were applied in similar exercises for the US (Bricker et al., 2011), the EA (ECB, 2013), the UK (IMF, 2011), Canada (Djoudad, 2012), Korea (Karasulu, 2008), Spain (IMF, 2012) and Austria (Albacete and Lindner, 2013).

These conventional thresholds are chosen by economic reasoning. Households with a DA ratio above 75% might have difficulties repaying their debt even if they sell all their assets. In this case, the 75% threshold was chosen to represent a plausible haircut, accounting for transaction costs, search costs, and the risk of future drops in asset prices. Likewise, an outstanding LTV ratio (stock) above 75% serves to identify households for whom bank losses given household default could be substantial. In the same vein, a ratio of total debt to gross income in excess of three suggests that households will remain indebted for a long period of time and are therefore more exposed to future shocks that could affect their repayment capacity.

As regards debt service, households with a DSI (or MDSI) ratio above 40% devote an important share of their current gross income flow to debt service. Therefore, any shock increasing the debt service flow or decreasing the income flow would jeopardise debt repayment. Finally, a NLAI ratio below 2 may indicate a household that is unable to cover debt payments following a sudden drop in income. However, the thresholds chosen might seem somewhat arbitrary. Thus, we perform a sensitivity analysis of the share of vulnerable households and of the changes between the two waves.

We also identify vulnerable households by combining several of the indicators above. The aim is to focus on those vulnerable households that could run into serious problems which would represent a risk of losses for the lender. The single indicator approach may identify many households as vulnerable because they have high DSI and/or MDSI ratios and a low NLAI ratio. However, many of these households will not represent a substantial loss because they are not highly leveraged (i.e. low DA, and/or outstanding LTV ratios (stock)). Even if these household default, bank losses will be limited after liquidating household assets. Thus, a banks' loss given default perspective suggests to focus on households that meet the following conditions: (i) the DSI or MDSI ratio breaches its threshold and ii) the NLAI ratio breaches its threshold; as well as (iiia) the DA ratio *or* (iiib) outstanding LTV ratio (stock) breach their threshold. Finally, we also report the share of indebted households satisfying at least one of these conditions (i.e. the union of the conditions instead of their intersection).

In order to calculate the debt burden indicators, this paper uses household micro data from the 1st and 2nd wave of the LU-HFCS. Both are representative samples of the population of households resident in Luxembourg. The 1st wave was conducted mostly in 2010 and included 950 households. The 2nd wave was conducted in 2014 and included 1601 households. Both waves were conducted by computer-assisted personal interviews (CAPI). Table 1 provides also the underlying number of observations for the analysis. Four indicators are defined for the indebted population. The MDSI can only be calculated for households with mortgage debt and the outstanding LTV ratio (stock) is defined for HMR mortgage holders only.

Survey data are not free of drawbacks. In general, they suffer from a bias due to underreporting and missing responses, especially among the wealthiest households. In order to limit this bias, HFCS data is multiply imputed and the analyses included here account for uncertainty due to sampling and imputation methods. Unless indicated differently, the standard errors and confidence intervals reported below account for both sampling and imputation variability. They are based on 1000 replicate weights and 5 multiply imputed implicates of the dataset. This ensures a more accurate analysis of financial vulnerability for the full population of households resident in Luxembourg. References below to personal characteristics of a household (indicated by a *) always refer to those of the *"financially knowledgeable person"* (FKP). The FKP is the person within the household who was self-declared as the best informed about household finances and responded to survey questions on financial matters.

3 Results

We first describe the demographic and socio-economic characteristics of indebted households and provide an overview on the mean and median level of debt (subsection 3.1). Subsection 3.2 compares the debt burden indicators for 2010 and 2014 and subsection 3.3 identifies household characteristics most closely correlated with higher debt burden indicators in 2014. Subsection 3.4 compares the share of financially vulnerable households in 2010 and in 2014 and subsection 3.5 identifies household characteristics most closely correlated with financial vulnerability in 2014.

3.1 Indebted households

In 2014, 54.6% of all households were indebted. This is a 3.8 percentage point (ppt) decline compared to 2010. Girshina, Mathä, and Ziegelmeyer (2017; section 2.2) provide details on participation rates and mean/median debt across debt categories[7] conditional on participation.

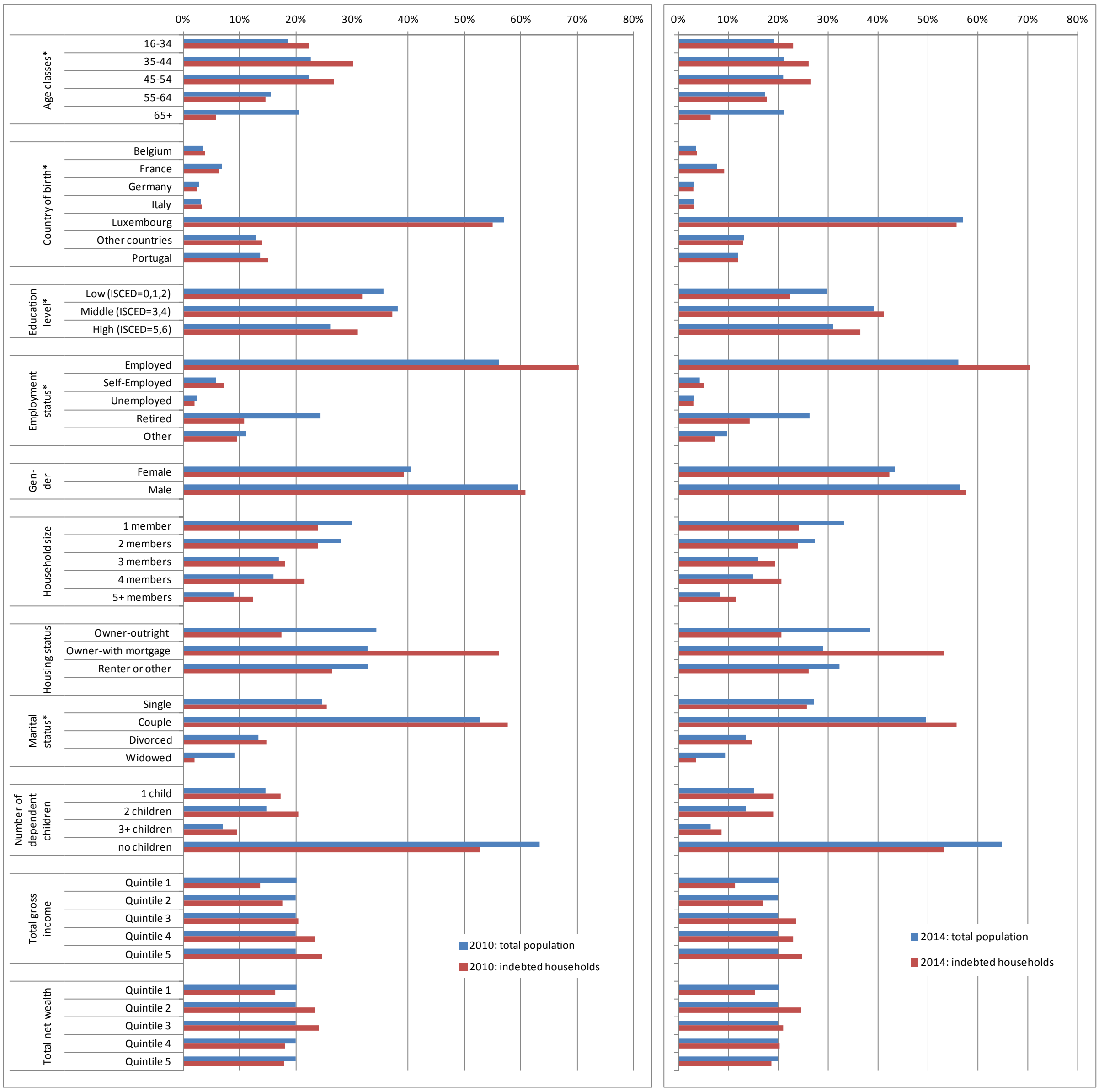
Figure 1 shows the population composition for all households and for indebted households according to various socio-demographic and economic variables for both 2010 and 2014. Indebted households are younger relative to the total population of households, have more household members, have more dependent children, and are less likely to be single and widowed. They are less likely to have low educational attainment and more likely to have high educational attainment. Indebted households are more likely to be (self-)employed, more likely to belong to the higher income quintiles, less likely to belong to the top or the bottom net

[7] Mortgage debt comprises that on the HMR and that on other real estate property. Non-mortgage debt includes overdraft debt, credit card debt, private and consumer loans.

wealth quintile, but more likely to belong to the second lowest net wealth quintile. More than half of indebted households have outstanding mortgage debt.

Population composition – all households and indebted households

Figure 1



Source: Own calculations based on the 1st and 2nd wave of the LU-HFCS; data are multiply imputed and weighted.

The share of households that were indebted declined from 2010 to 2014. However, among those households that were in debt, the mean level of total debt increased by 27% (the median level rose by 22%). The nominal mean value of debt reached € 178,400 in 2014 (the median level reached € 89,800). This increase was mainly driven by mortgage debt on the HMR and exceeded the increase in total real assets, whose mean value rose by only 4.3% (median value rose 7%). The different growth of debt and real assets corroborates the analysis in BCL (2016) and will influence the debt burden and vulnerability measures as discussed below.

3.2 Debt burden indicators

Table 2 presents the median value of several debt burden indicators in the population of indebted households in Luxembourg. These ratios suggest that households that were indebted in 2014 carried a heavier debt burden than those that were indebted in 2010. The increase in debt exceeded the increase in the value of assets which could be pledged as collateral, as well as the increase in annual gross income. However, the p-values in the final column indicate that the difference between 2010 and 2014 was only statistically significant for the DI and outstanding LTV ratios (stock). The DSI ratio, instead, declined between 2010 and 2014, mainly driven by the lower cost of non-mortgage debt.

Median debt burden indicators

Table 2

Debt burden indicators	Year	Median	Std. err.	[90% conf.	interval]	p-value	
Debt-to-asset ratio	2010	18.2%	2.1%	14.6%	21.7%	16.1%	
	2014	22.2%	2.1%	18.7%	25.6%		
Debt-to-income ratio	2010	86.9%	11.2%	68.4%	105.4%	8.9%	*
	2014	114.1%	10.6%	96.7%	131.5%		
Debt service-to-income ratio	2010	15.7%	0.9%	14.3%	17.2%	36.7%	
	2014	14.8%	0.6%	13.8%	15.8%		
Mortgage debt service-to-income	2010	16.3%	0.7%	15.2%	17.3%	17.3%	
	2014	17.6%	0.7%	16.4%	18.7%		
Outstanding loan-to-value ratio of main residence (stock)	2010	27.5%	2.6%	23.2%	31.7%	5.6%	*
	2014	34.6%	2.8%	30.1%	39.2%		
Net liquid assets to income	2010	12.2%	2.2%	8.6%	15.9%	79.0%	
	2014	11.5%	1.7%	8.8%	14.2%		

Source: Own calculations based on the 1st and 2nd wave of the LU-HFCS; data are multiply imputed and weighted; variance estimation based on 1000 replicate weights. P-values indicate whether difference between 2010 and 2014 is significant: *** p<0.01, ** p<0.05, * p<0.1.

In part, these changes reflect macro-economic developments between the two waves of the survey. Weakness in the EA and abroad lead to a drop in inflation that prompted the Eurosystem to implement a series of unprecedented monetary policy measures (both conventional and unconventional). This lowered the cost of borrowing as well as the return on many financial investments. This context could explain why the increase in the median DA ratio was not statistically significant in Luxembourg. On the other hand, the statistically significant increase in the DI ratio may reflect the fact that around 70% of indebted households are reported as "employed" (see Figure 1), and wages progressed little given low inflation during those years (mean household gross income increased by only 4% between 2010 and 2014; the median was unchanged). Finally, the accommodating monetary policy stance contributes to lower the cost of debt service.

3.3 Linking debt burden and household characteristics

We use a median regression[8] (see Christelis et al. 2013; Bauer et al., 2011) to quantify the correlation between the debt burden indicators defined above and the household characteristics shown in Table 3.[9] We run the median regressions only for 2014 as we are interested in identifying groups of households with higher debt burdens using the most recent data (estimated coefficients are shown in Table 3). A statistically significant effect on the median identifies correlation not necessarily causation, so the results should be interpreted as descriptive analysis. For some indicators, income or wealth appears on both sides of the regression (as a ratio for the dependent variable and a set of dummy variables for the independent variables), so we acknowledge that there is a potential simultaneity bias, although this may be limited given the different nonlinear transformations used. Despite this drawback, the regression approach provides the important advantage that we can control for other explanatory variables when testing for a significant correlation.

The benchmark or reference group is defined for each explanatory variable separately: it is a household with a male FKP, between 16 and 34 years old, born in Luxembourg, low educated, married, and employed. Referring to the household characteristics the reference group is also defined for each explanatory variable separately: single person household, no dependent children, renting the HMR, belonging to the highest quintiles of gross income and net wealth. Given that our independent variables are all binary, the estimated coefficients presented in Table 3 indicate the difference with respect to the median of the reference group. The estimated coefficient on the intercept term represents the median of the reference group. Coefficient estimates reported in Table 3 demonstrate that some household characteristics are significantly related to the debt burden indicators. These characteristics include net wealth quintiles, age classes, and (to a lesser extent) gross income quintiles. As will be explained below, the pattern of the estimated coefficients is consistent with theoretical models of the life-cycle (Modigliani and Brumberg, 1954; Friedman, 1957). First, net wealth correlates negatively with most debt burden indicators (except the DSI ratio). This was expected, particularly for the DA ratio and the outstanding LTV ratio (stock), as higher assets (or lower debts) increase net wealth while reducing these ratios. Less wealthy households have less net liquid assets relative to their gross income, as confirmed by the larger (negative) coefficient for higher net wealth quintiles in column 6 (Net liquid assets to income ratio).[10] For instance, a household in the middle net wealth quintile has a median ratio of net liquid assets to gross income which is 64ppt smaller than in the highest net wealth quintile. Surprisingly, differences in the median NLAI ratio across gross income quintiles are not statistically significant.

8 Median regression, also known as least-absolute-deviations regression, is a quantile regression at the median. While quantile regression minimizes a sum of absolute errors with asymmetric penalties for over- and underprediction, the median regression uses symmetric penalties and therefore provides the optimal prediction at the conditional median.

9 We use a bootstrap procedure for complex survey data using the *bs4rw* command in Stata. It is based on 1000 replicate weights to ensure that our estimates are representative of the population (Kolenikov, 2010).

10 Net wealth quintiles are almost the only explanatory variables significantly correlated with the median NLAI.

Median regression – Debt burden indicators on household characteristics – 2014

Table 3

VARIABLES	(1) Debt-to-asset ratio	(2) Debt-to-income ratio	(3) Debt service-to-income ratio	(4) Mortgage debt service-to-income ratio	(5) Outstanding loan-to-value ratio of HMR (stock)	(6) Net liquid assets as a fraction of annual gross income
Female	0.009	0.097	0.013	0.016	0.005	0.058
	(0.025)	(0.150)	(0.012)	(0.014)	(0.027)	(0.049)
Age class 35-44	-0.053	-0.002	0.020	0.013	-0.091*	0.013
	(0.047)	(0.259)	(0.016)	(0.021)	(0.049)	(0.065)
Age class 45-54	-0.144***	-0.594***	-0.009	-0.005	-0.231***	-0.010
	(0.052)	(0.229)	(0.018)	(0.026)	(0.059)	(0.086)
Age class 55-64	-0.154***	-0.835***	0.003	-0.018	-0.265***	0.076
	(0.052)	(0.275)	(0.021)	(0.030)	(0.064)	(0.117)
Age class 65+	-0.117*	-0.753**	0.020	0.023	-0.193	0.161
	(0.063)	(0.340)	(0.036)	(0.046)	(0.160)	(0.199)
Country of birth: PT	0.034	0.071	-0.042*	-0.059**	0.053	0.081
	(0.048)	(0.282)	(0.024)	(0.027)	(0.056)	(0.068)
Country of birth: FR	-0.035	-0.300	0.011	-0.010	-0.024	-0.023
	(0.038)	(0.231)	(0.020)	(0.027)	(0.063)	(0.089)
Country of birth: BE	-0.027	-0.307	-0.023	-0.041	0.060	0.126
	(0.046)	(0.260)	(0.027)	(0.032)	(0.074)	(0.157)
Country of birth: IT	0.080	0.088	-0.031	0.012	0.116**	0.061
	(0.310)	(0.338)	(0.032)	(0.037)	(0.059)	(0.123)
Country of birth: DE	0.061	0.043	0.024	0.002	0.051	0.153
	(0.055)	(0.679)	(0.032)	(0.029)	(0.064)	(0.304)
Country of birth: Other	-0.056*	-0.560***	-0.037**	-0.049***	-0.012	0.007
	(0.030)	(0.203)	(0.015)	(0.018)	(0.038)	(0.084)
1 child	0.078**	0.275	0.021	0.030	0.063	-0.105
	(0.035)	(0.247)	(0.020)	(0.023)	(0.053)	(0.083)
2 children	0.051	0.108	0.012	0.017	0.027	-0.132
	(0.039)	(0.287)	(0.024)	(0.030)	(0.064)	(0.103)
3+ children	0.082	0.144	0.049	0.008	0.068	-0.179
	(0.063)	(0.487)	(0.038)	(0.061)	(0.110)	(0.166)
Education: ISCED=3,4	0.008	0.028	-0.025	-0.025	0.031	0.102
	(0.028)	(0.193)	(0.020)	(0.024)	(0.049)	(0.062)
Education: ISCED=5,6	0.043	0.319	-0.023	-0.005	0.091*	0.179*
	(0.034)	(0.244)	(0.022)	(0.027)	(0.053)	(0.092)
Self-employed	0.034	0.227	-0.027	0.022	0.090	-0.073
	(0.040)	(0.330)	(0.032)	(0.044)	(0.064)	(0.108)
Unemployed	-0.179	-0.481	-0.084*	-0.059	-0.130	0.105
	(0.115)	(0.391)	(0.047)	(0.055)	(0.164)	(0.177)
Retired	-0.011	0.062	-0.061***	-0.054*	0.014	-0.096
	(0.029)	(0.219)	(0.022)	(0.028)	(0.052)	(0.123)
Other employment status	-0.005	0.085	-0.039*	-0.022	-0.001	-0.120
	(0.053)	(0.258)	(0.022)	(0.052)	(0.141)	(0.131)
Owner-outright	0.084*	0.916***	0.010			-0.158
	(0.046)	(0.328)	(0.021)			(0.133)
Owner with mortgage	0.174***	2.246***	0.111***			-0.065
	(0.041)	(0.300)	(0.018)			(0.081)
Gross income quintile 1	-0.113**	0.573	0.153***	0.208*	-0.173**	0.041
	(0.057)	(0.355)	(0.049)	(0.117)	(0.084)	(0.115)
Gross income quintile 2	-0.044	0.286	0.080***	0.142***	-0.067	0.003
	(0.040)	(0.308)	(0.019)	(0.034)	(0.059)	(0.110)
Gross income quintile 3	-0.046	0.318	0.063***	0.101***	-0.063	0.035
	(0.029)	(0.210)	(0.015)	(0.022)	(0.046)	(0.084)
Gross income quintile 4	-0.027	0.277	0.022	0.035**	-0.038	-0.031
	(0.025)	(0.198)	(0.014)	(0.017)	(0.036)	(0.069)
Net wealth quintile 1	0.852***	0.695*	-0.012	0.206*	0.974***	-1.023***
	(0.112)	(0.402)	(0.030)	(0.120)	(0.205)	(0.191)
Net wealth quintile 2	0.361***	1.088***	0.022	0.019	0.412***	-0.751***
	(0.035)	(0.305)	(0.019)	(0.031)	(0.049)	(0.163)
Net wealth quintile 3	0.103***	-0.004	0.001	0.009	0.163***	-0.642***
	(0.036)	(0.242)	(0.017)	(0.021)	(0.040)	(0.148)
Net wealth quintile 4	0.039*	-0.150	-0.009	0.007	0.068*	-0.564***
	(0.022)	(0.194)	(0.016)	(0.017)	(0.036)	(0.162)
Constant	0.085	-0.122	0.056	0.098*	0.244**	0.827***
	(0.075)	(0.562)	(0.039)	(0.051)	(0.098)	(0.214)
Observations	952	952	952	664	547	952

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Source: Own calculations based on the 2nd wave of the LU-HFCS; data are multiply imputed and weighted; variance estimation based on 1000 replicate weights. The reference group is defined for each explanatory variable separately: it is a household with a male FKP, between 16 and 34 years old, born in Luxembourg, low educated, married, and employed. Referring to the household characteristics the reference group is also defined for each explanatory variable separately: single person household, no dependent children, renting the HMR, belonging to the highest quintiles of gross income and net wealth. Dummies related to household size and marital status are not shown as they are not statistically significant. Significant results are highlighted in grey.

Second, columns 1, 2 and 5 suggest that debt is lower among households where the FKP is older. The outstanding LTV ratio (stock) declines with age, confirming that households purchase their main residence at early stages of their active life.

As expected, the median DSI and MDSI ratios (columns 3 and 4) gradually decline with gross income. However, the first quintile of gross income is associated with a significantly lower DA ratio and a lower outstanding LTV ratio (stock). These results indicate that low income households are also those with the lowest median leverage.

3.4 Vulnerable households

3.4.1 Single indicator approach

For each debt burden indicator, Table 4 reports the share of the population of indebted households that are identified as financially vulnerable. Comparing the wave in 2010 to the one in 2014, these results do not signal a substantial change in financial vulnerability. The only statistically significant increase (at the 5% significance level) is for the share of households with a DI ratio higher or equal than 3. The increases in the share of households with DSI ≥ 40% and those with MDSI ≥ 40% are not statistically significant. Finally, the share of households with outstanding LTV ≥ 75% is lower than in 2010 (not statistically significant), possibly reflecting regulatory changes introduced between the two waves. These changes in the share of vulnerable households tend to be consistent with changes in median debt burden indicators (described in section 3.2).

Share of vulnerable households: single indicator approach

Table 4

Vulnerability measures	Year	Mean	Std. err.	[90% conf. interval]		p-value	
Debt-to-asset ratio ≥ 75%	*2010*	12.8%	1.6%	10.2%	15.5%	70.0%	
	2014	12.0%	1.4%	9.7%	14.3%		
Debt-to-income ratio ≥ 3	*2010*	20.6%	1.9%	17.5%	23.7%	4.7%	**
	2014	25.8%	1.8%	22.8%	28.8%		
Debt service-to-income ratio ≥ 40%	*2010*	7.0%	1.3%	4.9%	9.2%	31.4%	
	2014	8.9%	1.3%	6.8%	11.0%		
Mortgage debt service-to-income ratio ≥ 40%	*2010*	6.8%	1.6%	4.1%	9.5%	10.7%	
	2014	10.3%	1.7%	7.4%	13.1%		
Outstanding loan-to-value ratio of main residence (stock) ≥ 75%	*2010*	15.9%	2.3%	12.0%	19.8%	40.7%	
	2014	13.4%	1.9%	10.3%	16.4%		
Net liquid assets < 2 months income	*2010*	55.5%	2.5%	51.4%	59.7%	94.6%	
	2014	55.7%	1.9%	52.6%	58.9%		

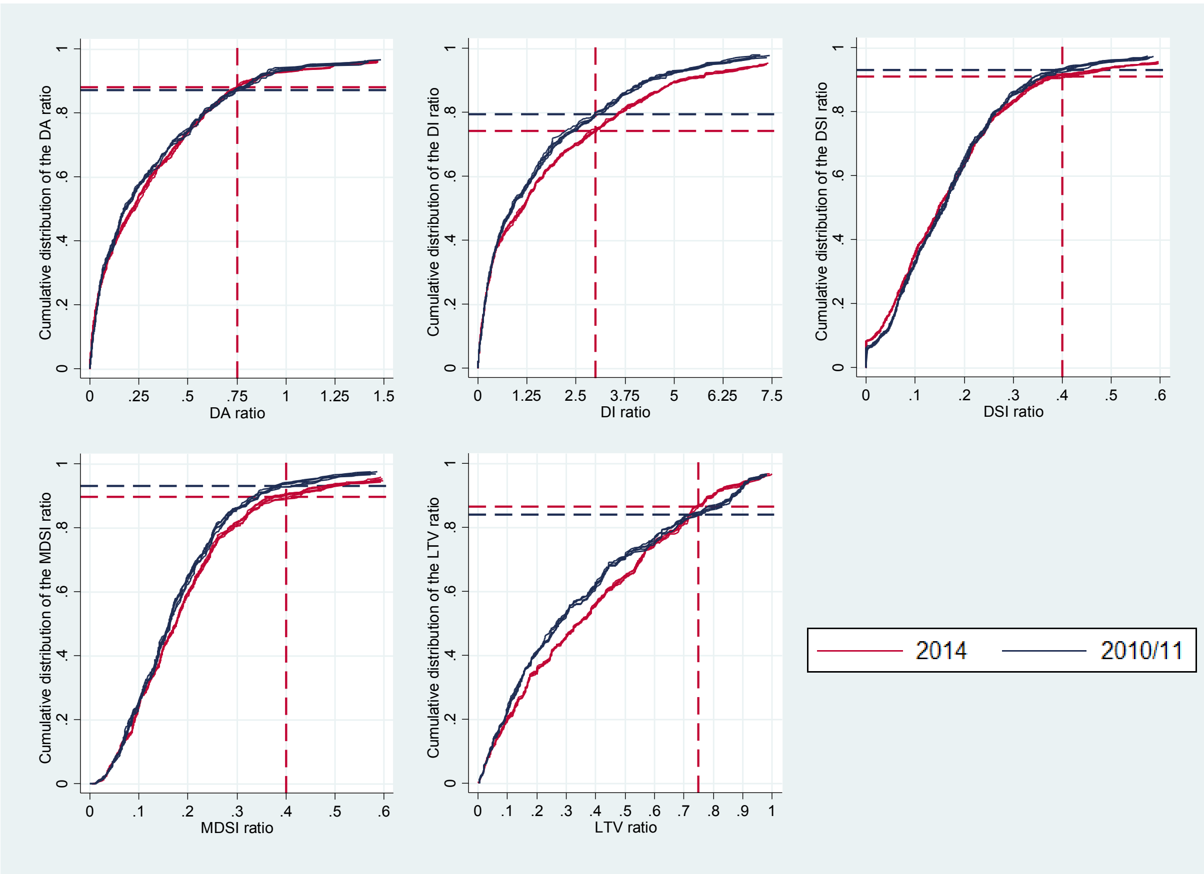
Source: Own calculations based on the 1st and 2nd wave of the LU-HFCS; data are multiply imputed and weighted; variance estimation based on 1000 replicate weights. P-values indicate whether difference between 2010 and 2014 is significant: *** p<0.01, ** p<0.05, * p<0.1.

The vulnerability thresholds we employ are conventional in the literature, but they remain somewhat arbitrary. In order to assess the robustness of the result (share of vulnerable households) to alternative values of the threshold, Figure 2 depicts the cumulative distributions for each debt burden indicator in 2010 (blue lines) and in 2014 (red lines). The dashed horizontal lines represent the conventional thresholds reported in Table 1 and applied in Table 4. Moderate changes in the threshold around their conventional levels would not generally produce significant changes in the share of vulnerable households. This reflects a fairly flat slope of the cumulative distributions in the relevant range.

On the other hand, a small change in the threshold of the liquidity indicator, the NLAI ratio, would make a dramatic difference to the share of vulnerable households identified on this measure (Figure 3). In fact, the cumulative distribution is relatively steep around the conventional threshold for the net liquid assets to income ratio, which is set at 0.17 (equivalent to two months of annual income). This means that small changes in the threshold will switch the status of relatively many households. A closer look reveals that the conventional threshold for the NLAI ratio occurs near the population median, while the conventional thresholds for the other indicators only cut off 10-20% of the population in the tail of the distribution. Therefore, according to the conventional threshold for the NLAI ratio, it appears that more than half of Luxembourg's indebted households suffer from insufficiently liquid balance sheets (last row in Table 4). This does not seem plausible and suggests that the conventional threshold is not appropriate for Luxembourg. In fact, according to international evidence from the HFCN, annual gross income is significantly higher for households in Luxembourg than in other EA countries (HFCN, 2013, 2016). While a data-driven selection of the vulnerability thresholds might be more appropriate, we propose to leave this for future research.

Cumulative distribution of debt burden indicators

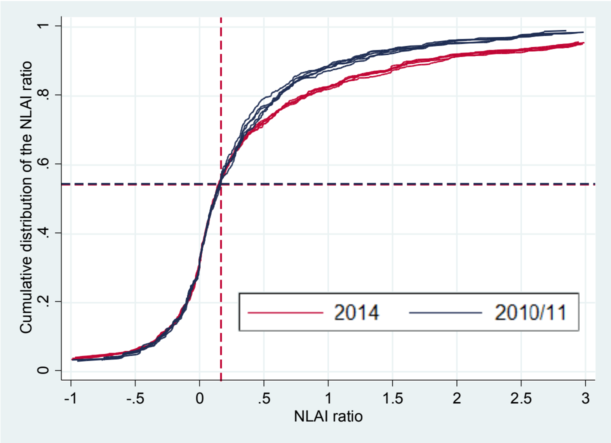
Figure 2



Source: Own calculations based on the 1st and 2nd wave of the LU-HFCS; data are multiply imputed and weighted; the cumulative distribution functions are calculated and displayed for each implicate separately.

Cumulative distribution of net liquid assets to income ratio indicators

Figure 3



Source: Own calculations based on the 1st and 2nd wave of the LU-HFCS; data are multiply imputed and weighted; the cumulative distribution functions are calculated and displayed for each implicate separately.

The difference in the share of vulnerable households between 2010 and 2014 also turns out to be robust to small changes in the level of the vulnerability thresholds for most debt burden indicators. In Figure 2, the cumulative distributions in 2010 and in 2014 do not differ much. The only possible exception is the outstanding LTV ratio (stock), where the distributions cross. In fact, in the neighbourhood of the conventional threshold the slope of the cumulative distribution appears to flatten in 2010 while it appears to steepen in 2014. Therefore, a small increment in the threshold for this indicator would reduce the share of vulnerable households much more in 2014 than in 2010.

Finally, focussing on the DI ratio, the 2014 distribution stochastically dominates the 2010 distribution (weak dominance at order one). This means that the statistically significant increase in the share of vulnerable households reported for this indicator would probably also hold using other threshold levels (spanning almost the full distribution). In particular, we have already shown a significant difference at the median (Table 2). Accordingly, in section 3.2 we argue that the combination of slack economic conditions and accommodating monetary policy contributed to debt growing faster than income while leaving debt service almost unchanged.

3.4.2 Multiple indicator approach

We also calculate the share of vulnerable households using the more restrictive multiple indicator approach presented in section 2. We argued that such an approach would focus on those households that could run into serious problems and represent a more acute risk of bank losses. Table 5 reports the outcome. Households simultaneously meeting condition (i) a debt service-to-income ratio above the threshold and condition (ii) a net liquid assets to income ratio below the threshold represent 4.3% of the indebted population in 2010 and 6% in 2014. If condition (i) is restricted to mortgage debt, the share of vulnerable households more than doubled from 3.3% in 2010 to 6.8% in 2014.

Share of vulnerable households across waves: multiple indicator approach

Table 5

	Year	(i) DSI ratio ≥ 40% or MDSI ratio ≥ 40%	Additional conditions (ii) Net liquid assets < 2 months income	(iiia) DA ratio ≥ 75%	(iiib) Outstanding LTV ratio of HMR (stock) ≥ 75%
DSI ratio ≥ 40%	2010	7.1	4.3	1.4	-
	2014	8.9	6.0	2.2	-
MDSI ratio ≥ 40%	2010	6.8	3.3	-	1.6
	2014	10.9	6.8	-	2.6

Source: Own calculations based on the 1st and 2nd wave of the LU-HFCS; data are multiply imputed and weighted. The rows on the DSI ratio refer to all indebted households. The rows on the MDSI ratio refer only to households with mortgage debt on their main residence.

Bank losses will only be important if these vulnerable households are also highly leveraged. When we add condition (iiia), a DA ratio breaching the threshold, there remain 1.4% of indebted households in 2010 and 2.2% in 2014 (the change between years is not statistically significant). If instead we add condition (iiib), the outstanding LTV ratio (stock) on the HMR breaching the threshold, there remain 1.6% of indebted households in 2010 and 2.6% in 2014 (the change between years is not statistically significant). The aggregate value of banks' exposure of default can be approximated by summing up the debt holdings of these population shares. In future research, we plan to calculate loss given default, exposure at default and probabilities of default at the individual household level in a stress test of household balance sheets.

While Table 5 focuses on households with a debt service-to-income ratio above the 40% threshold, Figure 4 provides more detailed information on the whole distribution of indebted households, including those with DSI ratios below the threshold. The upper panel refers to the population of all indebted households, while the bottom one focuses only on households with mortgage debt on their main residence. The bar on the far right in each panel provides the same information as in Table 5.

Most households have moderate DSI ratios below 20% or 30% (first two columns on the left account for 83.2% of indebted households in 2014). Comparing household groups according to their DSI ratios (the different bars) reveals heterogeneous distributions of the NLAI ratio. In 2014, the share of households with net liquid assets above 2 months income (green segment) decreases from around 50% for indebted households with a DSI below 20% (first bar) to around 32% for households with a DSI above 30% (last two bars). In addition, the share of households that combine an insufficient NLAI ratio with an excessive DA ratio (red segment) increases from 7% for households with a DSI below 20% (first bar) to 25% for households with a DSI of more than 40% (last bar). Thus, households with high DSI ratios tend to have proportionally less favourable NLAI and DA ratios. The pattern is generally confirmed if we focus on debt service-to-income ratio from mortgage on the main residence only (lower panel).

Distribution of households by multiple indicators

Figure 4

Source: Own calculations based on the 1st and 2nd wave of the LU-HFCS; data are multiply imputed and weighted. The upper panel on the DSI ratio refers to all indebted households. The lower panel on the MDSI ratio refers only to households with mortgage debt on their main residence. The figures in the bottom row provide the share of households in the respective category.

Finally, we complement these analyses by calculating the shares of the indebted population that satisfy at least one of the vulnerability conditions used in Table 5. While relatively few indebted households fell in the intersection of the three vulnerability conditions (see Table 5), we expect a larger share to be captured by the union of conditions. The outcome is depicted in Table 6. The share of indebted households that breach the vulnerability threshold for either the DSI or the DA ratio is 18% in 2010 and in 2014. Similarly, the share of households that breach the vulnerability threshold for either the MDSI or the outstanding LTV ratio (stock) is around 21% in both waves. These shares increase dramatically when we add those households that breach the vulnerability threshold of the NLAI ratio (last column of Table 6). However, as discussed above, the latter result is not robust to small changes in the vulnerability threshold of the NLAI ratio (see section 3.4.1).

Share of households classified as vulnerable by at least one indicator

Table 6

	Year	Additional conditions (iia) DA ratio ≥ 75%	(iib) Outstanding LTV ratio of HMR (stock) ≥ 75%	(iii) Net liquid assets < 2 months income
DSI ratio ≥ 40%	2010	18.0	-	60.7
	2014	18.0	-	59.3
MDSI ratio ≥ 40%	2010	-	21.1	73.9
	2014	-	21.2	73.4

Source: Own calculations based on the 1st and 2nd wave of the LU-HFCS; data are multiply imputed and weighted. The rows on the DSI ratio refer to all indebted households. The rows on the MDSI ratio refer only to households with mortgage debt on their main residence.

3.5 Linking vulnerability and household characteristics

We use a probit model to estimate the probability that a given household is classified as vulnerable (using the conventional thresholds and the standard single indicator approach). This adds to the median regression on the debt burden indicators as the probit model helps identifying the characteristics of vulnerable households which are by definition in the tail of the corresponding distribution (the conventional vulnerability thresholds are, for 5 out of 6 measures, at the right tail of the distribution, Figure 2 and Figure 3). As one can see below, the relevant characteristics differ in the two exercises.

The dependent variable is unity if the household is identified as vulnerable on a given measure and zero otherwise. Thus, the model can be written as follows:

$$\Pr(V_i = 1 \mid x) = \Pr(V_i^* > 0 \mid x) = \Phi(x) \quad (1)$$

$$V_i^* = \beta_0 + \beta_X X_i + \varepsilon_i \quad (2)$$

Household *i's* probability of being classified as vulnerable is expressed as a function of several determinants *x*, which influence a latent variable V_i^*. We use the same explanatory variables as for the median regression on debt burden indicators (Table 3). Again, we aim to identify household characteristics which are correlated with financial vulnerability while controlling for other household characteristics. Marginal effects are calculated at the observation level and then averaged. Potential simultaneity bias may also arise in this setting. Table 7 reports the estimated average marginal effects. These are strong for net wealth, gross income and the age of the FKP in the household. Including four net wealth quintiles allows the DA ≥ 75% regression in column 1 to perfectly identify households in our sample. This is why only the first net wealth quintile is included in column 1. In column 5, the marginal effect on the probability that LTV ≥ 75% is highest for households in the first net wealth quintile and the marginal effects tend to decrease with higher wealth. For instance, the probability that a household in the lowest net wealth quintile is vulnerable is 54% higher compared to a household in the reference (highest) quintile. In column 6, low net liquid assets relative to gross income are more likely for low wealth households. Marginal effects decline steadily with higher wealth. In column 4, the probability that the MDSI ratio exceeds 40% is significantly higher for households in the lowest net wealth quintile compared to those in the reference (highest) quintile. The average marginal effects in this column are negative for quintiles 2 and 3. This means that households belonging to these middle quintiles are less likely to be classified as vulnerable on this criterion compared to those in the reference (highest) net wealth quintile.

As expected, gross income tends to play a significant role in columns 3 and 4 (probability that total DSI or MDSI exceeds 40%). According to these indicators, the probability of being identified as vulnerable is lowest for the top gross income quintile and increases steadily as one approaches the lower end of the income distribution.

If the indicator is based on the stock of debt (columns 1, 2 and 5), the probability that the household will be classified as vulnerable decreases with the age of the FKP. This is consistent with the life cycle pattern of indebtedness, which suggests that high DI ratios are in line with models of optimal portfolio choice over the life-cycle.

Some results in Table 7 may appear puzzling at first sight, such as those concerning ownership status, education level and occupation. The positive and highly significant coefficient for outright owners compared to renters might be surprising in columns 2, 3 and 6. We also ran the regressions omitting net wealth quintiles from the set of explanatory variables (results not shown to save space). In this case, owners (with or without a mortgage) were less likely to be identified as vulnerable in column 6. This suggests a high correlation between net wealth and housing status that may be biasing the coefficient on the latter variable.

Similarly, in columns 2 and 4 households where the FKP is highly educated tend to be more vulnerable. This may be related to a higher potential income growth. Likewise, in columns 2-4 households where the FKP is self-employed are more likely to be vulnerable, while in column 1 those where the FKP is unemployed are less likely to be vulnerable. The latter result might be explained by credit constraints facing the unemployed.

We conclude that highly leveraged households (columns 1, 2 and 5) and household with a high debt servicing burden (columns 3 and 4) tend, on the one hand, to be part of the less vulnerable socio-economic groups of the population (in terms of education, employment and HMR ownership status) but, on the other hand, also to be part of more vulnerable groups (low income and wealth), which is at least partly opposite to the findings for the median regression reported in Table 3.

Probit regression - Probability of financial vulnerability on household characteristics - 2014

Table 7

VARIABLES	(1) Debt-to-asset ratio ≥ 75%	(2) Debt-to-income ratio ≥ 3	(3) Debt service-to-income ratio ≥ 40 %	(4) Mortgage debt service-to-income ratio ≥ 40 %	(5) Outstanding loan-to-value ratio (stock) ≥ 75 %	(6) Net liquid assets < 2 months gross income
Female	0.016	0.006	0.004	-0.025	0.040	-0.049
	(0.020)	(0.029)	(0.022)	(0.025)	(0.028)	(0.039)
Age class 35-44	-0.059**	-0.026	0.013	0.045	-0.080**	0.033
	(0.026)	(0.042)	(0.028)	(0.034)	(0.035)	(0.061)
Age class 45-54	-0.104***	-0.173***	-0.033	0.002	-0.110**	0.086
	(0.031)	(0.047)	(0.036)	(0.043)	(0.047)	(0.064)
Age class 55-64	-0.159***	-0.207***	-0.009	-0.000	-0.176***	-0.046
	(0.049)	(0.074)	(0.055)	(0.063)	(0.065)	(0.073)
Age class 65+	0.008	-0.081	-0.035	-0.049	†	-0.094
	(0.059)	(0.101)	(0.087)	(0.088)		(0.115)
Country of birth: PT	-0.001	-0.036	-0.036	-0.067	0.075*	-0.075
	(0.032)	(0.052)	(0.035)	(0.050)	(0.040)	(0.066)
Country of birth: FR	-0.029	-0.067	-0.116**	-0.103	0.054	0.026
	(0.034)	(0.054)	(0.045)	(0.064)	(0.051)	(0.073)
Country of birth: BE	0.001	-0.120	-0.201***	-0.146***	0.064	-0.168*
	(0.037)	(0.075)	(0.055)	(0.054)	(0.062)	(0.099)
Country of birth: IT	0.055	-0.020	-0.101**	-0.082*	0.064	-0.043
	(0.044)	(0.084)	(0.048)	(0.049)	(0.068)	(0.093)
Country of birth: DE	-0.108**	0.064	0.079	0.065	-0.275***	-0.045
	(0.045)	(0.101)	(0.060)	(0.051)	(0.090)	(0.114)
Country of birth: Other	-0.074**	-0.177***	-0.099***	-0.076*	-0.096*	-0.012
	(0.034)	(0.049)	(0.037)	(0.040)	(0.058)	(0.057)
Household size: 2	0.025	-0.022	0.072**	0.101**	0.091*	0.109
	(0.036)	(0.055)	(0.035)	(0.044)	(0.053)	(0.070)
Household size: 3	-0.012	-0.092	0.042	0.080	0.017	0.228**
	(0.056)	(0.072)	(0.052)	(0.065)	(0.077)	(0.096)
Household size: 4	0.040	-0.012	0.068	0.115*	0.020	0.181*
	(0.054)	(0.079)	(0.061)	(0.067)	(0.068)	(0.102)
Household size: 5	-0.116	-0.070	0.155**	0.245***	-0.504	0.203
	(0.226)	(0.105)	(0.069)	(0.072)	(0.312)	(0.164)
1 child	0.004	0.117**	-0.003	-0.027	-0.037	-0.009
	(0.048)	(0.054)	(0.041)	(0.047)	(0.055)	(0.077)
2 children	-0.011	0.025	-0.019	-0.052	-0.001	-0.028
	(0.050)	(0.062)	(0.052)	(0.060)	(0.064)	(0.079)
3+ children	0.191	0.100	-0.041	-0.078	0.631**	0.044
	(0.217)	(0.098)	(0.061)	(0.067)	(0.305)	(0.154)
Single	-0.066**	-0.013	-0.007	-0.000	-0.014	0.078
	(0.030)	(0.042)	(0.032)	(0.038)	(0.035)	(0.051)
Divorced	0.018	0.059	0.022	0.023	0.017	0.034
	(0.035)	(0.048)	(0.032)	(0.038)	(0.049)	(0.067)
Widowed	0.077	-0.127	-0.011	†	†	-0.046
	(0.048)	(0.140)	(0.073)			(0.106)
Education: ISCED=3,4	-0.000	0.024	0.008	0.051	0.056	-0.146***
	(0.027)	(0.046)	(0.026)	(0.031)	(0.040)	(0.056)
Education: ISCED=5,6	0.005	0.088*	0.029	0.063*	0.028	-0.221***
	(0.033)	(0.054)	(0.031)	(0.035)	(0.057)	(0.062)
Self-employed	-0.055	0.105**	0.081**	0.102***	-0.023	0.083
	(0.038)	(0.050)	(0.033)	(0.035)	(0.058)	(0.075)
Unemployed	-0.133**	-0.219	†	†	†	-0.002
	(0.066)	(0.133)				(0.118)
Retired	-0.148***	0.015	0.001	0.028	†	0.043
	(0.049)	(0.101)	(0.074)	(0.070)		(0.083)
Other employment status	0.012	0.004	0.018	0.060	0.018	0.036
	(0.037)	(0.068)	(0.043)	(0.046)	(0.050)	(0.087)
Owner-outright	-0.089	0.160**	0.086*			0.162**
	(0.062)	(0.070)	(0.052)			(0.079)
Owner with mortgage	0.071**	0.358***	0.146***			0.076
	(0.036)	(0.053)	(0.045)			(0.067)
Gross income quintile 1	0.080*	0.209***	0.278***	0.347***	0.003	-0.007
	(0.045)	(0.079)	(0.051)	(0.059)	(0.072)	(0.096)
Gross income quintile 2	0.060	0.259***	0.170***	0.235***	0.007	0.006
	(0.040)	(0.059)	(0.041)	(0.048)	(0.075)	(0.071)
Gross income quintile 3	0.092***	0.167***	0.086**	0.111**	-0.019	0.023
	(0.031)	(0.050)	(0.043)	(0.047)	(0.046)	(0.059)
Gross income quintile 4	0.029	0.132***	0.066*	0.081**	-0.034	0.012
	(0.030)	(0.045)	(0.037)	(0.041)	(0.043)	(0.049)
Net wealth quintile 1	0.257***	0.089	0.045	0.156***	0.543***	0.726***
	(0.030)	(0.079)	(0.054)	(0.053)	(0.078)	(0.094)
Net wealth quintile 2	†	0.138***	-0.040	-0.076*	0.160***	0.384***
		(0.052)	(0.038)	(0.043)	(0.049)	(0.074)
Net wealth quintile 3	†	-0.005	-0.084**	-0.156***	0.038	0.248***
		(0.051)	(0.037)	(0.042)	(0.050)	(0.059)
Net wealth quintile 4	†	0.001	-0.054	-0.041	0.073	0.171***
		(0.051)	(0.035)	(0.039)	(0.061)	(0.063)
Observations	952	952	952	664	547	952

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; † variable omitted to avoid perfect collinearity.

Source: Own calculations based on the 2nd wave of the LU-HFCS; data are multiply imputed and weighted; variance estimation based on final weights. The reference group is defined for each explanatory variable separately: it is a household with a male FKP, between 16 and 34 years old, born in Luxembourg, low educated, married, and employed. Referring to the household characteristics the reference group is also defined for each explanatory variable separately: single person household, no dependent children, renting the HMR, belonging to the highest quintiles of gross income and net wealth. Marginal effects are calculated at the observation level and then averaged. Dummies related to the marital status are not shown as they are not statistically significant. Significant results are highlighted in grey.

4 Conclusion

This paper investigates household financial vulnerability in Luxembourg using balance sheet information from the 1st (2010) and 2nd (2014) wave of the Luxembourg Household Finance and Consumption Survey. To account for different dimensions of household vulnerability, we calculate several indicators for each household in a representative sample.

The evidence we provide does not lead to one overarching key message but draws a mixed picture on the changes of household indebtedness and financial vulnerability in Luxembourg across the two currently available waves (the third wave is planned to be conducted at the end of 2017/ beginning of 2018). Indebted households in 2014 carried a heavier burden than indebted households in 2010, mainly because of mortgage loans on the main residence. However, increases in the median ratios between 2010 and 2014 are only statistically significant for the debt-to-income ratio and the outstanding loan-to-value ratio (stock). The median debt service-to-income ratio declined, although mostly due to lower costs of non-mortgage debt.

First we analyse the distribution of median debt burden indicators across household characteristics. The median regression estimates indicate that low income households are also those with the lowest median leverage. Thus, debt appears to be concentrated on the less vulnerable households.

Then we identify financially vulnerable households as those where debt burden indicators exceed conventional thresholds. On several measures, financial vulnerability of indebted households appears to have increased between 2010 and 2014. However, only the debt-to-income ratio suggests a statistically significant increase in the share of vulnerable households. On the one hand, disadvantaged socio-economic groups (in terms of education, employment status and HMR ownership status) are less often financially vulnerable. On the other hand, low income and wealth increases the likelihood of households' vulnerability.

In addition to the standard single indicator approach, we also combine the information derived from several indicators. The multiple indicator approach shows a larger increase (in relative terms) than the single indicator approach but the increase is still not statistically significant. The share of financially vulnerable households is 2.2% of the indebted population and 2.6% of the population with mortgages on their main residence in 2014.

Finally, we conclude with some suggestions for further research. First, our assessment of household financial vulnerability depends on the thresholds chosen for the different indicators. These are set at conventional levels that remain somewhat arbitrary. In future research one could develop a data driven selection of these thresholds when measuring household financial vulnerability. Second, the impact of a rise in household financial vulnerability on bank balance sheets also depends on other negative shocks facing the sector. Therefore, we plan to implement alternative severe but plausible macroeconomic scenarios in a stress test of individual Luxembourg households.

5 References

Albacete, N., and P. Lindner (2013): Household Vulnerability in Austria – A Microeconomic Analysis Based on the Household Finance and Consumption Survey. Financial Stability Report 25, Österreichische Nationalbank, June.

Bauer, T. K., D.A. Cobb-Clark, V.A. Hildebrand, and M. Sinning (2011): A comparative analysis of the nativity wealth gap. Economic Inquiry, 49(4), 989-1007.

BCL (2013): L'endettement des ménages au Luxembourg. Bulletin 2013-2, Encadré 3, 38-44.

BCL (2015): Revue de Stabilité Financière de la Banque centrale du Luxembourg, June.

BCL (2016): Mesure de l'endettement des ménages et évaluation de leur vulnerabilité. Revue de Stabilité Financière, Encadré 1.1, 21-23.

BCL (2017): Revue de Stabilité Financière de la Banque centrale du Luxembourg, May.

Bricker, J., Bucks, B., Kennickell, A., Mach, T., and Moore, K. (2011): Surveying the Aftermath of the Storm: Changes in Family Finances from 2007 to 2009. Finance and Economics Discussion Series, Federal Reserve Board, 2011-17.

Christelis, D., D. Georgarakos, and M. Haliassos (2013): Differences in portfolios across countries: Economic environment versus household characteristics. Review of Economics and Statistics, 95(1), 220–236.

Djoudad, R. (2012): A Framework to Assess Vulnerabilities Arising from Household Indebtedness Using Microdata. Discussion Paper Number 2012-3. Bank of Canada.

European Systemic Risk Board (2016): Vulnerabilities in the EU residential real estate sector. November 2016, ISBN 978-92-95081-86-4 (online).

ECB (2013): Financial Stability Review. November 2013, ISSN 1830-2025 (online).

Friedman, M. (1957): A Theory of the Consumption Function. Princeton: Princeton University Press.

Girshina, A., Mathä, T., and M. Ziegelmeyer (2017): The Luxembourg Household Finance and Consumption Survey: results from the 2nd wave. Banque centrale du Luxembourg Working Paper 106.

Household Finance and Consumption Network (2013): The Eurosystem Household Finance and Consumption Survey – Results from the First Wave. ECB Statistics Paper No. 2.

Household Finance and Consumption Network (2016): The Household Finance and Consumption Survey – results from the second wave. ECB Statistics Paper No. 18.

IMF (2011): United Kingdom: Vulnerabilities of Household and Corporate Balance Sheets and Risks for the Financial Sector Technical Note. IMF Country Report No. 11/229. July.

IMF (2012): Spain: Vulnerabilities of Private Sector Balance Sheets and Risks to the Financial Sector. Technical Notes. IMF Country Report No. 12/140. June.

Karasulu, M. (2008): Stress Testing Household Debt in Korea. IMF Working Paper WP/08/255.

Modigliani, F., and R. Brumberg (1954): Utility analysis and the consumption function: An interpretation of cross-section data. in: Flavell, J. H., and L. Ross (eds): Social Cognitive Development Frontiers and Possible Futures. Cambridge, NY: University Press.

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Household debt burden and financial vulnerability in Luxembourg[1]

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Central Bank of Luxembourg

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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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Household debt burden and financial vulnerability in Luxembourg

Gaston Giordana and Michael Ziegelmeyer

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Motivation

- LU households are generally more indebted than households in other EA countries (HFCN, 2013, 2016).
  - BCL Financial Stability Review (FSR) identifies the household sector as a potential source of systemic risk (BCL 2015, 2016).
  - In Nov. 2016 the ECB FSR raised concerns about a potential real estate bubble in LU.
  - European Systemic Risk Board (ESRB, 2016) addressed a warning to LU about residential real estate developments and their financial stability consequences.
- Assessment of household debt sustainability in Luxembourg using micro-data (might deliver a different message) is needed as complement.
  - Analyses based on aggregate data cannot properly account for differences in distributions.

Overview

- Data
- Household debt burden indicators and financial vulnerability thresholds
- Results
  - Indebted households
  - Debt burden indicators
  - Linking debt burden and household characteristics
  - Vulnerable households (single-indicator and multiple-indicator approaches)
  - Linking vulnerability and household characteristics
- Summary

Dataset

- **Luxembourg Household Finance and Consumption Survey** (LU-HFCS)
- Separate analysis of wave 1 and 2 with a focus on wave 2.
  - Wave 2010/11: 950 hhs (representative of 186,440 hhs)
  - Wave 2014: 1601 hhs (representative of 210,965 hhs)

Definitions of debt burden indicators and thresholds

Consider several indicators as they shed light on household debt burden and vulnerability from different perspectives.

Debt burden indicators

- Debt-to-assets ratio (DA)
- Debt-to-income ratio (DI)
- Debt service-to-income ratio (DSI)
- Mortgage debt service-to-income ratio (MDSI)
- Current loan-to-value ratio of HMR (LTV)
- Net liquid assets to income (NLAI)

HFCN (2013)

Vulnerability thresholds

- DA ≥ 75%
- DI ≥ 300%
- DSI ≥ 40%
- MDSI ≥ 40%
- LTV ≥ 75%
- NLA ≤ 2 months income

Thresholds common in literature: US (Bricker et al., 2011), EA (ECB, 2013), UK (IMF, 2011), Canada (Djoudad, 2012), Korea (Karasulu, 2008), Spain (IMF, 2012) & Austria (Albacete & Lindner, 2013).

Debt participation

- Reference population: Indebted population
- In 2014, 54.6% of all households were indebted.
- Decrease of 3.8 percentage points compared to 2010.
- Characteristics of indebted households compared to total population:
  - younger +
  - household members +
  - dependent children +
  - single or widowed -
  - education low -; high +
  - (self-)employed +
  - income +
  - hump shaped across net wealth quintiles

Debt amounts

- Conditional **mean** of total debt strongly increased by 27%.
  - Nominal increase from €140,200 (2010) to €178,400 (2014).
- Conditional **median** of total debt strongly increased by 22%.
  - Nominal increase from €73,400 (2010) to €89,800 (2014).
- This increase is mainly **driven by HMR mortgage debt**.

- Lower nominal increase from 2010 to 2014 for
  - Total real assets: 4% (mean) and 7% (median)
  - Total gross income: 4% (mean) and 0% (median)

→ The different growth rates of debt, real assets and income *influence* debt burden indicators and the share of vulnerable households.

Debt burden indicators

Debt burden indicators	Year	Median	Std. err.	[90% conf.	interval]	p-value	
Debt-to-asset ratio	*2010*	18.2%	2.1%	14.6%	21.7%	16.1%	
	2014	22.2%	2.1%	18.7%	25.6%		
Debt-to-income ratio	*2010*	86.9%	11.2%	68.4%	105.4%	8.9%	*
	2014	114.1%	10.6%	96.7%	131.5%		
Debt service-to-income ratio	*2010*	15.7%	0.9%	14.3%	17.2%	36.7%	
	2014	14.8%	0.6%	13.8%	15.8%		
Mortgage debt service-to-income	*2010*	16.3%	0.7%	15.2%	17.3%	17.3%	
	2014	17.6%	0.7%	16.4%	18.7%		
Outstanding loan-to-value ratio of main residence	*2010*	27.5%	2.6%	23.2%	31.7%	5.6%	*
	2014	34.6%	2.8%	30.1%	39.2%		
Net liquid assets to income	*2010*	12.2%	2.2%	8.6%	15.9%	79.0%	
	2014	11.5%	1.7%	8.8%	14.2%		

*Source: Own calculations based on the 1st and 2nd wave of the LU-HFCS; data are multiply imputed and weighted; variance estimation based on 1000 replicate weights. P-values indicate whether difference between 2010 and 2014 is significant: *** p<0.01, ** p<0.05, * p<0.1.*

- Increases in the median DI ratio and outstanding LTV ratio are statistically significant, but those for other debt burden indicators are not.
- The median DSI ratio actually declined, reflecting lower costs of non-mortgage debt.

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Debt burden indicators across HH characteristics

- **Median regression** to quantify the **correlation** between debt burden indicators and household characteristics.
- Focus on wave 2.
- **Summary**:
  - Net wealth correlates negatively with most debt burden indicators (except the DSI ratio).
  - Low income households are also those with the lowest median leverage.
  - Debt is lower among households where the financially knowledgeable person is older.

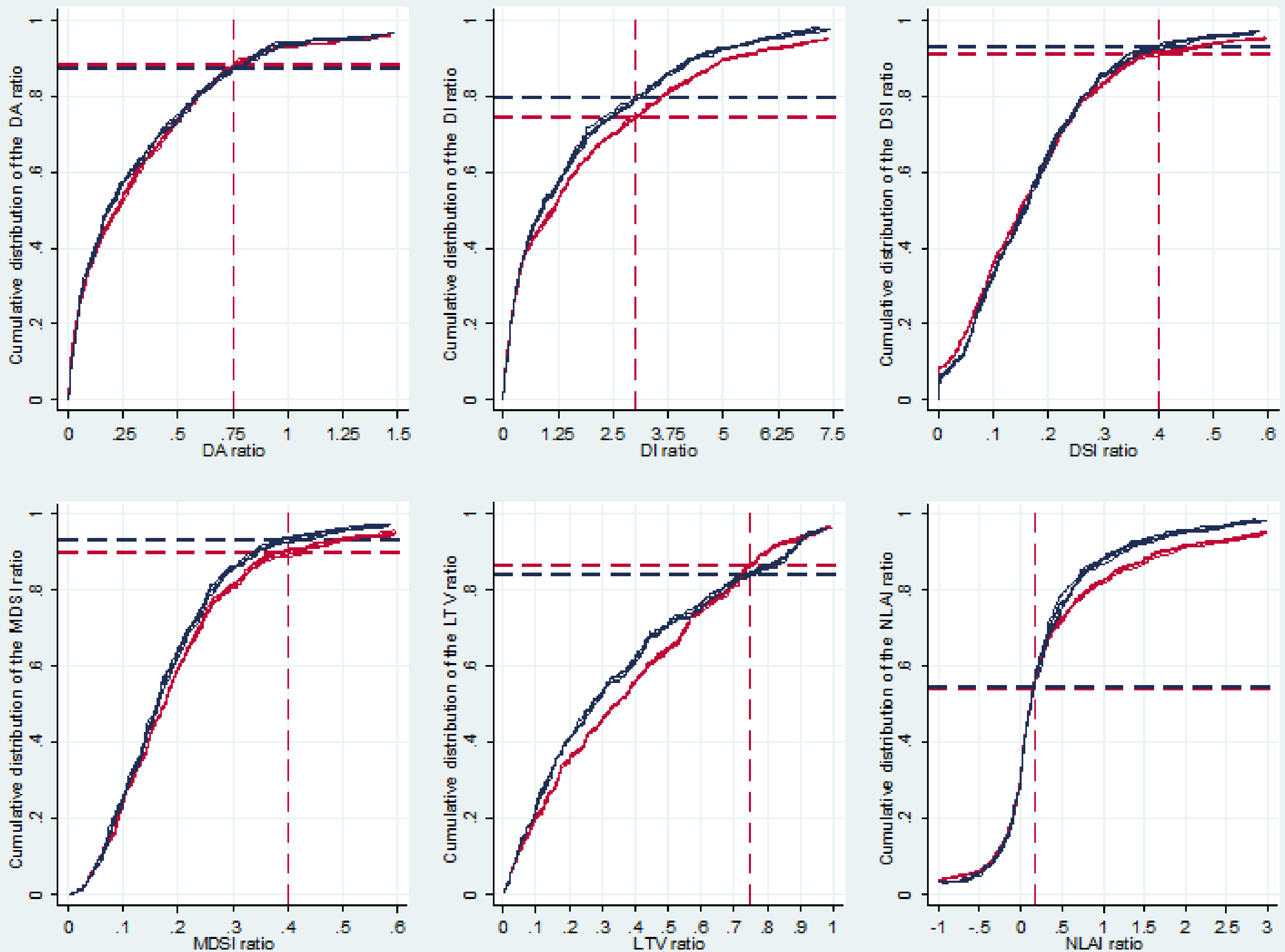
Share of vulnerable households: single-indicator approach

Vulnerability measures	Year	Mean	Std. err.	[90% conf.	interval]	p-value	
Debt-to-asset ratio>=75%	*2010*	12.8%	1.6%	10.2%	15.5%	70.0%	
	2014	12.0%	1.4%	9.7%	14.3%		
Debt-to-income ratio>=3	*2010*	20.6%	1.9%	17.5%	23.7%	4.7%	**
	2014	25.8%	1.8%	22.8%	28.8%		
Debt service-to-income ratio>=40%	*2010*	7.0%	1.3%	4.9%	9.2%	31.4%	
	2014	8.9%	1.3%	6.8%	11.0%		
Mortgage debt service-to-income ratio>=40%	*2010*	6.8%	1.6%	4.1%	9.5%	10.7%	
	2014	10.3%	1.7%	7.4%	13.1%		
Outstanding loan-to-value ratio of main residence>=75%	*2010*	15.9%	2.3%	12.0%	19.8%	40.7%	
	2014	13.4%	1.9%	10.3%	16.4%		
Net liquid assets < 2 months income	*2010*	55.5%	2.5%	51.4%	59.7%	94.6%	
	2014	55.7%	1.9%	52.6%	58.9%		

*Source: Own calculations based on the 1st and 2nd wave of the LU-HFCS; data are multiply imputed and weighted; variance estimation based on 1000 replicate weights. P-values indicate whether difference between 2010 and 2014 is significant: *** p<0.01, ** p<0.05, * p<0.1.*

- Three measures show that the share of financially vulnerable households appears to have increased between 2010 and 2014.
- However, the increase is only statistically significant for the DI ratio.

Cumulative distribution of debt burden indicators (1)



Source: Own calculations based on the 1st and 2nd wave of the LU-HFCS; data are multiply imputed and weighted; the cumulative distribution functions are calculated and displayed for each implicate separately for 2014 (red) and 2010/11 (blue).

Cumulative distribution of debt burden indicators (2)

- Moderate changes in the thresholds around conventional levels would not generally produce significant changes in the share of vulnerable households.
  - Exception is the NLAI ratio: small change in the threshold makes a difference.
  - Conventional threshold for the NLAI ratio nearly cuts the population in half, while for the other indicators the conventional threshold usually cuts off only 10-20% of the population in the tail of the distribution.
- Cumulative distributions in 2010 and in 2014 do not differ much.
  - Moderate changes in thresholds would not much affect the share of vulnerable households from 2010 to 2014.
  - Exception is the outstanding LTV ratio.

Share of vulnerable households: multiple-indicator approach

- Focus on those vulnerable households that represent a risk of losses for the lender.
- Identify households that meet several conditions:

	Year	(i) DSI ratio ≥40% or MDSI ratio ≥40%	Additional conditions (ii) Net liquid assets < 2 months income	(iiia) DA ratio≥75%	(iiib) Outstanding LTV ratio of HMR≥75%
DSI ratio≥40%	2010	7.1	4.3	1.4	-
	2014	8.9	6.0	2.2	-
MDSI ratio≥40%	2010	6.8	3.3	-	1.6
	2014	10.9	6.8	-	2.6

Source: Own calculations based on the 1st and 2nd wave of the LU-HFCS; data are multiply imputed and weighted.
The rows on the DSI ratio refer to all indebted households. The rows on the MDSI ratio refer only to households with mortgage debt on their main residence.

→ Relative increase in the share of vulnerable households is more sizable but still not statistically significant.

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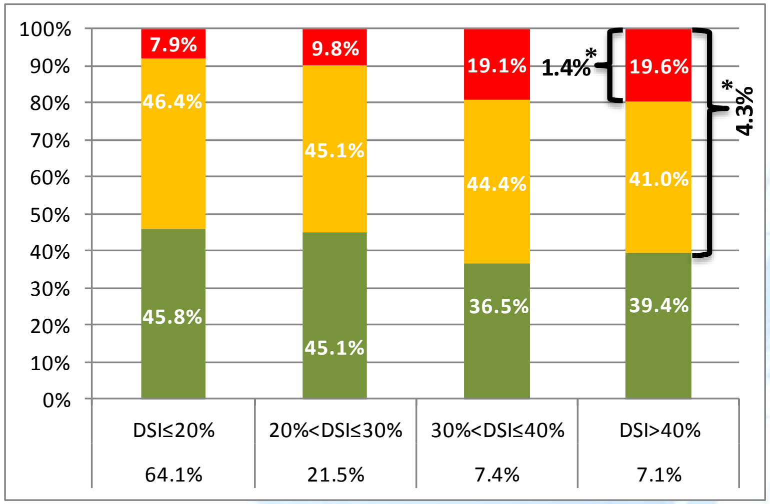
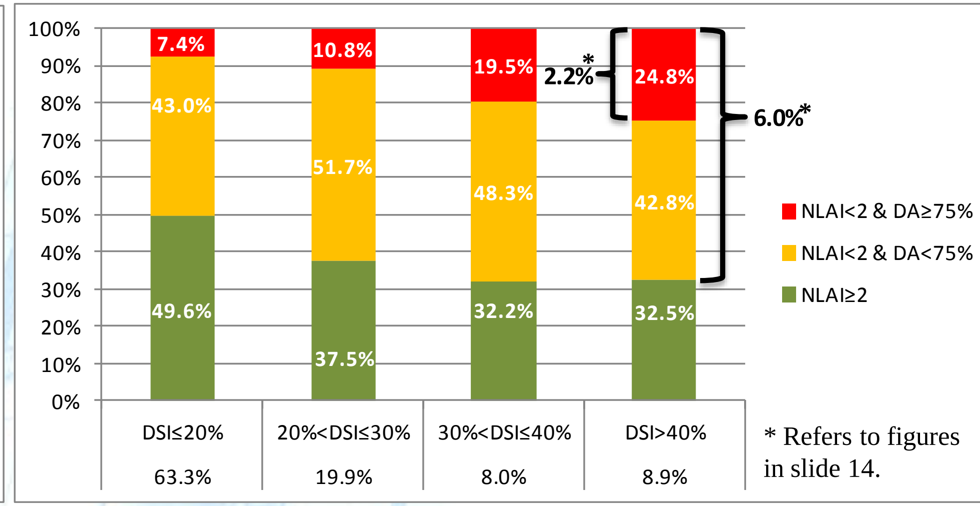
Distribution of households by multiple-indicators

2010



2014



Source: Own calculations based on the 1st and 2nd wave of the LU-HFCS; data are multiply imputed and weighted.
The upper panel on the DSI ratio refers to all indebted households. The figures in the bottom row provide the share of households in the respective category.

- Most households have moderate DSI ratios below 20% or 30%.
- Share of households with NLA > 2 months income (green segment) decreases with increasing DSI ratio.
- Share of households that combine a low NLAI ratio with a high DA ratio (red segment) increases with increasing DSI ratio.

→ **Households with high DSI ratios tend to have proportionally less favourable NLAI and DA ratios.**

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Vulnerability indicators across HH characteristics

- **Probit analysis** to quantify the **correlation** between the vulnerability indicators and household characteristics.
- Focus on wave 2.
- **Summary**:
  - Highly leveraged households and household with a high debt servicing burden tend …
    - to be part of more vulnerable groups (low income & wealth);
    - to be part of the less vulnerable socio-economic groups of the population (in terms of education, employment and HMR ownership status).

Summary

- **Mixed picture** on the changes of household indebtedness and financial vulnerability in LU across the two waves.

	Summary statistics	Across the distribution
+	▪ Debt participation rate decreased ▪ Most median debt burden indicators show no statistically significant changes ▪ The share of vulnerable households does not change significantly for most indicators	▪ More advantaged households hold debt ▪ Low income households have lower leverage than high income households ▪ Most households have moderate DSI ratios below 20% or 30% ▪ Disadvantaged socio-economic groups (in terms of education, employment status & HMR ownership status) tend to be less financially vulnerable
-	▪ Total debt increased (more than assets and income) ▪ Median DI ratio & outstanding LTV ratio increased statistically ▪ DI ratio suggests a statistically significant increase in the share of vulnerable households	▪ Households with high DSI ratios tend to have proportionally less favourable NLAI and DA ratios ▪ Low income and wealth increase the probability of being identified as financially vulnerable

Thank you!

Irving Fisher Committee on
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BANK FOR INTERNATIONAL SETTLEMENTS

IFC-National Bank of Belgium Workshop on "*Data needs and Statistics compilation for macroprudential analysis*"

Brussels, Belgium, 18-19 May 2017

Household finance in Europe[1]

Miguel Ampudia, European Central Bank,

Russell Cooper, Pennsylvania State University and NBER,

Julia Le Blanc, Deutsche Bundesbank,

and Guozhong Zhu, University of Alberta

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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.

Household Finance in Europe

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Brussels, 18 May 2017

Motivation

- Understanding how households respond to changes in income and wealth is crucial for evaluating the macroeconomic impact of policies.
- Recent research suggests that heterogeneous responses matter for aggregate consumption.
- Heterogeneity of households in several layers:
  - demographic characteristics (micro data),
  - institutional setup (within and across countries),
  - deep (preference) parameters (unobservable).
- Relatively little research for Europe that combines micro data and computational techniques to characterize preferences and marginal propensities to consume out of income.

Overview

- **Paper**
  - Life-cycle model with portfolio choice, credit constraints, bequest motive and precautionary savings.
  - Careful calibration to country-specific income and return processes.
  - Estimate the model using data from the HFCS for France, Germany, Italy and Spain.
  - Use model to simulate policies (using the distribution of MPCs).
- **Contribution**
  - Interpret quantitatively role of key factors for wealth accumulation across countries.
  - Combine micro data and model for policy evaluation.
  - Identify vulnerabilities of households in several dimensions.

Literature – Portfolio choice/heterogeneity in MPCs/country differences

- **Life-cycle models with portfolio choice:** Cooper and Zhu (2015), Cocco et al. (2005), Epstein and Zin (1989) and Weil (1990)...
- **Heterogeneity:** Kaplan et al. (2016), Carroll et al. (2015), Jappelli and Pistaferri (2014)
- **Wealth effects on consumption:** Mian et al. (2013), Carroll et al. (2014), Dynan (2012), Dynan et al. (2004)

Some data facts – Moment Conditions

- Education is a key determinant for household behavior.
- Between and within country heterogeneity.

Table: Moment Conditions

	France		Germany		Italy		Spain	
	Low	High	Low	High	Low	High	Low	High
part. rate	0.454	0.667	0.392	0.560	0.232	0.470	0.195	0.360
stock share	0.500	0.447	0.500	0.445	0.508	0.451	0.473	0.376
WI	0.350	0.749	0.303	0.552	0.180	0.399	0.287	0.519
WI(h)	1.038	3.133	4.113	4.794	8.039	7.650	5.563	6.064
average age	52.5	53.0	54.8	43.7	54.4	47.0	56.7	51.0
sample size	2085	1480	10833	4173	3988	2209	7013	938

This table displays the participation rate (direct and indirect stock holdings), the share of stocks (for participants), the median wealth income ratio, with and without housing (h) for households in each country by education attainment. The moments come from the HFCS Euro Area Survey.

The model – Main features

- **Households maximize expected lifetime utility**
  - Households choose: consumption (C), bond holdings (B) and stock holdings (S).
- **Idiosyncratic shocks to income and risky financial assets**
  - Exogenous income process: deterministic and stochastic components.
  - Risky asset return stochastic (R^s), bond return fixed (R^b).
- **Liquidity constraints, financial frictions, bequest motive**
  - Participation and re-balancing costs.
  - Bequest motive.
- **Consumption floor** ($\underline{c}$) coming from government transfer.
- Ingredients produce **precautionary savings** and a distribution of MPCs.

The model – Income processes

- Deterministic income profile plus a stochastic shock.
- Estimated from ECHP data.

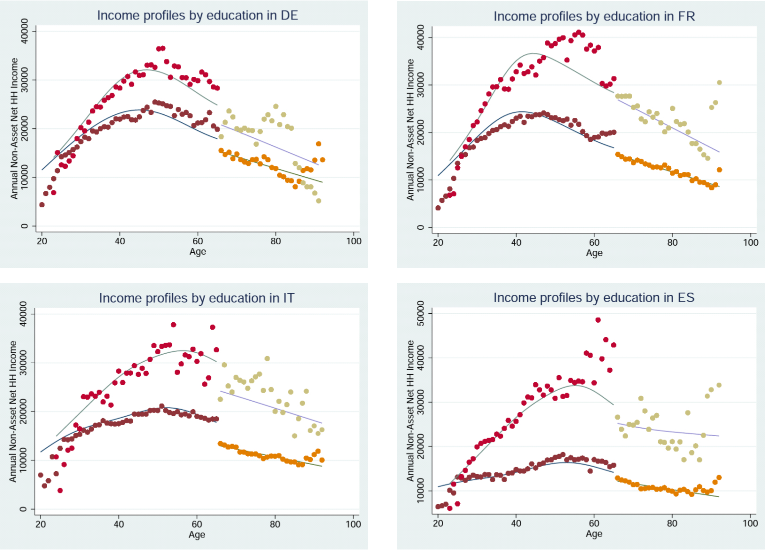
  - Income profile

$$log(Y_{i,t}) = const. + polynomial(age) + HHComp + TimeEff.$$

  - Income shocks

$$\begin{aligned} \tilde{y}_{i,t} &= z_{i,t} + \epsilon_{i,t} \\ z_{i,t} &= \rho z_{i,t-1} + \eta_{i,t} \end{aligned}$$

The model – Income profiles



The model – Asset returns

- Real return on bonds is set at 2% for all countries
- Mean and standard deviations for real stock returns taken from historical data

Table: Return Processes by country

	Germany	**France**	**Italy**	**Spain**
mean	1.085	1.092	1.046	1.077
std	0.310	0.291	0.290	0.245

The model – Solution and estimation

- **Finite dynamic optimization problem solved by backward recursion**
  - Discretized shocks, initial distribution of assets...
  - Value function iteration
- **Simulated method of moments estimation**
  - Participation rate, stock share, (liquid) wealth-to-income ratio are moments to be matched
  - Explain moments by age and education (plus home equity controls)
- **Estimate MPC**
  - For each single household
  - Matching the liquid wealth distribution

Results – Homogeneous parameters

Table: Parameter estimates by country

	β	γ	F	Γ	L	ϕ	$\underline{c}$	θ	Fit
Germany	0.841	6.003	0.02	0.028	0.088	1.952	0.251	0.626	12.047
Spain	0.836	7.733	0.013	0.018	0.053	2.821	0.206	0.636	37.992
France	0.872	6.624	0.012	0.028	0.09	2.569	0.157	0.511	66.985
Italy	0.861	5.381	0.02	0.023	0.073	2.346	0.29	0.555	1.806

- Discount factors lower than conventional value (0.95)
- High risk aversion coefficients (US around 4)
- High stock participation costs and risk aversion
- Importance of bequests stronger in some countries

Results– Heterogeneous parameters

Table: Heterogeneous parameter estimates by country and education

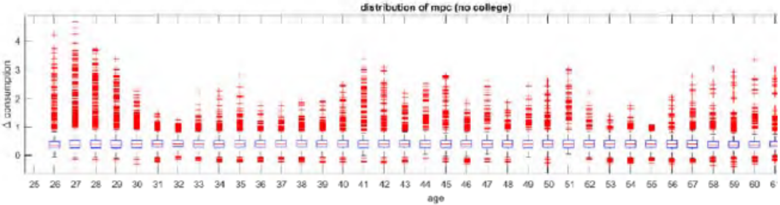
	β_0	β_1	γ	F_0	F_1	Γ	L	ϕ	$\underline{c}$	θ	Fit
						Heterogeneous β					
Germany	0.862	0.901	9.990	0.010		0.033	0.084	2.434	0.300	0.662	15.363
Spain	0.845	0.905	9.689	0.016		0.032	0.091	1.942	0.308	0.677	35.715
France	0.866	0.895	9.974	0.013		0.031	0.077	2.696	0.282	0.694	59.269
Italy	0.871	0.880	6.924	0.023		0.027	0.075	2.455	0.239	0.653	1.261
						Heterogeneous F					
Germany	0.817		6.5733	0.0191	0.0163	0.0292	0.0809	2.2569	0.3481	0.6123	9.6950
Spain	0.8623		9.5633	0.0190	0.0223	0.0305	0.0701	2.9954	0.2721	0.7329	40.7167
France	0.8655		9.9800	0.0115	0.0209	0.0329	0.0808	2.8703	0.2951	0.6811	42.7357
Italy	0.8587		5.7937	0.0292	0.0197	0.0286	0.0617	2.9979	0.2405	0.4970	0.9441

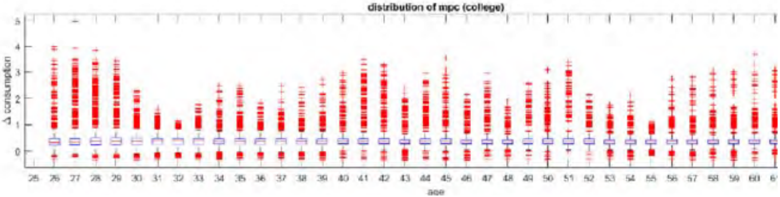
This table reports parameter estimates. For the heterogeneous β (F) case, the subscript 0 is for the low education group and the subscript 1 is for the high education group. The pooled groups are reported under the subscript 0 case.

- Lower educated households are less patient than college grads.
- Participation cost heterogeneity differs across countries.

Distribution of MPCs across the Life Cycle

- MPCs significantly different from zero across the life cycle with a median $\approx$ 0.2–0.6, wide heterogeneity
- Life cycle pattern, heterogeneity across education





Distribution of MPCs across Countries

- **Depending on wealth distribution**
  - MPC are higher in countries in which HH hold less liquid wealth or where wealth inequality is higher.
  - Results in line with Carroll et al. (2014) who find aggregate MPC between 0.2 and 0.4.
- **Depending on demographics**
  - Low wealth (and income) households are more sensitive to shocks.
  - MPCs are highest for the young, stable through middle age and increase in older age.
- **Policy evaluation**
  - Same policy (e.g. change in rates) has different effects that can be related to different household characteristics.
  - Helpful in understanding the transmission mechanism of monetary policy.

Conclusion

- **A state-of the art model** with portfolio choice implies significant differences in estimates within and across countries
  - Differences by education, countries.
  - Underlines the importance of cross-country household data sets for model-based research.
- **Same policies have different effects in different countries**
  - Cross-country heterogeneity in MPCs.
  - Distribution of MPCs driven by wealth distribution and household preferences.
- **Further applications extend to household stress testing, monetary and fiscal policy evaluation**

References

Carroll, Christopher, Jiri Slacalek, Kiichi Tokuoka, and Matthew N White (2015), “The Distribution of Wealth and the Marginal Propensity to Consume,” Johns Hopkins University.
http://econ.jhu.edu/people/ccarroll/papers/cstwMPC.pdf

Carroll, Christopher D, Jiri Slacalek, and Kiichi Tokuoka (2014), “The Distribution of wealth and the MPC: Implications of new European data,” *The American Economic Review*, 104(5), 107–111.

Cocco, Joao F, Francisco J Gomes, and Pascal J Maenhout (2005), “Consumption and portfolio choice over the life cycle,” *Review of financial Studies*, 18(2), 491–533.

Cooper, Russell, and Guozhong Zhu (2015), “Household Finance: Education, Permanent Income and Portfolio Choice,” *Review of Economic Dynamics*, 20, 63–89.
doi:10.1016/j.red.2015.12.001

Dynan, Karen (2012), “Is a household debt overhang holding back consumption?” *Brookings Papers on Economic Activity*, 299–362.

Epstein, L.G., and S.E. Zin (1989), “Substitution, risk aversion, and the temporal behavior of consumption and asset returns: A theoretical framework,” *Econometrica: Journal of the Econometric Society*, 937–969.

Jappelli, Tullio, and Luigi Pistaferri (2014), “Fiscal policy and MPC heterogeneity,” *American Economic Journal: Macroeconomics*, 6(4), 107–136.

Kaplan, Greg, Benjamin Moll, and Giovanni L. Violante (2016), “Monetary Policy According to HANK,” Working Paper 21897, National Bureau of Economic Research, doi:10.3386/w21897.
http://www.nber.org/papers/w21897

Mian, Atif R, Kamalesh Rao, and Amir Sufi (2013), “Household balance sheets, consumption, and the economic slump,” *Quarterly Journal of Economics*, 128(16871726).

Weil, P. (1990), “Nonexpected utility in macroeconomics,” *The Quarterly Journal of Economics*, 105(1), 29–42.

Backup Slides

The model – Income proesses

Table: Stochastic Processes by education and country

	Germany			France		
	ρ	σ_η^2	σ_ϵ^2	ρ	σ_η^2	σ_ϵ^2
No college	0.895***	0.022***	0.016***	0.971***	0.031***	0.006*
	(0.005)	(0.001)	(0.001)	(0.014)	(0.006)	(0.003)
College	0.937***	0.020***	0.011***	0.941***	0.023***	0.018***
	(0.008)	(0.001)	(0.001)	(0.007)	(0.003)	(0.002)
	Italy			**Spain**		
	ρ	σ_η^2	σ_ϵ^2	ρ	σ_η^2	σ_ϵ^2
No college	0.944***	0.072***	0.020***	0.951***	0.092***	0.016***
	(0.005)	(0.003)	(0.002)	(0.007)	(0.004)	(0.002)
College	0.921***	0.029***	0.022***	0.986***	0.058***	0.004**
	(0.016)	(0.01)	(0.006)	(0.007)	(0.004)	(0.002)

Robust standard errors in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$

Model—Preferences

- Value Function expressed as *recursive utility*, following Epstein-Zin-Weil

$$V_t = \left\{ (1-\beta)c_t^{1-1/\theta} + \beta \left[(1-\nu_{t+1}) \left(E_t V_{t+1}^{1-\gamma} \right)^{\frac{1}{1-\gamma}} + \nu_{t+1} \left(E_t B_{t+1}^{1-\gamma} \right)^{\frac{1}{1-\gamma}} \right]^{1-1/\theta} \right\}^{\frac{1}{1-1/\theta}}$$

  ν_{t+1} conditional prob to die; γ risk preference; θ substitution effect

- Bequest function:

$$B(Z) = L(\phi + Z)$$

  L bequest intensity; ϕ degree of luxuriousness

Optimization Problem

- Maximize

$$v_t(\Omega) = \max\{v_t^a(\Omega), v_t^n(\Omega), v_t^x(\Omega)\}$$

- where $\Omega = (y, A)$ is the current household state

- Household chooses to adjust

$$v_t^a(\Omega) = \max_{A^{b'} \geq \underline{A}^b, A^{s'} \geq 0} u(c) + \beta E_{y'|y} \left\{ (1 - \nu_{t+1}) v_{t+1}(\Omega') + \nu_{t+1} B(R^b A^{b'} + R^{s'} A^{s'}) \right\}$$

- s.t. budget constraints and transfer income

$$c = y + TR + \sum_{i=b,s} R^i A^i - \sum_{i=b,s} A^{i'} - F$$

$$TR = \max\{0, \underline{c} - (y + \sum_{i=b,s} R^i A^i)\}$$

Structural Estimation

- Simulate model using the calibrated values.
- Use moments from the cross-sectional data (participation rate, stock share, wealth-to-income ratio).
- Estimate $\alpha \equiv \{\beta, \gamma, \theta L, \phi, F, \Gamma, \underline{c}\}$ by SMM, minimizing distance of model from data:

$$\left(G_Q - G_{\hat{Q}}(\theta)\right)' D \left(G_Q - G_{\hat{Q}}(\theta)\right)$$

- Need to recompute model for each estimation and simulation loop.

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Household financial exclusion in the Eurozone: the contribution of the Household Finance and Consumption survey[1]

Jérôme Coffinet and Christophe Jadeau,
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.

Household financial exclusion in the Eurozone: the contribution of the Household Finance and Consumption Survey[1]

Jérôme Coffinet[2] and Christophe Jadeau[3]

Abstract

In this paper, we use the data of the Eurosystem's Household Finance and Consumption Survey (HFCS) in order to analyze the factors determining financial exclusion in the euro area. We find that the information content of this database is extremely useful to the definition and the understanding of financial inclusion in the Eurozone. As regards the household individual characteristics, we show that older, unemployed, lower-income, lower-educated and less wealthy households of the euro area are less likely to owe a current account. But the definition of financial exclusion matters: savings accounts discriminate less by age, while access to credit is more probable for younger and lower-income people. As far as country specificities are concerned, we find a strong heterogeneity across the euro area.

Keywords: financial inclusion, household finance

JEL classification: G21, G28, D14

[1] The views expressed in the paper are the sole responsibility of the authors and do not necessarily represent those of the Banque de France. We thank Luc Arrondel and Bertrand Couillault for useful comments. All remaining errors are our own responsibility.

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Introduction

Understanding and preventing financial exclusion is a major concern for policymakers worldwide, especially since the 2009 G20 Pittsburgh summit. Indeed, in September 2009 G20 leaders '*reiterat(ed) (their) strong commitment to financial inclusion and recognize(d) the benefits of universal access to financial services'*. The G20 noted *'the overarching and cross-cutting nature of financial inclusion and therefore has included financial inclusion as one of the main pillars of the development agenda*'. In addition, the G20 recognized several steps for the implementation of the agreed principles, among which the establishment of a Global Partnership for Financial Inclusion (GPFI), and set up key action items. In particular, one of them '*encourage improving the quality of measurement and data on financial inclusion (of households/individuals).*'

While the access to financial services is a crucial matter for developing countries, it is also a major issue for advanced economies: financial exclusion of households is less frequent but potentially associated with a severe social exclusion, as other sources of familial or social solidarity are less prevalent. Demirgüç-Kunt and Klapper (2013) point out the importance of informal financial inclusion in those developing countries with respect to developed economies, not only for sight accounts, but also for savings and loans. Hence, 36% of the adults worldwide use formal or informal savings (against 22% for formal savings only), 9% of the world population has contracted a loan in a formal financial institution, whereas 23% have borrowed money in an informal network. Reasons for not using formal financial services include: lack of money, the too high cost of financial services, the use of an account owned by another member of the family, the geographical distance to banks, weak financial literacy, the lack of trust in the financial institutions and finally religious reasons.

Nevertheless, the ownership of a formal bank account is considered as a first step to many types of economic and social inclusion: it is often necessary to get a salary or public subsidies; it allows more liquidity and gives access to savings; it reduces transaction costs; it is useful to access credit; it strengthens the financial autonomy for women; it helps to smooth consumption and investments; it reduces the risk of fraud.

Financial inclusion is also a major issue in the context of access to secured and efficient payments, which involve another key stakeholder of financial inclusion, namely central banks. Hence, the Committee on Payments and Market Infrastructure of the Bank for International Settlements and of the World Bank Group has issued in 2015 a report on the payment aspects of financial inclusion (Bank for International Settlements and the World Bank Group, 2015), quoting several examples of harmonization (Single Euro Payment Area – SEPA – project in Europe) and promotion of payment channels (electronic money). Every type of transaction between consumers, businesses and the public sector are concerned by financial inclusion issues, and especially in case of numerous transactions of small amount. The Irving Fisher Committee has also issued a report on the central bank perspective on financial inclusion measures (Irving Fisher Committee, 2016), insisting on the need for central banks to define financial inclusion, collect data and stay updated on the subject. The report reveals some differences between countries in the definition of financial inclusion and of the legal roles of central banks.

At the national level, some National Central Banks have made the follow-up of banking inclusion a reality in the creation of observatories, where appropriate associating the Treasuries. This is the case for instance in France, where the 'Observatoire de l'inclusion bancaire' chaired by the Governor of the Banque de France is responsible for following the practices of credit institutions in the field of banking inclusion, particularly with regard to financially fragile populations. The 'Observatoire de l'inclusion bancaire' brings together representatives of public authorities, credit institutions and consumer, family and anti-exclusion associations. Its work should provide data to monitor and evaluate banking practices to identify areas for improvement. Its installation session was held on September 11, 2014 and it releases a report each year on the achievements in the matter (e.g. Banque de France, 2017).

In the meantime, the measure and the characterization of financial inclusion have been an emerging subject for institutional and academic economic research.

Already in 2008, the European Commission proposed an overview of the stance: "Financial Services Provision and Prevention of Financial Exclusion" (2008), focusing particularly on geographical zones and sociodemographic determinants of financial exclusion. The report stresses the involuntary motives of financial exclusion. It considers the access to an account as well as to credit, savings and insurance. Several levels of access to a bank account are distinguished, as well as the difference between appropriated and unappropriated credit. Using the Eurobarometer survey, the report concluded that 10% of the European population does not have a bank account. In the ten (at the time) new countries, this ratio rose to 47%. The percentage of total exclusion was 7% in the EU (15 members) and 2% in France, 3% in Germany, 8% in Spain and 16% in Italy. The determinants of exclusion were identified as following: low level of income, unemployment, single parenthood, unemployability, age, low level of education, immigration and living in a disadvantaged area.

In that respect, the World Bank has computed a very detailed database on access to finance, in partnership with the Gallup World Poll and sponsored by the Bill & Melinda Gates Fundation: the Global Findex is based on interviews with about 150 000 adults in 140 countries in 2011 and 2014. Since then, a major part of the economic literature on financial exclusion uses the data from the Global Findex, for global studies as well as for regional focuses.

If financial inclusion can be defined at a first level as the access to financial services, generally associated with the ownership of a bank account, it is useful and especially relevant for developed countries to take into account broader definitions of financial exclusion. For instance, Allen, Demirgüç-Kunt, Klapper, and Martinez Peria (2012) define three levels of financial inclusion: ownership of a formal bank account; use of a formal savings account; frequent use of the account (three withdrawals or more every month). Using data from the Findex survey, they find that banking inclusion (at the first level) is higher among richer, older, urban, educated, employed and married individuals, in countries where the fees are lower and in countries where savings are encouraged through tax incentive schemes. According to Fungáčová and Weill (2015), in BRICS countries (Brazil, Russia, India, China, South Africa), the main reasons of financial exclusion are the lack of money to justify the opening of an account and the use of another account in the family. At the individual level, the income is positively correlated with the ownership of an account but not with credit and savings. The level of education and the gender are linked with the bank accounts and credits, but not with savings. The impact of age is positive on the three types of inclusion. Focusing on the Argentina case, Tuesta, Sorensen, Haring and Cámara (2015) remark that the level of financial exclusion has increased since the 2002 crisis accompanying the development of alternative finance is encouraging: mobile phone finance, financial intermediaries in geographical zones without any bank agency. In Argentina, the level of education, the income and the age broadly explain both the financial exclusion itself and the subjective perception of the barriers.

The situation of developed countries raises different issues, because financial exclusion is more discriminant and more scarce: according to Ampudia and Ehrmann (2015), the ratio of individuals without any access to financial services (whether involuntarily or not) is 7% in the United States and 3% only in the euro area. They use some regional surveys: the Survey of Consumer Finance (SCF) for the United States and the Household Finance and Consumption Survey (HFCS) for the Euro Area. Not surprisingly, they find that low-income households, unemployed households and those with a poor education are the most likely to be affected by financial exclusion, and remarkably more so in the United States than in the euro area. More importantly, they quantify the economic effect of being banked vs. unbanked on wealth accumulation: banked households report substantially higher net wealth than their unbanked counterparts, with a gap of around €74000 and $42000 in the euro area and the United States.

Our paper adds to the existing literature in three dimensions. First, it seeks to assess the factors underlying financial exclusion in the euro area. It takes advantage of the use of a homogenous database over those countries, the Household Finance and Consumption Survey, whose first two waves were carried out in 2008-2009 and 2014-2015. Finally, as a too narrow definition of financial inclusion based on the sole current account criteria may blur the results, it rests on various definitions of financial exclusion, based on current accounts, savings accounts, and access to credit.

The remainder of the paper is structured as follows. The second part presents the data used and some descriptive statistics on the database. Section 3 explains the econometric models used in the paper and elaborates on the main results. Section 5 concludes and draws some policy conclusions.

A first look at the data

Our analysis rests on household-level data collected from the Household Finance and Consumption Survey. The HFCS collects household-level data on households' finance and consumption. The fieldwork took place for most countries in 2010 and 2011 for the first wave and between 2013 and the first half of 2015 for the second wave. Those survey data are key to understanding both individual behavior and developments in aggregate variables, evaluating the impact of shocks, policies and institutional changes, both for households and for different institutional structures, better understanding the implications of shocks for macroeconomic variables, building and calibrating realistic economic models incorporating heterogeneous agents, and gaining important insights into issues such as monetary policy transmission and financial stability.

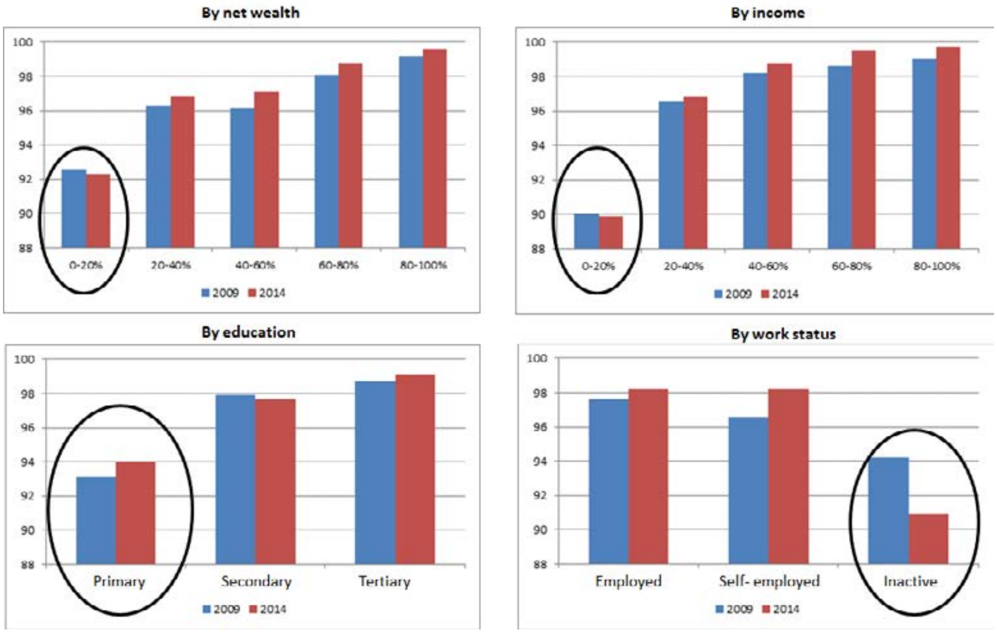
Effectively, the data cover more than 50000 households in the first wave and more than 58000 in the second wave, across 13 countries (Austria, Belgium, Cyprus, Germany, Spain, France, Greece, Italy, Luxembourg, Netherlands, Portugal, Slovenia, Slovakia) in the first wave and 16 countries in the second wave (adding Hungary, Latvia and Poland to the former). Data from Finland were discarded as the reported current account participation rate reached in that country is 100%, which highlights some very specific national features and may blur the final results.

The HFCS contains very useful information about the socio-demographic characteristics of households, financial and real assets, liabilities, income and consumption behavior. With the help of weighting procedures, those survey data are representative of households of a single country and of the euro area as a whole.

While the HFCS data provide very useful information on sociodemographic characteristics of households, it may nonetheless lead to slightly biased figures because, especially, of the sampling scheme. First, since wealth is distributed very unequally, in order to make aggregates as representative as possible of the whole population, all participating countries are encouraged to explore methods for oversampling the wealthiest households, which by corollary induces an under sampling of the poorest. Second, the sampling frame and stratification criteria used in different countries are not the same. Whatever the countries, however, the sampling frame of the HFCS leaves out the whole of the institutionalized population was left out of the sampling frame. More importantly related to the topic of financial exclusion, the sample does not include homeless people as the sample drawing rests in general on housing census or at least the existence of the main residence. Individuals belonging to some of the excluded groups, however, can be included in the sample, if they are considered as part of a household that is part of the sampling frame. Third, the panel component of the survey, which allows to follow the development of the situation of specific households over time, is not carried out in all countries. In wave 2, only 7 out of 19 countries reported information on panel households.

A first set of descriptive statistics based on current accounts allows for a confirmation of some intuitions. At the euro area level, the ownership rate of current accounts reaches about 96.9% and has slightly increased from the first wave. The household size does not play an important role in the probability of not having a current account, likewise the age of the reference person of the household. Rather, financial variables discriminate more the population, especially the income and the net wealth: being in the low-quintile of the distribution of income (resp. net wealth) decreases the participation rate to 89.9% (resp. 92.3%). In addition, having a low education or a more fragile work status also decreases the participation rate. These are those financially more vulnerable people, whose participation rates have decreased throughout the crisis.

Figure 1: probability of having a current account in the euro area…



As regards national situations, it is rather clear that the participation rate is highly country-specific. In wave 2, the participation rates for current accounts range from 73.9% in Greece to 99.7% in Austria. While this rate has increased, or remained stable, in most of the euro area countries, it has dramatically decreased in Cyprus, and to a lesser extent in Slovakia and in the Luxembourg.

Table 1: participation rate in deposits accounts

	Wave 2	Wave 1
Austria	99.7	99.4
Belgium	97.5	97.7
Cyprus	76.3	81.2
Germany	99	99
Spain	99.6	98.1
France	99.6	99.6
Greece	73.9	73.4
Italy	93.2	91.8
Luxembourg	96.7	98
Latvia	78.5	NA
Netherlands	98.6	94.2
Poland	82.8	NA
Portugal	96.1	94.8
Slovenia	93.3	93.6
Slovakia	88.2	91.2

As it is crucial to distinguish between those different factors, we decide to estimate probit models allowing for a quantification of financial exclusion depending on different financial products.

A simple econometric investigation of the determinants of financial exclusion

The determinants of financial exclusion in the aftermath of the crisis

The ownership of a transaction account is usually seen as the first degree of financial inclusion, and the other issues such as credit and savings are, at least partially, dependent of this general measure. Therefore, our first model "transaction account" explains the probability for a household to have no transaction account by a Probit regression on independent variables.

The literature and a descriptive analysis both suggest that the effect of age is not linear because of the coexistence of the impact of age itself (i.e. the position of the person of reference in the life cycle) and of generation. Thus, we perform a discretization of age and we maximize its significance in the model by using five categories (15-25, 25-35, 35-50, 50-70, 70 or more) consistent with the main stages of the life cycle.

The impact of the employment of the person of reference of the household on financial inclusion is obtained by simplifying the information contained in the survey, up to three categories: employed, unemployed and not in the labour force.

We also use the quartiles of income by country on the one hand and of assets[4] on the other to take into account the global financial wealth of the household. For the level of education of the person of reference, we merge the upper secondary and the tertiary levels, as opposed to primary education in the one hand and lower secondary education in the other hand.

The size of the household is also discretized: 1 person, 2 persons, 3 persons, 4 persons, 5 persons and more. Dummies for countries are also used in the model, and Germany is considered as the reference modality for country-specific aspects.

All these choices have been made in order to allow the independent variables to fit the general model but also, when possible, other models about credit and savings. It is worth noting at this stage that all of our variables are this discretionary.

The main model on the ownership of transaction account can be written as follows:

$$P(Y_{\text{no account}} = 1|X) = \Phi(\alpha + X'\beta)$$

Where $Y_{\text{no account}} = 1$ if the household does not own a transaction account, $\Phi \hookrightarrow N(0,1)$ and:

$$\beta = \begin{pmatrix} \beta_{\text{age}} \\ \beta_{\text{employment}} \\ \beta_{\text{income}} \\ \beta_{\text{education}} \\ \beta_{\text{household composition}} \\ \beta_{\text{Assets}} \\ \beta_{\text{country}} \end{pmatrix}^t \quad \text{and} \quad X = \begin{pmatrix} X_{\text{age}} \\ X_{\text{employment}} \\ X_{\text{income}} \\ X_{\text{education}} \\ X_{\text{household composition}} \\ X_{\text{Assets}} \\ X_{\text{country}} \end{pmatrix}$$

4 We merge the 3rd and the 4th quartiles of assets, since preliminary results show that the distinction between them does not seem to be discriminant regarding financial inclusion.

Our second model "savings" uses the same independent variables as previously in order to predict the probability not to have any kind of savings (including from the informal sector). In the model "savings 2", the distribution of ages is slightly different, in order to test for the hypothesis that savings behavior is more continuous at the beginning of the life cycle: "15-40", "40-50", "50-70" and "70 or more" (reference value).

Our third model "credit" is exactly the same as the model on the ownership of a transaction account but the explained variable is the ownership of an outstanding credit from the formal or the informal sector.

For each variable we have defined a reference: this is the difference between that reference and the variable modality that has to be interpreted.

Therefore, each model is estimated on the data of wave 1, and of wave 2, separately. As we carry out logistic modeling with categorical predictors, we have to define for each variable a reference modality. While the choice of the reference variable remains a debated issue, some common sense principles should determine this modality in that specific context: using a normative category; using the largest category; use the category in the middle of at one of the ends.

As a result, for the sake of results readability, we define in general as references the modalities at the extreme of each variable, that is to say: households whose reference person is aged over 70 years for the 'age' variable, households not in the labour force for the 'labour force status' variable, households in the fourth quartile of income and in the third and fourth quartile of net wealth, households with an upper secondary or tertiary education for the 'education' variable. For the country variable, we chose the largest country, for which financial inclusion remained in addition stable and high throughout the period, namely Germany.

Our main results for the second wave of the HFCS are presented in table 2. Post-estimation diagnosis appears good enough so as to interpret the results.

We find that the probability of being financially excluded in the sense of not having a current account is higher for older, lower-educated, unemployed and less wealthy households. The effect of income is massive in magnitude and monotonous: higher income means lower financial exclusion, with the latter being in relative terms extremely important for the first quartile of income. The size of the household only plays a minor role in magnitude, though being statistically significant, with households of 2 or 3 people being more financially included. The use of categorical variables allows us the comparison of coefficients across variables. In that respect, as regards country specificities, noteworthy that the magnitude of the coefficients related to countries is much higher than those related to individual characteristics, meaning that the estimation captures especially country-specific and more systemic features. In particular, households living in Greece, Cyprus, Latvia, Slovakia, Hungary or Poland significantly experiment a higher probability of being financially excluded. On the contrary, households from Spain (especially), Austria, France and Germany experiment a lower financial exclusion, all other things equal. It is remarkable that those characteristics of financial exclusion in the sense of current account are extremely close to those of Allen, Demirgüç-Kunt, Klapper, and Martinez Peria (2012), thus highlighting the features of fragile households. Our results nevertheless tend to show a higher risk for older people.

Table 2: estimation results

Dependent variable (probability of exclusion)	Transaction account		Savings		Credit	
Constant	-3.102***	[0.09]	-1.683***	[0.038]	-1.955***	[0.047]
Age: 15-25	-0.335***	[0.064]	-0.047	[0.042]	-0.27***	[0.042]
Age: 25-35	-0.275***	[0.044]	-0.08***	[0.028]	-0.625***	[0.029]
Age: 35-50	-0.196***	[0.036]	0.058**	[0.024]	-0.66***	[0.024]
Age: 50-70	-0.187***	[0.025]	0.114***	[0.018]	-0.483***	[0.017]
Age : > 70	*Ref.*		*Ref.*		*Ref.*	
Situation: employed	-0.248***	[0.027]	-0.05***	[0.017]	-0.307***	[0.017]
Situation: unemployed and seeking for a job	0.183***	[0.036]	0.083***	[0.027]	0.004	[0.027]
Situation: not in the labour force	*Ref.*		*Ref.*		*Ref.*	
Income: first quartile (in the country)	0.898***	[0.035]	0.739***	[0.022]	0.697***	[0.022]
Income: second quartile (in the country)	0.508***	[0.033]	0.481***	[0.019]	0.407***	[0.019]
Income: third quartile (in the country)	0.185***	[0.033]	0.28***	[0.018]	0.171***	[0.018]
Income: fourth quartile (in the country)	*Ref.*		*Ref.*		*Ref.*	
Education: primary	0.413***	[0.029]	0.205***	[0.019]	0.604***	[0.02]
Education: lower secondary	0.343***	[0.025]	0.237***	[0.017]	0.238***	[0.018]
Education: upper secondary and tertiary	*Ref.*		*Ref.*		*Ref.*	
Household composition: 1 person	-0.096**	[0.041]	-0.297***	[0.027]	0.317***	[0.028]
Household composition: 2 persons	-0.139***	[0.04]	-0.256***	[0.025]	0.162***	[0.026]
Household composition: 3 persons	-0.169***	[0.041]	-0.131***	[0.026]	0.052*	[0.027]
Household composition: 4 persons	-0.095**	[0.042]	-0.117***	[0.026]	-0.065**	[0.028]
Household composition: 5 persons or more	*Ref.*		*Ref.*		*Ref.*	
Assets : first quartile (in the country)	0.463***	[0.023]	0.754***	[0.016]	0.134***	[0.016]
Assets : second quartile (in the country)	0.232***	[0.023]	0.366***	[0.015]	-0.054***	[0.015]
Assets : third and fourth quartiles (in the country)	*Ref.*		*Ref.*		*Ref.*	
Country: Austria	0.031	[0.114]	-0.065	[0.04]	0.261***	[0.053]
Country: Belgium	0.342***	[0.104]	0.126***	[0.041]	0.807***	[0.051]
Country: Cyprus	2.374***	[0.087]	1.128***	[0.045]	1.222***	[0.058]
Country: Germany	*Ref.*		*Ref.*		*Ref.*	
Country: Spain	-0.64***	[0.12]	0.931***	[0.031]	0.522***	[0.044]
Country: France	-0.062	[0.089]	-0.359***	[0.031]	1.944***	[0.04]
Country: Greece	3.695***	[0.083]	0.754***	[0.036]	2.532***	[0.047]
Country: Hungary	1.821***	[0.079]	1.001***	[0.03]	2.081***	[0.042]
Country: Italy	1.309***	[0.08]	1.315***	[0.03]	1.886***	[0.041]
Country: Luxembourg	0.608***	[0.107]	0.186***	[0.046]	0.184***	[0.07]
Country: Latvia	1.848***	[0.089]	2.125***	[0.05]	2.065***	[0.054]
Country: Netherlands	0.524***	[0.115]	-0.278***	[0.057]	0.661***	[0.061]
Country: Poland	1.775***	[0.082]	2.432***	[0.039]	2.009***	[0.045]
Country: Portugal	0.512***	[0.086]	0.835***	[0.032]	1.285***	[0.044]
Country: Slovenia	1.13***	[0.087]	1.424***	[0.036]	1.069***	[0.049]
Country: Slovakia	1.745***	[0.084]	1.66***	[0.039]	2.336***	[0.048]
Observations	64 908		64 910		64 910	
Percent Concordant	92.7		83.9		84.7	
Percent Discordant	7.0		16.0		15.1	
Percent Tied	0.3		0.2		0.2	

Standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

As far as saving accounts are concerned, our results show again that being younger increases the probability of being excluded, likewise an unemployed work status. Income, education level (to a lesser extent), net wealth (to a higher extent) play the same role as for current account financial. Being a smaller household decreases the probability of not having a savings account, which might relate to the fact that consumption needs are higher for more numerous households *ceteris paribus*. The effect of net wealth is higher than for current accounts, meaning that being less wealthy yields more exclusion from savings than from current accounts. For most of the countries results are similar to those obtained for current accounts, although with coefficients smaller than for the former equation, meaning that country-specific factors should not discriminate as much for savings as for current accounts. We nonetheless find a higher exclusion on savings for households in Spain, for which current accounts exclusion was low, and a higher participation in France and the Netherlands, meaning that in relative terms, having a savings account in those latter countries might appear easier than a current account one. It is interesting to notice that incentives might play a role, as current accounts benefit relative interesting interest rates in Spain, while savings accounts in France ('Livret A') benefit specific fiscal exemptions with interest rates in average higher than those that remunerate current accounts.

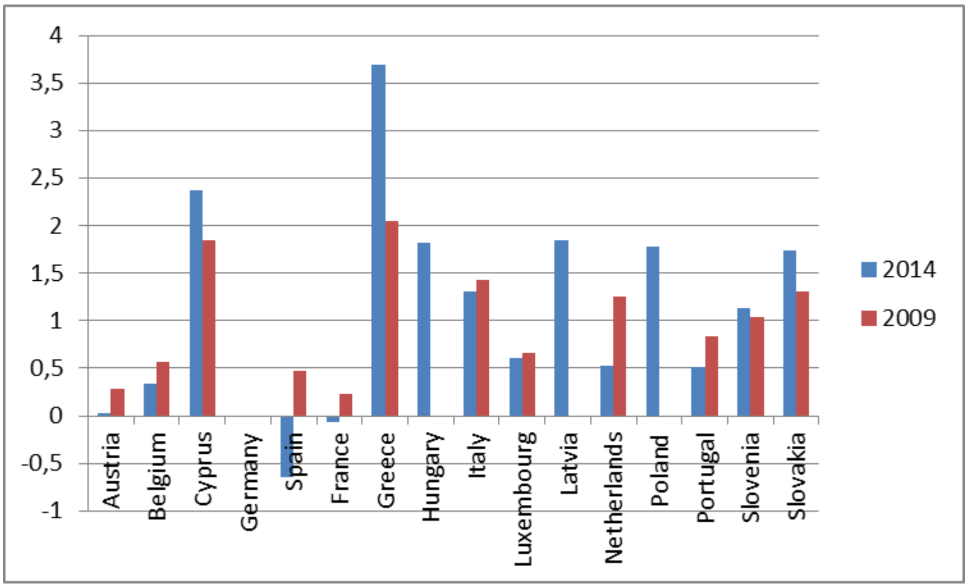
Looking at credit exclusion, we find that being aged between 25 and 50 decreases significantly the probability of not having a credit, which is consistent with the life cycle model. The probability of exclusion is smaller for employed people, numerous households, higher income and wealthier households, although for this latter characteristic the effect is smaller than for other, meaning that the credit allocation may rather depend on criteria about income than on net wealth (through the collateral channel). Being lower educated appears also as a significant factor of exclusion. Again, country-specific variables matter much more than individual characteristics, indicating that national legislations, practices or banking system functioning, play a key role in credit exclusion. In that respect, households that are less included in the credit market all other things kept equal live in Greece, Hungary, Slovakia, Latvia and Poland.

Effect of the crisis on financial exclusion

The first equation is estimated on the first wave data, with the intention to estimate whether the crisis yielded significant changes in financial exclusion. The comparison of coefficient magnitudes and signs allows us to draw the following conclusions.

As regards current accounts, after the crisis are more excluded younger households, and inactive people, while surprisingly, financial variables such as income and net wealth does not seem to play a more important role in wave 2 rather than in wave 1. Household composition was a higher source of financial exclusion in wave 1 than in wave 2, as the magnitude of coefficients has decreased. Financial exclusion on these grounds seems more related in wave to the composition of the households than financially-based. We also find that, in comparison with the reference modality, current account financial exclusion has decreased in countries that have relatively well born the crisis (Austria, Germany, France, the Netherlands), while it has increased in others (Cyprus, Greece). Surprisingly, it seems to have significantly decreased in Spain but, beyond any measures undertaken in favor of household inclusion, it should also be reminded that HFCS data for Spain in wave 2 were collected in 2011. In that respect, it is worth mentioning that coefficients differences between wave 1 and wave 2 estimations are much more important with country-specific variables than individual characteristics, pointing to systemic phenomenon related to a weakening of households situation in those countries dramatically hit by the crisis, or by mistrust from those households towards their financial systems' resilience. This seems to be the case in Cyprus and Greece, but not for instance in Italy, Portugal and Spain. Figure 2 below represents the value of the country-specific coefficient estimated in our first model on the data of the first wave (red) and second wave (blue).

Figure 2: country-specific contributions to current account participation rate (%)



Conclusion and policy lessons

Financial exclusion plays an important role, not only for social reasons, but also for economic purposes, as for instance financial inclusion is highly correlated to national wealth (Ampudia and Ehrmann, 2015). Hence, understanding the determinants of financial inclusion remains of the essence.

In this paper, we estimate probit models so as to identify the determinants of financial exclusion, based on various definitions. We find that being an older, unemployed, low-income, low-educated and low-wealth household increases the probability of not having a current account. But the definition of financial exclusion matters: savings accounts discriminate less by age, while access to credit is more probable for younger and lower-income people. There is a strong heterogeneity across Euro area, with households from Greece, Cyprus, Poland and Slovakia being more financially excluded.

The aftermath of the crisis did not increase the financial exclusion of vulnerable households as a whole, but had rather country-specific effects, pointing out systemic risks over some banking systems.

This paper adds to the existing literature in identifying the characteristics of financial exclusion based on three different definitions and over the crisis. It shows that current account and savings account exclusion remains essentially a country-specific issue, while access to credit is relatively more related to the individual characteristics of the households.

References

Allen F., A. Demirgüç-Kunt, L. Klapper and M. S. Martinez Peria (2012), "The Foundations of financial Inclusion: Understanding Ownership and Use of Formal Accounts", *World Bank's Policy Research Working Paper* WPS6290, December.

Ampudia M. and M. Ehrmann (2017), "Financial inclusion-what's it worth?", *European Central Bank Working paper series* nb. 1990, January.

Bank for International Settlements and World Bank Group (2015), Committee on Payments and Market Infrastructure, "Consultative report – Payment aspects of financial inclusion".

Banque de France (2017), "Annual report of the Observatoire de l'inclusion bancaire', 26 June 2017, available online at https://publications.banque-france.fr/sites/default/files/medias/documents/inclusion_bancaire_rapport_2016.pdf.

Demirgüç-Kunt A. and L. Klapper (2013), "Measuring Financial Inclusion: Explaining Variation in Use of Financial Services across and within Countries", *Brookings Papers on Economic Activity*, vol. 44, issue 1 (Spring), pages 279-340.

European Commission (2008), "Financial Services Provision and Prevention of Financial Exclusion", May, available online http://www.bristol.ac.uk/media-library/sites/geography/migrated/documents/pfrc0807.pdf.

Fungáčová Z. and L. Weill (2015), "Understanding financial inclusion in China", *China Economic Review,* n°134, pp. 196-206.

Irving Fisher Commitee on Central Bank Statistics (2016), "Measures of financial inclusion – a central bank perspective", availaible online https://www.bis.org/ifc/publ/ifc_finan_inclu.pdf.

Tuesta D., G. Sorensen, A. Haring and N. Cámara (2015), "Financial inclusion and its determinants: the case of Argentina", *BBVA research Working Paper,* January.

IFC-National Bank of Belgium Workshop on "*Data needs and Statistics compilation for macroprudential analysis*"

Brussels, Belgium, 18-19 May 2017

Household financial exclusion in the Eurozone throughout the crisis[1]

Jérôme Coffinet and Christophe Jadeau,

Bank of France

1 This presentation 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.

Household financial exclusion in the Eurozone throughout the crisis
IFC-NBB Workshop, Brussels

May 18th, 2017

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The views expressed in the paper are the sole responsibility of the authors and do not necessarily represent those of the Banque de France

Why studying financial exclusion in the euro area?

Motivations

- The access to financial services is a crucial matter for developing countries (e.g. 2009 G20 Pittsburgh summit)

- But also a major issue for advanced economies:
  - Financial exclusion of households is less frequent
  - But yields a major economic and social exclusion

Strong interest by stakeholders

- Reports – among others – by Committee on Payments and Market Infrastructure, Bank for International Settlements and World Bank Group, Findex/Gallup database

- Irving Fisher Committee report on the central bank perspective (2016):
  - measures of financial inclusion
  - need for central banks to define financial inclusion, collect data and stay updated on the subject
  - some differences between countries in the definition of financial inclusion and of the legal roles of central banks

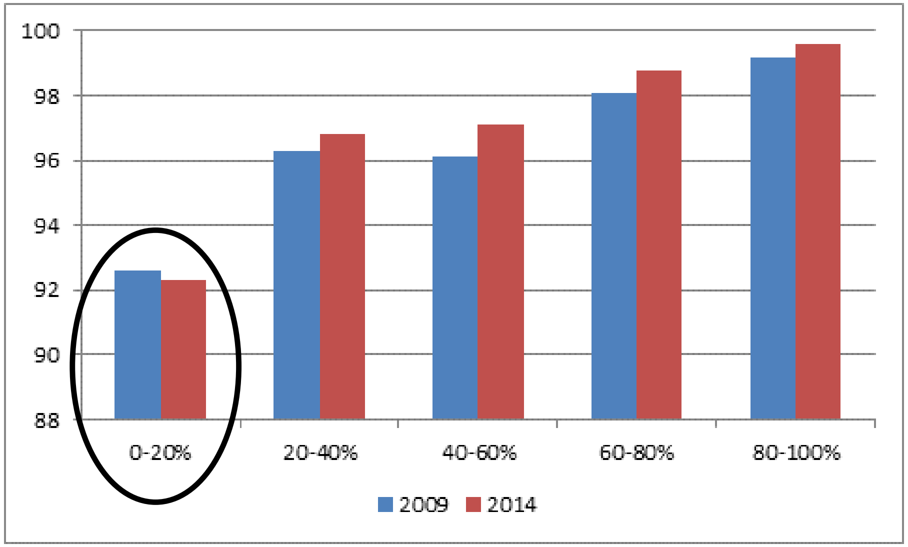
A strong need to improve our knowledge financial inclusion in the euro area

Describing the data

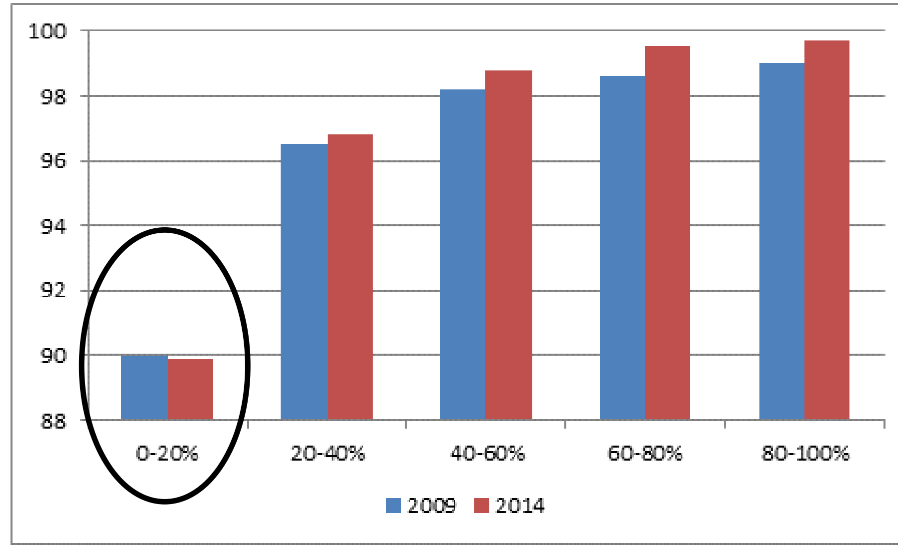
- Household-level data on households' finance and consumption based on Household Finance and Consumption Survey (HFCS).
- Fieldwork in 2010 and 2011 (first wave) and between 2013 and 2015 (second wave).
- Over 50000 households in first wave and over 58000 in the second wave, across 17 countries.
- Information about socio-demographic characteristics of households, financial and real assets, liabilities, income and consumption behavior,
- Three definitions of financial inclusion:
  - Having a current account
  - Having a savings account
  - Having a loan

A first look at the data: probability of having a current account in the euro area…

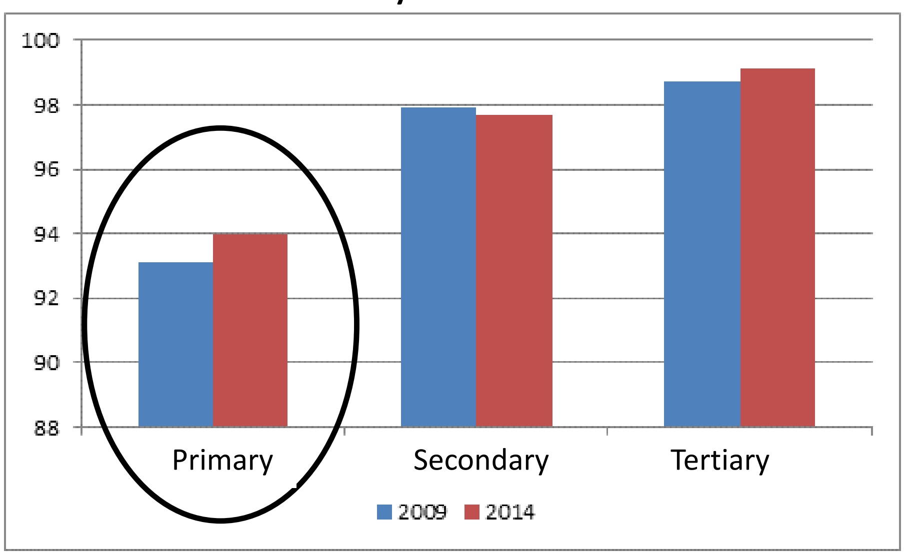
By net wealth



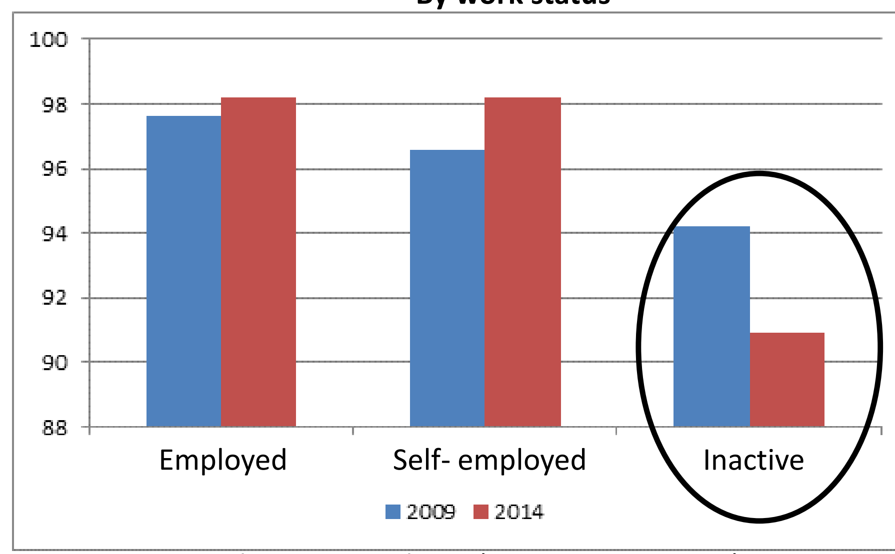
By income



By education

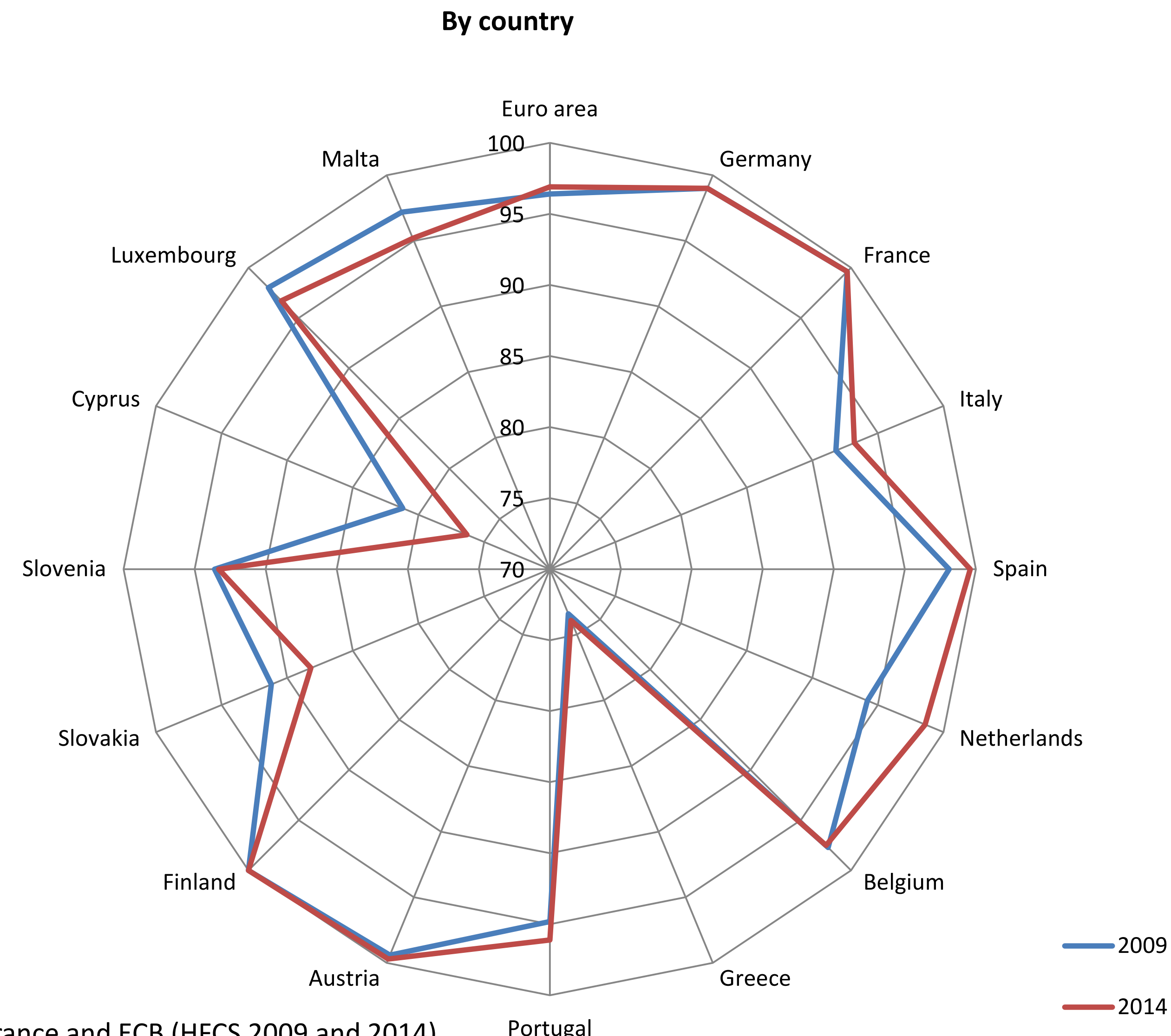


By work status



Source : Banque de France and ECB (HFCS 2009 et 2014)

A first look at the data: probability of having a current account in the euro area…



Source : Banque de France and ECB (HFCS 2009 and 2014)

- Endogenous variable: probability for a household to have no transaction account / no savings account / no loan

- Probit regression on independent variables

- $P(Y_{\text{no account}} = 1|X) = \Phi(\alpha + X'\beta)$

- $\beta = \begin{pmatrix} \beta_{\text{age}} \\ \beta_{\text{employment}} \\ \beta_{\text{income}} \\ \beta_{\text{education}} \\ \beta_{\text{household composition}} \\ \beta_{\text{Assets}} \\ \beta_{\text{country}} \end{pmatrix}^t$ and $X = \begin{pmatrix} X_{\text{age}} \\ X_{\text{employment}} \\ X_{\text{income}} \\ X_{\text{education}} \\ X_{\text{household composition}} \\ X_{\text{Assets}} \\ X_{\text{country}} \end{pmatrix}$

- Categorical independent variables

Results (second wave)

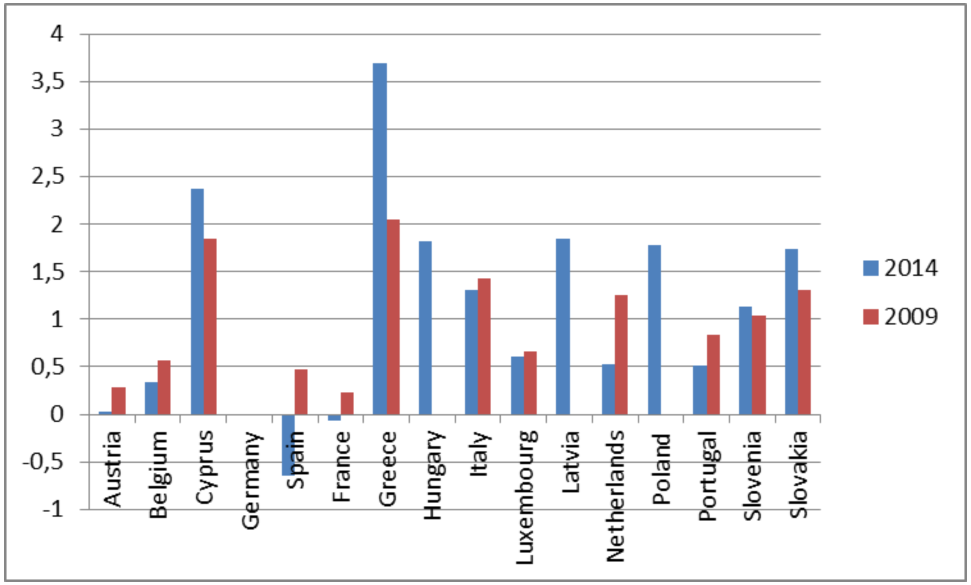
- **Current account:**
- Probability of being financially excluded (not having a current account) increases for older, lower-educated, unemployed and less wealthy households
- Effect of income massive and monotonous: lower income means higher financial exclusion, especially for the poorest. Size of the household plays a minor role in magnitude
- The magnitude of the coefficients related to countries is much higher than those related to individual characteristics
- Greece, Cyprus, Latvia, Slovakia, Hungary and Poland significantly experiment a higher probability of having households financially excluded

- **Savings account:**
- Same results but education level plays a more minor role while net wealth increases more the probability of having a savings account
- Country-specific factors should not discriminate as much for savings as for current accounts

- **Loans:**
- Middle-aged households participate more in the loan market (life cycle model)
- Exclusion smaller for employed, numerous households, higher income and wealthier households
- Country-specific variables matter much more than individual characteristics

- **Effect of the crisis:**
- Are more excluded from current account and savings accounts: younger households and inactive people
- The role of individual financial variables (net wealth and income) has decreased over the crisis
- On the contrary, the magnitude of country-specific effects has increased!
- Credit: the role of individual characteristics has increased but that of country-specific variables has decreased

- **Country-specific contributions (current accounts):**



- A new source of data on households, both on financial characteristics and behaviors, and on socio-demographic features, which may complement already existing databases

- Not fully harmonized on the sampling scheme, which may yield some country-specific differences resulting from methodological design

- Older, unemployed, lower-income, lower-educated and less wealthy households of the euro area are less likely to have a current account

- The definition of financial exclusion matters: savings accounts discriminate less by age, while access to credit is more probable for younger and lower-income people.

- A strong heterogeneity across the euro area.

- The aftermath of the crisis did not increase the financial exclusion of vulnerable households as a whole, but had rather country-specific effects, pointing out systemic risks over some banking systems.

Thank you for your attention

Any questions?

Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

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Statistical work on shadow banking: development of new datasets and indicators for shadow banking[1]

Anna Maria Agresti and Rok Brence,
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.

Statistical work on Shadow banking: Development of new datasets and indicators for shadow banking

Anna Maria Agresti[1] and Rok Brence[2,3]

Abstract

This paper provides an overview of the statistical work on shadow banking in the EU context related to its size, existing data gaps and risks measures. It focuses in particular on the "macro-mapping" exercise as recommended by the Financial Stability Board, which represents an initial approach in addressing the mapping of shadow banking. The paper shows how data gaps and regulatory differences between the EU member states prevent full implementation of the framework and how new initiatives on macro and micro data might help overcome these issues also for risk assessment purposes.

The paper first presents the EU macro approach and underlying methodology employed by the ESRB in mapping the shadow banking sector as well as advantages and limitations in using aggregated data for shadow banking purposes. The second section describes how macro financial data help construct risk indicators and dispersion measures. The third section points to the current data gaps and presents initiatives taken by the ECB to address these gaps e.g. developing statistics on financial corporations involved in lending (FCLs). Finally, the usage of new granular data sets and regulatory data (such as AIFMD) might reduce identified data gaps and narrow informational gaps between micro and macro approaches in the shadow banking measurement.

JEL code: C82, G21

Keywords: Macroprudential analysis, Shadow banking

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3 The views expressed in this paper are those of the authors and do not necessarily reflect those of the European Central Bank.

1. Introducing the macro approach to mapping shadow banking

Disruptive events in the financial system during the global financial crisis led international policymakers, through Financial Stability Board (FSB), to embark on a worldwide project to measure, monitor and regulate the shadow banking system and its inherent risks. The FSB defines the shadow banking system as "credit intermediation that involves entities and activities fully or partially outside the regular banking system". This approach allows the use of data from financial accounts and other related financial statistics, such as the balance sheet data of non-bank financial institutions, which ensures consistency on both a global and a regional level (e.g. the EU). On the European level, the ESRB is developing a monitoring framework for the European shadow banking system, which is broadly consistent with the definitions and approaches provided by the FSB. In particular, the ESRB framework distinguishes between risks stemming from financial institutions (entity-based approach) and their activities (activity-based approach).

The entity-based approach draws on the aggregated balance sheet data of financial institutions taken from financial accounts and monetary statistics, based on the ESA 2010 framework. In an initial step, the "broad measure" includes all entities of the financial sector except banks and insurance corporations and pension funds (ICPFs). The aim is to cover all areas where shadow banking-related risks to the financial system might potentially arise. In a second step, the focus is narrowed down to entities that have more specific potential to pose systemic risks, predominantly through their engagement in credit intermediation, liquidity and maturity transformation, leverage and interconnectedness with the banking system. However, the entity-based approach described above is incomplete due to the limitations of the available balance sheet data for the risk analysis. For example, off-balance sheet exposures and use of financial derivatives provide additional sources of risks or, if used prudently, may provide a valuable tool for risk mitigation.

Therefore, the activity-based approach aims to complement the entity-based approach and to capture activities which are not restricted to specific entities or which contribute to interconnectedness between shadow banking system and regular banking system (e.g. through securities financing transactions (SFTs), derivatives and credit enhancements). In addition, entities which are not captured in the entity-based approach but engage in some shadow banking activities are captured with the activity-based approach (e.g. insurance companies engaging in the SFTs or providing credit enhancement). A full coverage of the shadow banking activities does however present particular challenges due to the data limitations. New datasets collected under European Market Infrastructure Regulation (EMIR), Securities Financing Transactions Regulations (SFTR), Alternative Investment Fund Managers Directive (AIFMD), the Money Market Statistical Reporting (MMSR) and the AnaCredit will provide highly standardized, high frequency and low latency data with wide coverage of market participants and activities.

Turning to the size of shadow banking sector in the EU, the "broad measure" captures all non-bank financial intermediaries other than insurance corporations and pension funds, i.e. it is based on investment funds and other financial institutions (OFIs)[4], as summarised in Table 1. This broad measure is useful as a harmonised basis for international comparisons and allows assessing interconnectedness across sectors based on available statistical data. However, such measure also includes entities which bear little relevance when assessing shadow banking risks to financial stability. Entities posing no shadow banking related risks include for instance holding companies of non-financial corporations, entities consolidated into banking groups and thus subject to prudential regulation, and specialised financial institutions which may be set up for the management of intra-group transactions.

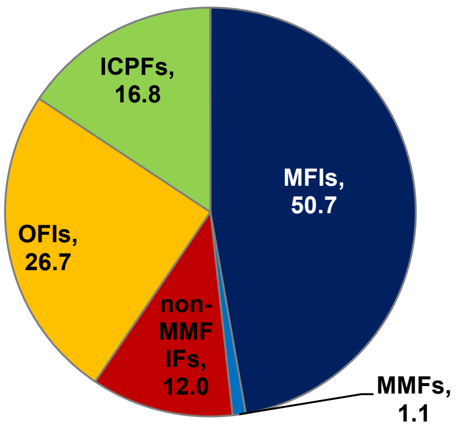
4 See Grillet-Aubert, L., Haquin, J.-B., Jackson, C., Killeen, N. and Weistroffer, C., "Assessing shadow banking – non-bank financial intermediation in Europe", Occasional Paper Series, No 10, ESRB, July 2016 which provides methodological detail on the components of the EU shadow banking system.

The EU shadow banking sector according to the ESRB amounts to around 37% of the EU financial sector. Its size grew with an average annualized growth rate of 11% between 2003 and 2016, resulting in almost quadrupled size over the same period. Chart 1 shows total assets for subsectors in the EU financial sector and Chart 2 presents growth trends in the EU and euro area shadow banking, based on the broad measure.

Chart 1

EU financial sector

(€ trillions; last observation: Q4 2016)



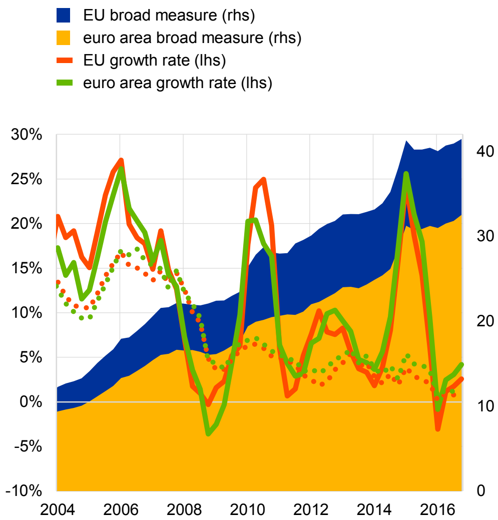
Source: ECB and ECB calculations.

Notes: Based on financial accounts data on the total financial assets of the financial sector of the euro area plus non-euro area EU Member States.

Chart 2

Broad measure of EU and euro area shadow banking (investment funds and other financial institutions)

(€ trillions and annual growth rates; last observation: Q4 2016)



Source: ECB and ECB calculations.

Notes: Annual growth rates based on changes in outstanding amounts are indicated with the continuous lines. Dotted lines indicate annual growth rates based on transactions – i.e. excluding the impact of FX or other revaluations and statistical reclassifications.

Table 1: Overview of investment funds and OFIs (based on ESA 2010 classification)

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 financial sector assets and the assets held by all known subsectors; the residual is usually classified under S.125
	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

Due to the significant heterogeneity of entities within the broad measure and in the extent of their engagement in shadow banking activities, a distinction should be made with respect to the degree of shadow banking functions and risks – such as maturity and liquidity transformation, use of leverage, credit intermediation and interconnectedness with the regular banking sector. Based on this, a narrow measure of shadow banking can in principle be constructed, within which entities with greater level of engagement in risks are identified. The lack of granular information on some subsectors, especially the residual OFIs, however, prevents a definitive assessment of risk. A number of initiatives have been undertaken by the Eurosystem and at the national levels in recent years to better identify types of entities within the non-bank financial sector, the “OFI residual” and its relevance for shadow banking.

In the narrowing down process the first step is to exclude equity investment funds from the broad definition as they do not primarily engage in credit intermediation, although some activities (e.g. the use of securities lending or derivatives) may have a modest impact on the assessment of these funds' shadow banking characteristics. Second, retained securitisations – i.e. securitisations where the asset-backed securities are held by the originating banks, generally for use as collateral in central bank refinancing operations – are excluded since there is no transfer of credit risk from the banking system. Furthermore, non-securitisation special purpose entities and holding companies might be excluded from a narrow view of shadow banking if they are not part of a credit intermediation chain. Similarly, a large part of the total assets of SDDs appears to be consolidated in large banking groups and, consequently, they may be subject to regulatory requirements on liquidity and capital and might be excluded from the narrow measure. In the described narrowing down process, the ERSB only partially endorsed this approach, as entities prudentially consolidated within banking groups are not excluded from the narrow perimeter of the shadow banking sector.

In addition, in its Global Shadow Banking Monitoring Report 2015[5] the FSB introduced the narrow measure of global shadow banking based on five economic functions through which non-bank credit intermediation may pose bank-like systemic risks to the financial system. Table 2 presents economic functions as defined by the FSB and lists entities that typically engage in activities related to each function.

While in principle the FSB and ESRB approaches are broadly in line, there are two main differences between the two approaches. Firstly, the FSB economic functions approach is not completely aligned with the ESRB methodology on the narrow measure. The FSB, for example, excludes entities prudentially consolidated within banking groups from the narrow perimeter of the shadow banking sector – an approach that was also followed by the European Banking Authority in its work in this area. The main reason why the ESRB measures do not exclude consolidated entities is the lack of data. Furthermore, in order to exclude consolidated entities, a stronger justification is needed based on supervisory and regulatory frameworks treating these entities (e.g. addressing intragroup liquidity and capital allocation). Additionally, the activity based approach is not flexible enough to allow for the exclusion of activities performed by the consolidated entities.

Besides the consolidation issues mentioned above additional difficulties exist in the implementation of the FSB approach on the EU level as it is not feasible to map OFI subsectors to the five economic functions as data breakdowns are not yet available, making a quantitative reclassification of the OFIs subsectors into the five economic functions groups. To assess the risks in EU shadow banking, it would be better to replace or complement the economic functions approach with an analysis of risk indicators of the broader OFI subsectors by finding relative benchmarks and critical values. This paper presents the progress on development of additional risk indicators for various OFI subsectors that could be potentially included in the ESRB's risk metrics framework.

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5 See section 2.1 Economic functions approach of the FSB Global Shadow Banking Monitoring Report 2015: http://www.fsb.org/wp-content/uploads/global-shadow-banking-monitoring-report-2015.pdf

Table 2: Classification by economic functions

Economic Function	Definition	Typical entity types
EF1	Management of collective investment vehicles with features that make them susceptible to runs	Fixed income funds, mixed funds, credit hedge funds, real estate funds
EF2	Loan provision that is dependent on short-term funding	Finance companies, leasing companies, factoring companies, consumer credit companies
EF3	intermediation of market activities that is dependent on short-term funding or on secured funding of client assets	Broker-dealers
EF4	Facilitation of credit creation	Credit insurance companies, financial guarantors, monolines
EF5	Securitisation-based credit intermediation and funding of financial entities	Securitisation vehicles

2. Risk indicators and their dispersion measures

The FSB economic functions approach builds on competent authorities' assessment of potential sources of shadow banking risks arising from the activities of non-bank financial entities located in their jurisdictions. It takes the financial stability perspective, by either classifying an entity with reference to the above-mentioned five economic functions or excluding the entity based on the assessment that it does not pose shadow bank-like risks[6]. One critic of this approach is that it does not appear to be based on any quantitative assessment of risks across different entities and does not seem to improve the quantitative monitoring of risks associated with the shadow banking sector.

Similarly, also the risk metrics developed by the ESRB and included in its reports[7] are not tools that would give a quantitative assessment of shadow banking risks. The indicators proposed by the ESRB are a selection of financial ratios that represent measures of risk which characterize shadow banking activities and entities. As such, the framework is not intended to be necessarily forward-looking and does not provide early-warnings. Since there are no established definitions of critical values related to risk measures in any of the ESRB macroprudential policies, the interpretation of these indicators is difficult (e.g. if they are too high or too low).

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6 See FSB Global Shadow Banking Monitoring Report 2015 http://www.fsb.org/2015/11/global-shadow-banking-monitoring-report-2015/

7 See ESRB Assessing shadow banking –non-bank financial intermediation in Europe https://www.esrb.europa.eu/pub/pdf/occasional/20160727_occasional_paper_10.en.pdf and EU Shadow Banking Monitor https://www.esrb.europa.eu/pub/pdf/reports/20160727_shadow_banking_report.en.pdf?af1a2b4f032060dab0c5c3c8bcd2945b

While limitations exist in constructing a framework for risk assessment, this section presents some suggestions on the possible ways to construct benchmark values for the subsectors of the shadow banking. Without the objective to propose any metric for policy measures and possible related actions, the focus of this exercise is to provide an additional tool, based on the information available, for addressing the risks in the shadow banking subsectors. This paper presents a first investigation on the possible way to construct critical values (benchmarks) for some shadow banking entities such that they might also be used for the development of an heat map.

The ESRB has developed a set of indicators for assessing shadow banking risks through a consistent risk mapping framework, which are presented in Table 3.

However, the benchmark values for risk intensities are not available and the ESRB continues to work on the enhanced monitoring of the EU shadow banking to provide more detailed analysis of risks. As a part of this work, some initial benchmark values for the purpose of constructing a heat map are currently under development. These benchmarks are based on the percentile distribution of indicators across the EU countries and on clustering of indicators' values in various buckets.

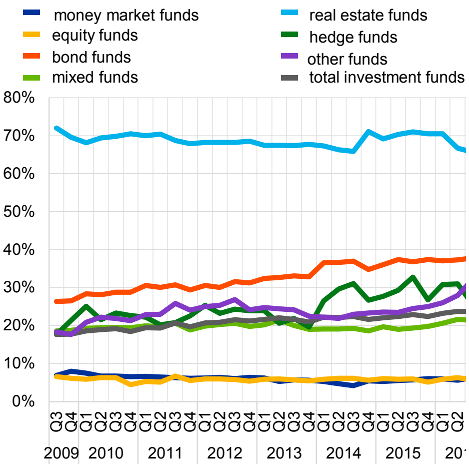
Shadow banking activities and entities are very heterogeneous, and consequently it is not possible to construct critical values for the consolidated shadow banking system. In order to construct meaningful critical values, it is necessary to separately analyse key subsectors (i.e. investment funds, FCLs and SDDs) for selected indicators (liquidity, leverage and maturity). Two approaches were chosen to build up the benchmark values, namely analysis with percentile distribution and the bucketing of indicators' values. In particular, the former approach analyses the distribution of indicator levels across countries by means of dispersion measures, to address differences between countries that are not visible in the aggregated EU wide indicators. The latter approach, builds on the EU legislative texts to construct risk buckets that are in line with legislation covering financial sector. This approach uses also results on the ESRB policy task force on liquidity and leverage and guidelines published by the FSB and the IOSCO on the risk indicators for the OFI sector.

Table 3: Framework of risk indicators for the shadow banking system

Risk indicator	Risk indicator metric	Ref.
Maturity transformation	Short-term assets / Total assets	MAT 1
	Long-term assets / Total assets	MAT 2
	Short-term liabilities / Short-term assets	MAT 3
	Long-term assets / Short-term liabilities	MAT 4
Liquidity transformation	(Total assets - Liquid assets) / Total assets	LIQ1
	Short-term liabilities / Liquid assets	LIQ2
	Short-term assets / Short-term liabilities (current ratio)	LIQ3
	Liquidity mismatch: Liquid liabilities less liquid assets, as share of total assets	LIQ4
	(Deposits with MFIs + Short-term debt holdings + Equity holdings) / NAV	LIQ5
Leverage	Leverage = Loans received / Total liabilities	LEV1
	Leverage multiplier = Total assets / Equity	LEV2
Credit intermediation	Loans / Total assets	CRE1
	"Credit assets" (loans and debt securities) / Total assets	CRE2
Interconnectedness with the regular banking system	Assets with credit institution counterpart / Total assets	INT1
	Liabilities with credit institution counterpart / Total assets	INT2

Chart 3

EU investment funds: Liquidity transformation
(LIQ1, percentages; last observation: Q4 2016)



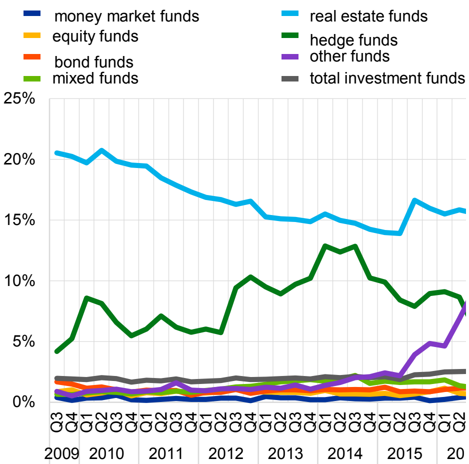
Source: ECB and ECB calculations.

Notes: Based on available data for the EU; Bulgaria, Croatia, Denmark, Sweden and the United Kingdom are not included. Total assets minus liquid assets (deposits, sovereign bonds, debt securities issued by MFIs and equity and investment fund shares), as a share of total assets. Closed-ended funds are not included. Estimates are made for holdings of non-euro area securities and funds not resident in the euro area. During 2016, some hedge funds were reclassified as 'other funds' affecting the series for these types of funds.

Chart 4

EU investment funds: Financial leverage

(LEV1, percentages; last observation: Q4 2016)



Source: ECB and ECB calculations.

Notes: Based on available data for the EU; Bulgaria, Croatia, Denmark, Sweden and the United Kingdom are not included. Leverage is calculated as the ratio of loans received to total liabilities. During 2016, some hedge funds were reclassified as 'other funds' affecting the series for these types of funds.

This analysis will start with the investment funds. The assessment made by the ESRB[8] shows that "part of the EU investment fund sector engages in maturity and liquidity transformation and may be subject to run risk, i.e. to the extent that fund shares are callable at short notice. Some funds, especially in the hedge fund sector, are significantly leveraged, while others have moderate leverage created through securities lending or derivatives exposure. Any metric based on aggregate statistics masks heterogeneity between various types of fund and risk at the entity level. A breakdown by investment focus, such as bond, equity and mixed funds therefore appears useful". This assessment is based on the metrics from the Table 3 and constructed with aggregated balance sheet statistics. Charts 3 and 4 present liquidity transformation and leverage indicators for the EU investment fund sector. These indicators give us a relative measure of exposures of investment funds across various investment policies. However, without absolute critical values for risk indicators we cannot conclude if investment funds, within the same investment policy, are over exposed towards particular risks. Furthermore, the EU aggregated indicators say nothing about national exposures, which can vary enormously.

Dispersion measures can provide additional information on the cross country variations in risk intensities. Chart 5 shows dispersion of the liquidity indicator LIQ1 across countries together with the EU aggregated indicator for the whole investment fund sector. We can notice large variation of liquidity transformation between countries and that the EU aggregate lies above the interquartile range (i.e. difference between third and first quartile) and thus slightly overestimates the median

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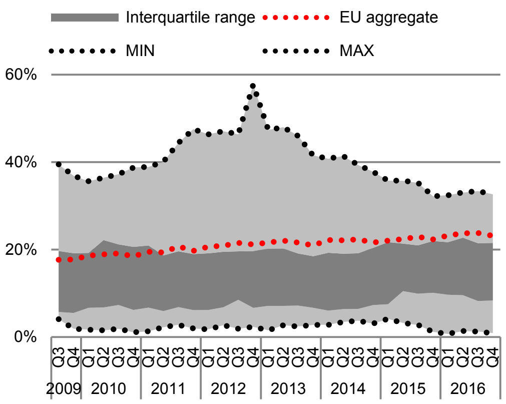
8 See Assessing shadow banking – non-bank financial intermediation in Europe https://www.esrb.europa.eu/pub/pdf/occasional/20160727_occasional_paper_10.en.pdf

value. Another interesting observation is that the EU aggregate is relatively stable during the time, while the maximum reached its peak in the late 2012 and decreased thereafter. Chart 6 shows the same indicator for the real estate funds sector, which, based on the Chart 3, engages in the most pronounced liquidity transformation. This should not be a surprise, since assets of these funds comprise mostly illiquid investments in the real estate properties. However, more surprising is the large variation between countries, especially the very low minimum, which states that around 85% of total assets of real estate funds comprise liquid assets. A possible explanation for this high variation could be differences in classification methodologies applied in different countries since there is no unified approach across the EU on how to classify investment funds. The EU aggregate in this case lies inside the interquartile range, which is however not very informative due to the large width of the interquartile range. Additionally, there is also no trend in the direction of liquidity transformation over the time neither in the variation of distribution (e.g. narrowing of dispersion measures).

Chart 5

Liquidity transformation: total investment funds
(LIQ1, percentages; last observation: Q4 2016)



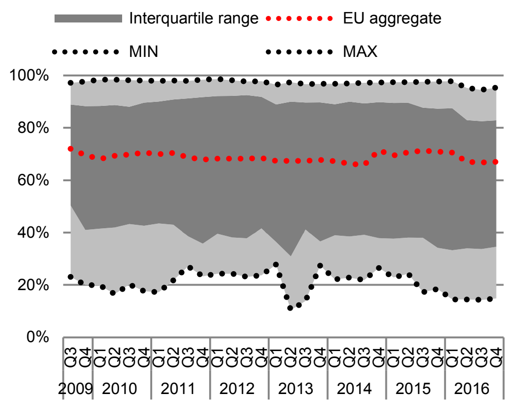
Source: ECB and ECB calculations.

Notes: Based on available data for the EU; Bulgaria, Croatia, Denmark, Sweden and the United Kingdom are not included. Total assets minus liquid assets (deposits, sovereign bonds, debt securities issued by MFIs and equity and investment fund shares), as a share of total assets. Closed-ended funds are not included. Estimates are made for holdings of non-euro area securities and funds not resident in the euro area. During 2016, some hedge funds were reclassified as 'other funds' affecting the series for these types of funds.

Chart 6

Liquidity transformation: real estate funds

(LIQ1, percentages; last observation: Q4 2016)



Source: ECB and ECB calculations.

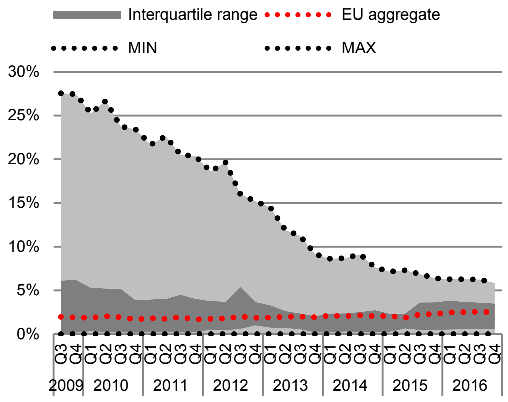
Notes: Based on available data for the EU; Bulgaria, Croatia, Denmark, Sweden and the United Kingdom are not included. Total assets minus liquid assets (deposits, sovereign bonds, debt securities issued by MFIs and equity and investment fund shares), as a share of total assets. Closed-ended funds are not included. Estimates are made for holdings of non-euro area securities and funds not resident in the euro area. During 2016, some hedge funds were reclassified as 'other funds' affecting the series for these types of funds.

Similar analysis can be done for the financial leverage indicator LEV1. Chart 8 shows that stability of financial leverage indicator over time for the total investment funds can be confirmed by stability of interquartile range. Low difference between first and third quartile and the EU aggregate that lies in between indicates consistency of the aggregated measure. Apparent is also that the maximum has negligible effect on the EU aggregate. Chart 8 presents the same indicator for the real estate funds, which are, based on the Chart 4, the most leveraged type of funds. Chart 4 shows gradual deleveraging of the real estate funds, however, closer look to the country distribution does not provide so clear conclusion. First, the maximum exhibits clear decreasing trend, which has an effect on the EU aggregated measure. This effect is more pronounced than in the case of total investment funds (Chart 7) because for the real estate funds the dispersion is much wider (interquartile range as well as the minimum and the maximum). On the other hand, the interquartile range and the median show slightly increasing trend, which is in contrast to the conclusion based on the EU aggregate.

Chart 7

Financial leverage: total investment funds

(LEV1, percentages; last observation: Q4 2016)



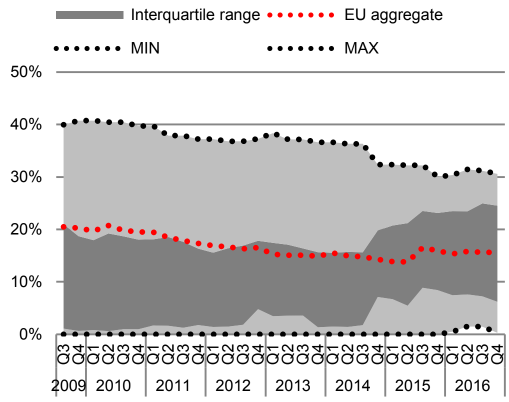
Source: ECB and ECB calculations.

Notes: Based on available data for the EU; Bulgaria, Croatia, Denmark, Sweden and the United Kingdom are not included. Leverage is calculated as the ratio of loans received to total liabilities. During 2016, some hedge funds were reclassified as 'other funds' affecting the series for these types of funds.

Chart 8

Financial leverage: real estate funds

(LEV1, percentages; last observation: Q4 2016)



Source: ECB and ECB calculations.

Notes: Based on available data for the EU; Bulgaria, Croatia, Denmark, Sweden and the United Kingdom are not included. Leverage is calculated as the ratio of loans received to total liabilities. During 2016, some hedge funds were reclassified as 'other funds' affecting the series for these types of funds.

Four examples presented above try to highlight the heterogeneity behind the aggregated risk measures. This heterogeneity can take many different shapes and can, if not taken into account, lead to deceiving conclusions. While the distribution approach showed that risk measures among countries vary considerably, it might be useful to obtain additional information on the intensity of risks. This can be achieved using the bucketing approach in conjunction with benchmark values. The aim of cluster analysis (Clustering of indicators' values in various buckets) is to identify groups of similar objects (Liquidity indicators of subsector of OFIs) according to selected variables (level of Liquidity indicators) that might represent larger and different level of risks.

In the EU, investment fund leverage and liquidity are regulated by the Undertakings for Collective Investments in Transferable Securities (UCITS) Directive and the Alternative Investment Fund Managers Directive (AIFMD). Regulations and supervisory practices can vary between the UCITS and non-UCITS funds. For instance, the UCITS Directive imposes direct restrictions on the use of balance sheet and synthetic leverage, whereas AIFMD does not place any hard limits but requires the asset manager to apply "reasonable" leverage limits to the funds it manages. For the purpose of risk monitoring, it may therefore be useful to distinguish between UCITS and alternative investment funds (AIFs). However, the official ECB investment fund statistics do not allow such differentiation, and this distinction cannot be made at the moment.

According to the UCITS Directive funds are required to be liquid, which in practice means they must be able to meet redemption requests twice a month and redemption proceeds have to be paid within a maximum of ten business days. In order to meet this liquidity requirements, the underlying investments in UCITS funds must also be liquid. In practice this is achieved by adherence to the eligible assets and diversification requirements. Redemptions on any trading day can be limited to 10% of the NAV of the fund with the balance carried over to the next trading day.

These considerations suggest construction of a liquidity indicator in line with the UCITS methodology, i.e. to construct the ratio of liquid assets (deposits with MFIs + short term debt holdings + equity) to the NAV. The proposed critical value for this indicator is 10% of NAV, which is equal to the maximum amount of redemptions on any trading day, as specified in the UCITS Directive. It is easy to observe that according to this criterion, the funds that appear more risky are the bond funds followed by the real estate funds, as presented in the Chart 9. For the other investment fund types the data does not point to any liquidity risks also according to the bucketing.[9]

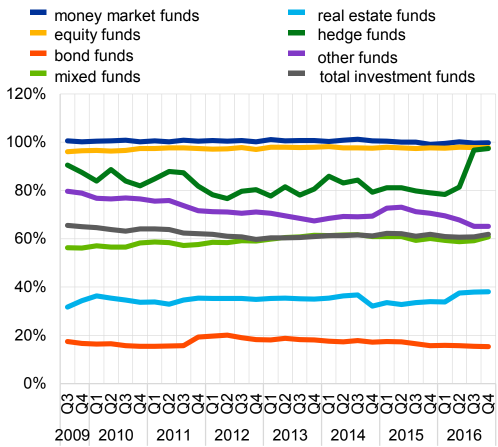
Regarding leverage, some initial help in calculating the benchmark values at the fund level can be found in the EU Directives. As for liquidity, the key legislations that govern leverage in the investment fund sector are the UCITS Directive and the AIFMD Directives. In most cases the leverage is measured as a ratio between the fund exposure and its net asset value.

UCITS funds can invest in a wide range of assets, including shares, corporate and government bonds, units in other UCITS, other types of approved securities and derivatives. They can place deposits with banks and invest in money market instruments. Under the commitment approach, UCITS exposure relating to derivative instruments cannot exceed the total net value of the portfolio. Leverage is strictly limited for UCITS funds: they can borrow only up to 10% of their assets provided that such borrowing takes place on a temporary basis. This legal requirement can be taken as a limit for leverage. In particular, our suggestion is to use the leverage indicator defined as loans received to total assets, where the critical value can be the one from the UCITS Directive. From the Chart 4 above it is possible to see that, hedge funds and real estate funds are above the threshold of 10%, showing high level of leverage compared to the chosen benchmark.

[9] Bucketing has been made on some qualitative assessment and results are available upon request.

Chart 9

EU investment funds: Liquidity transformation
(LIQ5, percentages; last observation: Q4 2016)



Source: ECB and ECB calculations.

Notes: Based on available data for the EU; Bulgaria, Croatia, Denmark, Sweden and the United Kingdom are not included. Deposits with MFIs plus short-term debt holdings plus equity holdings, as a share of net asset value, approximated by the total equity. During 2016, some hedge funds were reclassified as 'other funds' affecting the series for these types of funds.

The leverage ratio indicators used by the UCITS are also in line and consistent with the IOSCO and the FSB. The IOSCO calculated leverage as the gross notional exposure (GNE) over NAV, where the GNE is the absolute sum of all long and short positions, including gross notional value (delta-adjusted where applicable) for derivatives. Unfortunately, the data on these exposures for the EU are not available within the current statistics. On the other side, the FSB proposed a leverage indicator defined as market value of total assets to NAV. While it is possible to construct this indicator using the EU wide available statistics, the FSB does not provide any benchmark value based on which risks in funds could be assessed.

Additional suggestions can be made in assessing the risks of other entities, such as FCLs and SDDs. The data for these entities are not yet available, however, they will be soon published by the ECB for the euro area aggregate.[10] According to different surveys conducted by the ECB and the EBA, FCLs and SDDs are present in most of the euro area countries and in some countries are consolidated in banking sector.[11] As these entities are consolidated in banking groups, it might be appropriate to apply the regulatory requirements in the banking sector for leverage and liquidity as benchmark values for SDDs and FCLs. Furthermore, data on leverage and liquidity for banks are available from the ECB statistics of consolidated banking data and from the ESRB risk dashboard[12]. The proposal for macro prudential purposes is to apply the same benchmark values for the shadow banking entities already applied to banks for consolidated entities.

In conclusion, some initial work on the intensity of risks for shadow banking entities is currently ongoing. Legal frameworks, international initiatives and entities consolidated in banking sector, might give some guidance on how to construct benchmark values. However, lack of data and lack of macro prudential setting prevent a complete analysis and assessment on these issues.

[10] See the next section.

[11] See also https://www.esrb.europa.eu/pub/pdf/occasional/20160727_occasional_paper_10.en.pdf

[12] See https://www.esrb.europa.eu/pub/rd/html/index.en.html

3. Data gaps and data initiatives to improve the measurement of shadow banking

While the use of macro data is acknowledged to be suitable for macro assessment of non-bank financial intermediation, data gaps might prevent an adequate assessment of all the risks related to shadow banking. The ESRB made an assessment of the data gaps on the euro area level. Results show that "A significant part of the euro area financial sector however is not covered by detailed balance sheet statistics – specifically OFIs other than FVCs (so called OFI residuals)"[13]. Data gaps have been identified with respect to the entities not covered by the ECB statistical regulations, i.e. OFIs other than FVCs. These entities are mainly financial corporations involved in lending (FCLs) and securities and derivatives dealers (SDDs).

Consequently additional data initiatives are in place to fill these gaps for monitoring purposes. The aim of this section is to present the ECB initiative of the new aggregated data set to address these data gaps (i.e. FCLs). It has to be emphasised that considerable work on data collection, especially on the residuals, has been done also at the national levels. In context of the overall monitoring of OFIs there is a specific need to focus on SDDs and FCLs, as these entities play a relevant role in the financial intermediation and might constitute an important part of the shadow banking system in many developed economies.

FCLs are defined as financial corporations principally specialised in asset financing for households and non-financial corporations. This includes financial leasing, factoring, mortgage lending and consumer lending companies. While for some countries only leasing or factoring corporations are covered, in other countries finance companies that provide credit to consumers are also included. As the first step, the ECB conducted a survey across the Eurosystem with an aim to better harmonize data collection practices across countries. Furthermore, since the FCLs may be regarded as a part of the shadow banking system if they engage in credit intermediation outside the regulatory perimeter and since their business is highly interconnected with the regular banking system, the survey also investigated different business models. The results showed that a large part of the total assets of these entities appears to be consolidated in banking groups, although this varies among countries. However, according to the survey, funding from banks does not appear to be the main source of financing for FCLs.

SDDs classified as OFIs are financial corporations authorised to provide investment services to third parties by investing in financial instruments on their own account as their business and principally engaged in the following financial intermediation activities: a) Trading on their own account and/or risk, as 'securities and derivatives dealers', in new or outstanding financial instruments through the acquisition and sale of those financial instruments for the exclusive purpose of benefiting from the margin between the acquisition and sale price. This also includes market-making activities. b) Underwriting financial instruments and/or placing financial instruments on a firm commitment basis. c) Assisting firms in issuing new financial instruments through the placement of new financial instruments involving either a firm underwriting commitment or standby commitment to issuers of new issues[14].

Regulatory regime plays an important role in ensuring consistency in the definition. Definition and regulatory regimes are similar in all the respondent countries for the SDDs. The reason for this homogeneity is that countries use Markets in Financial Instruments Directive to classify SDDs at national level.

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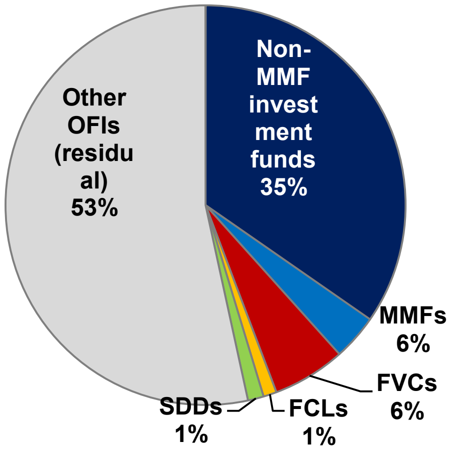
[13] See https://www.esrb.europa.eu/news/pr/date/2016/html/pr160727.en.html. Over half of the OFI residual is in just two countries, Luxembourg and the Netherlands.

[14] The definition is consistent with the Guideline of the ECB on monetary and financial statistics (recast) (ECB/2014/15) (2014/810/EU) https://www.ecb.europa.eu/ecb/legal/pdf/oj_jol_2014_340_r_0001_en_txt.pdf

The significance of SDDs and FCLs in terms of total assets of the OFIs at the euro area aggregated level is almost the same for the two subsectors and relatively significant (2.4% of OFI total assets). However not all euro area countries provide the information required. Work is on-going to improve the data collection.

Chart 10

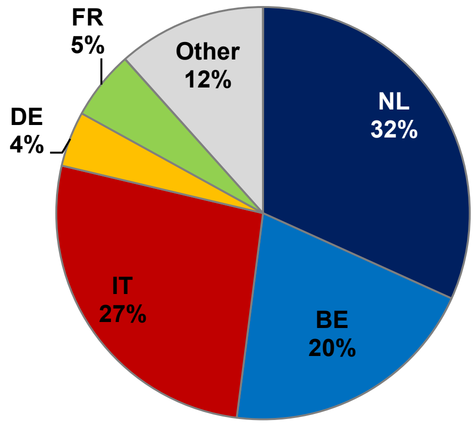
Breakdown of euro area investment funds and OFIs by type
(percentages; last observation: Q3 2016)



Source: ECB and ECB calculations.

Chart 11

Breakdown of euro area FCLs by total assets
(percentages; last observation: Q3 2016)



Source: ECB and ECB calculations.

Notes: Other includes Austria, Cyprus, Estonia, Greece, Lithuania, Latvia, Malta, Portugal, Slovenia and Slovakia.

On the funding side, the ECB survey showed that bank funding does not represent the major source of funding for the SDDs. A similar pattern is observed for the FCLs. However, some differences among countries exist on the way FCLs are funded by credit lines provided by banks as in some cases FCLs are controlled or consolidated in the banking groups. Percentages of SDDs assets consolidated in the banking sectors vary among countries. While in several euro area countries SDDs assets and activities are fully consolidated (e.g. France), this is not the case for all countries. The percentage is larger for those countries, whose share of SDDs total assets in the euro area is larger. For the FCLs the assets consolidated in the banking sector vary among the countries and only in two countries are fully consolidated in banking sector.

In general, business models of SDDs and FCLs are not very well known. Their activities typically fall within one of the shadow banking activities, i.e. maturity transformation, liquidity transformation, use of leverage, and credit risk transfer (through securitisation and/or credit derivatives). Regarding the involvement in the specific activities of shadow banking, qualitative and quantitative information is very limited. Furthermore the allocation of the FCLs in the shadow banking sector cannot be conclusively agreed.

The ECB is in the process to publish the euro area aggregated balance sheet data for the FCLs. However, the national breakdowns will not be available since data are not collected. The data will be published annually and available on the quarterly frequency. Outstanding amounts (on aggregated basis, i.e. positions between FCLs will not be netted out) and differences in outstanding amounts adjusted for reclassifications will be made available. On asset side four categories will be presented: 1) Loans, granted by the FCLs to other institutions. Breakdown on loans to MFIs and non-MFIs will be available as well; 2) Equity, which includes FCLs' holdings of shares and other equity (investment fund shares/units are not included); 3) Debt securities held; and 4) Remaining assets for FCLs defined as "assets not included elsewhere". The liability side will present the following four categories: 1)

Deposits and loans taken; 2) Debt securities issued; 3) Capital and reserves; and 4) Remaining liabilities.

Breakdown of total assets for euro area FCLs is presented in Chart 11. It follows that over three quarters of the euro area FVC total assets are concentrated in just three countries, namely the Netherlands, Belgium and Italy.

4. The role of micro data

While the work on closing the macro data gaps is ongoing in terms of aggregated data collection on the OFI subsectors, which will improve the monitoring of shadow banking under the entities approach, the scope of available micro data is widening as well. Micro data will allow further analysis of risks based on the activities approach. The aim of this section is to show how several methodological and information gaps in the shadow banking can be solved with the use of micro data.

As clarified in section one, an important issue in narrowing down the perimeter of shadow banking is whether to include or exclude entities consolidated in the banking groups. In this respect, additional granular data coming from the supervisory database will provide more information on the entities consolidated in the banking groups. Assessment of shadow banking entities consolidated in banking groups using supervisory data can thus shed some light on the risks and characteristics of these entities.

Another important aspect in mapping the perimeter of shadow banking is the banking activities carried outside the banking sector. The EBA has already worked on this aspects and follow-up to the report on the perimeter of credit institutions[15] is also expected. As Register of Institutions and Affiliates Database (RIAD) collects lists of financial institutions maintained for statistical purposes it might be useful to map the EBA results with the RIAD database to asses possibility of capturing entities that undertake credit activities outside the banking perimeter and their consolidation within banking groups.

Furthermore, several ECB initiatives as well as EU market regulations and directives including AIFMD, EMIR[16] and SFTR will increase data availability permitting the further development of risk metrics for the shadow banking sector. Data for securities financing transactions (SFTs) might come from the Money Market Statistical Reporting (MMSR). The MMSR micro data on activities might allow to match money market entities that carry out these activities with their counterparties, which are often OFI entities. By combining new databases the ECB might help to improve the measurement of the riskiness of shadow banking as for example the interconnectedness with the regular banking system and its systemic risk. Starting with data to be collected via AnaCredit[17], more information on loans to FCLs, SSDs, IFs and other OFIs will be available. This will in turn permit a better assessment of MFIs interconnectedness with the OFIs subsectors.

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15 Opinion addressed to the European Commission, relating to the perimeter of credit institutions and namely to the different approaches across the EU Member States on the interpretation of the definition of 'credit institution' in the Capital Requirements Regulation. See https://www.eba.europa.eu/-/eba-publishes-an-opinion-on-the-perimeter-of-credit-institutions

16 See ESRB Occasional Paper, "Shedding light on dark markets: First insights from the new EU-wide derivatives dataset": *https://www.esrb.europa.eu/pub/pdf/occasional/20160922_occasional_paper_11.en.pdf?c067e1f68ae0fe23925b88c613c546a8*

17 AnaCredit should provide high-quality and timely information on debtors and their respective credits (i.e. type of credit, outstanding debt, number of days past due date, date of origination and contractual maturity, type of interest rate and currency of the credit).

Conclusion

The ECB and the ESRB are closely following developments in the EU shadow banking sector and recognize the increasing need for more granular statistical data. Several initiatives on the Eurosystem level as well as on the national levels are ongoing with an aim to close the existing data gaps, especially the ones in relation to the OFI sector. Entities consolidated in the banking groups and relation between entity-based and activity-based approaches still remain open methodological issues that make complete assessment of shadow banking risks a difficult task. New micro datasets developed by the ECB and/or made available through various EU legislations may offer rich data sources that can in future be used to derive additional indicators, complementing existing aggregated datasets, allow for a more detailed assessment of risks in this part of the EU financial system and overall enhance macroprudential analysis. Additional efforts are required, however, to close data gaps so as to enable a consistent mapping of cross-border and cross-sector risks and provide a more holistic view of other financial institutions and their engagement in shadow banking activities.

References

Agresti, A M (2015): "Shadow banking: Some considerations for measurements purposes".

Agresti, A., Israël, J-M., and Jackson, C. (2013): "Non-bank financial intermediation in the euro area: current challenges", Banks and Bank Systems, Vol. 8(4).

Agresti A, Patrizia B and Poloni (2008): "The ECB and IMF indicators for the macro-prudential analysis of the banking sector: a comparison of the two approaches".

Bakk-Simon, K, Borgioli, S, Giron, C, Hempell, H, Maddaloni, A., Recine, F and Rosati, S (2012): "Shadow banking in the euro area: an overview", ECB Occasional Paper Series, No. 133.

Bank of England (2014): "Financial Stability Report", December.

BIS (2015): "Consolidation and corporate groups: an overview of methodological and practical issues" Prepared by a Task Force of the Inter-Agency Group on Economic and Financial Statistics August 2015.

Claessens, S. and Ratnovski, L. (2014): "What is Shadow Banking?", IMF Working Paper, No. 14/25.

Constâncio, V, (2015): "Financial stability risks, monetary policy and the need for macro-prudential policy", speech at the Warwick Economics Summit, 13 February.

Deloitte (2012): "The Deloitte Shadow Banking Index: Shedding light on banking's shadows", Deloitte Center for Financial Services.

EBA (2015): "Consultation Paper Draft EBA Guidelines on limits on exposures to shadow banking entities which carry out banking activities outside a regulated framework under Article 395", Regulation (EU) No. 575/2013", London 2015.

EBA (2014): "Opinion on the perimeter of credit institutions".

ECB (2011): "The financial crisis in the light of the euro area accounts: a flow-of-funds perspective", Monthly Bulletin, October, pp. 99-120.

Errico, L, Harutyunyan, A, Loukoianova, E, Walton, R, Korniyenko, Y, Amidžic, G, AbuShanab, H, and Shin, H, S (2014): "Mapping the Shadow Banking System Through a Global Flow of Funds Analysis", IMF Working Paper, No. 14/10.

ESRB (2016), Occasional Paper: "Shedding light on dark markets: First insights from the new EU-wide derivatives dataset".

ESRB (2016a): "ESRB Macroprudential policy beyond banking: an ESRB strategy paper" July 2016.

ESRB (2016b): "Assessing shadow banking – non-bank financial intermediation in Europe" No 10/ July 2016.

ESRB (2017): "Second ESRB EU Shadow Banking Monitor".

FSB (2011a): "Shadow Banking: Scoping the Issues. A Background Note of the Financial Stability Board", 12 April.

FSB (2011b), "Shadow Banking: Strengthening Oversight and Regulation. Recommendations of the Financial Stability Board", 27 October.

FSB (2012), Global Shadow Banking Monitoring Report 2012, 18 November.

FSB (2013a), Strengthening Oversight and Regulation of Shadow Banking. Policy Framework for Strengthening Oversight and Regulation of Shadow Banking Entities, 29 August.

FSB (2013b), Global Shadow Banking Monitoring Report 2013, 14 November.

FSB (2014a), Consultative Document: Assessment Methodologies for Identifying Non-Bank Non-Insurer Global Systemically Important Financial Institutions, 8 January.

FSB (2014b), Global Shadow Banking Monitoring Report 2014, 5 November.

FSB (2014c), Standards and processes for global securities financing data collection and aggregation, 13 November.

Godfrey, B, and Golden, B, (2012): "Measuring Shadow Banking in Ireland using Granular Data", Central Bank of Ireland Quarterly Bulletin, October, pp. 82-96.

Harutyunyan, A., Massara, A., Ugazio, G., Amidzic, G., Walton R. (2015): "Shedding Light on Shadow Banking", IMF Working Paper, No. 15/1.

IMF (2013): "Global Financial Stability Report 2013", October.

IMF (2014a): "Global Shadow Banking Monitoring Report 2014", April.

IMF (2014b): "Global Shadow Banking Monitoring Report 2014", October.

Pozsar, Z, Adrian, T, Ashcraft, A and Boesky, H (2010): "Shadow banking", Federal Reserve Bank of New York Staff Report, No. 458, July.

Pozsar, Z, and Singh, M (2011): "The nonbank-bank nexus and the shadow banking system", IMF Working Paper, No. 11/289.

Pozsar, Z, (2014): "Shadow banking: The Money View", Office of Financial Research Working Paper, No. 14/4.

Tarullo, D,K, (2013): "Shadow Banking and Systemic Risk Regulation".

Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

IFC-National Bank of Belgium Workshop on "*Data needs and Statistics compilation for macroprudential analysis*"

Brussels, Belgium, 18-19 May 2017

Statistical work on shadow banking: development of new datasets and indicators for shadow banking[1]

Anna Maria Agresti and Rok Brence,

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
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Statistical Work on Shadow Banking: Development of new Datasets and Indicators

Anna Maria Agresti
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Irving Fisher Committee Workshop –
National Bank of Belgium
Brussels, 18-19 May 2017

Overview of presentation

1. Introduction
2. ESRB and FSB approaches
3. Risks and measurement
4. New data sets
5. Use of Micro data
6. Conclusions

Introduction

- **Macro-mapping"** exercise recommended by the Financial Stability Board as *methodological framework* **broadly** endorsed at EU level by the European Systemic Risk Board (ESRB)
    - Use of aggregated data and some differences might be observed

- Macro data help construct *risk indicators*

- **Intensity of risks** assessed via *dispersion measures* and *bucketing of indicators' values*

- Current data gaps and on-going initiatives by ECB to address them
    - e.g. new statistics on *financial corporations involved in lending* (FCLs)

- **New granular data sets** and regulatory data (such as AIFMD) might also reduce data gaps

Macro measurement: FSB and JEGS 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*:
    - The FSB introduced a narrow measure: via *economic concept*

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**"*

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*

- 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

ESRB approach: narrowing down

- FSB **narrowing down approach** excludes *equity investment funds* from the broad definition as they do not primarily engage 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

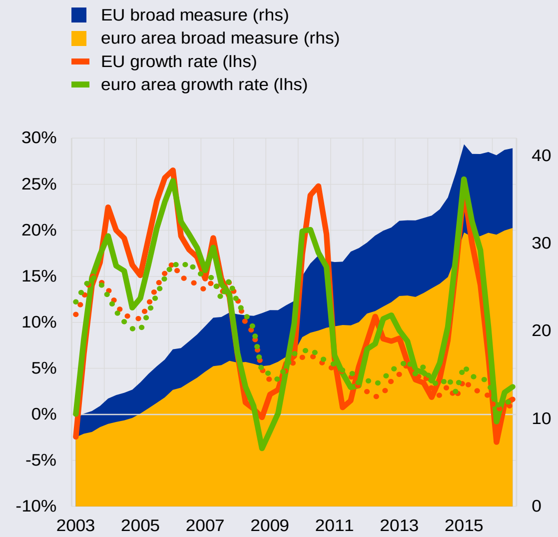
- The main reason why ESRB measures do not exclude consolidated entities is the *lack of reliable data*

ESRB approach: Macro measurement (4/4)

- Broad measure comprises the **OFI sector plus IFs**
- Total assets amount *in Q3 2016*
  - EU-wide to **€ 39 trillion**
  - Euro area to **€ 30 trillion**
- Outstanding amounts grew **300%** over the past decade; **upward trend** is clear
- Share is **37%** of EU financial sector assets
- ESRB decided **not to apply** FSB criterion for narrowing down focus on risks

Chart: Broad measure of EU and euro area shadow banking (investment funds and other financial institutions)
(*€ trillions and annual growth rates; last observation: Q3 2016*)

Source: ECB and ECB calculations.



Notes: Annual growth rates based on changes in outstanding amounts are indicated with the continuous lines. Dotted lines indicate annual growth rates based on transactions – i.e. excluding the impact of FX or other revaluations and statistical reclassifications.

Risks measure : ESRB indicators (1/4)

Risk indicator	Risk indicator metric	Ref.
Maturity transformation	Short-term assets / Total assets	MAT1
	Long-term assets / Total assets	MAT2
	Short-term liabilities / Short-term assets	MAT3
	Long-term assets / Short-term liabilities	MAT4
Liquidity transformation	(Total assets - Liquid assets) / Total assets	LIQ1
	Short-term liabilities / Liquid assets	LIQ2
	Short-term assets / Short-term liabilities (current ratio)	LIQ3
	Liquidity mismatch: Liquid liabilities less liquid assets, as share of total assets	LIQ4
	(Deposits with MFIs + Short-term debt holdings + Equity holdings) / NAV	LIQ5
Leverage	Leverage = Loans received / Total liabilities	LEV1
	Leverage multiplier = Total assets / Equity	LEV2
Credit intermediation	Loans / Total assets	CRE1
	“Credit assets” (loans and debt securities) / Total assets	CRE2
Interconnectedness with the regular banking system	Assets with credit institution counterpart / Total assets	INT1
	Liabilities with credit institution counterpart / Total assets	INT2

Risks measure : Different approach (2/4)

- ESRB continues to work on the enhanced monitoring of the EU shadow banking to provide **more detailed analysis of risks**.

    - ➢ **ESRB** ***risk metrics*** does not provide benchmark values for risk intensities

- **FSB *economic approach*** does not appear to be based on any quantitative assessment of risks

- As a part of this work, some initial benchmark values

    - ➢ Activities and entities **are very heterogeneous**, not possible to construct critical values for the entire shadow banking.

- **Two approaches were chosen** to build up the benchmark values,

    - ➢ analysis with ***percentile distribution***

    - ➢ ***bucketing of indicators' values*** (on clustering of indicators' values in various buckets)

Risks measure : Dispersion measure (3/4)

- ***Dispersion measures*** of liquidity indicator LIQ1 show large variation of liquidity transformation between countries
- ***EU aggregate*** lies above interquartile range (i.e. difference between third and first quartile) and thus slightly overestimates median value.

- Same indicator for the **real estate funds** sector, shows sector engages in the most ***pronounced liquidity transformation***.

Chart 5

Liquidity transformation: total investment funds (LIQ1, percentages; last observation: Q4 2016)

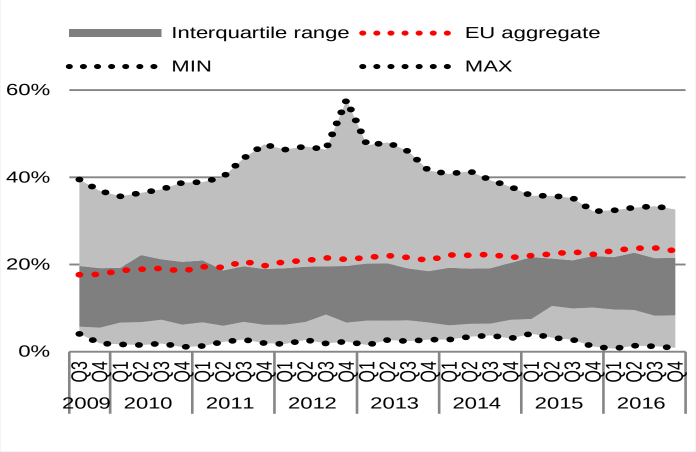
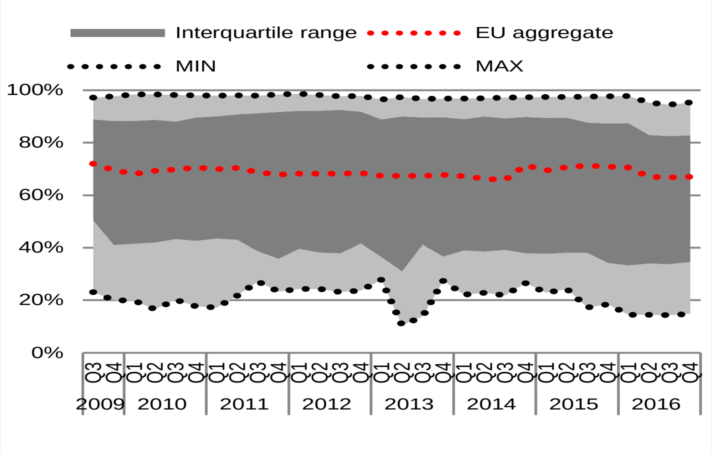


Chart 6

Liquidity transformation: real estate funds (LIQ1, percentages; last observation: Q4 2016)



Risks measure : Liquidity indicator for IF (4/4)

The aim of **cluster analysis** is to identify groups of similar objects (Liquidity indicators of subsector of OFIs)

- ***according to selected variables*** (level of Liquidity indicators that might represent larger and different level of risks).
- Clustering of indicators' ***values in various buckets***

UCITS. Redemptions on any dealing day can be limited to ***10% of NAV*** of the fund with the balance carried over to the next dealing day.

- If a UCITS opts for bi-monthly liquidity, the maximum redemption pay out in any one month can be limited to **20% of NAV**

Under ***10% and 15% scenarios*** (total net outflow/total net assets expressed in %), corporate bond and securitisation markets might be under stress.

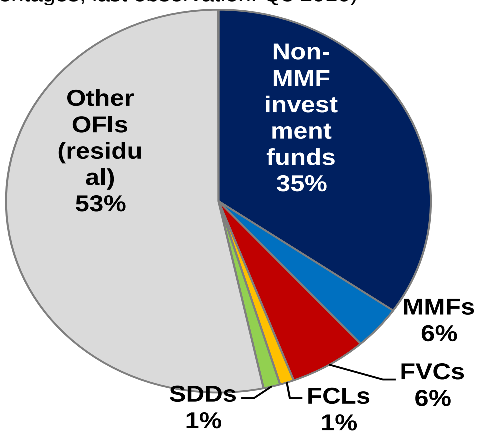
- (Result from ESRB *JEGS policy task force*)

Macro measurement: New data sets

- **Additional data initiatives** in place to fill gaps for monitoring purposes.
- ECB initiative to publish new aggregated data set to address these data gaps (**i.e.** ***Financial Corporation engaged in Lending*** **FCLs**).

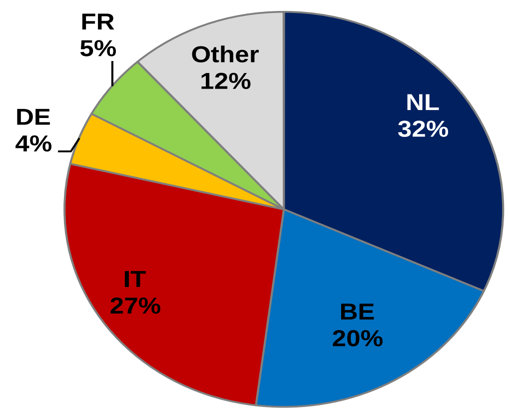
- **ECB survey showed** some differences among countries exist on the way **FCLs** are funded by credit lines provided
  - ➢ Some cases FCLs are ***controlled*** or ***consolidated*** in the banking groups

Chart 8
Breakdown of euro area investment funds and OFIs by type
(percentages; last observation: Q3 2016)



Source: ECB and ECB calculations.

Chart 9
Breakdown of euro area FCLs by total assets
(percentages; last observation: Q3 2016)



Source: ECB and ECB calculations.

Notes: Other includes Austria, Cyprus, Estonia, Greece, Lithuania, Latvia, Malta, Portugal, Slovenia and Slovakia.

Micro approach: Granular data

- **Micro data** will allow further analysis of risks based on activities approach.

- *Supervisory database* will provide more information on the entities **consolidated in the banking groups**.
  - Assessment ***using supervisory data*** can thus shed some light on the risks and characteristics on these entities.

- ESCB *Register of Institutions and Affiliates Database* (**RIAD)** collects lists of financial institutions maintained for statistical purposes

- Possible to map **entities that undertake credit activities *outside the banking perimeter*** and their consolidation within banking groups.

- EU market regulations and directives including **AIFMD, EMIR and SFTR** will *increase data availability* and further development of risk metrics

Conclusions and way forward

- **ECB and the ESRB** closely follow developments in EU shadow banking sector
  - ➢ recognize increasing need for more granular statistical data.

- Several initiatives at Eurosystem level and at national level ongoing with aim to close existing **data gaps**

- **Entities consolidated in the banking groups** and relation between entity-based and activity-based approaches still remain open

- **New micro datasets** developed by the ECB and/or made available through various EU legislations are offering new data source
  - ➢ Can be used to derive **additional indicators**, allow for more detailed assessment of risks
  - ➢ **overall enhance** macroprudential analysis.

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Peer-to-peer lending: an emerging shadow banking data gap[1]

James Younker,

Bank of Canada

[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.

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Peer-to-Peer Lending:

An Emerging Data Gap in Shadow Banking

May 2017

James Younker
Data and Statistics Office
Bank of Canada

This presentation reflects the views of the author and not the Bank of Canada

Peer-to-Peer Lending: An Emerging Data Gap in Shadow Banking

The key takeaways

1. There is an emerging need for more data on peer-to-peer lending.

2. Collecting this data is feasible and several options exist.

Peer-to-Peer Lending: An Emerging Data Gap in Shadow Banking

The presentation is structured in four parts

1. Overview of peer-to-peer lending
2. Why peer-to-peer lending is important to a regulator
3. How peer-to-peer lending is currently regulated
4. How data on peer-to-peer lending can be collected

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Overview of peer-to-peer lending

Peer-to-peer lending companies match borrowers and lenders online

- Peer-to-peer lending is a form of shadow banking where loans can be made through an online platform outside of traditional institutions.
- Normally the peer-to-peer lending company collects a service fee while not being a credit counterparty.

Examples:

Lending Club (US)
Prosper (US)
RateSetter (UK)
Zopa (UK)
Funding Circle (UK)

Lending Loop (Canada)
Auxmoney (Germany)
Younited Credit (France)
CreditGate24 (Switzerland)

Overview of peer-to-peer lending

Typical business model of a peer-to-peer lender

- Website matches borrowers to lenders, collects a fee and administers loans.
- Loans are frequently personal and small business loans.
- Lenders are frequently conventional lenders and securities investors.
- Customers are attracted by lower rates and/or flexible lending standards.
- Market position is established by low overhead cost and possibly new credit analysis techniques.

Overview of peer-to-peer lending

Variations upon the typical business model

- Additional loan products including mortgages and wholesale lending
  - Examples: in the UK peer-to-peer mortgage lending is established and one large firm has also published details on notable wholesale lending to other lenders.
- Securitization and sale of peer-to-peer originated loans
  - Examples: beginning in 2016 large US and UK firms began partnering with securities dealers to securitize peer-to-peer originated loans.
- Funding loans with retail deposits (using a banking licence)
  - Example: one large UK firm is currently in the process of applying for a banking licence.

Overview of peer-to-peer lending

Variations upon the typical business model (continued)

- Cross-border lending
  - Example: one large European firm has significant cross border activity matching borrowers in four countries with lenders internationally.

- Maturity transformation
  - Example: one large UK firm use to offer borrowers terms of 12 months or more and lenders terms of 1 month or more implicitly creating a maturity transformation.

Why peer-to-peer lending is important to a regulator

It is important for two main reasons

1. Peer-to-peer lending is growing at a very rapid rate.
2. Several peer-to-peer lending companies have failed, raising concerns about regulatory adequacy.

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Why peer-to-peer lending is important to a regulator

Peer-to-peer lending is growing at a very rapid rate

Driven by competitive pricing and/or flexible lending standards the peer-to-peer market has rapidly grown across 20+ countries.

Peer-to-Peer Lending Activity**		
	Outstanding Loans (USD) [Approximate values +/- 30%]	Approximate Year-over-Year Growth
UK	4 billion	37%
US	4 billion	NA
Canada	1 billion*** (<1% booked in Canada)	NA
China	130 billion	73%

** Data sources and compilation methodology is described in end notes.

***The Canadian booked abroad amount largely reflects conditional commitments for loan purchases.

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Why peer-to-peer lending is important to a regulator

Several peer-to-peer lending companies have failed raising concerns about regulatory adequacy

Failure due to fraud

- The lack of industry transparency and online nature of peer-to-peer lending has created an environment prone to fraud and this has lead to failures.
    - Examples: a Swedish peer-to-peer lender failed as a result of fraud and a large number of fraud failures have been documented in China including one Ponzi scheme that cost investors $7.6 billion.

Failure due to poor credit analytics

- Many peer-to-peer lenders have attempted to achieve market share by developing new credit analytics, and some of these analytical approaches have performed poorly and resulted in failures.
- The problem is compounded by many of the novel big data based approaches to credit analytics not having historical data to thoroughly test performance during crisis periods.
    - Examples: there have been multiple well publicised cases in the UK of peer-to-peer lenders failing due due to poor credit analytics.

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Why peer-to-peer lending is important to a regulator

Several peer-to-peer lending companies have failed raising concerns about regulatory adequacy (continued)

Failure due to mismanaged loss provisioning plans

- Many peer-to-peer lenders collect a percentage of loan originations to create a reserve fund in order to cover loan losses.
- Typically the reserve fund is used to guarantee investors zero losses on their loans conditional on the survival of the reserve fund.
- If a loss provisioning plan is mismanaged it can result in an outcome similar to a Ponzi scheme where the early investors are paid-off with the funds of the later investors until a catastrophic failure occurs.
  - Examples:
    - A number of peer-to-peer lenders have failed in China due to mismanaged loss provisioning plans leading to authorities banning the practice in 2016.
    - We do not have an example of this occurring in the developed world; however, several peer-to-peer lenders have been criticized for having mismanaged or dangerously low reserve funds including one large company in the UK.

How peer-to-peer lending is currently regulated

Regulation of peer-to-peer lending is evolving

- Banking or securities authorities have established regulations for peer-to-peer lending in most jurisdictions.
- Unlike other online markets, regulators have been generally successful applying regulations. This is because lenders typically need to comply with regulations for debts to be legally enforceable.
- However, many open questions remain relating to: transparency, loss provisioning, securitizations, recovery/resolution, and credit analytics.
- Overall there is an expectation that the regulation of peer-to-peer lending will continue to evolve with the industry.

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How data on peer-to-peer lending can be collected

Evolving regulations will likely require additional data and several options are available

1. Direct regulatory data collection
2. Indirect regulatory data collection (via other financial institutions)
3. Collection of publicly available data (via web-scraping)

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How data on peer-to-peer lending can be collected

Direct regulatory data collection

- This option consists of mandatory reports submitted to the regulatory supervisor.
- The approach has already been implemented by the FCA and SEC and is likely feasible for the regulatory authority in most jurisdictions.
- Direct regulatory data collection has the broadest coverage and produces the most detailed information; however, it also incurs the largest industry cost.

How data on peer-to-peer lending can be collected

Indirect regulatory data collection (via other financial institutions)

- This option consists of regulators acquiring data on peer-to-peer lending through the direct regulatory data collections from other financial institutions.
- What makes this option feasible is that in most countries regulated financial institutions are a large proportion of the lenders in the peer-to-peer market.
- The approach has frequently been used by central banks or macro-prudential authorities in situations where they have system wide oversight responsibility but lack authority to collect information from some entities.
- Indirect regulatory data collection has less market coverage and produces more limited information than the direct approach; however, it may be useful in cases where the direct approach is not permitted or incurs too much industry cost.

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How data on peer-to-peer lending can be collected

Collection of publicly available data (via web-scraping)

- This option consists of regulators retrieving data from publicly available websites through an automated web-scraping process.
- What makes this option feasible is that peer-to-peer lending websites post a large amount of detail online about current lending and outstanding loans.
- The methodology of web-scraping data collections is well understood, but there are technical limitations and issues relating to reputational risk.
- Publicly available data collections produces the most limited information of the three options; however, it also incurs the little to no industry cost.

Key Takeaways

1. There is an emerging need for more data on peer-to-peer lending.

2. Collecting this data is feasible and several options exist.

Notes

The values for approximate outstanding loans presented on slide nine are compiled as follows. The data for the UK is taken from the website of the industry association P2PFA. The data for China is from Wangdaizhijia as reprinted by the Financial times on April 3 2017. The data for Canada and the US was compiled by the author from publications of individual firms. Finally all amounts were converted in to USD equivalent. These values are only meant to serve as an approximation and should be used with caution.

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Interconnectedness of shadow banks in the euro area[1]

Celestino Girón and Antonio Matas,
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.

Interconnectedness of shadow banks in the euro area

Celestino Girón, Antonio Matas-Mir[1]

Abstract

The ESCB is working towards the identification of shadow banks in the framework of the sector accounts. So far, the OFI sector –which encompasses the ESA 2010 sectors other financial institutions (S125), financial auxiliaries (S126) and captive institutions and others (S127)- is the best proxy available to capture the phenomenon in the euro area, notwithstanding certain conceptual limitations. At the same time, the availability of counterpart sector information for financial assets and liabilities in sector accounts, or who-to-whom (w-t-w) data, has notably improved for euro area countries recently with the extension of the ECB data requirements in the field to debt securities, quoted shares and investment fund shares.

We use this data framework to make a comparison of shadow bank interconnectedness across the various euro area countries. We construct debt networks with the newly available w-t-w data, and characterise the linkages of the OFIs sector with the rest of the economy using eigenvector centrality, a network centrality metrics.

Keywords: sector accounts, financial accounts, shadow banking, other financial intermediaries, who-to-whom matrices, financial networks, eigenvector centrality, Euro Area Accounts (EAA)

JEL classification: C65, E16, G23

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Contents

1. Introduction

The interconnectedness of shadow banks with the rest of the financial system and the overall economy is widely recognised as a key element in monitoring systemic risks. For instance, the Financial Stability Board (FSB) has been regularly examining interconnectedness indicators (see FSB, 2017) within the shadow banking annual monitoring exercise it conducts since 2011. Characterising and quantifying their degree of connectedness helps, inter alia, to understand potential financial distress contagion channels mediated by these entities and the ensuing propagation and amplification dynamics.

However, metrics of interconnectedness typically focus on direct linkages between economic agents whilst failing to capture indirect, more intricate connections. For instance, the FSB uses the indicator *"bank interconnectedness funding risks from OFIs"*, defined as the ratio of bank liabilities to selected financial institutions to total assets. Yet risks on bank funding stemming from funding risks faced by OFIs themselves are *not* captured by this indicator[2].

In this paper we examine macro-economic level linkages also accounting for indirect linkages by using "eigenvector centrality", an interconnectedness measure borrowed from network theory. We construct financial linkage networks using who-to-whom (w-t-w) financial accounts data newly available in the framework of the Guideline of the European Central Bank (ECB) on financial accounts[3], and characterise the degree of interconnectedness of shadow banks using the above metrics.

In line with one of the FSB's monitoring aggregates, we use a broad measure of shadow banks, namely the Other Financial Institutions (OFIs) grouping as defined in the aforementioned ECB Guideline. This grouping may encompass activities and agents that may not be usually thought as shadow banks, whilst excluding others that are. Nevertheless, data availability considerations and the lack of a universally applicable definition of shadow banking justify our choice.[4]

We apply eigenvector centrality to networks constructed for an aggregate of debt instruments capturing only credit intermediation relationships (i.e. equity linkages are excluded). We use in our analysis data on tradable debt instruments on a w-t-w basis that are available for all euro area countries only since 2016. This

[2] A prime example of this during the financial crisis was the funding crisis faced in 2007 by the UK bank Norther Rock. Its business model relied heavily on funding mortgage originations through the capital markets by way of their subsequent securitisation. The drying up of demand for securitised products, which represented liabilities of non-bank securitisation vehicles, did eventually impact the funding of the bank itself.

[3] Guideline of the European Central Bank of 25 July 2013 on the statistical reporting requirements of the European Central Bank in the field of quarterly financial accounts (recast) (ECB/2013/24) (2014/3/EU).

[4] The FSB uses the term "Other financial Intermediaries", also under the acronym OFIs, for its "broad measure" of shadow banking. The definition we use here for OFIs is different from the FSB one. For a discussion, see section 3.

paper is the first one making a comparison of sectoral financial interconnectedness in the euro area based on an (almost) complete w-t-w debt network that also incorporates tradable instruments.

Section 2 introduces the w-t-w data used. Section 3 discusses the choices made for approximating shadow banks. Section 4 presents the methodology used, eigenvector centrality, and section 5 shows and compares the results of applying this approach to the euro area as a whole and to the individual country members. Section 6 concludes.

2. Who-to-whom financial data in the euro area

W-t-w accounts extend financial accounts by tracking counterparty information for both assets and liabilities in the system. For instance, the non-financial corporations (NFC) sector may hold debt securities recorded as an asset item on their balance sheet. In addition to the amount outstanding for the item, w-t-w accounts further break it down by sector of the issuer of the debt. A similar breakdown applies to each recorded liability, so that e.g. loans received by NFCs are broken down by sector of the lender. This applies to all sectors in the system, yielding one table of creditor/debtor relationships for each financial instrument presented on a w-t-w basis.

These tables facilitate a detailed analysis of the paths followed by financial investment flows to meet the final financing needs, inter alia allowing to identify bottlenecks and sectoral dependences. When prepared for balance-sheet data, w-t-w tables provide a portrait of intersector financial exposures and financing risks. Ideally, w-t-w accounts are fully consistent with the rest of elements in the financial accounts system. With creditor sectors in rows and debtor sectors in columns, each column total coincides with total liabilities for each sector in a given instrument, while each row sum coincides with total assets. This helps analysts link different aspects of related phenomena.

W-t-w tables embed information on indirect intersector financing patterns and on indirect exposures and risks. Applying appropriate tools, the analyst can identify investment flows that go from one sector to another but are channelled through a third sector. Indirect exposures between two sectors, say A and B, resulting from A's holdings of liabilities of a third sector C which in turns holds assets on B, can be quantified. Since w-t-w data are susceptible to be represented as mathematical matrices or network graphs, tools from these fields are particularly well suited to analyse quantitatively these kinds of relationships.

In the euro area, w-t-w tables are fairly complete since the ECB adopted a new Guideline on quarterly financial accounts (ECB/2013/24, footnote 1) to align to the new national accounts standard ESA 2010. Various enhancements were also adopted with the new Guideline, among which was the extension of the scope of w-t-w breakdowns for both the euro area as well as individual EU countries. W-t-w data for stocks and transactions of loans and deposits had already been available since 2010 reaching back to Q1 1999. With the new Guideline, they were extended to debt securities, quoted shares and fund share/units, with data back to Q4 2013. Only unquoted shares, other equity, financial derivatives, insurance technical reserves and other accounts are not yet available on this basis.

For euro area countries, the national w-t-w data cover relationships between domestic sectors and links of domestic sectors with sectors resident in other members of the euro area countries. In the case of loans, debt securities, quoted shares and mutual fund shares, cross-border data refer to assets of domestic sectors broken down by foreign issuing sector, while for deposits the data refer to liabilities of domestic sectors broken down by non-resident holding sector[5].

The cross-border data described above are instrumental to complete the full picture of intra euro area sector relationships included in the euro area w-t-w tables compiled by the ECB as part of the Euro Area Accounts –EAA (see Box 1 for a discussion of all sources used for euro area w-t-w tables). For the new instruments covered by the Guideline ECB/2013/24, euro area w-t-w tables have been published for the first time in April 2016[6].

Box 1

Compilation of who-to-whom tables in Euro Area Accounts[1]

The compilation of the euro area w-t-w accounts involves the combination and confrontation of a multitude of data sources. A predetermined data hierarchy is used to resolve cases where more than one candidate source exists for the same statistical concept. At the top of the data selection hierarchy are the euro area aggregates of the monetary financial institutions (MFI) statistics and the euro area balance of payments (BOP). This is justified by their reliability relative to other competing sources, but also to respond the users' preference to minimize discrepancies with these statistics within the financial accounts. Other euro area-level statistics used include investment fund (IF) statistics and government finance (GFS) statistics. It should be noted that as regards total loan borrowing and total debt issuance by general government the highest priority is assigned to GFS sources.

Data at the level of individual euro area countries from the national quarterly financial accounts (available in ECB/2013/24) are also used as a source. The need to combine both euro area-level primary statistics and national financial accounts stems, on the one hand, from the fact that the rest of the world financial account for the euro area is not the simple summation of national rest of the world accounts. This also extends to w-t-w accounts, since they include the rest of the world as both creditor and debtor sectors. On the other hand, national financial accounts data are required to cover sectors for which euro area level statistics are either not available, are not sufficiently detailed or are difficult to align with the ESA methodological requirements. This is the case for large sections of the other financial intermediaries, non-financial corporations, pension funds, and households.

The compilation of w-t-w tables proceeds in a fairly similar fashion for all instruments. For instance, deposits are mostly compiled from the counterparty detail available in MFI and BOP statistics, with some gaps covered by national financial accounts. The loans tables are also mostly determined by MFI and BOP statistics, again with the exceptions of some gaps. Securities are compiled following a similar approach, except for two specificities. Unlike for loans and deposits, MFIs do not report on the counterpart sector to their liabilities in the form of marketable securities. This must be sourced from the national financial accounts, which in turn obtain it from the various security-by-security databases on holdings available at national central banks (NCBs) and/or from the ECB's security holdings statistics (SHS). In addition, MFI statistics do not provide stocks of security holdings at market value, so that their compilation also falls back on the national financial accounts.

1) Extract from Matas-Mir and Willeke (2017)

Mainly due their better coverage, the interconnectedness analysis in this paper is restricted to debt instruments only, using an aggregate comprising deposits,

5 This asymmetry with respect to cross-border deposits is explained by the fact that the best quality information on this instrument can be typically collected from the issuer, rather than from the holder, of cross-border deposit liabilities.

6 Country data and euro area data can be found in the ECB websites (ECB 2017a, 2017b)

loans and securities other than shares. In any case, a focus on debt instruments is warranted on behavioural grounds in assessing systemic risk as equity investors already expect uncertain outcomes from their holdings whilst holders of nominal claims typically expect to be repaid in full. Insofar as we look in detail to shadow banks, it is therefore the relationships between regulated and non- (bank-like) regulated channels of credit intermediation that constitutes the focus of this paper.

At the same time, we concentrate on interconnectedness as measured from balance-sheet data, as opposed to net transactions, to capture relationships akin to risk exposures and systemic impact, although our choice is also conditioned by methodological considerations favouring the use of non-negative data like those provided by balance-sheets[7] (see section 4).

3. Shadow banking and the sector Other Financial Institutions (OFIs)

In its 2015 Global Monitoring Report, the FSB describes shadow banking as "credit intermediation involving entities and activities outside of the regular banking system". Some other definitions have been used in the related literature, but they all refer one way or the other to financial intermediation activities that share certain features with traditional banking -in particular the presence of high leverage and the engaging in maturity and liquidity transformation- but do not operate under the same regulatory and supervisory framework, nor enjoy the same backstop mechanisms as banks do. These activities have been identified as major sources of systemic risk and have been pointed out as main contributors to the global financial crisis of 2007-2009[8].

While an exhaustive analysis of shadow banking activities would probably require the use of microdata to isolate specific risks depending on the specific analytical concerns, economic statistics can still serve to monitor the size, growth and interaction with the rest of the economy of such activities at a macro level. Thus, the FSB has been monitoring shadow banking trends at the global level since 2011 making use of financial accounts data inter alia. Similarly, the review of the sector accounts templates in the context of the G-20 Data Gap Initiative-2[9] is considering the inclusion of additional sector and instrument detail to facilitate shadow banking analysis.

7 An analysis of interconnectedness in relation to funding and role-over risks and financing patterns would require the use of transaction data as opposed to balance-sheets. Gross, rather than net, transaction data would still be adequate for eigenvector centrality and probably be more appropriate for the kind of analysis suggested, but they are not available in the sector accounts framework which follows a strict net approach in this respect.

8 See Bakk-Simon et al. for a description of the size and the structure of shadow banking within the euro area using the statistical data sources available to the ECB/Eurosystem.

9 Recommendations 5 and 8 of the G-20 Data Gap Initiative-2. See first progress report in IMF and FSB (2016).

In this paper we follow partially the monitoring strategy of the FSB[10], and focus on a financial accounts aggregate of non-bank institutional units where most of the shadow banking activities takes place. We thus proxy shadow banking by means of the aggregate data collected under Guideline ECB/2013/24 under the heading "Other Financial Institutions (OFIs)". The data collected inseparably groups the following sectors from the European System of Accounts (ESA, Eurostat 2013): "Other financial intermediaries, except insurance corporations and pension funds (S.125)", "Financial auxiliaries (S.126)" and "Captive financial institutions and money lenders (S.127)".

The inseparability of the OFIs data collected under the Guideline owes mainly to the lack of developed quarterly primary sources for some of the subsectors encompassed under the heading. Data from units as diverse as factoring corporations, holding companies or securities brokers and dealers are therefore indistinguishably included in the aggregate. While primary data sources and harmonised coverage exist for some of these units, like for Financial Vehicle Corporations for which ECB legislation is in place, the rest of the sector is compiled on the basis of data sources with little harmonisation, including surveys, and on the basis of counterpart information – itself often available only at the OFI grouping level - and/or residual calculation.

Like the "broad measure" in the FSB monitoring context, the OFIs data include institutions and activities that would not qualify for shadow banking under a closer examination, notwithstanding the difficulty of delineating an all-purpose, universally accepted shadow banking perimeter. Similarly, institutions and activities presenting features common to shadow banks might not be covered by the aggregate. The choice of OFIs as our shadow banking proxy is driven mainly by data availability considerations, notably the availability of sufficient w-t-w data for the euro area, which in turn derives from the aforementioned Guideline requirements.

Our OFIs aggregate differs from the corresponding FSB "broad measure of shadow banking", also by the same acronym but standing there for "Other Financial Intermediaries"[11]. The FSB measure excludes financial auxiliaries and public (non-bank) financial institutions, while OFIs include them. Financial auxiliaries cannot be currently identified separately within the financial accounts framework in most of the euro area countries. Similarly, (non-bank) public financial institutions are not generally separately available, the provision of data on that sector only being a voluntary annual requirement in the European statistical legal context (and only for all financial institutions, without a bank/non-bank distinction). While the amounts of assets and liabilities held/ issued by auxiliaries are small and are therefore not a

10 The FSB defines three aggregates in its 2016 Monitoring Report (FSB, 2017): MUNFI (or Monitoring Universe of Non-bank Financial Intermediation) which includes all non-bank financial intermediation (except public financial institutions and financial auxiliaries), OFIs (Other Financial Intermediaries), or "broad measure", which excludes from the previous aggregate insurance corporations and pension funds, and the "narrow measure" of shadow banking constructed on the basis of the economic functions of the financial institutions. The last aggregate is largely a non-sector accounts concept and is the focus of the financial stability risk monitoring made by the FSB. In this paper we use a sector account aggregate similar, but not identical, to the FSB "broad measure".

11 The FSB brad measure by the name OFIs is in turn different from the ESA sector "Other financial intermediaries, except insurance corporations and pension funds (S.125)". The latter is a subset of both the FSB measure and the OFIs aggregate used in this paper.

major source of discrepancy between the two measures, public non-bank financial institutions are relevant in some countries since the start of the financial crisis as a result of the setting up of "bad-bank" structures[12].

At the same time the FSB measure includes institutions not included in the OFIs aggregate used in this paper. Money Market Funds (MMFs) are considered by the FSB as part of its broad shadow banking measure as their shares are substitutes for deposits and potentially subject to runs. However, in Guideline ECB/2013/23 they are reported together with Monetary Financial Institutions (MFIs, the aggregate for banks in the ESA). Although separate financial accounts for MMFs are available or could be derived for most euro area countries using primary data, a w-t-w coverage fully consistent with ECB/2013/23 would still be difficult to come by.

A separate case is that of Investment Funds (IFs) other than MMFs (sector S.124 in ESA), which is included in the FSB broad measure, but excluded from our OFIs measure. As opposed to the cases above, IFs are treated separately in the Guideline, including for the w-t-w requirements. Nevertheless we prefer not to include them within the scope of our shadow banking proxy for two methodological choices.

First, the characterisation of the investment fund industry as "shadow banking" is dubious. In general, there is no unambiguous "credit intermediation" dimension in their activity given that their liabilities are in most cases not debt-like, but rather equity-like, as e.g. reflected in their ESA classification ("investment fund shares/ units"). Neither can maturity transformation nor high leverage be taken as a central feature of the sector, in particular if we consider their liabilities as being mainly equity. The FSB recognises these difficulties by excluding part of them from its narrower measure, focusing instead on only those that have a clearer credit intermediation flavour: fixed income funds (including mixed funds), credit hedge funds and real estate funds. Unfortunately, such breakdowns are not available within the Guideline framework.

One could still work with an aggregate that includes all investment funds even if there are justified doubts about the nature as shadow bank of a great deal of them. After all, it is recognised that many of the units included in our proposed OFIs aggregate are anyway not shadow banks, like holding companies which are part of the ESA sector S.127. However, a second methodological issue relates to our aim to isolate exclusively a debt network. The consideration of some of the investment funds as shadow banks would also require the identification of the corresponding liabilities that are of a debt nature. This endeavour is tantamount to the split of the sector into fund categories, such as those above borrowed from the FSB approach, or into alternative ones based on the closeness of the investment fund shares/units to runnable liabilities. None of these splits are however supported by data availability in the financial accounts w-t-w framework[13].

This paper will therefore not include IFs within the aggregate shadow banking proxy examined, which will therefore strictly correspond to the "Other Financial Institutions (OFIs)" grouping as defined in the ECB Guideline. The diagram in Figure 1 below shows for clarity the relation between OFIs and the FSB broad measure. In

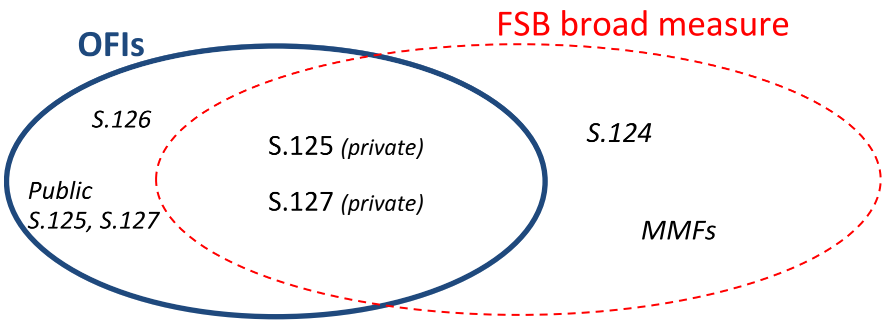
[12] Examples are SAREB in Spain and NAMA in Ireland.

[13] The obvious alternative of working with a total asset network, as opposed to a debt network, is not feasible given the lack of w-t-w detail in relevant equity instruments as explained in section 2.

addition to that, all investment fund shares will be characterised as equity liabilities for the purposes of the computation of centrality measures[14].

OFIs and FSB broad measure

Figure 1



MMFs: Money Market Funds; S.124: Investment Funds (other than MMFs); S.125: Other financial intermediaries, except insurance corporations and pension funds; S.126: Financial auxiliaries; S.127: Captive financial institutions and money lenders

4. Eigenvector centrality in who-to-whom networks

Measures of interconnectedness typically focus on direct links between agents. This fails to capture more complex interactions that transit through indirect links. For instance, exposures of banks to risks stemming from household mortgages financed by securitisation vehicles whose liabilities are part of bank portfolios would not be embedded in a direct interconnectedness measure; neither would the dependence of non-financial corporations on financing from the rest of the world, via domestic banks recourse to non-resident funding.

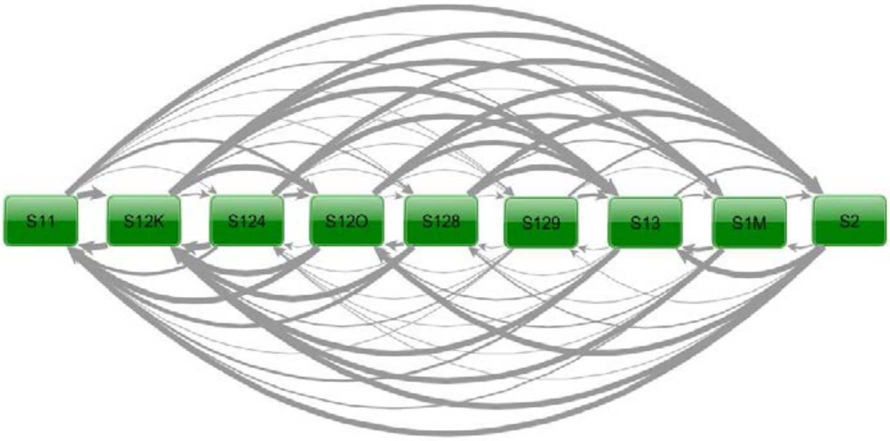
This paper proposes a measure of interconnectedness that takes into account direct and indirect linkages, of any order. To that purpose we view the w-t-w data as a network of interrelationships in which the nodes –the elements interlinked in the network- are institutional sectors and the edges –the links between nodes- are asset/liability links. The edges in the network are "weighted" by the amounts involved in every asset/liability relationship.

Figure 2 shows a directed graph representation of the network of debt instruments (see section 2 for a detailed explanation of the w-t-w data used) for the euro area at the end of 2016, with the width of the asset/liability edges being proportional to their "weight" in the network, i.e. to the corresponding amounts of credit-like claims outstanding between the different sectors.

[14] The debt centrality scores worked out in section 5 for our shadow banking proxy, the OFIs, are naturally not invariant to the definition of the sector, and in particular by the consideration of IFs as entities outside the proxy. In addition, the consideration of all investment fund shares as equity (and not as debt) also has a bearing on the results by precluding that fund share/units act as a channel of propagation of dependencies in our network. See section 4 for further details.

Debt network for the euro area

Balance-sheets. 2016 Figure 2



S11: Non-financial corporations; S12K: Monetary Financial Institutions (S.121+S.122+S.123 in ESA); S124: Investment Funds (other than MMFs); S12O: OFIs; S128: Insurance corporations; S129: Pension funds; S13: General government; S1M: Households and non-profit institutions serving households (S.14+S.15 in ESA); S2: Rest of the world

Network constructed with the sum of ESA instruments "Currency and deposits (F.2)", "Securities other than shares (F.3)" and "Loans (F.4)"

Arrow from sector SX to sector SY indicates assets of SX and liabilities of SY. Width of arrows proportional to amount of assets

In network analysis, eigenvector centrality is a measure of the influence of the various nodes in the network. It consists in an array of node scores that satisfy the principle that higher scores are assigned to nodes that are highly connected to nodes that in turn have high scores themselves[15]. It is therefore a metrics of a recursive nature capturing second, third and higher orders of influence in the network. The concept is therefore particularly well suited to our aim of emphasising also the importance of indirect links in measuring debt interconnectedness.

The score array corresponds to an algebraic property of a matrix, known as weight matrix, that represents the weights of the edges of the graph (see Box 2 for a detailed explanation). In our case the weight matrix corresponds to the matrix or table representation of the w-t-w data. Eigenvector centrality can be calculated on a weight matrix or on its transpose, representing two distinct properties of the underlying network: one represents node centrality insofar as edges outflow from the nodes and the other insofar edges inflow to the nodes.

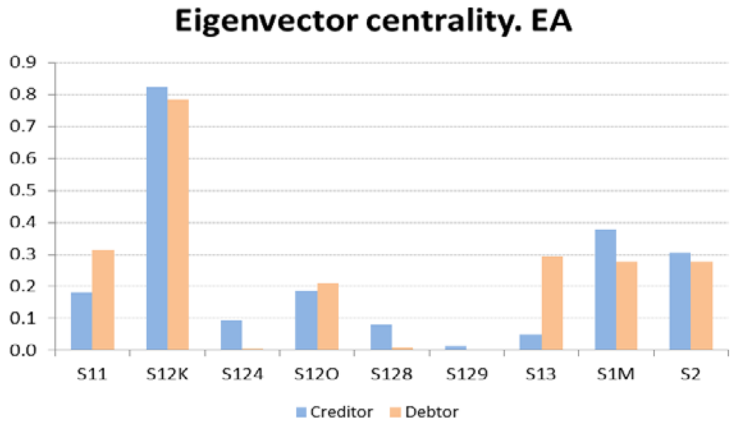
In our case, the eigenvector centrality calculated on w-t-we data tabulated as a matrix of creditor-debtor relationships represents the interconnectedness of a sector seen as a creditor, or "creditor" centrality. When calculated on the corresponding transposed matrix, i.e. on w-t-w data tabulated as a matrix of debtor-creditor relationships, it represents sector interconnectedness from the liabilities side, or "debtor" centrality[16]. The two measures are shown in Figure 3 for the euro area debt network at the end of 2016.

[15] For a reference, see for instance Newman (2010).

[16] Concepts similar to what we call "creditor centrality" and "debtor centrality" here have been identified in other contexts as "vulnerability" and "systemic risk" indices. See for instance Markose (2012).

Eigenvector centrality. Debt network. Euro area

Balance-sheets. 2016 — Figure 3



S11: Non-financial corporations; S12K: Monetary Financial Institutions (S.121+S.122+S.123 in ESA); S124: Investment Funds (other than MMFs); S12O: OFIs; S128: Insurance corporations; S129: Pension funds; S13: General government; S1M: Households and non-profit institutions serving households (S.14+S.15 in ESA); S2: Rest of the world

Network constructed with the sum of ESA instruments "Currency and deposits (F.2)", "Securities other than shares (F.3)" and "Loans (F.4)

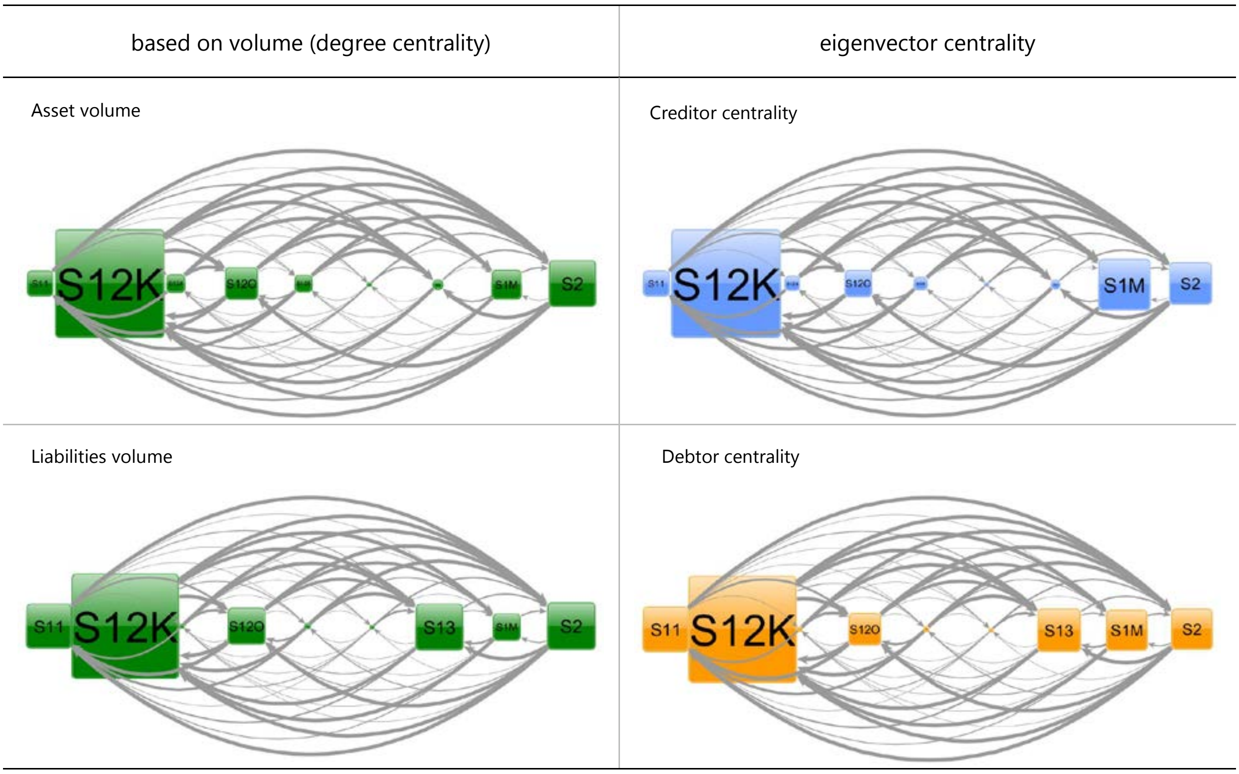
Units: components of the Perron's eigenvector (normalised) of a matrix with elements for row i and column j, a_{ij}, representing, in the case of "Creditor", assets of sector i and liabilities of sector j, and, in the case of "Debtor", assets of sector j and liabilities of sector i

Not surprisingly, MFIs (S12K) show up as the most central sector both from the creditor and the debtor perspectives. In turn, OFIs (S12O), our aggregate proxy for shadow banks, presents a much smaller degree of centrality, reflecting the fact that the euro area is an economy largely based on bank intermediation. Moreover, non-financial corporations (S11) and particularly government (S13) present much higher debtor centrality than creditor centrality, in line with their economic nature. The rest of the world also presents high centrality scores as a result of the high openness of the euro area economy to external financial flows. Thus, at least at first blush, eigenvector centrality does not appear to provide any further insight compared to simpler, direct measures such as debt volumes. Nevertheless some subtle, albeit important, differences exist, as discussed next.

Figure 4 shows graphically the centrality of the various sectors by making the size of the node representation proportional to their centrality. On the left column, rankings based on volume (ignoring indirect links and tantamount to "degree centrality" in graph theory) are shown, both for sectors as creditors (credit asset volumes) and debtors (credit liabilities volume). On the right column the corresponding eigenvector centrality measures are presented instead, again from both the creditor and debtor perspectives.

Sector centrality in the euro area debt network

Balance-sheets. 2016 — Figure 4



S11: Non-financial corporations; S12K: Monetary Financial Institutions (S.121+S.122+S.123 in ESA); S124: Investment Funds (other than MMFs); S12O: OFIs; S128: Insurance corporations; S129: Pension funds; S13: General government; S1M: Households and non-profit institutions serving households (S.14+S.15 in ESA); S2: Rest of the world

Network constructed with the sum of ESA instruments “Currency and deposits (F.2)”, “Securities other than shares (F.3)” and “Loans (F.4)”

Arrow from sector SX to sector SY indicates assets of SX and liabilities of SY. Width of arrows proportional to amount of assets. Size of nodes proportional to the corresponding centrality measure: volume of assets (or liabilities), eigenvector centrality for matrix representing investor/issuer (or issuer-investor)

The differences between the two measures become more apparent for the households sector (S1M). While credit assets held by non-residents (S2) are more than 160% as much as those held by resident households (upper-left-hand-side panel in Figure 4), creditor eigenvector centrality places households before the rest of the world, and only second to MFIs in creditor centrality (upper-right). This results from households holding large amounts of debt-like claims on MFIs, mainly in the form of deposits, coupled with the fact that MFIs are in turn very central (i.e., they channel the funds to all other sectors). In turn, the credit claims of non-resident are to a greater proportion liabilities of government (S13) and non-financial corporations (S11), sectors that usually do not employ any significant proportion of the proceeds for onward lending to other sectors.

Similarly, the debtor centrality of households is very similar to that of both the rest of the world and government (lower-right), in spite of having just around half the volume of debt liabilities of those two sectors (lower-left). This can be interpreted as a relatively higher systemic impact of households per unit of debt compared to e.g. government, which is explained by the fact that difficulties by households in servicing their debts would have an impact on banks mainly, which in turn would impact all other sectors in the network via bank debtor centrality. In comparison, government has a larger share of investors other than MFIs, like the rest of the world or pension funds, which have a lesser degree of debtor centrality[17].

[17] Pension fund holdings could be viewed as buffering the systemic impact of disturbances in the credit worthiness of government owing to the long-term nature of their liabilities relative to that of banks. Centrality measures computed on our debt-only network embed this idea by excluding pension technical reserves from the definition of credit.

Box 2

A probabilistic interpretation of eigenvector centrality

The “eigenvector centrality” scores of a weighted directed graph correspond to the components of an eigenvector associated to a specific eigenvalue of the weight matrix (the matrix containing the weights of the graph edges)1. Thus, the scores v_i of a graph with weights $w_{i,j} \geq 0$ (of edge from node i to node j) i, j= 1…n , satisfy the equality:

$$\boldsymbol{Wv} = \rho \boldsymbol{v}, \qquad \boldsymbol{v} = \begin{bmatrix} v_1 \\ \vdots \\ v_n \end{bmatrix}, \qquad \boldsymbol{W} = \begin{bmatrix} w_{1,1} & \cdots & w_{1,n} \\ \vdots & \ddots & \vdots \\ w_{n,1} & \cdots & w_{n,n} \end{bmatrix}$$

The specific eigenvalue, ρ ,called Perron-Fobrenius eigenvalue, is the one of maximum module, which is real and positive for “irreducible matrices”, i.e. for non-negative matrices that can be associated to strongly connected directed graphs (graphs that present direct or indirect connections between any pair of nodes). Weight matrices made of w-t-w balance-sheet data satisfy this condition.

It is guaranteed for irreducible matrices that an eigenvector can be chosen associated to the Perron-Fobrenius eigenvalue with all components v_i strictly positive[2]. Moreover, in this paper we choose eigenvectors of unit norm ($\boldsymbol{v}'\boldsymbol{v} = 1$) for the chart representations.

The specific characteristic of a Perron-Fobrenius eigenvector that makes it suitable for measuring centrality is the following property: for any vector $\boldsymbol{d}$ **,** it exists a Perron-Fobrenius eigenvector, $\alpha\boldsymbol{v}$, such as

$$\lim_{p\to\infty} \left(\frac{\boldsymbol{W}}{\rho}\right)^p \boldsymbol{d} = \alpha\boldsymbol{v}$$

In particular for $\boldsymbol{d} = \boldsymbol{1}$, the unitary vector, it results that $\alpha * v_i = \sum_{j=1}^{n} \left(\lim_{p\to\infty} \left(\frac{W}{\rho}\right)^p\right)_{i,j}$. Somewhat less formally,

it exists an integer sufficiently large q, such as $\alpha * \rho^p * v_i \approx \sum_{j=1}^{n} (W^p)_{i,j}$ for any $p > q$, i.e. the components (centrality scores) in $\boldsymbol{v}$ are approximately distributed as the row sums of the (sufficiently large) power of the weight matrix.

Our weight matrix consists in w-t-w stock data. As the eigenvectors of a matrix are invariant to its multiplication by a scalar, their eigenvector centrality scores are also those of the matrix resulting from dividing all w-t-w stocks by the total assets/ liabilities. Such matrix represent the probability distribution of the w-t-w links: each value $w_{i,j}$ is the

probability that a euro invested in the economy is invested in an asset of sector *i* on sector *j*. The sum of the elements in row *i* is the probability that a euro is invested by sector *i* (in any other sector).

Let’s calculate the probability that a euro is invested *indirectly* by sector *i* in sector j via sector *k* as $\frac{w_{i,k} * w_{k,j}}{t_2}$,

$t_2 = \sum_{a,b,c} w_{a,b} * w_{b,c}$ $a, b, c = 1, \dots, n$. Then, each of the numbers $\frac{(\boldsymbol{W}^2)_{i,j}}{t_2}$ represents the probability that an indirect

investment of a euro between any two sectors via a third one takes places between sectors *i* and *j* (via any other

sector). Similarly, $\frac{(\boldsymbol{W}^p)_{i,j}}{t_p}$ is the probability that an indirect investment link takes place between sector *i* in sector *j* when such indirect links involve any combination of *p-1 sectors* in-between, with $t_p = \sum_{a,b,c} (\boldsymbol{W}^{p-1})_{a,b} * w_{b,c}$.

As seen above the eigenvector centrality scores are distributed as the row sums of $\boldsymbol{W}^p$, for *p* sufficiently large,

and therefore as the row sums of $\frac{\boldsymbol{W}^p}{t_p}$, i.e. as **the probabilities of the various sectors being the originators of investment chains when such chains involve a large number of indirect steps**.

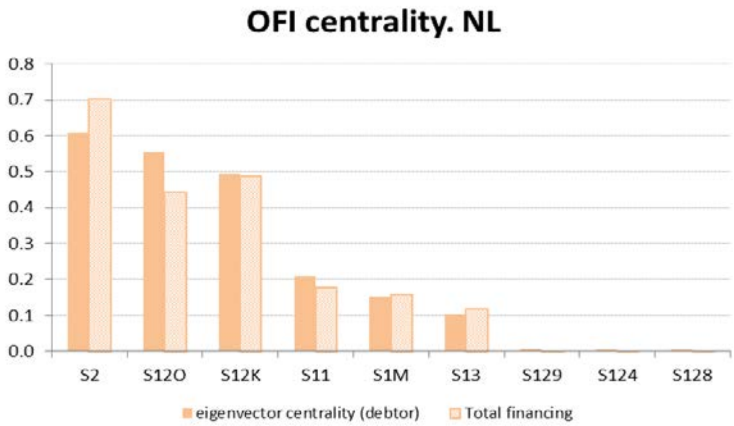
1) For a reference to eigenvalues and eigenvectors, see for instance Herstein (1964)
2) See for instance Meyer (2000)

Our chosen aggregate to proxy shadow banks, OFIs (S12O), presents eigenvector centrality scores similar to what results from direct assets and liabilities links only. As an exception, the OFIs sector is surpassed by households in debtor centrality for the reasons explained above. However, this result for the euro area does not extend to every individual country, in particular for those where the non-bank financial industry is more developed. That is the case for instance of the Netherlands, where debtor eigenvector centrality yields a score for the OFIs sector higher than for the MFIs, even though the latter issue more liabilities than the former. This is shown in Figure 5.

Eigenvector centrality (debtor) vs Share in total liabilities. The Netherlands

Balance-sheets. 2016

Figure 5



S11: Non-financial corporations; S12K: Monetary Financial Institutions (S.121+S.122+S.123 in ESA); S124: Investment Funds (other than MMFs); S12O: OFIs; S128: Insurance corporations; S129: Pension funds; S13: General government; S1M: Households and non-profit institutions serving households (S.14+S.15 in ESA); S2: Rest of the world

Network constructed with the sum of ESA instruments "Currency and deposits (F.2)", "Securities other than shares (F.3)" and "Loans (F.4)"

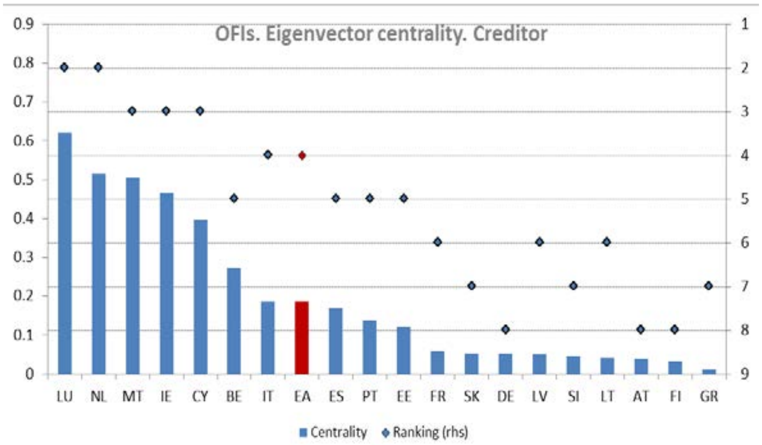
Units: for "eigenvector centrality (debtor)" components of the Perron's eigenvector (normalised) of a matrix with elements for row i and column j, a_{ij}, representing assets of sector j and liabilities of sector i; for "share in total liabilities", share of liabilities of sector i in total liabilities

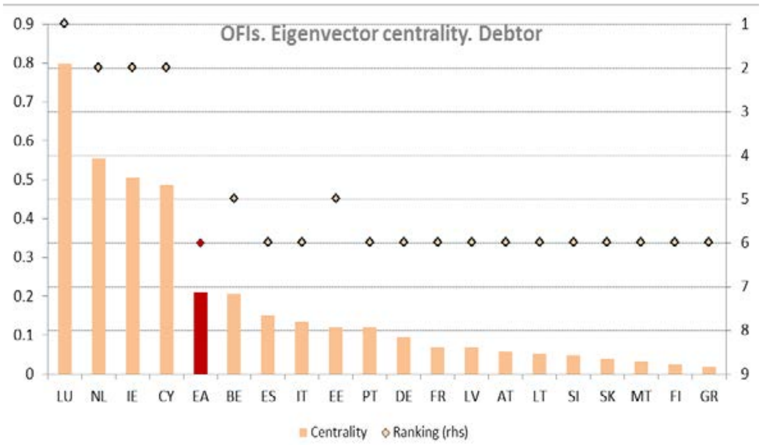
5. Interconnectedness of OFIs

Figure 6 shows the eigenvector creditor and debtor centrality scores for the OFIs sector in the 19 members of the euro area. The rank of the OFI sector resulting from ordering all sectors in each country by descending value of their centrality scores is also presented. Both creditor and debtor centrality of the OFI sector is significantly larger than for the euro area as a whole in Luxembourg, the Netherlands, Ireland and Cyprus. In all these countries, the OFI sector ranks first or second in debtor centrality, and second or third in creditor centrality. The centrality of the OFI sector in Malta, on the other hand, stems almost exclusively from its role as creditor, a feature that presumably relates to the significant presence of Special Purpose Entities (SPEs) whose main liabilities are in the form of equity.

Figure 6 - OFIs eigenvector centrality. Debt network

Balance-sheets. 2016





S11: Non-financial corporations; S12K: Monetary Financial Institutions (S.121+S.122+S.123 in ESA); S124: Investment Funds (other than MMFs); S12O: OFIs; S128: Insurance corporations; S129: Pension funds; S13: General government; S1M: Households and non-profit institutions serving households (S.14+S.15 in ESA); S2: Rest of the world

Network constructed with the sum of ESA instruments “Currency and deposits (F.2)”, “Securities other than shares (F.3)” and “Loans (F.4)

Units: components of the Perron’s eigenvector (normilised) of a matrix with elements for row *i* and column *j*, a_{ij}, representing, in the case of “Creditor”, assets of sector *i* and liabilities of sector *j*, and, in the case of “Debtor”, assets of sector *j* and liabilities of sector *i*

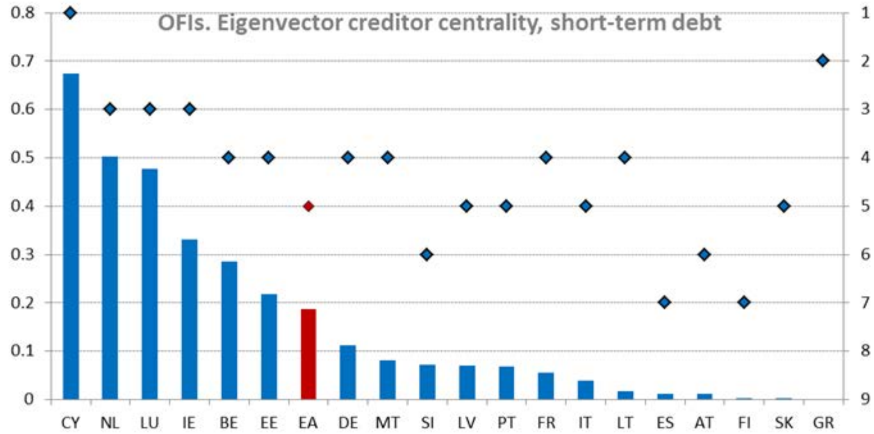
The centrality figures obtained above are naturally sensitive to the heterogeneity implicit in our aggregate measure of the OFI sector. As a cross-check, we compute similar measures for a network where only short-term debt is included (that is, the sum of loans, debt securities and deposits with original maturity of up to one year). A debt network restricted to short maturities can function, at least in part, as a definition of shadow banking more along the lines of the “activity based measures” approach employed by the Financial Stability Board. For instance, the creation of private quasi-money, potentially runnable, liabilities outside of the banking sector, one of the hallmarks of shadow banking activity, would possibly be better captured by such a network. Non-bank maturity transformation is also more likely to take place in entities whose debt liabilities are predominantly short-term[18]. The centrality results for this short-term debt only network are presented in Figure 7.

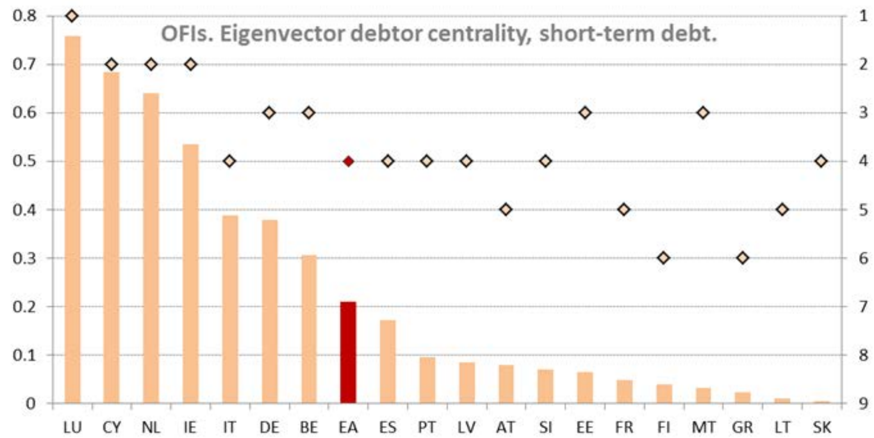
Compared to the network where all debt maturities were considered, a significant increase in OFI sector centrality can be observed in the short-term debt network for debtor measures (lower panel in Figure 7). For instance, the ranking of the OFI sector on that score is strictly higher in thirteen out of nineteen countries – in no case being lower. For the euro area as a whole, the OFI sector ranks fourth in debtor centrality, compared to sixth when all debt maturities were combined. Furthermore, Germany, Italy and Belgium show larger OFI centrality than the euro area as a whole, but did not when considering all maturities combined. For creditor centrality, in turn, considering only short-term debt within the network results overall in a similar picture in most cases. Nevertheless, we believe that debtor centrality is possibly a more significant concept in terms of characterising interconnectedness for the shadow-bank-like activities we were trying to, however imperfectly, proxy by employing only short-term debt.

[18] With respect to maturity transformation, the approach has the obvious caveat that we must restrict both assets and liabilities, not only liabilities, to be short-term debt. This is because in a debt network, or in a who-to-whom presentation, every sector asset is some other sector's liability.

Figure 7 - OFIs eigenvector centrality. Short-term debt network.

Balance-sheets. 2016





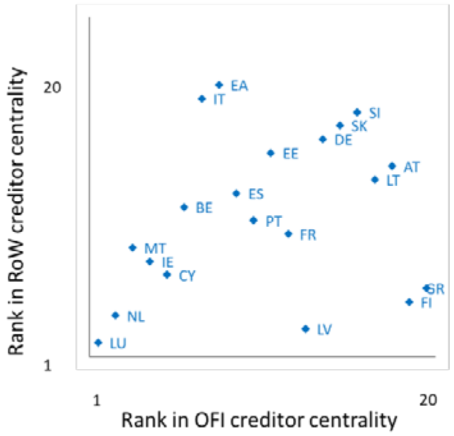
S11: Non-financial corporations; S12K: Monetary Financial Institutions (S.121+S.122+S.123 in ESA); S124: Investment Funds (other than MMFs); S12O: OFIs; S128: Insurance corporations; S129: Pension funds; S13: General government; S1M: Households and non-profit institutions serving households (S.14+S.15 in ESA); S2: Rest of the world

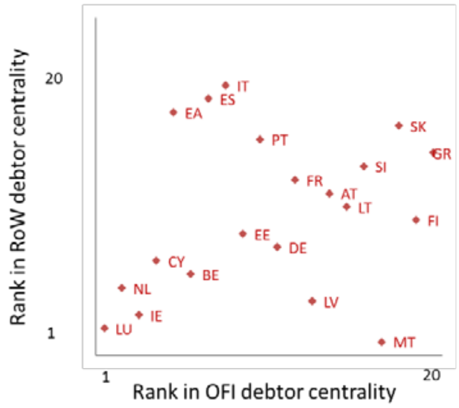
Network constructed with the sum of ESA instruments "Currency and deposits (F.2)", "Securities other than shares (F.3), of which original /ear" and "Loans (F.4), of which original maturity up to one year". For deposits, official financial accounts data on maturity on a who-to-xist. To restrict deposits to those with original maturity up to one year, the proportions of short-term deposits over total deposits that can B statistics on the Monetary Financial Institutions sector (BSI statistics) were calculated and applied to their financial account counterparts.

Units: components of the Perron's eigenvector (normilised) of a matrix with elements for row *i* and column *j*, a_{ij}, representing, in the case of "creditor centrality", assets of sector *i* and liabilities of sector *j*, and, in the case of "debtor centrality", assets of sector *j* and liabilities of sector *i*

Coming back to the all maturities combined debt network, countries with high creditor and debtor centrality of the OFI sector appear to also have a high interconnectedness of their domestic sectors with the rest of the world. This can be seen from Figure 8, which plots the rank obtained when ordering countries by descending value of their OFI centrality score, against the rank derived from ordering them by the centrality of their rest of the world sector. In general, a positive relationship can be observed which, to an extent, is not an unexpected. The type of activities undertaken by OFIs are in many cases driven by a favourable environment in their jurisdictions relating to specific financial activities, often relating to tax, regulatory, statutory advantages, and/or a concentration of know-how in these areas. This may imply that a large part of the business of OFI originates beyond their jurisdiction's borders.

Figure 8 - Country ranks in OFI centrality vs. rank in rest of the world centrality





We wish to shed more light on this external dimension of OFI centrality in the four countries that present with both high OFI and rest of the world centrality in the network, namely Luxembourg, Netherlands, Ireland and Cyprus. For that purpose, we make use of data reported under the Guideline that break down claims (or liabilities in the case of deposits) by the domestic sectors on/to the rest of the world by institutional sector of the euro area counterparties[19]. This allows us to construct an extended network including 17 nodes as opposed to the 9 nodes employed thus far, as described below.

Our expanded network decomposes the rest of the world node within the original network into eight nodes, each representing positions with non-resident euro area institutional units grouped by institutional sector, plus one extra node collecting positions with non-euro area counterparties. The construction of this expanded network requires some data to be estimated, since the Guideline data only breaks down on a who-to-whom basis the claims on, but not the debts to, residents in other euro area countries[20]. The missing who-to-whom, cross-border data on debt is estimated by assuming that its structure equals that observed for the euro area as a whole.

The debtor eigenvector centrality measures relating to these cross-border relationships with other euro area countries, as well as with non-euro area institutional units, are presented in Figure 9[21]. For both Netherlands and Luxembourg non-financial corporations in other euro area countries present the highest centrality among euro area counterparties. This is consistent with a priori

19 The breakdown by institutional sector of the counterpart is not available for counterparties resident outside of the euro area, for which nevertheless an aggregate 'all sectors combined' does exist. .

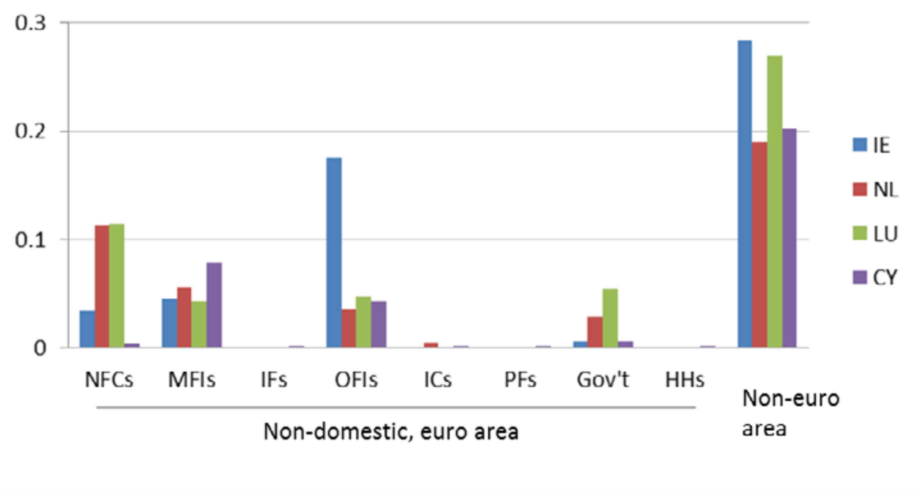
20 For deposits, the reported data take the opposite perspective, i.e. liabilities (rather than claims) of resident sector are broken-down by institutional sector of the creditor for euro area counterparties.

21 We only discuss debtor centrality, since creditor centrality would be more sensitive to the fact that who-to-whom data on non-domestic creditors was estimated.

knowledge that large euro area non-financial corporations issue significant amounts of marketable debt by way of subsidiary vehicles resident in these two jurisdictions, with the funds raised subsequently channelled to their parent companies. In Ireland, a high score for OFIs resident in other euro area countries is verified instead, possibly suggesting a more complex web of cross-border relationships.

At the same time, MFIs in other euro area member states do not seem to be driving external connectedness of the OFI sector, with the largest eigenvector score corresponding to Cyprus. Other institutional groupings of residents in other euro area countries, such as insurance corporations and pension funds, government or households, do not contribute a significant degree of debtor centrality in any of the four economies. In turn, non-euro area residents present the highest centrality scores in all four cases examined[22].

Figure 9 – OFI debtor centrality for groupings of non-residents by institutional sector



[22] This latter result is nevertheless not straightforward to interpret, since we cannot observe the scores that would obtain if non-euro area residents could be split by institutional sector. Their representation as a single node in the network, as opposed to eight distinct nodes, does have a bearing in the observed score since eigenvector centrality measures are not invariant to the level of disaggregation within a node.

6. Conclusions

The improvement in the availability of w-t-w data over the last years in Europe, but also worldwide, opens new possibilities for flow of funds analysis. Methodologies taken from matrix algebra or network theory can be used to better understand sector interlinkages, including propagation and contagion dynamics that escaped the traditional analysis of financial accounts.

In this paper we have explored the use of a network centrality concept, eigenvector centrality, to provide a euro area cross-country comparison of interconnectedness of shadow banks with the rest of the economy. By using eigenvector centrality we capture direct and indirect financial connection paths between sectors, improving alternative analysis of interconnectedness based only on direct links. We have used newly available w-t-w data supported by ECB statistical legislation, and our work constitutes the first complete comparison of euro area countries institutional sector interconnectedness.

We find a high level of centrality for our measure of shadow banks in countries where the non-bank financial industry is important, as would be also found with a poorer analysis that would not take into account indirect links. However, the results based on eigenvector centrality present relevant differences with those other simpler analysis in terms of both absolute and relative centrality as discussed in the paper.

A major drawback of our analysis is posed by the rest of the world sector. In sector accounts the rest of the world is, rather than an institutional sector proper, an analytical construct to “close” the system of accounts capturing the flows of the units resident in an economy that do not have as a counterpart units of that economy, but units resident in other economies. The flows for the rest of the world sector are not, as opposed to for the other sectors, aggregates of total flows of a certain group of economic agents: here only a subset of the flows of the agents grouped is considered -those having a resident agent as a counterpart.

In terms of eigenvector centrality, that implies that indirect links that travel via the node “rest of the world” are not captured as richly as those that travel via the nodes for the domestic sectors, where linkages between the various units grouped under the same node are taking into account as well. Moreover, the rest of the world sector/node groups together units of very different economic behaviour, not offering as a consequence enough “resolution” of interconnectedness.

We have made an attempt correct for this “rest of the world bias” to better understand OFI interconnectedness. For that we have used the more granular information on cross-border links provided by the financial accounts Guideline. However, even more detail would be needed to avoid such bias, and possibly the development of so-called Global Flow of Funds presenting full international investment-financing links.

Furthermore, our work on shadow banking centrality would benefit from increased availability of data that would allow for the construction of more relevant networks. This includes a better delineation of shadow banks, beyond the OFI aggregate here used, the full availability of equity on a w-t-w basis, including unquoted equity, and more detailed debt breakdowns. Regarding the latter, although in this paper we already make an analysis of short-term debt centrality and compare it with overall debt centrality, a more pertinent comparison would require the use of debt broken down by residual maturity, as opposed to original maturity.

References

Bakk-Simon, K., Borgioli, S., Girón, C., Hempell, H., Maddaloni, A., Recine, F. and Rosati, S. (2012), "Shadow Banking in the Euro Area: an Overview" ECB Occasional Papers, no 133

European Central Bank (2017, a), Euro Area Accounts, Who-to-whom detail, web http://sdw.ecb.europa.eu/reports.do?node=1000002345

European Central Bank (2017, b), Financing and Investment Dynamics, Euro Are Statistics, web https://www.euro-area-statistics.org/financing-and-investment-dynamics?cr=eur&lg=en

Eurostat (2013), "European System of Accounts. ESA 2010"

Financial Stability Board (2017), "Global Shadow Banking Monitoring Report 2016"

Herstein, I. N. (1964), "Topics In Algebra", Waltham: Blaisdell Publishing Company

International Monetary Fund, Financial Stability Board (2016), "Second Phase of the G-20 Data Gaps Initiative (DGI-2). First Progress Report"

Markose, S. M. (2012), "Systemic Risk from Global Financial Derivatives: A Network Analysis of Contagion and Its Mitigation with Super-Spreader Tax", IMF Working Paper WP/12/282, International Monetary Fund

Matas-Mir, A. and Willeke, C. (2017), "Compiling financial accounts: a European perspective", 61th ISI World Statistics Congress, IFC organized sessions

Meyer, C. (2000), "Matrix analysis and applied linear algebra", SIAM

Newman, M.E.J. (2010), "Networks: An Introduction", Oxford University Press

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IFC-National Bank of Belgium Workshop on "*Data needs and Statistics compilation for macroprudential analysis*"

Brussels, Belgium, 18-19 May 2017

Interconnectedness of shadow banks in the euro area[1]

Celestino Girón and Antonio Matas,
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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C Girón, A Matas

European Central Bank

Interconnectedness of shadow banks in the euro area

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Brussels, 18-19 May

Overview

1	"Who-to-whom" financial accounts networks
2	Eigenvector centrality
3	OFI interconnectedness
4	Cross-border analysis
5	Financial integration and w2w networks

Turn traditional balance-sheet representation into a *NETWORK* of sector interlinks. Matrix representation:

Columns break down a **sector's liabilities by counterparty.**

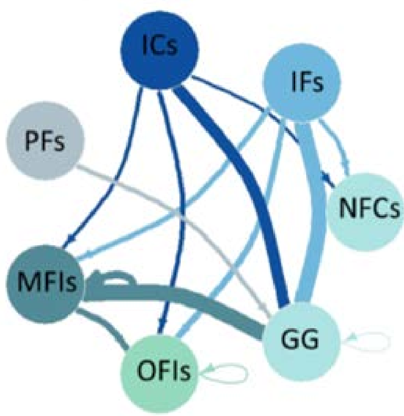
Rows break down its assets.

Government

Assets:	Liabilities :
Item 1 …	Item 1 …
Item 2 …	Item 2 …
	Debt issued : B+E+H

Banks

Assets:	Liabilities :
Item 1 …	Item 1 …
Item 2 …	Item 2 …
Debt held : A+B+C	

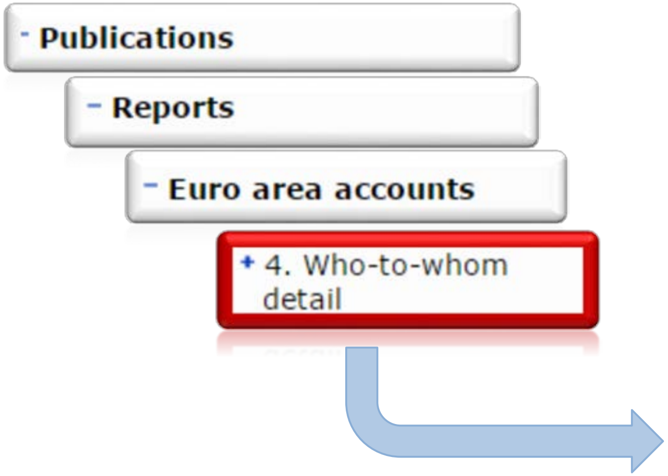


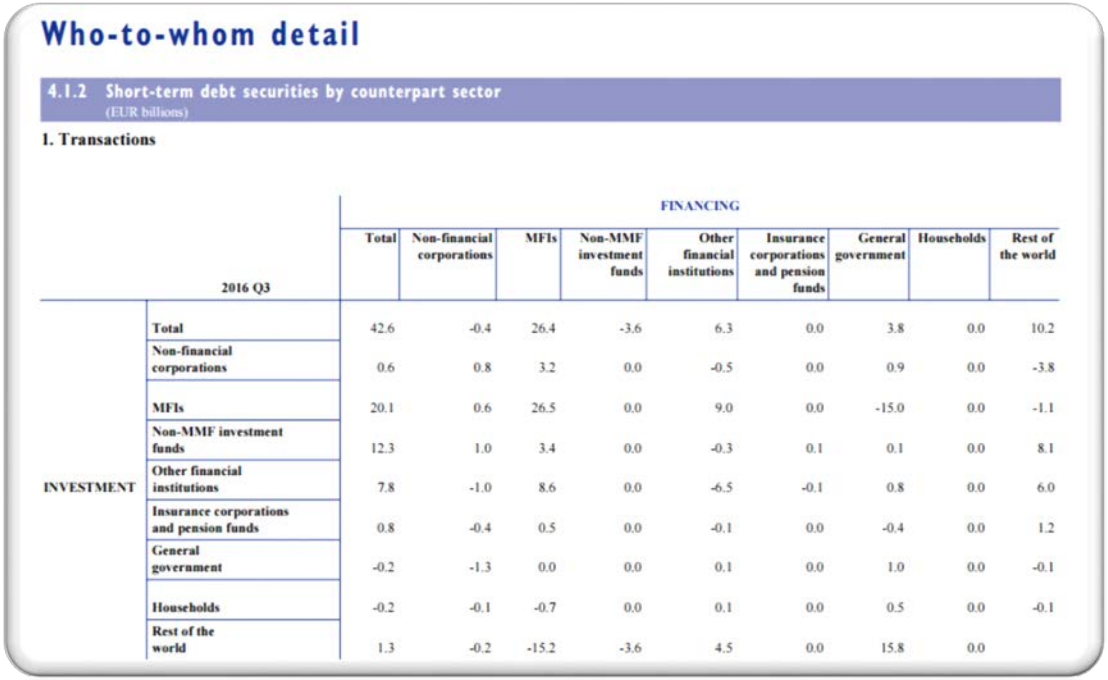
	Debtor (issuer)			
Creditor (holder)	Banks	Gov't	Corp.	**Total held**
Banks	A	B	C	Banks: A+B+C
Gov't	D	E	F	Gov't: D+E+F
Corp.	G	H	I	Corp.: G+H+I
Total issued	Banks: A+D+G	Gov't: B+E+H	Corp.: C+F+I	

www.ecb.europa.eu

The ECB provides euro area and country networks (with data from 13Q4) as data matrices…

- http://sdw.ecb.europa.eu/reports.do?node=1000005335





Who-to-whom detail

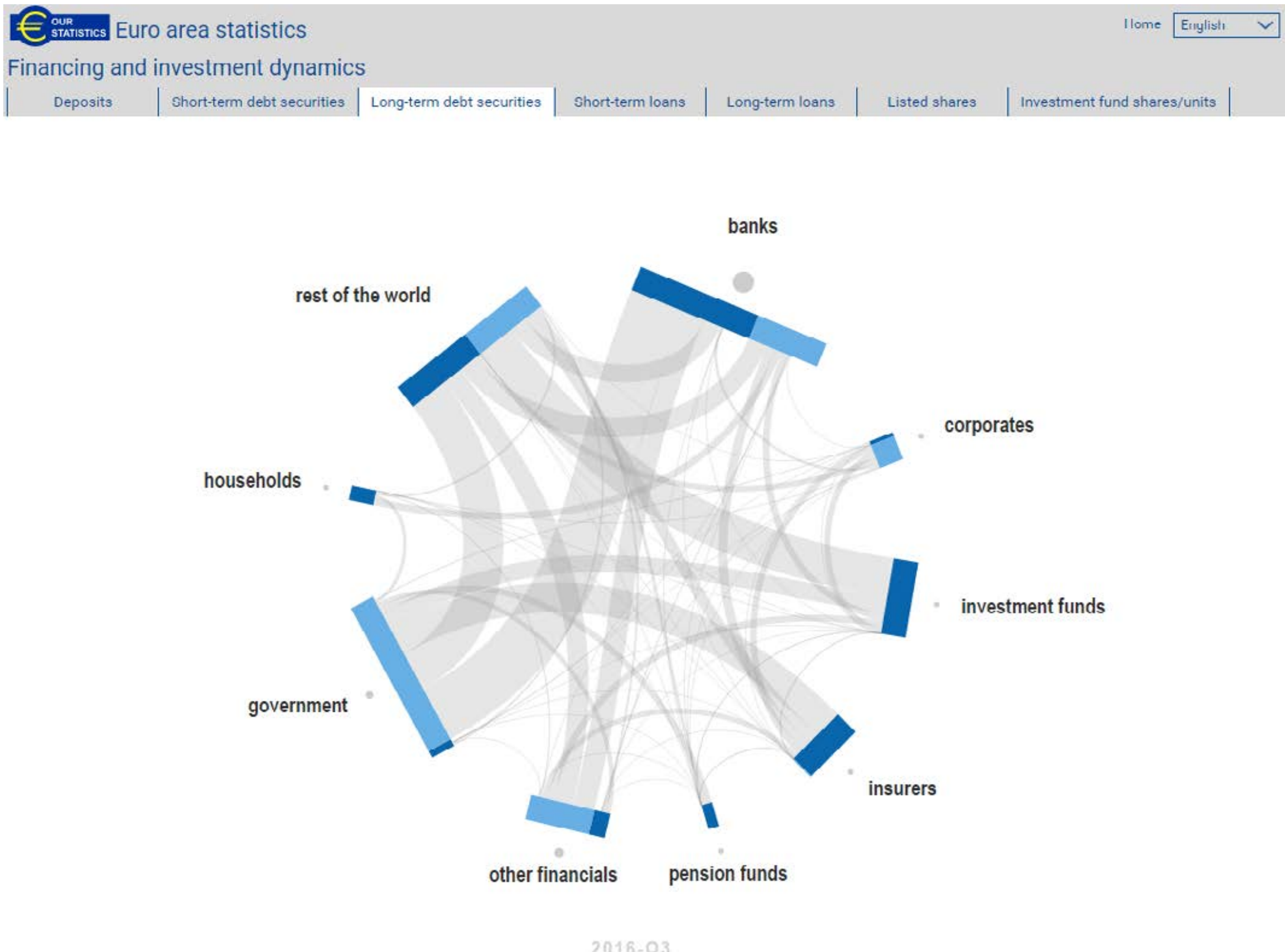
4.1.2 Short-term debt securities by counterpart sector
(EUR billions)

1. Transactions

2016 Q3		FINANCING: Total	Non-financial corporations	MFIs	Non-MMF investment funds	Other financial institutions	Insurance corporations and pension funds	General government	Households	Rest of the world
INVESTMENT	Total	42.6	-0.4	26.4	-3.6	6.3	0.0	3.8	0.0	10.2
	Non-financial corporations	0.6	0.8	3.2	0.0	-0.5	0.0	0.9	0.0	-3.8
	MFIs	20.1	0.6	26.5	0.0	9.0	0.0	-15.0	0.0	-1.1
	Non-MMF investment funds	12.3	1.0	3.4	0.0	-0.3	0.1	0.1	0.0	8.1
	Other financial institutions	7.8	-1.0	8.6	0.0	-6.5	-0.1	0.8	0.0	6.0
	Insurance corporations and pension funds	0.8	-0.4	0.5	0.0	-0.1	0.0	-0.4	0.0	1.2
	General government	-0.2	-1.3	0.0	0.0	0.1	0.0	1.0	0.0	-0.1
	Households	-0.2	-0.1	-0.7	0.0	0.1	0.0	0.5	0.0	-0.1
	Rest of the world	1.3	-0.2	-15.2	-3.6	4.5	0.0	15.8	0.0	

http://www.ecb.europa.eu/press/pr/stats/ffi/html/index.en.html

… and as network graphs



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1 “Who-to-whom” financial accounts networks

2 **Eigenvector centrality**

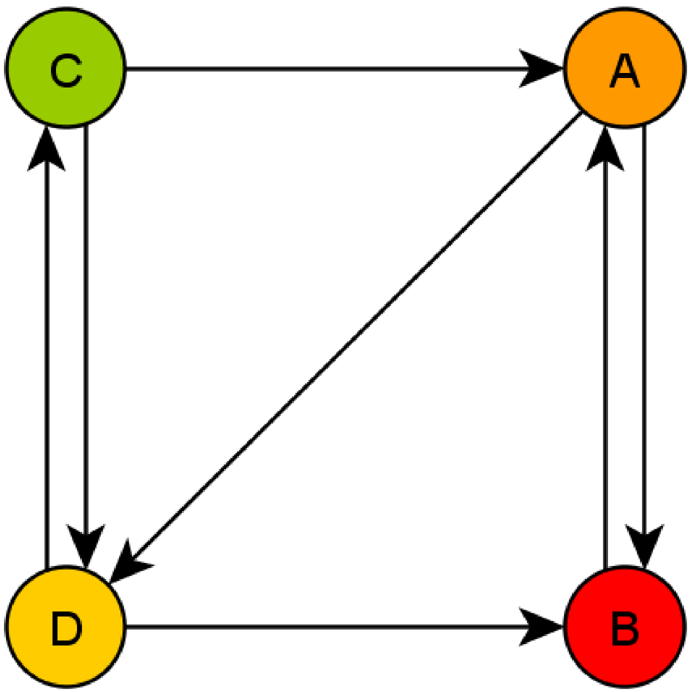
3 OFI interconnectedness

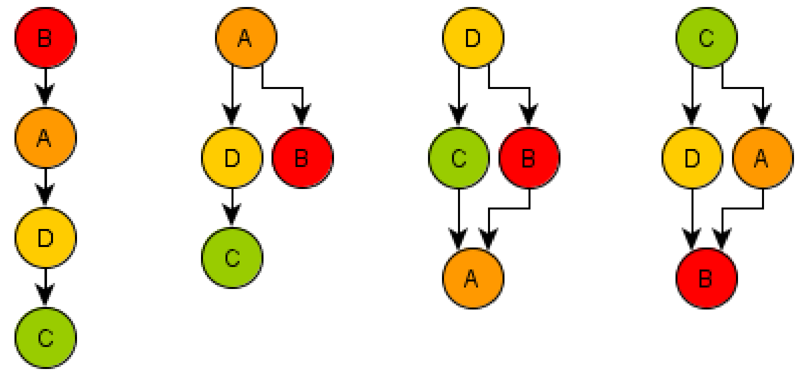
4 Cross-border analysis

5 Financial integration and w2w networks

“The Beggars”, Pieter Bruegel (1568)

Which node is more connected?





- ✓interconnectedness ranking: **C-D-A-B**
- ✓For more complex networks (in particular weighted networks), the solution is not trivial
- ✓**Eigenvector centrality** provides "interconnectedness" scores/ rankings on the basis of the matrix representation of the network: **Perron eigenvector** (principal vector of Perron eigenvalue)
- ✓ here **(0.50 0.29 0.61 0.54)**

Applied to w2w networks…

- ✓ indicates sector interconnectedness via direct (first order) investment and financing links, but also indirect (second and higher order) links via financial intermediation

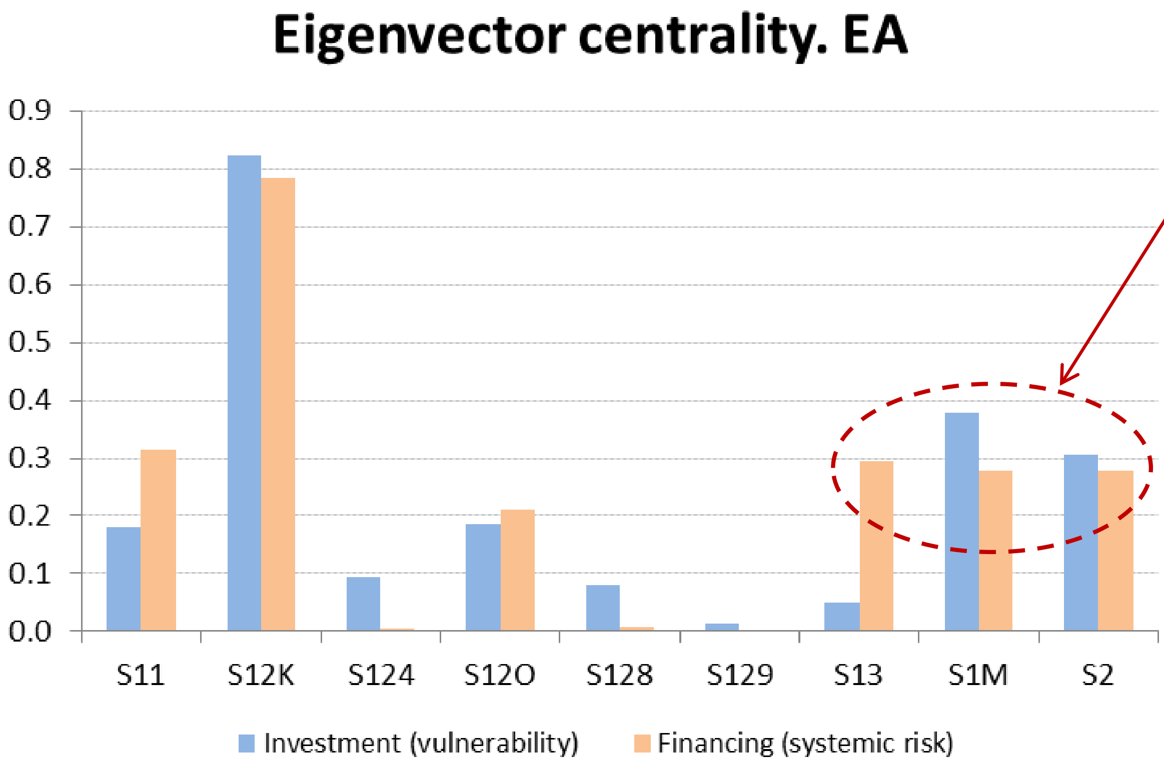
- ✓ Recursive interpretation: "the more a sector is linked to sectors with high score, the higher the score of the sector is"

- ✓ Perron's vector, when calculated on networks …

  - …showing **creditor-debtor** links, provides rankings of interconnectedness via investment: **vulnerability indicator**

  - …showing **debtor-creditor** links (represented by the transposed matrix of a creditor-debtor network), provides rankings of interconnectedness via financing: **systemic risk indicator**

Scores take into account indirect investment- financing links

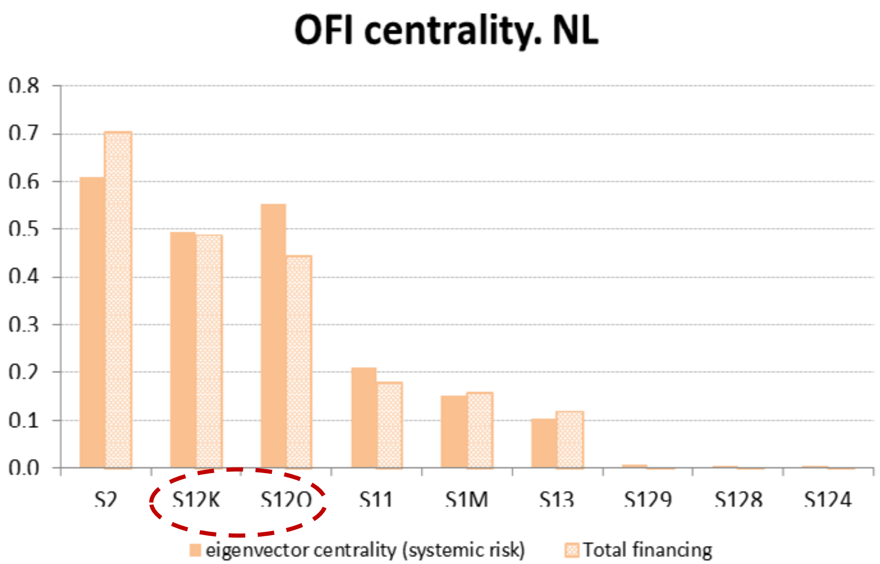


Households are as systemic as government and the rest of the world in spite of having half their liabilities!!!

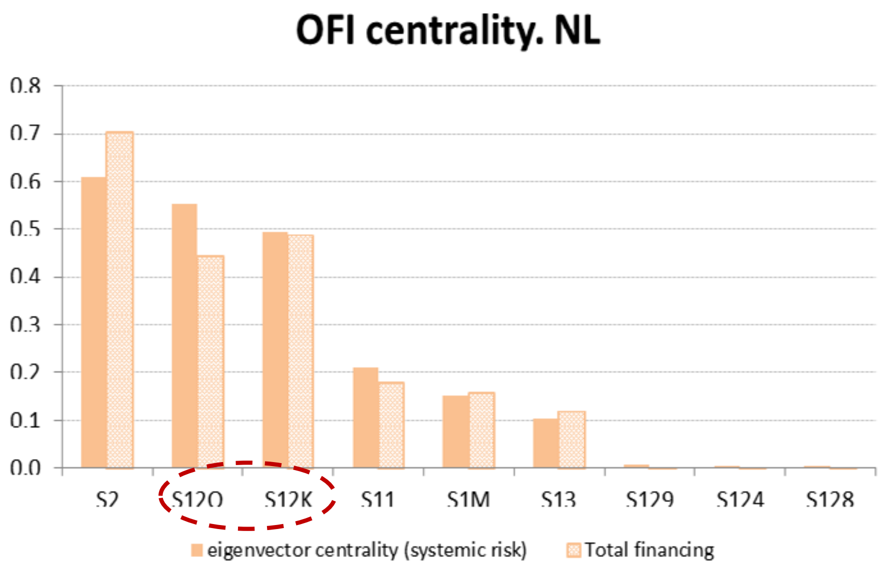
Notes:

- *Units: components of normalized Perron eigenvectors; network of debt (debt securities, loans and deposits); 16Q4*
- *S11: non-financial corporations; S12K: MFIs (S121+S122+S123); S124: investment funds; S12O: OFIs (S125+S126+S127); S128: insurance corporations; S129: pension funds; S13: general government; S1M: households and NPISHs (S14+S15); S12: rest of the world*

If complex w2w links exist, rankings might be different from plain volume rankings



Sorted by total financing



Sorted by eigenvector centrality

Note:

- *Units: S12O component in normalized Perron eigenvector (debt network, debtor-creditor links) and normialized weight of S12O financing (debt liabilitis) in total economy debt; 16Q4*

Some references for eigenvector centrality…

Elgammal, A.; Saleh, B. (2015) "Quantifying Creativity in Art Networks", Sixth International Conference on Computational Creativity (ICCC), June 29-July 2nd 2015, Park City, Utah, USA.

Markose, S. M., (2012), "Systemic Risk and Global Financial Derivatives: A Network Analysis of Contagion and Its Mitigation with Super-Spreader Tax", IMF Working Papers WP/12/282

and for w2w and network analysis…

Antoun de Almeida, L. (2015), "A Network Analysis of Sectoral Accounts: Identifying Sectoral Interlinkages in G-4 Economies" IMF Working Papers WP/15/111

Castrén, O.; Kavonius, I. K (2009), "Balance Sheet Interlinkages and Macro-Financial Risk Analysis in the Euro Area", ECB Working Papers No. 1124

Castrén, O.; Rancan, M. (2013), "Macro-Networks: an Application to Euro Area Financial Accounts", ECB Working Papers No. 1510

1 “Who-to-whom” financial accounts networks

2 Eigenvector centrality

3 **OFI interconnectedness**

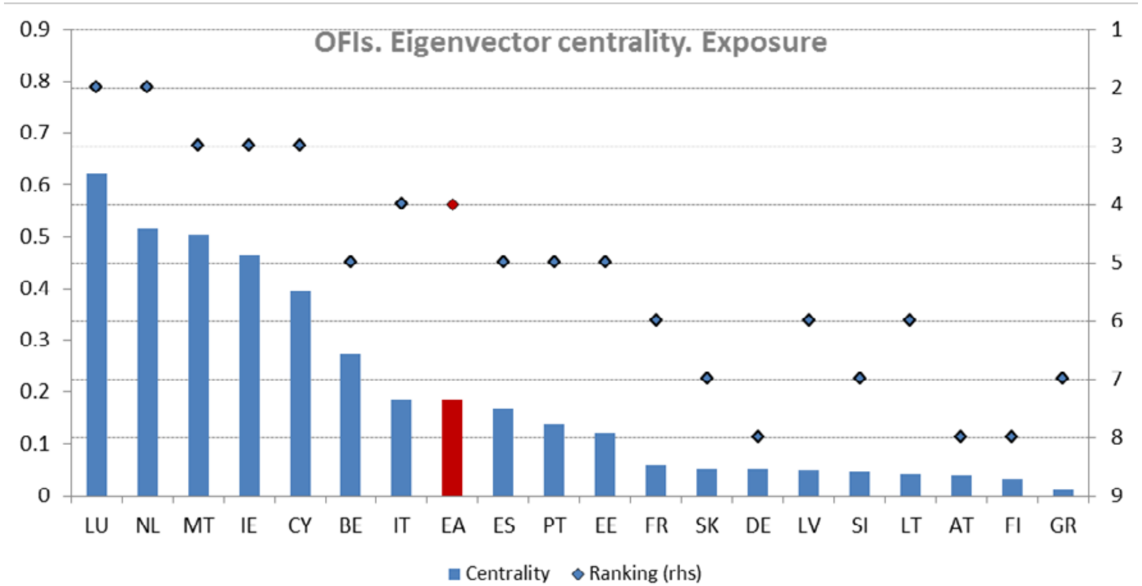
4 Cross-border analysis

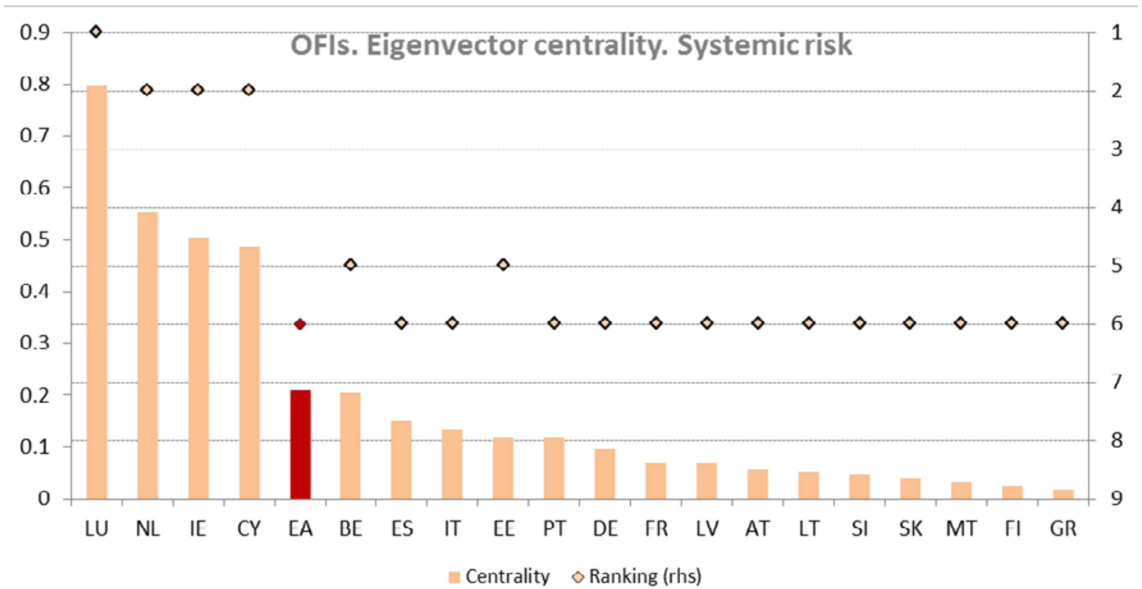
5 Financial integration and w2w networks

We examine shadow banking interconnectedness in euro area countries…

- ✓ using as a proxy for shadow banks the **OFI sector**, i.e. financial intermediaries other than MFIs and ICPFs, financial auxiliaries and captives financial institutions: roughly in line with the "broad measure" of shadow banking used in the FSB annual monitoring report, http://www.fsb.org/2017/05/global-shadow-banking-monitoring-report-2016/
- ✓ working with **w2w *debt* networks**: debt securities + loans + deposits
- ✓ looking into vulnerability and systemic risk indicators calculated from **eigenvector centrality,** with reference period 2016Q4

3. OFI interconnectedness



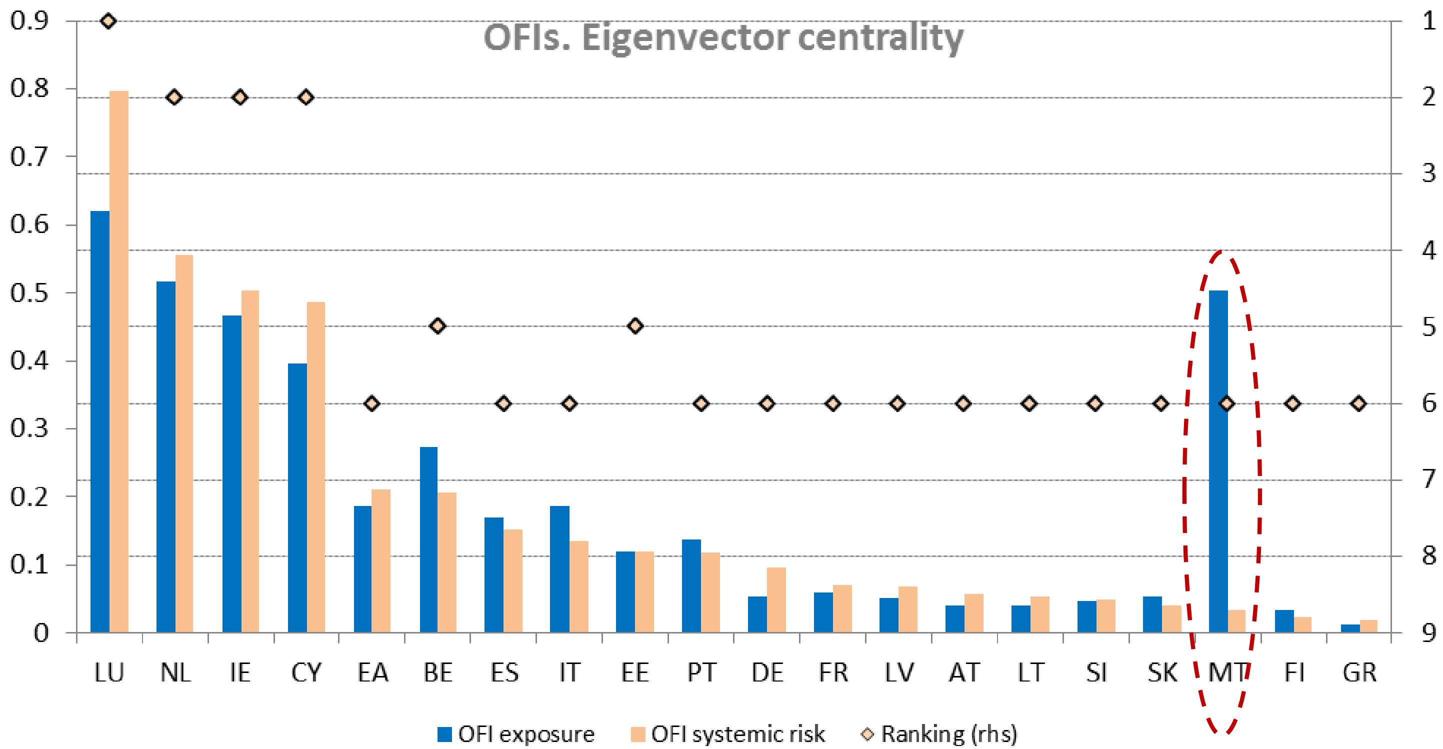


OFI in *LU, NL, IE, CY* present high vulnerability and systemic risk

Note:

- *Units: S120 component in normalized Perron eigenvectors; debt network ; 16Q4*

Vulnerability and systemic risk might present high heterogeneity



Notes:

- *Units: S120 component in normalized Perron eigenvectors; debt network; 16Q4*
- *Sorted by systemic risk*

1 “Who-to-whom” financial accounts networks

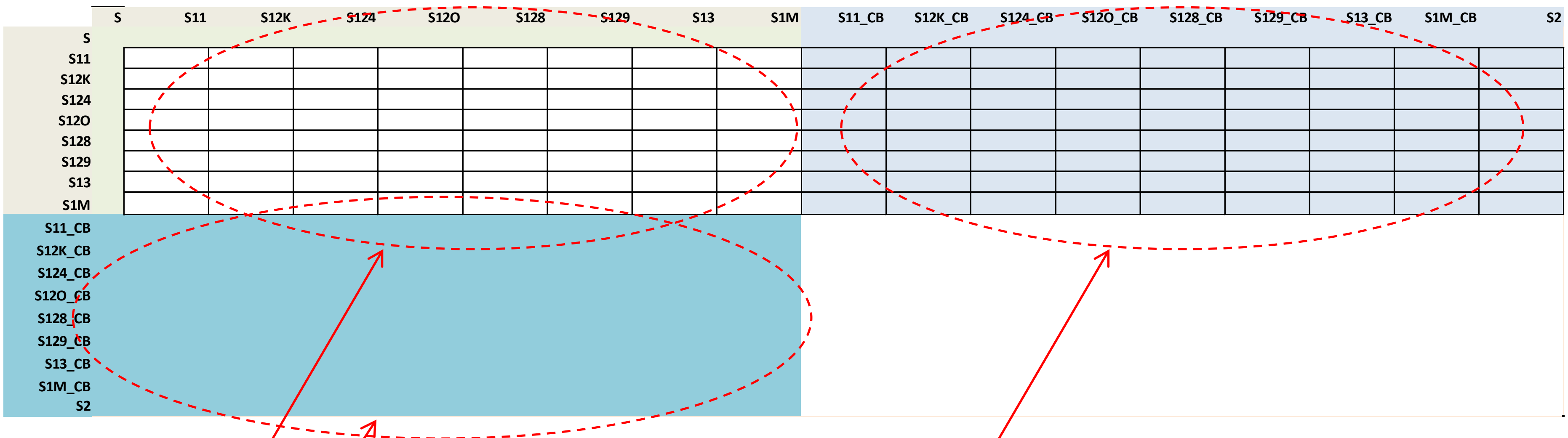
2 Eigenvector centrality

3 OFI interconnectedness

4 **Cross-border analysis**

5 Financial integration and w2w networks

For compiling euro area w2w, countries provide data for…



Domestic w2w

Domestic creditors vis-à-vis other euro area debtors and rest of the world (C_{ij})

But do not send data on “domestic debtors vis-à-vis euro area creditors and rest of the world”… **need to be estimated!!** (D_{ij})

Estimating "domestic debtors (*j*) to euro area creditors (*i*)" for country c, D_{ij}^{c}

$$D_{ij}^{c} = \sum_{d \neq c} \mathrm{a}_{ij}^{dc}$$

a_{ij}^{dc} being assets of sector *i* in country *d*, liabilities of sector *j* in country *c*

$D_{ij}^{c} \neq \sum_{d \neq c} \mathrm{a}_{ij}^{cd} = C_{ij}^{c}$, which is the cross-border information reported by each country *c*, but…

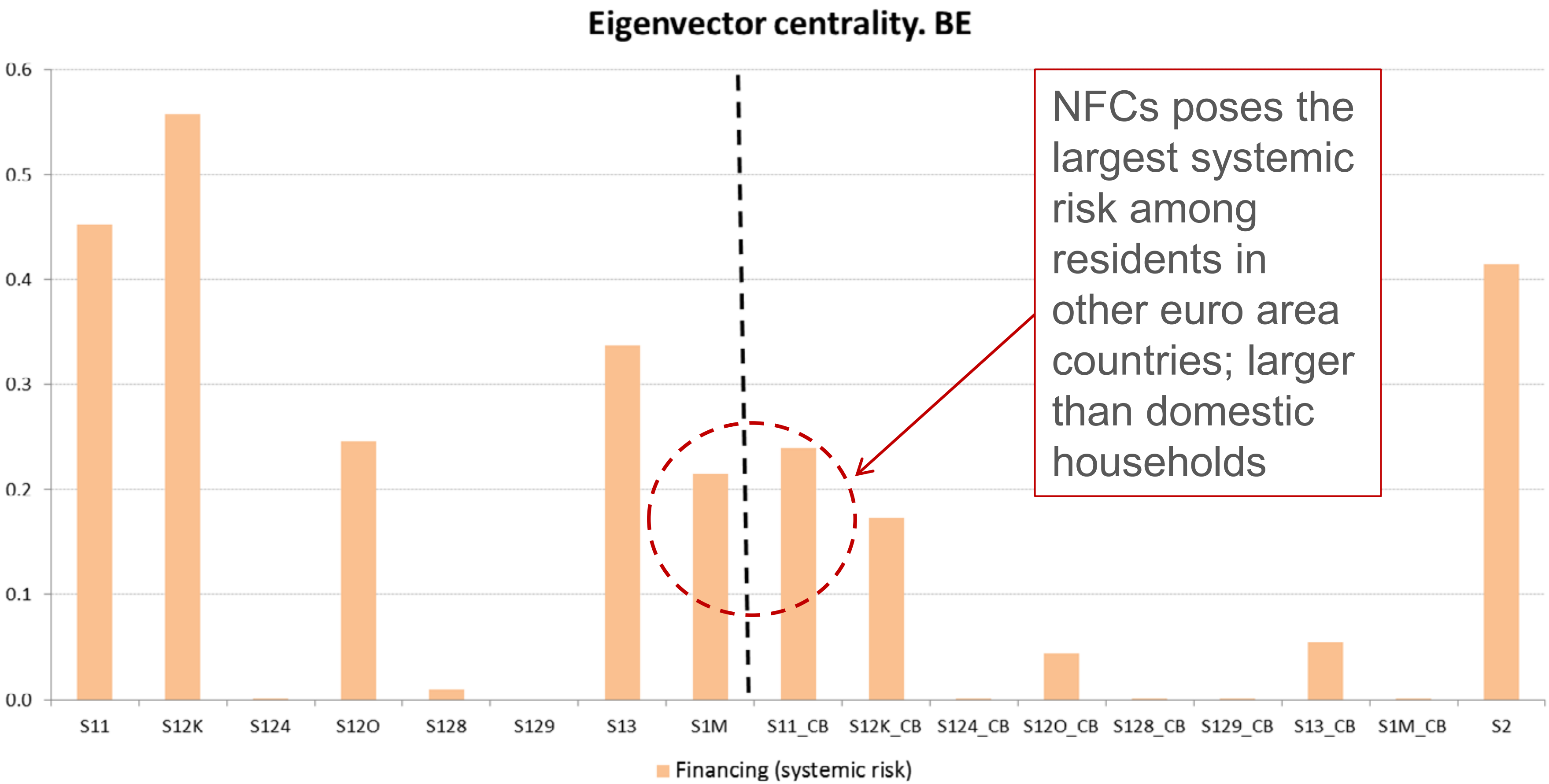
$$\sum_{c} D_{ij}^{c} = \sum_{c} \sum_{d \neq c} \mathrm{a}_{ij}^{dc} = \sum_{c} \sum_{d \neq c} \mathrm{a}_{ij}^{cd} = \sum_{c} C_{ij}^{c}$$

We assume that the distribution of D_{ij}^{c} across *i, j* is "similar" to that of $\sum_{c} D_{ij}^{c}$, *either by*

- *keeping identical structure, or*
- *by cross-entropy minimization (of Kullback–Leibler divergence)*

We look into…

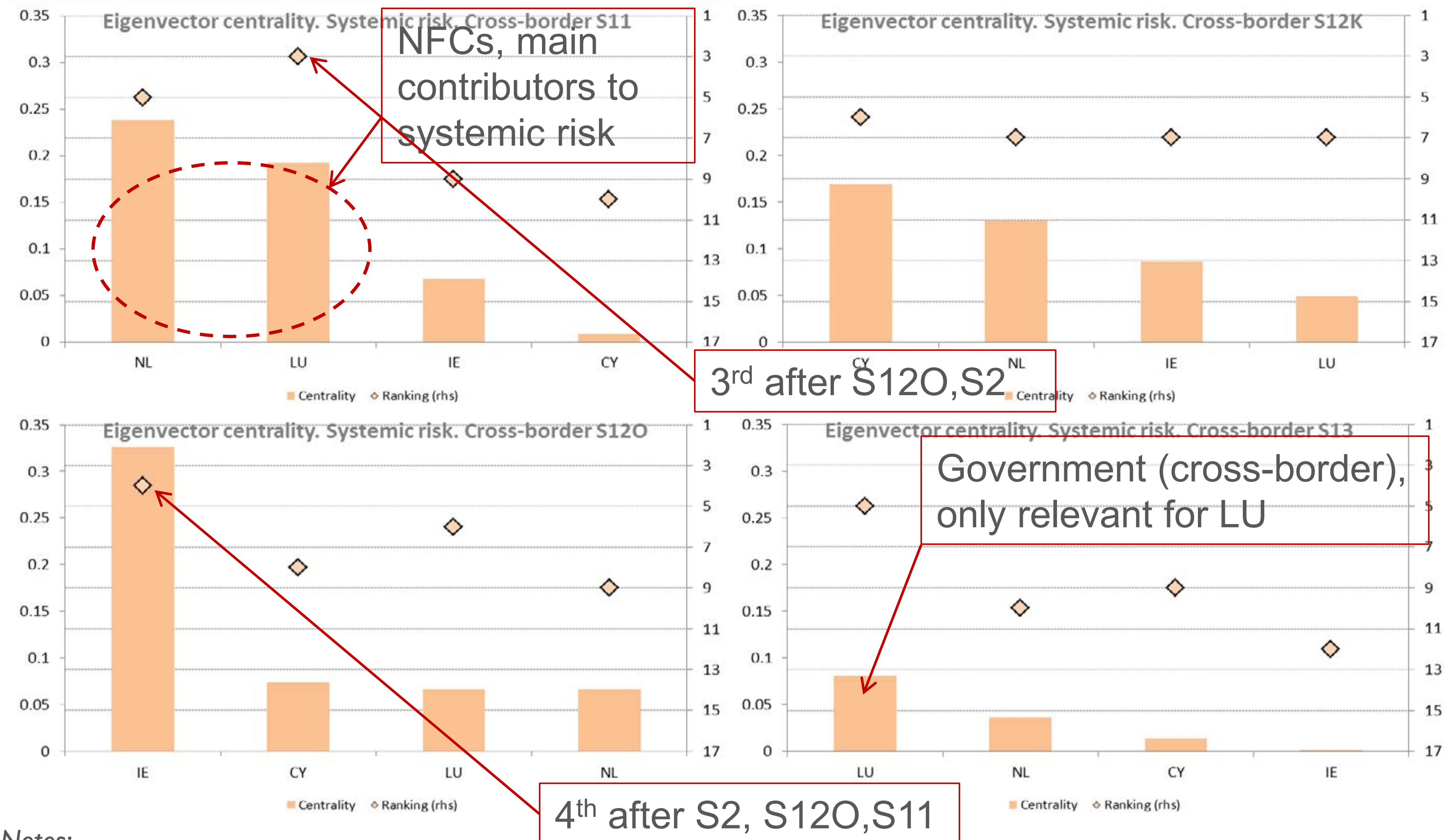
- ✓ **enlarged country networks ,** nodes for domestic sectors and for sectors resident in other euro area countries, (17 nodes in total); **for countries with high centrality of the OFI sector**
- ✓ eigenvector **centrality for "sectors in other euro area countries"**
- ✓ Caveats:
  - "sectors in other euro area countries" only covered in so far as they present links to domestic sectors: high order **indirect exposures/ risks via links within sectors resident in other euro area countries are not covered**
  - accuracy of estimates for links of "domestic debtors to euro area creditors", D_{ij}^{c}, on the basis of euro area averages might be poor for the countries of interest: eigenvector **systemic risk better estimated** (first order exposures based on reported data)



Notes:

- *Units: components of normalized Perron eigenvectors; enlarged network of debt ; debtor-creditor links; 16Q4*
- *Sector codes without suffix: domestic sectors; sector codes with suffix _CB: residents in other euro area countries; S2: extra euro area*

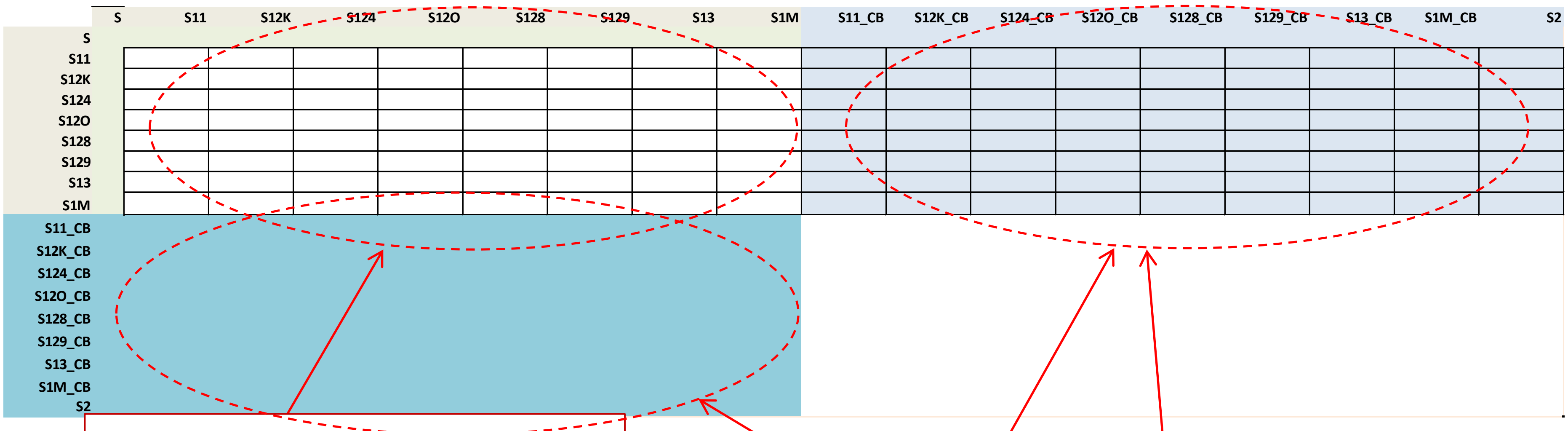
The "other euro area countries" sectors in OFI-central countries



Notes:

- *Units: components of normalized Perron eigenvectors; enlarged debt network ; 16Q4*
- *Sorted by centrality*

For the <u>euro area</u>, an “enlarged network” can also be compiled, but having a different interpretation



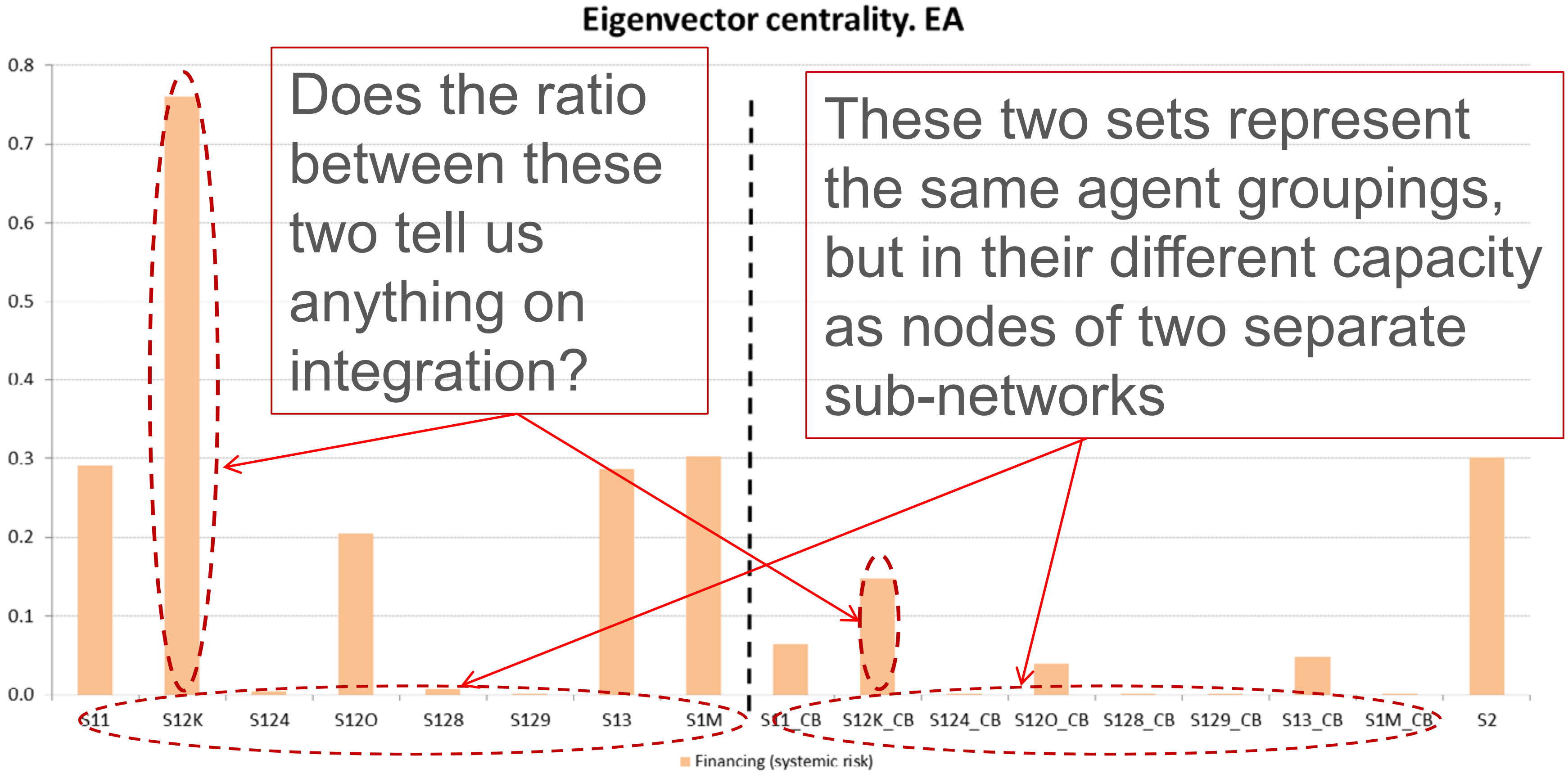
Domestic (only within borders) intra euro area links

$\sum_c C_{ij}^c$ cross border intra euro area links

$\sum_c D_{ij}^c$ cross border intra euro area links

These two matrices are identical. **No estimation needed!!**

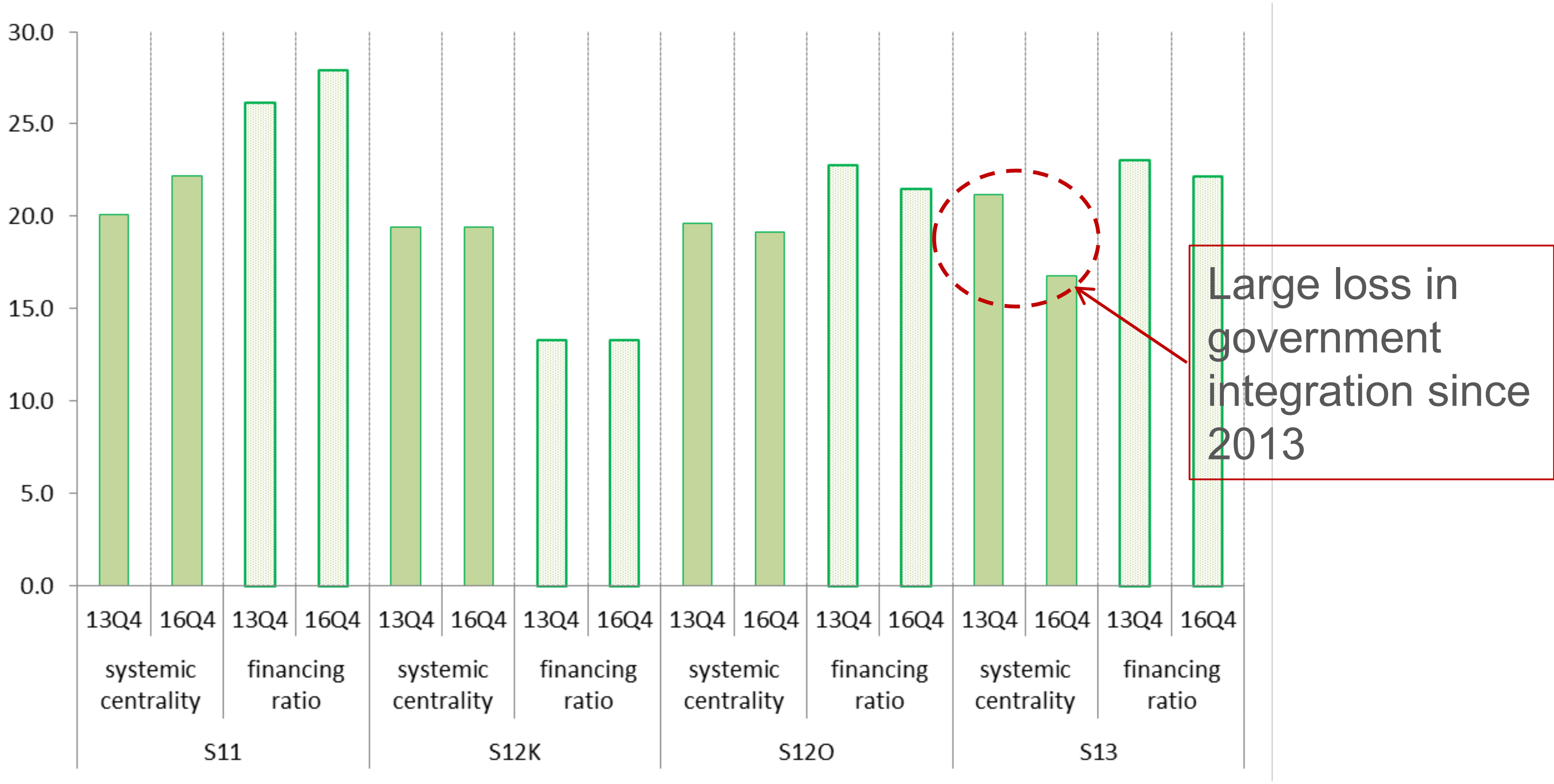
Difficult interpretation of Perron eigenvector



Notes:

- *Units: components of normalized Perron eigenvectors; enlarged network of debt; debtor-creditor links; 16Q4*
- *Sector codes without suffix: domestic sectors; sector codes with suffix _CB: residents in other euro area countries; S2: extra euro area*

More uniformity in sector integration if measured on Perron's eigenvector components (as opposed to volume ratios)



Notes:

- *Units: ratios in percentages of components of normalized Perron eigenvectors of debtor-creditor enlarged network (for systemic centrality), and of total debt liabilities (for financing ratio); for each sector, cross-border component (or cross-border financing) to domestic component (domestic financing)*

Conclusions

- ✓ Eigenvector centrality calculated on w2w financial accounts networks provides a convenient way to measure interconnectedness that accounts for indirect, second and higher order sector links

- ✓ NL, LU, IE, CY present high centrality scores for the OFI sector, both for the vulnerability and systemic risk metrics, surpassing sectors with higher total investment and financing

- ✓ For those countries, systemic risks posed by residents in other euro area countries are mainly coming from NFCs

- ✓ Ratios of eigenvector components for a euro area enlarged w2w financial accounts network might be used to measure financial integration: sectors present uniform integration levels, and the government shows a dramatic fall in integration since 2013

Thank you for your attention !

EUROPEAN CENTRAL BANK

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IFC-National Bank of Belgium Workshop on "*Data needs and Statistics compilation for macroprudential analysis*"

Brussels, Belgium, 18-19 May 2017

Measuring interlinkages between non-financial firms, banks and institutional investors: How securities common identifiers can 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 author and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

Measuring interlinkages between non-financial firms, banks and institutional investors: How securities common identifiers can help?[1]

Jose Maria Serena[2]

Abstract

We describe how to construct a dataset measuring financial interlinkages between non-financial companies and their creditors through their exposures to debt securities. We exploit that securities have common identifiers: using them, we first identify firms' liability exposures to these securities, and then creditors' exposures. These two steps fully define bilateral exposures. To illustrate the advantages of the bilateral exposures at the firm-level, we construct a small-scale dataset and depict recent leverage and profitability trends by firms with different types of creditors.

Keywords: firm-level data, matching datasets, securities common identifiers

JEL classification : C80, C81, F36, G15

Contents

[1] Paper for the IFC-NBB Workshop 'Data needs and statistics compilation for macroprudential analysis', Brussels, 18-19 May 2017

[2] Bank for International Settlements (Jose.Serena@bis.org)

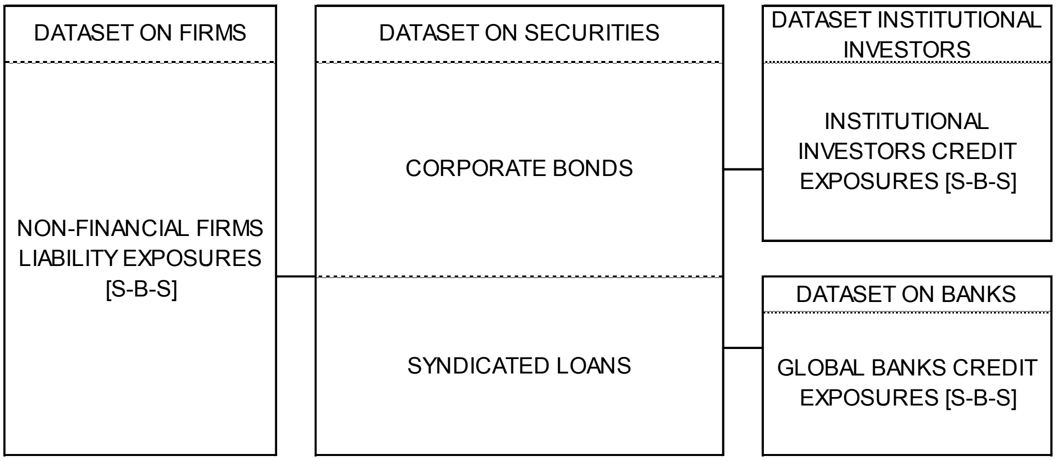
1. Introduction

Due to interlinkages between institutions, significant financial risks can remain hidden in firm-level metrics. Despite many data collection initiatives, information on interlinkages is scarce and constitutes a data gap.

In this paper, we describe how to construct a dataset of bilateral exposures between firms and their creditors, and this way partially overcoming this data gap. Our strategy consists in identifying firms' liability-side, and creditors' asset-side exposures to securities. Since securities (corporate bonds and syndicated loans) have common identifiers –ISINs or Bloomberg FIGI-, researchers can combine a securities dataset with the relevant pieces of information: a firm-level dataset containing liabilities on a security-by-security basis; and datasets on investors' holdings on securities, on a security-by-security basis. As described in Graph 1, combining all three datasets, we obtain the interlinkages between non-financial firms and their creditors (banks and institutional investors).

Measuring financial interlinkages: exposures to securities

Graph 1



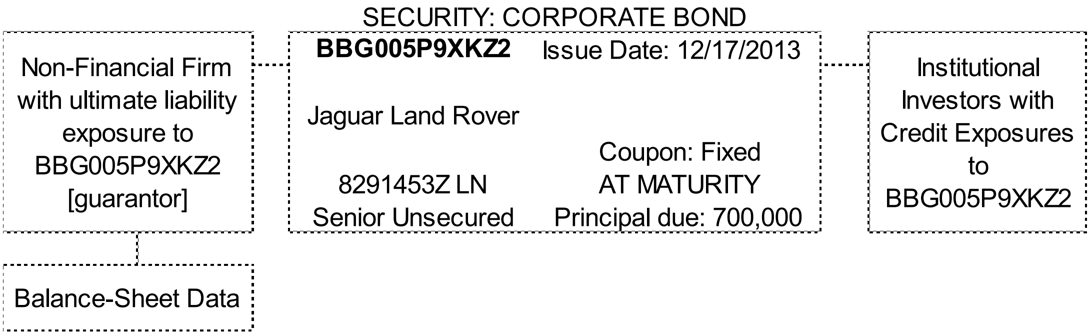
Source: own elaboration

The dataset is constructed in two steps. First, after defining a set of securities, we match them with a firm-level dataset containing their liabilities on a security-by-security basis. We focus on the ultimate risk-bearing entity: we consider that the company guaranteeing the security (not the issuer, nor the parent company) has the ultimate liability exposure. Second, and separately, we match securities with a security-by-security basis dataset on investors' holdings of bonds, and a similar dataset on parties involved in syndicated loans. To measure credit exposures, we focus on direct (immediate) exposures, thus treating creditors on a solo basis.

This method overcomes the drawbacks of the standard approach to compute bilateral exposures, which consists in using firm-level qualitative identifiers from a securities dataset (for instance, the "borrowers' name" in the syndicated loan dataset) and to match the latter with a firm-level dataset. The standard approach has drawbacks since qualitative identifiers often differ slightly across datasets; accordingly researchers need to decide if minor differences in firms' names reflect writing conventions, or are meaningful (ie, refer to different entities). Overall, matching using qualitative identifiers involves substantial judgment. In contrast, securities common identifiers are alphanumeric codes. Consequently, our procedure can be used on a large-scale and easily replicated. On top of this, the standard approach cannot be used to input information on the creditors; as a consequence researchers can only use the information available on the securities database, which is typically rather poor and often inexistent.

Exposures to corporate bond BBG005P9XKZ2

Graph 2



Source: Bloomberg, own elaboration.

We illustrate how the method works with an example in Graph 2, where we depict the interlinkages between a firm and its creditors defined by exposures to the corporate bond with Bloomberg FIGI BBG005P9XKZ2. This security is a senior unsecured plain-vanilla bond, issued the 12/17/2013; it pays a fixed coupon, and the principal is payed at maturity. The indenture of the corporate bond BBG005P9XKZ2 states that it was issued by Jaguar Land Rover –assigned an equity ticker 8291453Z LN-, who also has the legal obligation to repay it. Next, we find out which institutional investors hold the bond, and thus have credit exposures to BBG005P9XKZ2. Upon successful completion of these two steps, the financial interlinkages between a non-financial firm (ie, Jaguar Land-Rover) and their creditors (ie, institutional investors holding the bond) are neatly determined.

We argue that datasets constructed using this method provide important insights into system-wide risks in global financial markets, since they exhibit bilateral, firm-level exposures. To illustrate the type of insights we can get, we prepare a small-scale dataset measuring the interlinkages of the top 100 non-financial companies in the world financial markets. Then we depict differences in profitability and leverage for firms with different creditors. For the subset of companies with outstanding loans, we compare those with loans arranged by a G-SIFI with a capital surcharge>2%, versus the rest. For the subset of firms with outstanding bonds, we compare those in which Blackrock is the top holder of at least a bond, versus the others.

A final word on our purpose: in this paper we seek to emphasize a method to match datasets, and not to stress the sources of information we have used. Our method consists in placing securities at the center of the stage: we show that by exploiting securities common identifiers, researchers can jump from one database to another. We emphasize that researchers can use any dataset containing securities identifiers. The method can be applied generally, and works independently of the sources of information[3].

The rest of the article is structured as follows. Section 2 summarizes previous research and statistical initiatives matching datasets. Section 3 discusses our methodology, step-by-step. Section 4 illustrates the advantages of having a dataset on financial interlinkages using a small-scale dataset. Section 5 presents the main conclusions.

2. Matching datasets: An overview of previous methodologies

Measuring financial interlinkages between firms and their creditors requires matching datasets. To combine datasets, researchers need identifiers simultaneously present in the different sets of information. So far, firms' Legal Economic Identifiers –LEIs- are not fully available. Consequently, the standard approach to measure interlinkages consists in combining a firm-level and a securities dataset using firm qualitative-identifiers. Firm qualitative-identifiers are, for instance, firm name, or the parent-company name.

For instance, Ferreira and Matos (2012, 2015) match a large sample of syndicated loans with their borrowers (ie, non-financial firms' data) to investigate lending relationships. They obtain syndicated loans from DealScan, while non-financial firms' data is obtained from Datastream/Worldscope. To merge the data they focus on the Borrower-Parent field in DealScan, which they use to identify the firm's country and ticker and subsequently obtain the firm-level information. But, as they describe, this strategy sometimes fails and they need to resort to manual matching.

Similarly Ongena et al. (2015) construct a bank-firm level data for a sample of Eastern European countries combining bank-level information from Bankscope and firm-level data from Amadeus. They use the 2010 vintage of Kompass to identify lending relationship between banks and firms. In this case, they cannot match datasets using the name, since writing conventions differ in the two datasets. In this way they complement borrowers' names with information on website, email address and/or telephone number. If information on the borrower of the security coincides in all these dimensions (name, website, email address, telephone number) with the equivalent information on the firm-level dataset, they assume both entities are the same and subsequently merge the datasets. The main problem with this procedure is that it involves judgment: coincidence in the chosen fields does not ensure that the two entities are equivalent. Moreover, the information on lenders is often poor or unavailable.

Overall, matching datasets using firm-level qualitative identifiers has drawbacks. As this method involves judgement, it is difficult to conduct the procedure on a large

[3] Datasets provided by private vendors (eg, Thomson Reuters, Bloomberg, S&P IQ, Worldscope) have important pieces of information, which often contain similar information; separately central banks micro-level datasets (for instance, the ECB SHS, CBDH) contain relevant information. In our specific case, we have used Bloomberg. Similarly, in this paper, we use the FIGI (Bloomberg Global Identifier) as our security identifier, but alternatively we could have used the ISIN.

scale, regularly update the dataset, or replicate other researchers' work. On the other hand, it is not possible to use firm-level qualitative identifiers to input creditors' information, since datasets on securities-by-securities holdings rarely contain the name of the issuer or its parent company.

For this reason, we propose exploiting the fact that securities –corporate bonds and syndicated loans- have common identifiers[4]. Upon issuance, securities receive two distinct identifiers: the ISIN (International Securities Identification Number), and the FIGI (Financial Instrument Global Identifier). The ISIN is the International Securities Identification Number, which is an alphanumeric twelve-digit code assigned to securities such as bonds, shares, options, derivatives, futures, and syndicated loans. The ISIN has global reach and encompasses national coding schemes such as CUSIP (which identifies US and Canadian securities), or SEDOL (similar for the UK Stock Exchange). The FIGI is the Financial Instrument Global Identifier previously known as the Bloomberg Global Identifier), also a twelve-character alphanumeric identifier. It was introduced by Bloomberg in 2014, and it is assigned to instruments of all asset classes[5].

Securities identifiers are readily available in securities datasets. Thus we are able to combine the securities dataset with any other containing them -we can jump from one dataset to another-.

Our proposal to make use of common identifiers to combine datasets is aligned with ongoing statistical initiatives using micro data. So far common identifiers have been used in work focusing on firm-bank linkages in a specific country, which might combine up to three central banks' datasets using in-house identifiers: credit register, bank balance sheets and income statements, and firm balance-sheets and income statements[6].

Some recent research has also used common identifiers to match securities datasets with other pieces of information on a cross-country setup. Bruno and Shin (2016) match a firm-level and a securities dataset using the ultimate parent CUSIP as firm-identifier (that is, the CUSIP or the equity security listed by the firm). This CUSIP is available in the securities dataset they are using (SDC Platinum New Issues Database from Thomson Reuters), so they do not need to resort to qualitative firm-identifiers. Fuertes and Serena (2015) match a firm-level and a securities dataset using securities common identifiers. None of these papers, however, combines the securities dataset with information on creditors. On the other hand, some research has combined securities holding (creditors) data with bond-level datasets, but not with borrowers' information. Barbu et al. (2016) use securities common identifiers to combine the Bundesbank Investment Funds Statistics with the ESCB Centralised Securities Database. Becker and Ivanisha (2015) combine data on institutional

4 Syndicated loans are treated as a debt-security, since can be traded in secondary markets; accordingly since 2004 they receive an ISIN; Bloomberg also identifies them as well by a FIGI.

5 While there is some debate between advocates of each of them, for our practical purposes both are equally useful. Their advantage is that each security has a sole financial identifier. It is straightforward to identify corporate bonds and syndicated loans either by their ISIN or their FIGI.

6 For instance De Jonghe et al. (2016) merge firm-bank level credit data to investigate credit reallocation, using data from the National Bank of Belgium (NBB). Baskaya et al. (2016, 2017) use data from the Central Bank of Turkey (CBRT) to construct a similar bank-firm dataset, combining also the three dimensions. Carabin et al. (2015) merge firms' data with loans and corporate bonds issued in both domestic and international markets, for the case of Mexico.

investors' holdings of corporate bonds, with securities data, and information on yields.

Overall, the use of common identifiers is taking off. They are also at the heart of existing, large-scale, security-by-security databases, such as the Central Securities Database of (CSDB) (Cornejo and Huertas (2016), Cornejo et al. (2017)). In this paper, we propose to extend their use to shed light on interlinkages between firms, banks, and institutional investors.

3. Matching process: Step-by-step

The matching process proceeds sequentially. As a preliminary step we define a group of securities (corporate bonds and syndicated loans). Each security is uniquely identified by an ISIN code, and a FIGI identifier. We separately identify the liability and the asset-side exposures to these securities. These two matching processes are fully independent, and upon completion, they define the financial interlinkages between non-financial companies and their creditors.

The identification of the liability-side exposures consists in two steps, which we illustrate in Graph 3 using as an example three corporate bonds issued by companies of the Tata Motors Ltd. conglomerate.

First, to measure firms 'exposures to securities we need to identify the ultimate risk-bearing entity (Tissot, 2016) in a firm-level dataset with a security-by-security breakdown. Such datasets shall list the securities (and the corresponding ISIN/FIGI) to which a firm is, in certain way, exposed. There are different ways of defining exposures: at the issuance level -securities issued by a given firm-; at the guarantor level -securities guaranteed by a company-; at the parent company level -securities issued by a company and all its subsidiaries-. In box 1 we briefly describe the structure of these datasets.

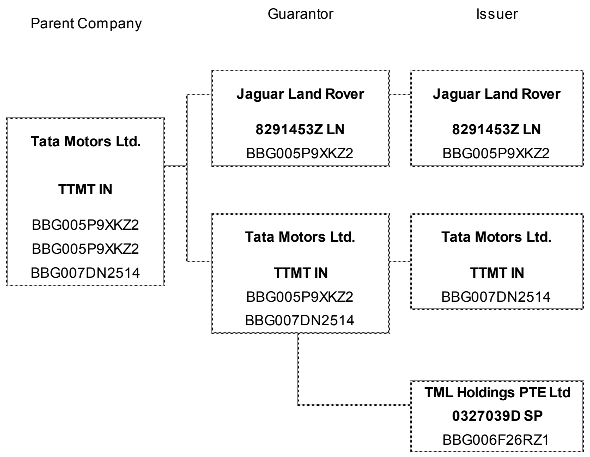
We posit that the ultimate risk-bearing entity is the company guaranteeing the security. This choice matters, as we describe in our example below –Graph 5-. Each of the three bonds has been issued by a different entity (Jaguar Land Rover, Tata Motors Ltd, and TML Holdings PTE Ltd). However, there are only two guarantors, since the corporate bond issued by TML Holdings PTE Ltd -with FIGI BBG006F26RZ1- receives a guarantee from Tata Motors Ltd. As previously described, the three bonds have been issued by companies of the same conglomerate, since Tata Motors Ltd fully owns both Jaguar Land Rover and TML Holdings PTE Ltd.

In the second step, we recover the financial information for each of these guarantors, and match this firm-level dataset with the securities dataset using the FIGI of each instrument (see Panel B). We input firms' financial information using firms' equity tickers as firm-identifiers. It is noteworthy that the financial metrics of Jaguar Land Rover and Tata Motors Ltd. exhibit important differences: the latter has higher leverage ratios, and lower profitability, although as expected it is a much larger company. This underscores the fact that choosing between the issuer, the guarantor, and the parent company matters.

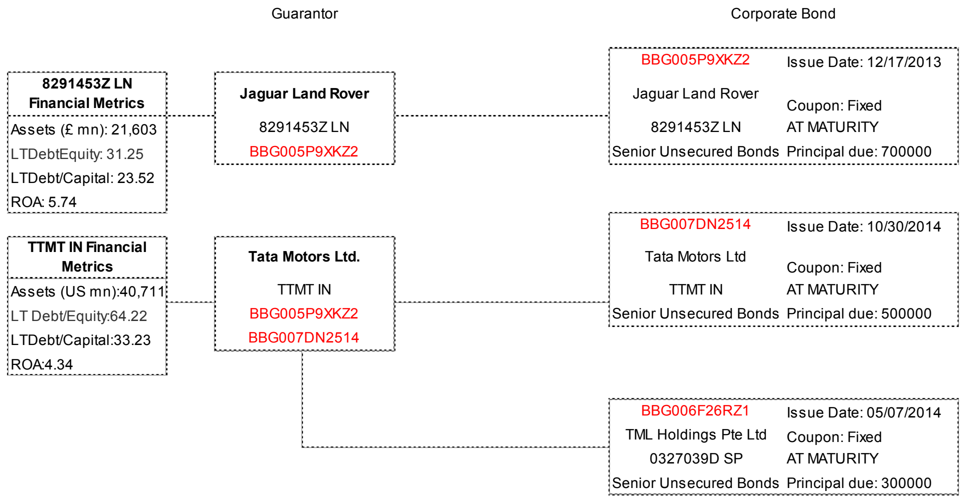
Identifying liability-side exposures to securities

Graph 3

Panel A. Issuance structure in the firm-level dataset with security-by-security breakdown



Panel B. Matching firm-level (guarantor) with securities dataset



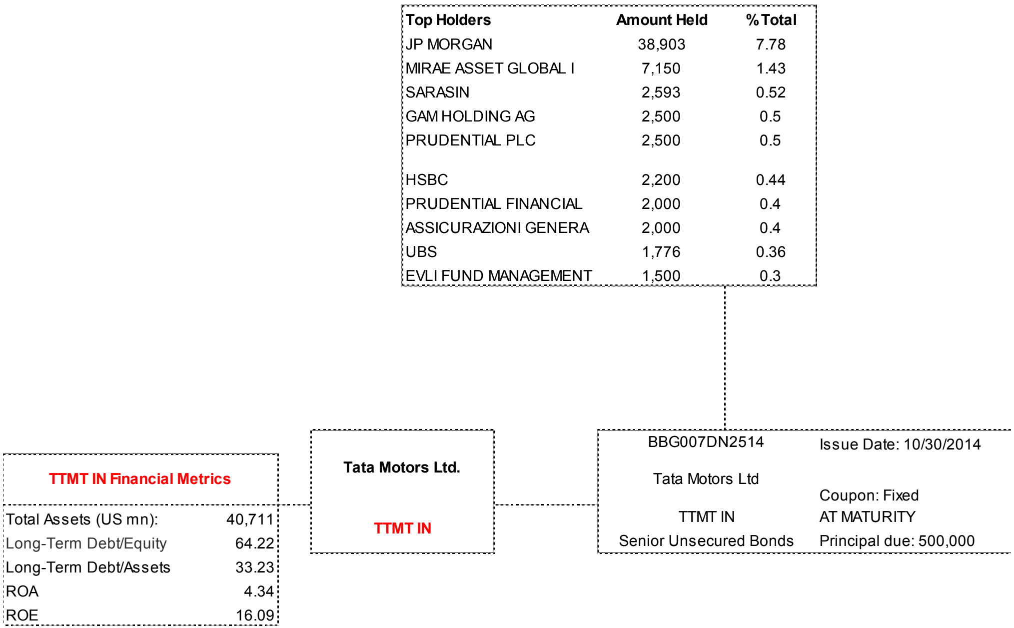
Source: Bloomberg, own elaboration

Next we identify the asset-side exposures to these securities, combining the current dataset with information on creditors. Here we need to pin down different pieces of information: on the one hand a dataset on bondholders on a security-by-security basis; on the other, a dataset on global banks' syndicated loans, also at the deal level. These datasets can be matched as long as they contain the relevant common identifier of the security (ISIN/FIGI).

Following up with our example, we detail investors' exposures to the corporate bond BBG007DN2514, inputting information on bondholders on a security-by-security basis. Researchers can obtain this information from different sources. In this exercise, we input it from Bloomberg (holdings as of April 2017). We report in Graph 4 the top 10 holders of the bond: JP Morgan holds 7.78% of the total, while the remaining holders have smaller fractions.

Identifying asset-side exposures: holders of corporate bond BBG007DN2514

Graph 4



Source: Bloomberg, own elaboration.

Similarly, in Graph 5 we input the initial exposures to the syndicated loan BBG00BVH29V7, and specific aspects of the deal. ANZ Banking Group act as the book runner. Many institutions took part in the deal, and ANZ Banking Group and Bank of Tokyo-Mitsubishi acquired the largest participations.

Overall, by completing these two steps, we have defined the firm-level interlinkages between firms and their creditors. We know, for instance, that the Korean Development Bank took a stake of 8% in a syndicated loan to Tata Motors Ltd in 03/11/2016, and in the last filings this company reported a ROA of 4,3%.

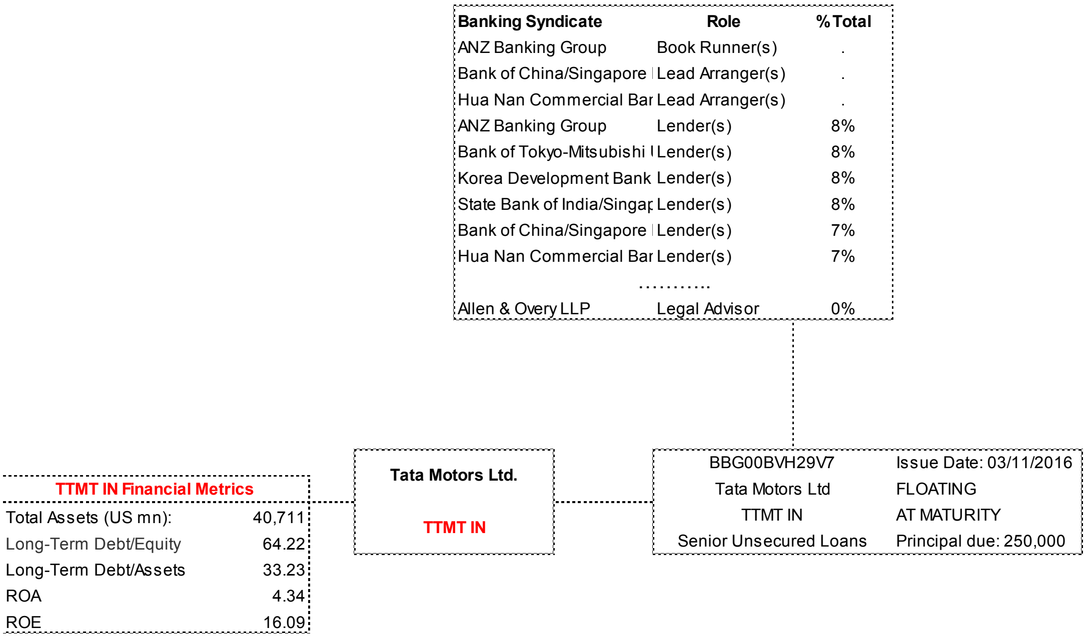
Using this methodology, we can construct a cross-country, firm-level dataset on bilateral interlinkages between firms and their creditors.

Our exercise still has several limitations, since we measure asset-side exposures on an immediate basis. Ultimate exposures can be substantially different due to derivatives transactions. Moreover, in the syndicated loan data, we have used reports the original parties, and not transactions in the secondary market. Finally, in the bondholders' data we have used only includes current holdings, but we do not have information on historical information.

It is important to stress that these limitations have to do with the specific data we have used, and not with the method. Researchers could compute ultimate exposures using derivatives transactions. They could also track syndicated loans transactions in the secondary market. Finally, they could input historical data on bondholders' exposures.

Identifying asset-side exposures: banking syndicate of loan BBG00BVH29VY

Graph 5



GraphFootnote

Source: Bloomberg, own elaboration.

4. Reaping the gains: bilateral exposures at the firm-level

In this section, we briefly illustrate the type of highly granular analyses that researchers can conduct with a dataset depicting firms' financial metrics by type of creditor. The main advantage is that it contains bilateral exposures at a firm-level.

For illustration purposes, we construct a small-scale dataset covering the top 100 firms in world financial markets, excluding non-financial firms and Chinese companies. Table 1 shows the summary statistics. The dataset covers 73 firms, most of which are based in the United States. They guarantee 2,454 securities, of which 2,352 are corporate bonds, and 102 are syndicated loans (we disregard municipal securities). We briefly summarize the number of creditors in the last two columns.

We exploit the fact that the dataset contains bilateral exposures at a firm-level, and we depict differences in profitability (Graph 7) and leverage (Graph 8) for firms with different creditors. This exercise is just for illustrative purposes, and we do not comment on the patterns below; we acknowledge that the sample is small and perhaps these patterns do not hold in a larger dataset.

Matched firm-securities-creditors dataset. Summary statistics[1]

Table 1

	Number of firms	Number of securities			Number of holders	
		Total	Bond	Loans	Parties in syndicated loan	Bond holders
Total	73	2,454	2,352	102	343	1098
United States	49	2,042	1,964	78	221	1020
Europe	15	326	309	17	154	431
Rest of the world	9	86	79	7	55	100

[1] Sample: Top 100 firms in the Bloomberg World global index, excluding financial companies, and Chinese firms. Municipal securities not included.

Sources: own elaboration.

With this caveat in mind, in the upper left-hand panel we compare differences in financial metrics between firms with, and without outstanding securities, as well as the overall mean. In the upper right-hand panel, we compare firms that are loan issuers, which those that are bond issuers. These panels exploit the information of the firm-level dataset with securities-by-securities breakdown; we can thus identify which firms have outstanding securities, and their type. We do not want to overstress the patterns. However, it seems that firms without securities are less profitable; despite this, they exhibit, perhaps surprisingly, a similar rising leverage trend.

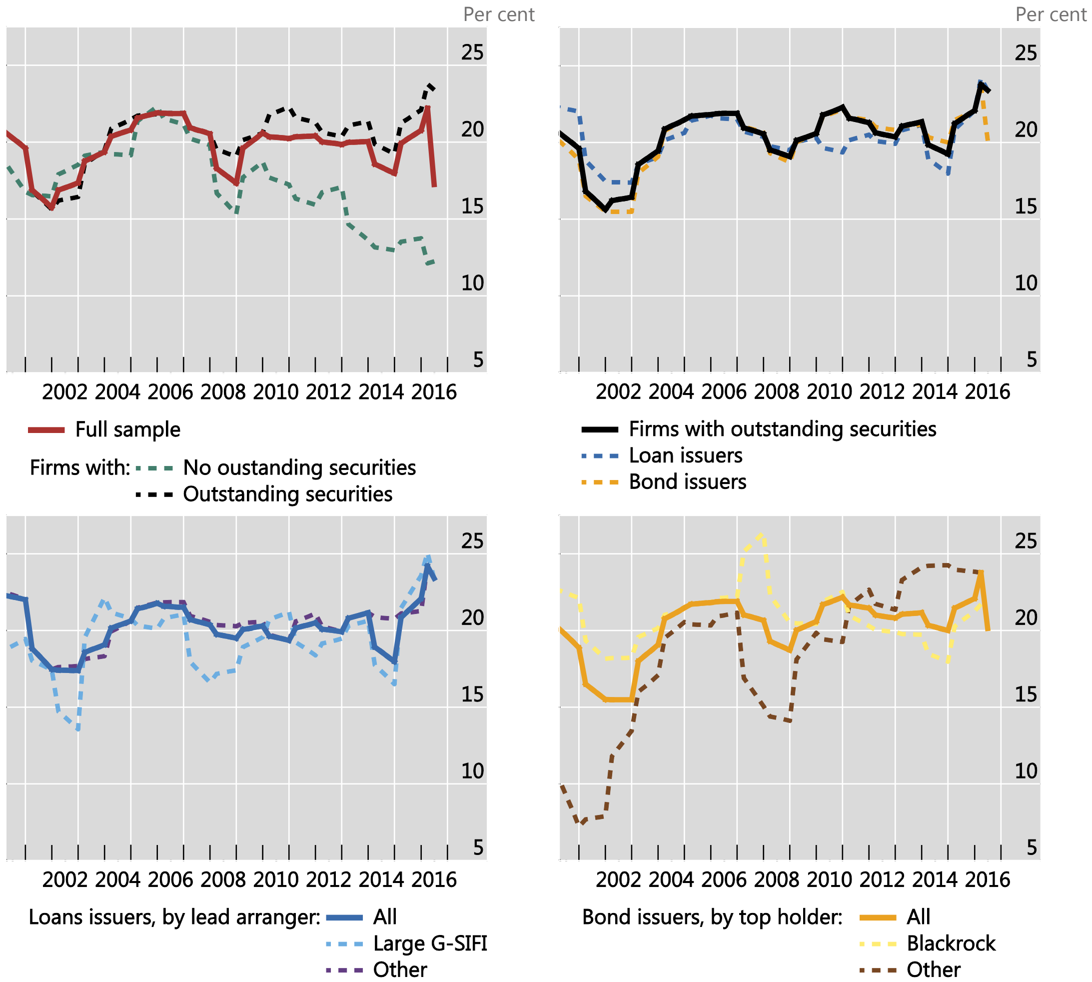
Next we exploit the bilateral exposures at a firm level. In the bottom left-hand panel we focus on the subset of companies with outstanding loans. For each loan we know the full list of members of the banking syndicate, as well as their type of involvement (ie, main lender, lender, legal advisor, and so on). To illustrate the power of a dataset on firm-level bilateral exposures, we compare firms that borrowed from a large global bank, with the rest. We consider that a firm borrowed from a large global bank when a G-SIFI with a capital surcharge>2% acted as lead arranger. We can carry out this exercise because the dataset contains information on the members of the banking syndicate that took part in each deal.

There are theoretical reasons why the financial metrics of these two groups of companies might exhibit non-random differences. On the one hand, large banks are likely to exhibit a major ex-post involvement in firms' decisions. This can lend to differences in their payout, expenditures, and borrowing and investment policies. On the other hand, large banks have a higher ability to oversee companies, so ex-ante might select different deals (for instance, more "complex" borrowers). Comparing firms' financial metrics can shed light on interesting questions: are financial metrics trends different for firms with loans vis-à-vis large banks? Are they more erratic, or systematically below, or above, their peers metrics? The differences in our sample are not remarkable, but it would be interesting to investigate this pattern in a dataset covering a much larger number of companies.

Non-financial firms' ROE

Median values, by type of financial interlinkage

Graph 6

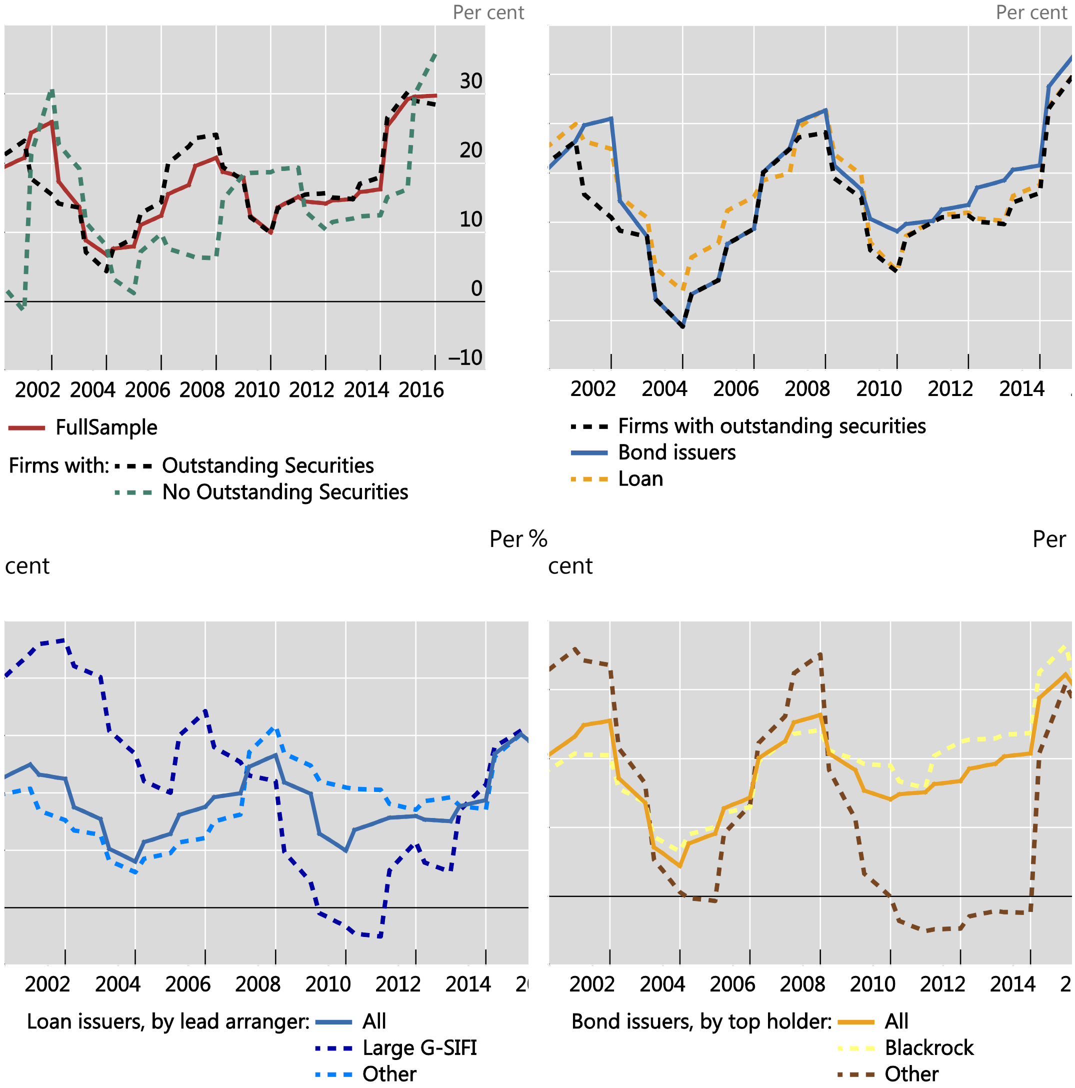


Source: Bloomberg, own elaboration.

Finally, in the bottom right-hand panel we focus on companies with at least an outstanding bond. For each bond we know the list of the ten largest holders. Consequently, we can compare if firms with bonds vis-à-vis different bondholders exhibit different metrics. We define a group with the subset of firms with at least an outstanding bond in which Blackrock is the top holder; the control group contains the remaining firms. We assume the major top holder has more power and interest in monitoring the company. Thus the very same arguments sketched above could explain differences in metrics between these two groups of firms (ie, Blackrock is a large company, and thus can exert a higher influence on firms, or select different deals). While we do not want to overstretch the results, the financial metrics of the firms with bilateral exposures to Blackrock seem less erratic.

Non-financial firms' leverage

Median values, by type of financial interlinkage | Graph 7



Source: own elaboration, Bloomberg.

5. Conclusions

Datasets on interlinkages between firms and their creditors are important to assess macroprudential risks. The process to construct such datasets is complex and requires combining different data in sources.

In this paper we propose a method to construct it. It consists in matching datasets using the securities identifiers. First, combining a securities dataset with a firm-level database with a security-by-security liability breakdown. Next merging the resulting dataset with information on bondholders on a security-by-security basis; and with information on the parties involved in syndicated lending.

To highlight the importance of measuring bilateral linkages, we construct a small-scale dataset. We compare differences in financial metrics for firms with different creditors. It is possible to use this procedure to construct a large-scale, cross-country, firm-level dataset on bilateral exposures.

References

Avdjiev,S., B, McCauley, and H. Shin, (2015), "Breaking free of the triple coincidence in international finance", Econ Policy (2016) 31 (87): 409-451

Barbu, A., C. Fricke, and E. Moench (2017), "Reach for Yield in Investment Funds", mimeo

Baskaya, Y.S., J. di Giovani, S. Kalemli-Ozcan, ad M. Fatih Ulu (2016), "International Spillovers and Local Credit Cycles", mimeo

Baskaya, Y.S., J. di Giovani, and S. Kalemli-Ozcan (2017), "Capital Flows and the International Credit Channel", mimeo

Bronzini, R. and A. D'Ignazio (2012), "Bank internationalisation and firm exports: evidence from matched firm-bank data", EFIGE Working Paper No. 59 August 2012

Carvalho, D., M.A. Ferreira, and P. Matos (2015), "Lending Relationships and the Effect of Bank Distress: Evidence from the 2007-2009 Financial Crisis", Journal of Financial and Quantitative Analysis Vol. 50 No. 6 Dec. 2015

CIEPR (2015), "Corporate Debt in Emerging Economies: A Threat to Financial Stability", Brooking Institutions

Clerc, L., A. Giovannini, S. Langfield, T. Peltonen, R. Portes, and M. Scheicher (2016), "Indirect contagion: the policy problem", ESRB Occasional Paper Series No.9 January 2016

Cornejo, A., J. Huerga, F. Mayerlen, J. Micheler (2017),"Unique identifiers in micro-data Management –the Centralised Securities Database (CSDB) experience", in "IFC Bulletin No.43 -Statistical implications of the new financial landscape"

Cornejo, A. and J. Huerga, (2016)," The Centralised Securities Database (CSDB) - Standardised micro data for financial stability purposes", in "IFC Bulletin No.41 - Combining micro and macro statistical data for financial stability analysis. Experiences, opportunities and challenges"

De Jonghe, O., H. Dewachter, K. Mulier, S. Ongena, and G. Schepens (2017), "Some borrowers are more equal than other: Bank funding shocks and credit reallocation", mimeo

Carabin, M., De la Garza, M., and O. Moreno (2015), "The effect of global liquidity on corporate financing in Mexico", mimeo

Ferreira, M. and P. Matos (2012), "Universal Banks and Corporate Control: Evidence from the Global Syndicated Loan Market" Review Financial Studies

McCauley, B,, P. McGuire, P., and V. Suskho (2015a), "Dollar credit to emerging market economies", BIS Quarterly Review December 2015

McCauley, B,, P. McGuire, P., and V. Suskho (2015b) "US monetary policy, leverage and offshore dollar credit" Economic Policy, vol 30, no 82, April 2015, pp 187-229.

Ongena, S., J.L. Peydro, and N. van Horen (2015), "Shocks Abroad, Pain at Home? Bank Firm Level Evidence on the International Transmission of Financial Shocks" IMF Economic Review November 2015

Tarashev, N., S. Avdjiev, and B, Cohen (2016), "International capital flows and financial vulnerabilities in emerging market economies: analysis and data gaps", Note submitted to the G20 International Financial Architecture Working Group

Tissot, B. (2016), "Globalisation and financial stability risks: is the residence based approach of the national accounts old-fashioned?", BIS Working Papers ° 587 October 2016

Box A

Liability breakdown at the firm-level

A firm-level database with a security-by-security liability breakdown lists all the securities guaranteed by a company. Securities shall be identified with their corresponding common identifier (ISIN/FIGI). Security-by-security breakdown are available in some firm-level datasets. We illustrate the structure of this dataset in Table A, using as example TTMT IN. In this specific example, we have obtained the information from S&P Capital IQ.

List of the latest eight securities guaranteed by TTMT IN (1)

Offer Date	Maturity Date	Issuer	Coupon	Offering Amount ($mm)	Outstanding Amount ($mm)	Coupon Type
Jun-22-2017	Jun-22-2022	Tata Motors Ltd	7.5	77.38	77.37	Fixed
Jan-25-2017	Jan-25-2020	Tata Motors Finance Ltd	-	22.04	23.21	Zero
Jan-10-2017	Jan-10-2020	Tata Motors Finance Ltd	-	36.63	38.68	Zero
Jan-10-2017	Apr-15-2020	Tata Motors Finance Ltd	-	25.64	27.08	Zero
Jan-10-2017	Mar-26-2020	Tata Motors Finance Ltd	-	25.64	27.08	Zero
Oct-30-2014	Apr-30-2020	Tata Motors Ltd	4.625	500.0	500.0	Fixed
Oct-30-2014	Oct-30-2024	Tata Motors Ltd	5.75	250.0	250.0	Fixed
May-07-2014	May-07-2021	TML Holdings Pte. Ltd.	5.75	300.0	300.0	Fixed

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BANK FOR INTERNATIONAL SETTLEMENTS

IFC-National Bank of Belgium Workshop on "*Data needs and Statistics compilation for macroprudential analysis*"

Brussels, Belgium, 18-19 May 2017

Measuring interlinkages between non-financial firms, banks and institutional investors: How securities common identifiers can help?[1]

Jose Maria Serena Garralda,

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.

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MEASURING INTERLINKAGES BETWEEN NON-FINANCIAL FIRMS, BANKS AND INSTITUTIONAL INVESTORS. HOW SECURITIES COMMON IDENTIFIERS CAN HELP?

Jose Maria Serena Garralda*

Irving Fisher Committee Secretariat

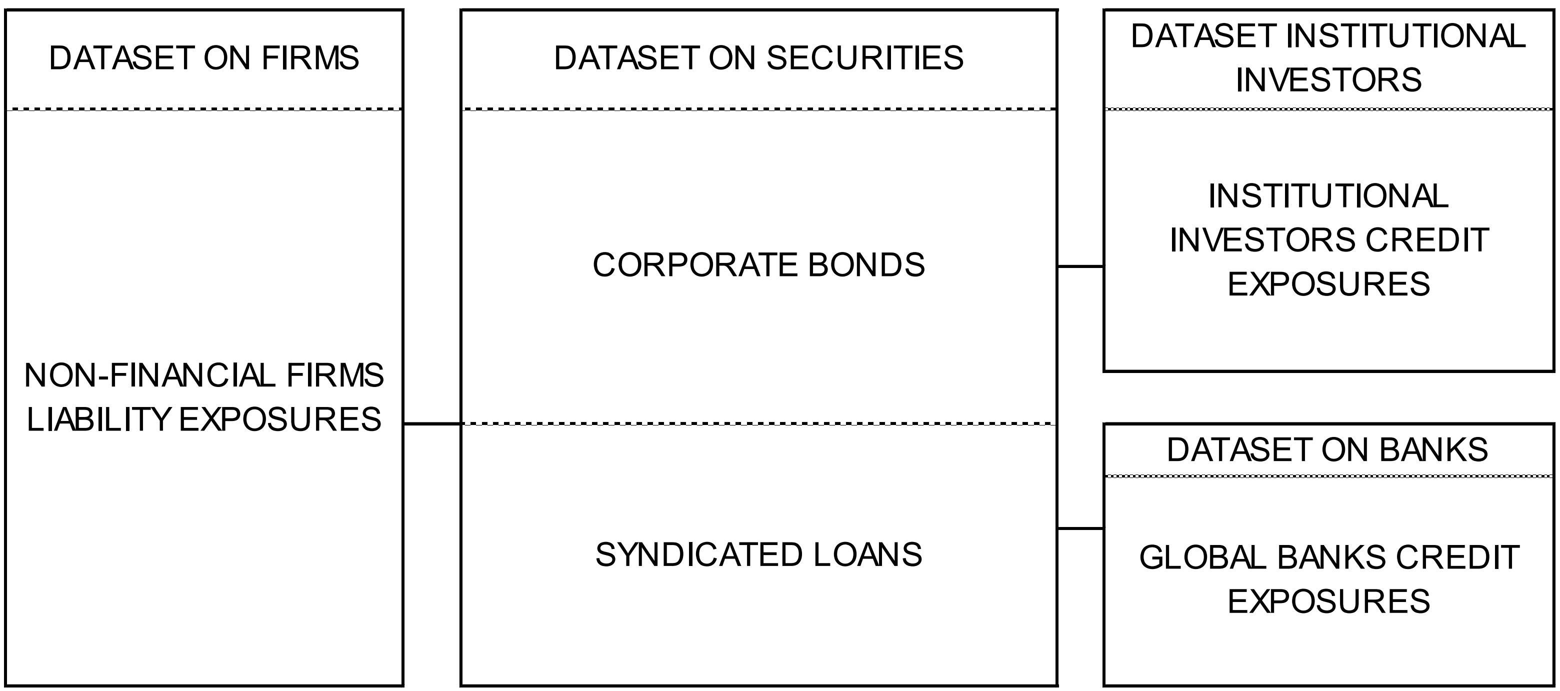
Bank for International Settlements

**Joint work with Kaushik Jayaram (BIS)*

The views expressed are those of the author and do not necessarily reflect those of the BIS or the IFC.

INTRODUCTION

- Macroprudential policy has two dimensions: the cyclical, and the system-wide. Financial interlinkages between firms and their creditors (banks and institutional investors) are an important aspect of the latter. But firm-level measurement is highly challenging.



INTRODUCTION

- This paper: addresses measurement problems and proposes a matching method which directly identifies institutions' credit and liability exposures using securities common identifiers (ISIN-FIGI).

SECURITY: CORPORATE BOND

Non-Financial Firm with ultimate liability exposure to BBG005P9XKZ2 [guarantor]

BBG005P9XKZ2 Issue Date: 12/17/2013

Jaguar Land Rover

Coupon: Fixed

8291453Z LN

AT MATURITY

Senior Unsecured

Principal due: 700,000

Institutional Investors with Credit Exposures to BBG005P9XKZ2

Balance-Sheet Data

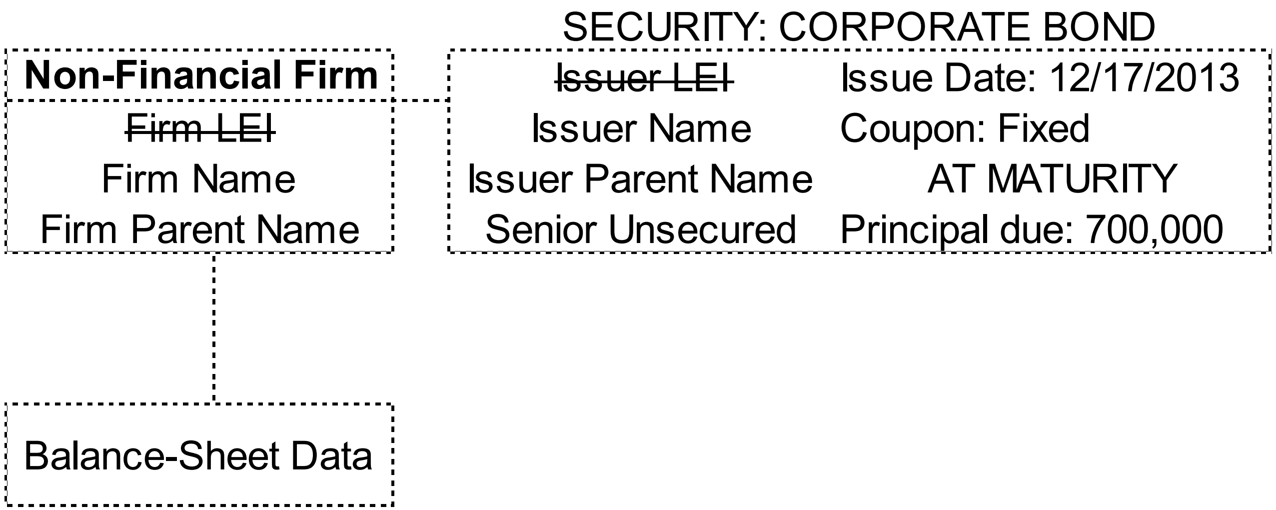
- Resulting datasets will enhance our understanding of system-wide risks. To illustrate this we construct a small-scale dataset and depict firms' profitability trends for companies with different interlinkages.

OUTLINE

1. Introduction
2. Securities common identifiers: their role
3. Matching process: step-by-step
4. The gains: ROE trends by financial interlinkages
5. Conclusions

SECURITIES COMMON IDENTIFIERS: THEIR ROLE

- **Old approach:** match firm and securities-level datasets using qualitative firm-level information; imprecise, and cannot be used to match creditors 'data.



"Matching process is rather cumbersome as only a small portion of the firms can be matched directly by name (as writing conventions differ between the two databases). (…)" Ongena, Peydro, and van Horen (2015), *IMF Economic Review*

SECURITIES COMMON IDENTIFIERS: THEIR ROLE

- **New approach:** exploit that securities [corporate bonds and syndicated loans] have common identifiers:
  - ISIN: corporate bonds, shares, options, derivatives, futures, and syndicated loans.
  - FIGI [Bloomberg]: twelve-character alphanumeric identifier, introduced in 2014 assigned to instruments of all asset classes.
- Then answer these two questions…
  - Which firms have liability exposure to these securities – identified by their ISIN/FIGI-?
  - Which investors (banks and institutional investors) have asset-side exposures to them?
- …using equity tickers as firm-identifiers (Bruno and Shin (2017), Fuertes and Serena (2016)); since LEIs are not well-defined.

SECURITIES COMMON IDENTIFIERS: SOME INTERESTING REFERENCES

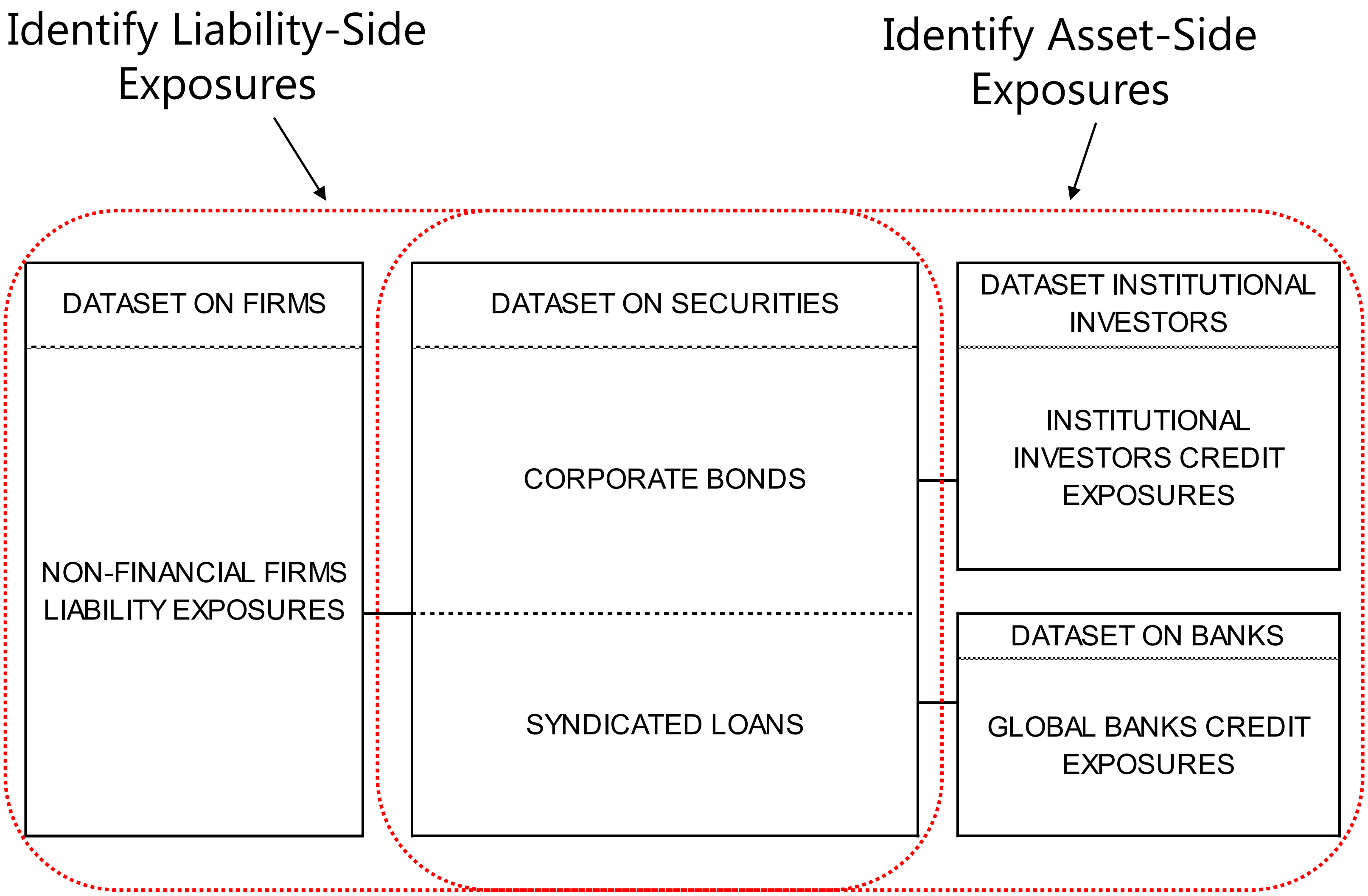
- Barbu, A., C. Fricke, and E. Moench, "Reach for Yield in Investment Funds", *mimeo*

- Bruno, V. and H. Shin (2017), "Global dollar credit and carry trades: a firm-level analysis", *Review of Financial Studies*, vol 30, no 3, 2017

- Cornejo, A., J. Huerga, F. Mayerlen, J. Micheler (2017),"Unique identifiers in micro-data Management –the Centralised Securities Database (CSDB) experience", in *"IFC Bulletin No.43 -"*

- Fuertes, A. and J. M. Serena (2016), "How firms borrow in international bond markets: Securities regulation and market segmentation", *Banco de Espana Working Paper* No. 1603

MATCHING PROCESS: STEP-BY-STEP



LIABILITY-SIDE EXPOSURES
STEP I. DEFINE ISSUANCE STRUCTURE

Parent Company | Guarantor | Issuer | Corporate Bond

Tata Motors Ltd.
TTMT IN

Jaguar Land Rover
8291453Z LN

Jaguar Land Rover
8291453Z LN

BBG005P9XKZ2
Jaguar Land Rover
8291453Z LN
Senior Unsecured Bonds

Issue Date: 12/17/2013
Coupon: Fixed
AT MATURITY
Principal due: 700,000

Tata Motors Ltd.
TTMT IN

Tata Motors Ltd.
TTMT IN

BBG007DN2514
Tata Motors Ltd
TTMT IN
Senior Unsecured Bonds

Issue Date: 10/30/2014
Coupon: Fixed
AT MATURITY
Principal due: 500,000

TML Holdings PTE Ltd
0327039D SP

BBG006F26RZ1
TML Holdings Pte Ltd
0327039D SP
Senior Unsecured Bonds

Issue Date: 05/07/2014
Coupon: Fixed
AT MATURITY
Principal due: 300,000

LIABILITY-SIDE EXPOSURES
STEP II. IDENTIFY THE GUARANTOR

Guarantor	Corporate Bond	
Jaguar Land Rover **8291453Z LN**	BBG005P9XKZ2 Jaguar Land Rover 8291453Z LN Senior Unsecured Bonds	Issue Date: 12/17/2013 Coupon: Fixed AT MATURITY Principal due: 700000
Tata Motors Ltd. **TTMT IN**	BBG007DN2514 Tata Motors Ltd TTMT IN Senior Unsecured Bonds	Issue Date: 10/30/2014 Coupon: Fixed AT MATURITY Principal due: 500000
	BBG006F26RZ1 TML Holdings Pte Ltd 0327039D SP Senior Unsecured Bonds	Issue Date: 05/07/2014 Coupon: Fixed AT MATURITY Principal due: 300000

LIABILITY-SIDE EXPOSURES
STEP III. FINANCIAL METRICS OF THE GUARANTOR

Guarantor

Corporate Bond

Financial Metrics
Assets (£m): 21,603
LTDebtEquity: 31.25
LTDebt/Capital: 23.52
ROA: 5.74
ROE: 18.3

Jaguar Land Rover
8291453Z LN

BBG005P9XKZ2
Jaguar Land Rover
8291453Z LN
Senior Unsecured Bonds
Issue Date: 12/17/2013
Coupon: Fixed
AT MATURITY
Principal due: 700000

Financial Metrics
Assets (US mn):40,711
LT Debt/Equity:64.22
LTDebt/Capital:33.23
ROA:4.34
ROE:16.09

Tata Motors Ltd.
TTMT IN

BBG007DN2514
Tata Motors Ltd
TTMT IN
Senior Unsecured Bonds
Issue Date: 10/30/2014
Coupon: Fixed
AT MATURITY
Principal due: 500000

BBG006F26RZ1
TML Holdings Pte Ltd
0327039D SP
Senior Unsecured Bonds
Issue Date: 05/07/2014
Coupon: Fixed
AT MATURITY
Principal due: 300000

ASSET-SIDE EXPOSURES
STEP I. FOR CORPORATE BONDS
[TTMT IN: BBG007DN2514]

Identify the holders of the corporate bond BBG007DN2514

Top Holders	Amount Held	% Total
JP MORGAN	38,903	7.78
MIRAE ASSET GLOBAL I	7,150	1.43
SARASIN	2,593	0.52
GAM HOLDING AG	2,500	0.5
PRUDENTIAL PLC	2,500	0.5
HSBC	2,200	0.44
PRUDENTIAL FINANCIAL	2,000	0.4
ASSICURAZIONI GENERA	2,000	0.4
UBS	1,776	0.36
EVLI FUND MANAGEMENT	1,500	0.3

TTMT IN Financial Metrics	
Total Assets (US mn):	40,711
Long-Term Debt/Equity	64.22
Long-Term Debt/Assets	33.23
ROA	4.34
ROE	16.09

Tata Motors Ltd.

TTMT IN

BBG007DN2514	Issue Date: 10/30/2014
Tata Motors Ltd	Coupon: Fixed
TTMT IN	AT MATURITY
Senior Unsecured Bonds	Principal due: 500,000

ASSET-SIDE EXPOSURES
STEP II. FOR SYNDICATED LOANS
[TTMT IN: BBG00BVH29V7]

Identify the members of the banking syndicate of the loan BBG00BVH29V7

Banking Syndicate	Role	% Total
ANZ Banking Group	Book Runner(s)	.
Bank of China/Singapore I	Lead Arranger(s)	.
Hua Nan Commercial Bar	Lead Arranger(s)	.
ANZ Banking Group	Lender(s)	8%
Bank of Tokyo-Mitsubishi U	Lender(s)	8%
Korea Development Bank	Lender(s)	8%
State Bank of India/Singap	Lender(s)	8%
Bank of China/Singapore I	Lender(s)	7%
Hua Nan Commercial Bar	Lender(s)	7%
………..		
Allen & Overy LLP	Legal Advisor	0%

TTMT IN Financial Metrics	
Total Assets (US mn):	40,711
Long-Term Debt/Equity	64.22
Long-Term Debt/Assets	33.23
ROA	4.34
ROE	16.09

Tata Motors Ltd.

TTMT IN

BBG00BVH29V7	Issue Date: 03/11/2016
Tata Motors Ltd	FLOATING
TTMT IN	AT MATURITY
Senior Unsecured Loans	Principal due: 250,000

FIRMS’ROE AND FINANCIAL INTERLINKAGES

- Dataset matching top companies worldwide, with all the securities guaranteed, and creditors (bond-holders and parties in syndicated loans) with asset side exposures:

Matched firm-securities-creditors database. Summary statistics

Table 1

	Number of firms[1]	Number of securities guaranteed[2]			Number of creditors[3]	
		Total	Bond	Loans	Parties in syndicated loan	Bond holders
Total	73	2,454	2,352	102	343	1,098
United States	49	2,042	1,964	78	221	1,020
Europe	15	326	309	17	154	431
Rest of the world	9	86	79	7	55	100

[1] Top 100 firms in the Bloomberg World global index, excluding financial companies, and Chinese firms. [2]Municipal securities not included.[3] Number of investors with claims on the firms (parties involved in syndicated loans); investors holding bonds (top 10 holders).

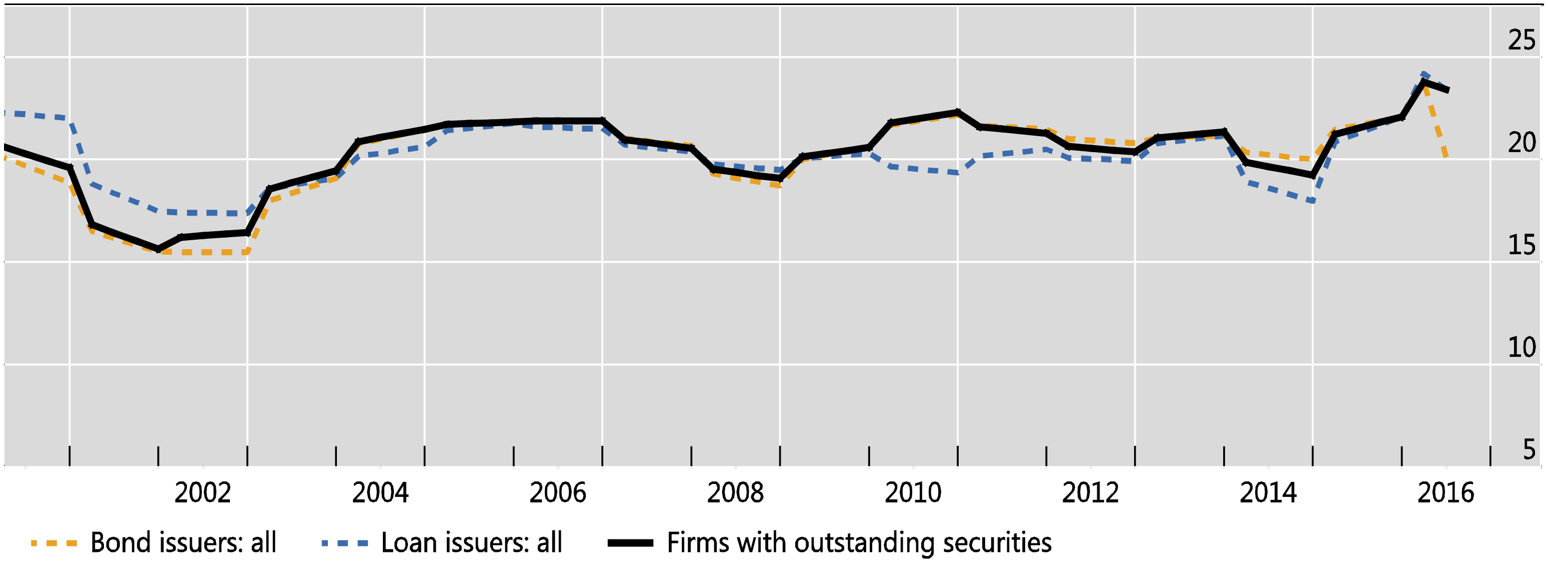
Sources: own elaboration.

FIRMS'ROE AND FINANCIAL INTERLINKAGES
MATCHING FIRM-LEVEL AND SECURITIES-LEVEL DATA

Return-on-equity: only firms with outstanding securities

In per cent

Graph 3



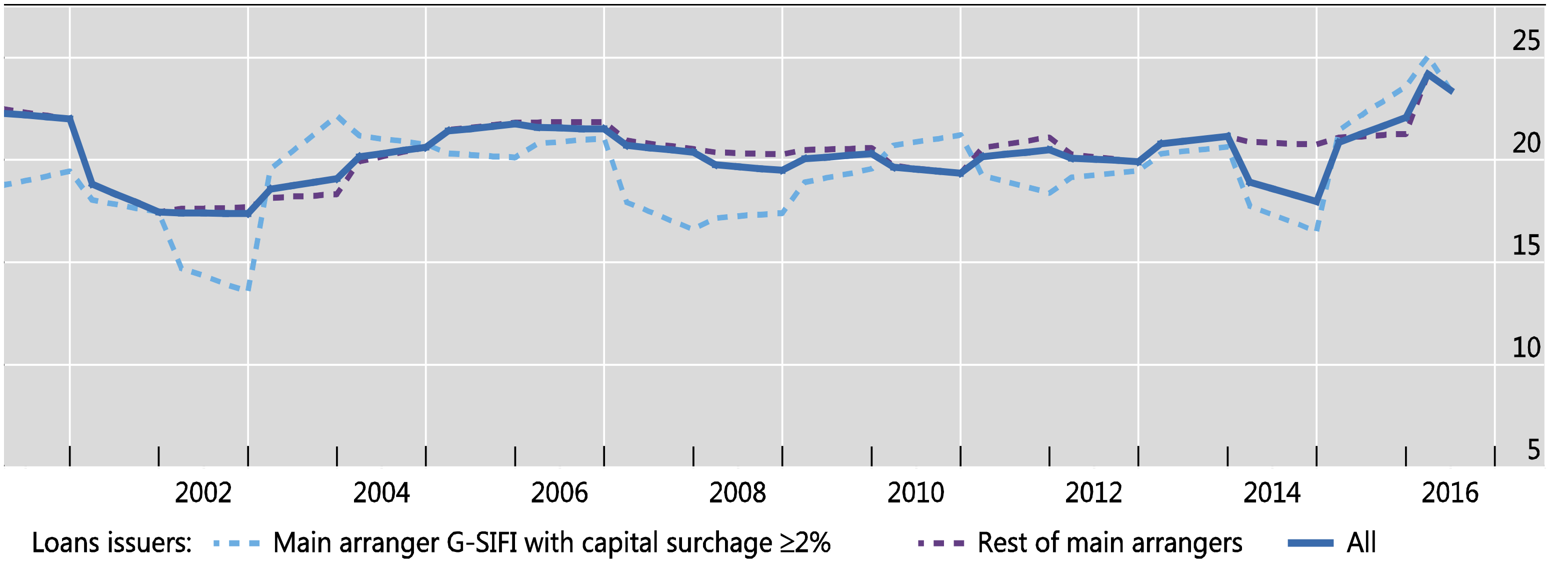
Source: Bloomberg.

FIRMS'ROE AND FINANCIAL INTERLINKAGES INPUTTING ALSO BANKING SYNDICATED DATA

Return-on-equity: only firms with outstanding loans

In per cent

Graph 4



Source: Bloomberg.

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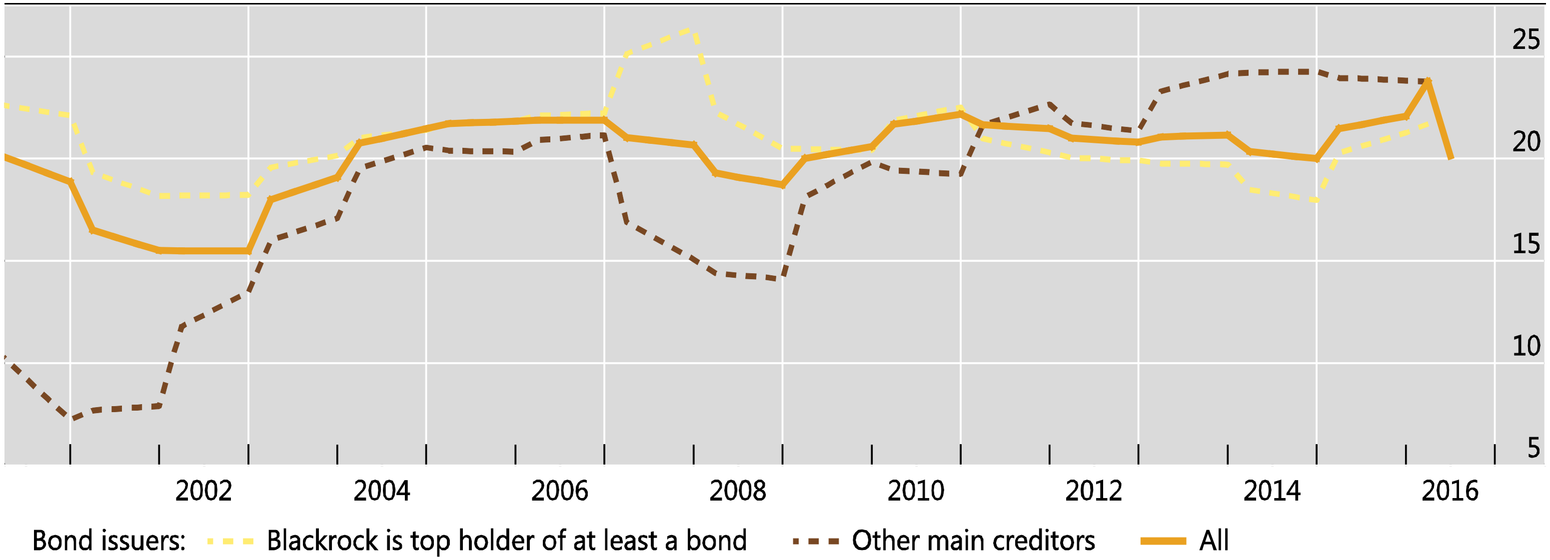
FIRMS'ROE AND FINANCIAL INTERLINKAGES INPUTTING ALSO BOND-HOLDERS DATA

Return-on-equity: only firms with outstanding corporate bonds

In per cent

Graph 5



Source: Bloomberg.

CONCLUSION

- In this paper we use securities identifiers to construct a dataset on financial interlinkages between firms and their creditors (banks and institutional investors). This way we overcome the problems of matching datasets with qualitative information.

- Resulting datasets allow understanding system-wide risks arising from interconnectedness. We illustrate the type of gains with a small-scale exercise.

- Our final objective is to construct a global, cross-country, firm-level dataset on interlinkages -work-ahead!

THANK YOU FOR YOUR ATTENTION

REFERENCES. MATCHING SYNDICATED LOANS WITH FIRM-LEVEL DATA

- Ferreira, M. and P. Matos (2012), “Universal Banks and Corporate Control: Evidence from the Global Syndicated Loan Market” *Review Financial Studies*

- Ongena, S., J.L. Peydro, and N. van Horen (2015), “Shocks Abroad, Pain at Home? Bank Firm Level Evidence on the International Transmission of Financial Shocks” *IMF Economic Review November 2015*

REFERENCES. MATCHING CORPORATE BONDS WITH BOND-HOLDERS DATA

- Barbu, A., C. Fricke, and E. Moench, "Reach for Yield in Investment Funds", *mimeo*

- Cornejo, A., J. Huerga, F. Mayerlen, J. Micheler (2017),"Unique identifiers in micro-data Management –the Centralised Securities Database (CSDB) experience", in *"IFC Bulletin No.43 -"*

- Cornejo, A. and J. Huerga, (2016)," The Centralised Securities Database (CSDB) - Standardised micro data for financial stability purposes", in *"IFC Bulletin No.41 -"*

- *ECB (2015),* "Who Holds What? New Information on Securities Holdings", *ECB Economic Bulletin Issue 2 /2015*

REFERENCES. MATCHING CORPORATE BONDS WITH FIRM-LEVEL DATA

- Bruno, V. and H. Shin (2017), “Global dollar credit and carry trades: a firm-level analysis”, *Review of Financial Studies*, vol 30, no 3, 2017

- Fuertes, A. and J. M. Serena (2016), “How firms borrow in international bond markets: Securities regulation and market segmentation”, *Banco de Espana Working Paper* No. 1603

- IADB (2016), “Time to Act: Latin America and the Caribbean Facing Strong Challenges”

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Brussels, Belgium, 18-19 May 2017

A critical review of the statistics on the size and riskiness of the securitization market: evidence from Italy and other euro-area countries[1]

Giorgio Nuzzo,
Bank of Italy

[1] This paper 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.

A critical review of the statistics on the size and riskiness of the securitization market: evidence from Italy and other euro-area countries[1]

Abstract

This note reviews the statistics currently used to evaluate the size and riskiness of the securitization market for euro-area countries. Entity-based measures of the securitization market, which use the total assets of Financial Vehicle Corporations (FVCs), produce an over-evaluation. This stems from the inclusion of retained securitizations and from not clearing out the difference between the nominal value and the purchase price of the securitized assets. This note proposes a new measure of the size of the securitization market which takes these issues into account. In addition, the note argues that some risk profiles (leverage, credit intermediation and interconnectedness with the regular banking system) are not properly addressed using entity-based data on FVCs, while other risks are not sufficiently investigated in the current debate, such as opaqueness/complexity, for which specific new indicators are proposed.

JEL Classification: E44, E58, G00, G01, G23.

Keywords: Shadow banking system, securitizations, risk measures.

1. Introduction

The global financial crisis that erupted in 2007 has highlighted the risks stemming from non-bank financial intermediation (Gorton and Metrick, 2012; Acharya et al., 2013; Adrian and Ashcraft, 2012).[2] The debate on these risks has expanded and the notion of shadow banking has been created (the term was coined by McCulley, 2007). However, the risks have been important mainly in Anglo-Saxon countries. In Italy, non-bank financial entities are fully regulated in accordance with the principle of "bank equivalent regulation" and have proved to be safe (see Gola et al., 2017 for a detailed description of the Italian supervisory and regulatory framework of non-bank financial intermediaries).

Among shadow banking activities, securitization is often indicated as one of the most significant and potentially harmful (e.g. Stein, 2010; Pozsar et al., 2013). Therefore, the international debate has paid increasing attention to measuring the size and riskiness of the securitization market. In this note size and riskiness are discussed separately, on the grounds that a bigger securitization market is not necessarily riskier than a smaller one.

The data on the balance sheets of financial vehicle corporations (FVCs) are a useful source for the analysis of the securitization market and in fact the European Central Bank (ECB) has been collecting them since 2009 (see Appendix for details). The main activity of FVCs is the "securitization"

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[2] Gorton and Metrick (2012) mainly describe the panic in the "repo" market in the years 2007-08. Acharya et al. (2013) highlight the role of regulatory arbitrage in widening the shadow banking system. For a review of the literature on shadow banking see Adrian and Ashcraft (2012).

of a bundle of assets (mainly loans) transferred from banks and other intermediaries by transforming them into debt securities. However, data on FVCs' balance sheet are complex and hide insidious technical details: on closer scrutiny they are likely to provide poor estimates of the size and riskiness of the securitization market. This note provides a critical review of the metrics mainly used in international fora and applies them to both Italy and the rest of the euro area; it also compares the results obtained by the standard analyses with those obtained using new indicators.

The analysis confirms that FVCs' total assets are not a satisfactory statistic for measuring the size of the securitization market. Rather, risk analysis should focus on specific areas such as maturity mismatch and the opaqueness/complexity of operations. According to more appropriate measures, the Italian securitization market is much smaller and characterized by a lower risk than those of other euro-area countries.[3] This evidence is in line with the negligible defaults of Asset Backed Securities (ABS) in Italy since the introduction of securitization in 1999.

The rest of the note is organized as follows. The second section analyses the measures of the size of the securitization market. The third section reviews risk indicators of securitization activities. Final remarks conclude.

2. How to measure the size of the securitization market

2.1 The trouble with the current measures

There are several definitions of shadow banking (See Financial Stability Board, 2013 in Annex 2.1 for an overview of those used in the literature). We focus on the most widely used definition, that proposed by the Financial Stability Board (FSB): "credit intermediation involving entities and activities outside the regular banking system" (FSB, 2013). According to the FSB, shadow banking includes all the non-bank financial intermediaries that create/bear bank-like risks, regardless of whether they are regulated and/or supervised.[4] The choice is motivated by the willingness of the FSB to "cast the net wide" and not to take account of specific country supervisory/regulatory frameworks. Here, we accept the point of not considering the supervision/regulation of these entities as a sufficient reason for excluding them from the shadow banking perimeter. Nevertheless, I argue that there are some critical issues with the current entity-based statistics of the size of shadow banking, in particular in the context of the securitization market.[5]

Indeed, standard measures of the size of the securitization market use FVCs' total asset as they are reported in the statistics on FVCs.[6] This approach can result in an over-estimation of the market's size for two reasons: the first is the presence in the assets of FVCs of retained securitizations (example A in the Appendix); the second stems from the failure to give adequate consideration to an accounting evaluation problem that occurs when loans (mainly non-performing ones) are securitized at a discount price (example B in the Appendix).

3 See Affinito and Tagliaferri (2010) on ex-ante determinants of bank loan securitization in Italy.

4 OECD (2016) also shows the mapping of shadow banking through national accounts as including all non-bank financial entities, even if they are regulated and supervised.

5 As an alternative to the FSB's entity-based measurement approach, IMF (2014) and Harutyunyan et al. (2015) have proposed an activity-based measure of the size of shadow banking that uses all non-core liabilities (i.e. other than deposits) of both bank and non-bank financial institutions. However, under their approach the contribution of securitizations to shadow banking cannot be singled out.

6 These data are available for all the euro-area countries.

As for the first issue, retained securitizations, i.e. those operations where securities issued by FVCs are mainly bought back by the originators of the securitized loans,[7] should not be considered in shadow banking, but more properly as a banking activity.[8] In the most recent reports by the FSB this issue is taken into account, even if only in the process of narrowing down the broad shadow banking definition. In FSB (2013) only self-securitizations (those operations where the bank acquires all the securities backed by its securitized loans), which are a part of all retained securitizations, are filtered out when calculating "narrow" shadow banking, while in FSB (2014, 2015) all FVCs prudentially consolidated in banking groups are more correctly ruled out.

In addition, it should be noted that in some euro-area jurisdictions originators' statistical reports continue to show the loans connected to retained securitizations in their balance sheets. For example, in Italy the International Accounting Standard (IAS) rules on derecognition apply to banks' statistics. Thus, derecognition is not allowed when originating banks transfer an asset but retain the related risks and rewards. FVCs' statistics record assets regardless of whether they are derecognized by the originators or not (see example A in the Appendix). Therefore, summing FVCs' and banks' assets to calculate total financial assets is not correct, since non-derecognized securitized assets are added twice; more properly they should be considered only as banks' assets. In other words from an accounting and risk perspective, these assets should be considered banks' assets. The issue is sizeable: in December 2016 loans securitized and non-derecognized (through euro-area FVCs) amounted to around 47 per cent of the total loans securitized by euro-area FVCs. The share is even higher for Italy (69 per cent; 29 per cent of total euro-area non-derecognized loans).

A double counting problem also arises for two entities both in the shadow banking system. This is the case of loans originated by other financial institutions (OFIs), especially financial intermediaries engaged in lending (FCLs), and securitized but not derecognized in their statistical reports. In the calculation of the size of shadow banking these securitized loans are counted twice: in both FVCs' and FCLs' balance sheets.

Therefore, there is room for further improvements on recent FSB reports by clearing out retained securitizations from the narrow shadow banking measure (FSB 2014, FSB 2015). Activities recorded for statistical purposes by other financial intermediaries which securitized but did not derecognize should be filtered out. This operation could rule out double counting among OFIs not participating in banking groups.

The second over-estimation is related to an accounting valuation problem. In FVCs' statistics securitized assets are evaluated at their nominal value (see example B in the Appendix). However originators can write down the assets before they are transferred to the vehicles so that FVCs purchase assets at a price below the nominal value. The issue is particularly significant in the case of the securitization of non-performing loans. The item "other liabilities" in FVCs' balance sheet may show the importance of this mismatch as it includes the difference between the nominal value and the purchase price of assets, in accordance with ECB regulations. In December 2016 the ratio between "other liabilities" and total securitized loans was 15 per cent for euro-area FVCs[9] and 36 per cent for Italian FVCs.

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7 Such operations became common in the years immediately after the collapse of Lehman Brothers in order to produce collateral to use in refinancing operations with the ECB. In recent years, the presence of alternative funding instruments, such as covered bonds, has reduced the importance of these operations.

8 However, Grillet-Aubert et al. (2016) argue that when retained securitizations are placed with investors, they should be taken into account again.

9 The data refer to the item published in the ECB statistical datawarehouse (SDW) related to traditional FVCs, which also includes "passive financial derivatives". According to confidential data available to national central banks, financial derivatives on the liability side of FVCs' balance sheet are a small part of the total item "financial derivatives and other liabilities". In addition, a reason to consider the item "other liabilities" as consisting mainly of the difference between nominal and acquisition values is the fact that its value is near zero in countries where securitizations of non-performing loans are rare.

The disposals of bad loans at a discount price usually occur outside the boundaries of banking groups. Therefore the FSB narrow shadow banking measure, which filters out FVCs consolidated in banking groups, is still affected by an over-estimation problem. In the FSB reports this question is not addressed, while it is highlighted in a recent report on shadow banking in Italy (Gola et al., cit.). This issue also poses a problem of comparability among shadow banking activities, since other important sectors (e.g. investment funds) are usually evaluated at market price.

To sum up, the two overestimating factors are not negligible and their impact is strikingly more important for Italian securitizations than for those of other euro-area countries.

2.2 An alternative measure of the size of the securitization market

A feasible measure[10] of the actual importance of the securitization market may be obtained as the difference between all debt securities issued by domestic FVCs and the FVCs' securities bought back by banks.[11] On the one hand, subtracting FVCs' securities bought back by banks clears up "retained securitization"; on the other, using debt securities issued by FVCs reduces valuation problems, since in a typical securitization the FVC issues debt securities at a value in line with the acquisition value of the assets.

However, this measure is accurate only for those euro-area countries, such as Italy, where securitization markets are self-contained at the domestic level; in addition, by definition, it is correct for the aggregate of the whole euro area.

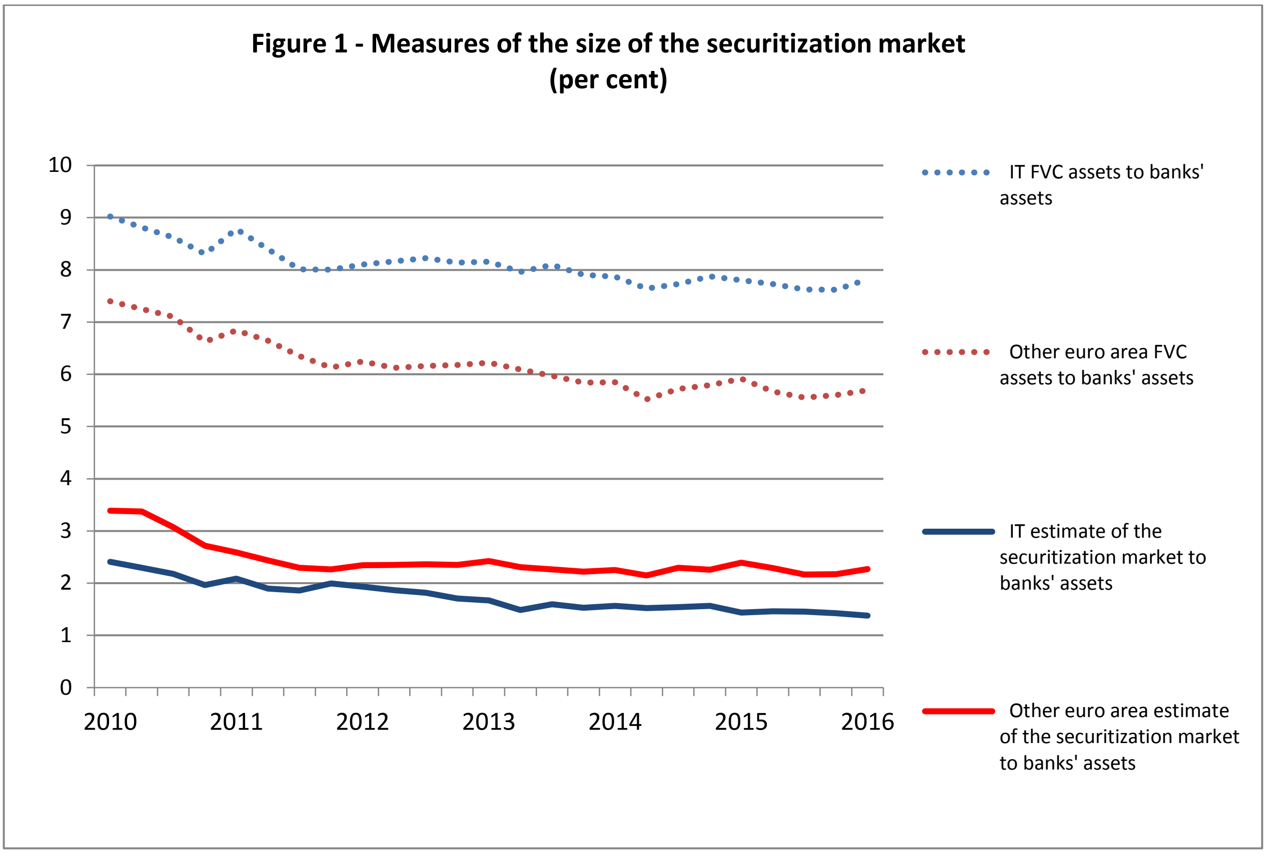
Figure 1 shows the proposed measure of the size of the securitization market compared with banks' total assets. Italy has a securitization market larger than the rest of the euro area when FVCs' total assets are considered, but it is significantly smaller when the alternative measure is considered.

The two measures also differ markedly in terms of their dynamics. In Figure 2 the two measures are reported as index numbers. While for the rest of the euro area both indexes have almost the same declining trend, in Italy the difference between them is quite striking: according to our measure, the securitization market in Italy contracted sharply during the years 2012-15. This better reflects developments in the Italian securitization market, where several self-securitizations were closed in advance or expired.

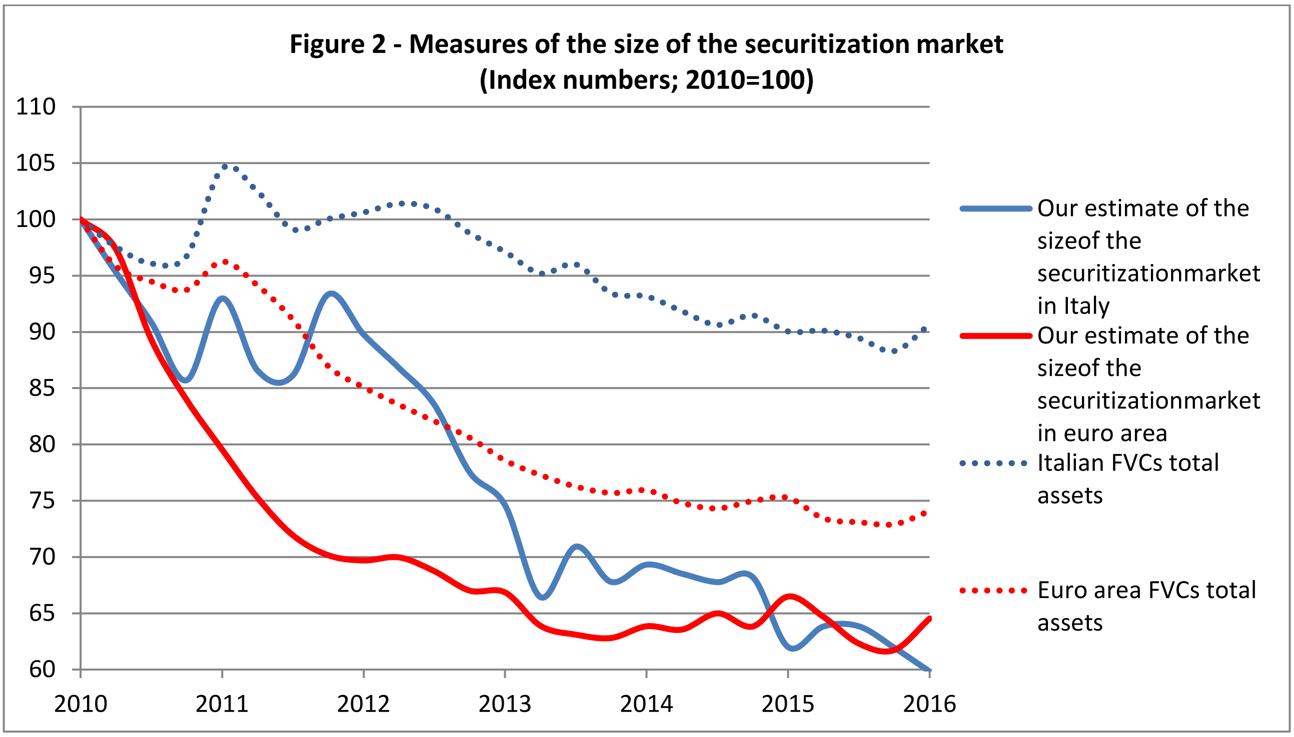
A possible alternative measure may be obtained as the difference between debt securities issued by domestic FVCs and the securitized loans not derecognized by domestic banks. This measure is correct where bank loans originated in a country are completely securitized by domestic FVCs, as is the case in Italy and in the euro area as a whole. However, this measure is able to clear-out self-securitizations only for jurisdictions, such as Italy, that apply strict criteria for derecognizing loans (in Italy IAS 39 criteria are applied). Nevertheless, in other jurisdictions, such as Belgium and France, even loans related to self-securitizations are cancelled from banks' balance sheet in their reporting for monetary aggregates. As for Italy, it is possible to confirm, using this alternative indicator, that the correct size of the securitization market lies between 2 and 1 per cent of total national banks' assets and followed a declining path from 2010 to 2016.

10 This measure is not applicable to synthetic securitizations or to activities (such as the direct lending permitted recently in Italian legislation on FVCs) not typically linked to securitizations.

11 Focusing on securities issued rather than on total assets is in line with IMF (2014) and its activity-based approach to measuring shadow banking with non-core liabilities. Nevertheless, the statistics proposed here make it possible, using entity-based data on FVCs, to identify the securitization component of shadow banking.



Source: our estimates on ECB data.



Source: our estimates on ECB data.

3. How to measure the riskiness of securitizations

Several attempts to measure the risks associated with shadow banking activities have been made to date. We focus on the recent work by Grillet-Aubert et al. (2016), who describes the monitoring framework developed by the European Systemic Risk Board (ESRB).[12] The paper provides a useful classification of risk indicators, but in our view it fails to properly recognize that very different non-bank financial intermediaries are included in the shadow banking system and have very diverse risk profiles.[13] For instance, Doyle et al. (2016) stress that investment funds are characterized by their own specific risks. The same is likely to hold for FVCs. This section is a first attempt to identify more specific risk measures for the securitization market.

Grillet-Aubert et al. identify the following common risk areas for all the non-bank financial intermediaries included in shadow banking:

maturity transformation;

liquidity transformation;

leverage;

credit intermediation;

interconnectedness with the regular banking system.

Risks related to maturity and liquidity transformation are important for securitizations. Risks stemming from maturity mismatch materialized during the global financial crisis, due to the widespread use of very-short-term liabilities, such as asset-backed commercial paper, typically in the U.S. (Gorton and Metrick, 2012). As for Italian securitizations, the issue of short-term securities is disincentivized by a penalizing fiscal treatment. Indeed, data on Italian FVCs show that at the end of 2016 no securities with original maturity of less than 1 year had been issued, while for the other euro-area countries they were about 6 per cent of total securities (3 per cent in December 2009).

On the contrary, risk areas such as leverage, credit intermediation and interconnectedness with the regular banking system are not very significant if assessed through FVCs' balance sheets.

Leverage is always very high for FVCs. In some jurisdictions they typically have only the minimum statutory shareholders' equity required by their respective national laws. In many jurisdictions, such as Italy, FVCs are bankruptcy free. Therefore, holders of ABS can claim on the cash flows of the securitized assets or the eventual rescue by the sponsoring banks[14] rather than on the FVCs' capital. In addition, data on euro-area countries reveal high heterogeneity in FVCs' capital, which severely affects leverage measures.

Nor are risks related to credit intermediation correct when addressed through FVCs' balance sheet. As highlighted in the previous section, FVCs' balance sheet record both derecognized and non-derecognized loans, which have a different role in credit intermediation. The derecognition of loans allows originators to free up capital. On the contrary, the main purpose of typical operations with non-derecognized loans, such as self-securitizations, is to provide temporary liquidity to

12 Recent FSB reports on shadow banking present risk areas similar to those of the ESRB and also apply indifferently to all shadow banking entities. OECD (2016) also provides an assessment of credit risk transfer, leverage and interconnectedness based on instruments available in national accounts for different sub-sectors, while not adequately identifying securitization peculiarities. Therefore, our main critical review of ESRB risk metrics also applies to the reports of the above-mentioned institutions.

13 However, Grillet-Aubert et al. (2016) complement their entity-based approach to risk measures with an activity-based approach which is more appropriate in the context of securitizations.

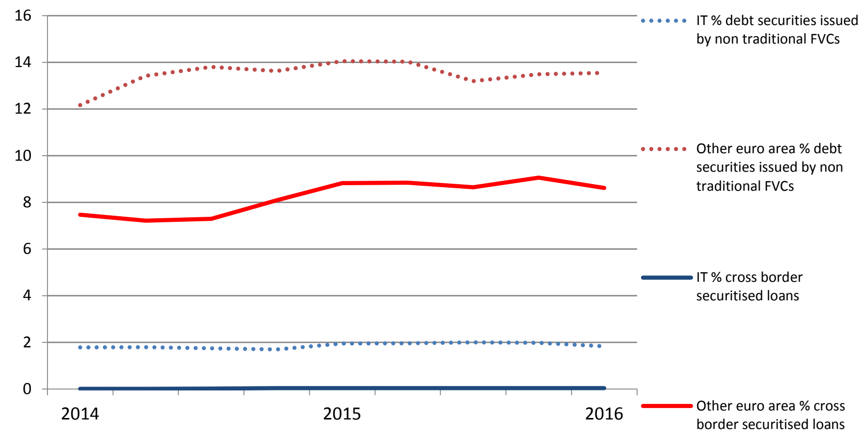
14 See Segura (2017) on the reasons why sponsoring banks rescue their structured investment vehicles despite having no contractual obligation to do so.

originators. Therefore, indicators on credit intermediation that include both these two kinds of securitized loans could be misleading.[15]

As for interconnection with the regular banking system, the evidence based on FVCs' statistics is not easy to interpret. For example, a higher interconnection related to self-securitization could be interpreted as an increase in the risk of contagion between banks and FVCs; however self-securitizations are banking operations and are therefore not part of shadow banking.

To sum up, only liquidity and maturity mismatch are assessed properly using FVCs' data. In addition, there are risk areas not mentioned by Grillet et al. that deserve the development of proper analytical tools. In particular, the financial crisis showed that complexity and opaqueness in securitization structures are closely correlated and pose several risks.[16] To fill this gap we propose two indicators calculated using FVCs' statistics.[17] The first is the percentage ratio of debt securities issued by synthetic securitizations[18] and other non-traditional FVCs[19] to the total debt securities issued by all FVCs. The second indicator is the percentage ratio of securitized loans with a non-domestic counterparty to total securitized loans. The two indicators are computed under the hypotheses that operations involving derivatives, non-credit assets and different jurisdictions can be considered more complex/opaque. Figure 3 shows that Italian FVCs are characterized by a negligible diffusion of non-traditional operations and by the importance of "domestic" securitizations, i.e. operations where operators and assets belong to the same jurisdiction.

Figure 3 - Measures of opaqueness/complexity of securitizations
(per cent)



Source: our estimates on ECB data.

15 Grillet-Aubert et al. (2016) also admit that retained securitizations do not contribute to risks in shadow banking; they nonetheless calculate risk indicators on FVCs' data that include retained securitizations.

16 IMF (2014) also identifies "opacity and complexity" as a risk profile relevant for shadow banking, but it fails to identify specific risk measures. Caballero and Simsek (2009) argue that opaqueness/complexity constitute vulnerabilities, since during periods of stress investors tend to retrench and flee to quality and transparency.

17 The measures proposed here cannot be used to properly estimate the importance of simple, transparent and standardized securitization for prudential purposes.

18 Synthetic securitizations imply the transfer of the credit risk of an asset or pool of assets through the use of credit derivatives, guarantees or some similar mechanism.

19 Those typically engaged in the securitization of non-credit related assets. ECB Regulation no. 40/2013 defines traditional securitizations as "securitizations where there is a transfer of credit risk of an asset or pool of assets achieved either by the transfer of legal title or beneficial interest of the assets being securitised or through sub-participation".

To conclude, in our selective analysis of risk areas, the Italian securitization market is found to be less risky than that of the other euro-area countries. Using less appropriate measures of credit intermediation and interconnectedness with the banking system could give more puzzling results, given the importance of retained securitization in Italy.

4. Concluding remarks

This note highlights some critical aspects related to the statistics currently used to evaluate the size and riskiness of the securitization market.

In order to produce proper statistics on the size of the market, retained securitization and the difference between nominal and acquisition value have to be taken into account. Thus, the simple use of FVCs' total assets implies an over-evaluation of the market. This is even more important in the Italian securitization market, characterized by a large share of loans which remain in their originators' balance sheets and by a significant difference between the values of securitized assets and the securities issued. Given these characteristics, a new measure of the size of the securitization market has been proposed. This provides a very different picture of the size and dynamics of the Italian securitization market compared with the measure based on FVCs' total assets.

As for risk metrics, the note argues that only some risk profiles (maturity mismatch and over-complexity of some operations) are properly addressed using FVCs' data, while other risks currently taken into account are meaningless or even misleading if assessed through an entity-based approach using FVCs' data (leverage, credit intermediation and interconnectedness with the regular banking system). The note proposes new risk indicators for risk areas not sufficiently investigated in the current debate, such as opaqueness/complexity. According to these indicators the riskiness of the Italian securitization market is lower than that of the other euro-area countries. In fact, Italian experience with securitizations shows low default rates and relatively good quality in assets securitized (Albertazzi et al., 2011). This is due mainly to a strict legal and supervisory framework.

References

Acharya, V., Schnabl, P. and Suarez, G. (2013), "Securitization Without Risk Transfer", *Journal of Financial Economics*, pp. 515-536.

Adrian, T. and Ashcraft, A.B. (2012), "Shadow Banking: A Review of the Literature", *Palgrave Dictionary of Economics*.

Adrian T. and H. Shin (2010b), "Liquidity and Leverage", *Journal of Financial Intermediation*, Vol.19, Issue 3, pp. 418–437.

Affinito M. and E. Tagliaferri (2010), "Why do (or did?) banks securitize their loans: evidence from Italy", Discussion papers 741, Bank of Italy.

Albertazzi U., G. Eramo, L. Gambacorta and C. Salleo (2011), "Securitization is not that evil after all", *Bank of Italy working papers*. n. 796.

Caballero, R., and Alp Simsek. 2009. "Complexity and Financial Panics", *NBER Working Paper*, n. 14997, *National Bureau of Economic Research*, Cambridge, Massachusetts.

Doyle N., L. Hermans, P. Molitor and C.Weistroffe (2016), "Shadow banking in the euro area: risks and vulnerabilities in the investment fund sector", *ECB working paper*, n.3.

European Central Bank and Bank of England (2014), "The case for a better function in the securitization market in the European Union", *Discussion Paper*.

Harutyunyan A., A. Massara, G. Ugazio, G.Amidzic, and R. Walton (2015), "Shedding Light on Shadow Banking", *IMF Working paper*, n.1 -2015.

International Monetary Fund (2014), "Shadow Banking Around the Globe: How Large, and How Risky?", Chapter 2 in *Global Financial Stability Report*, October (Washington).

Financial Stability Board (FSB) (2013), "Policy Framework for Strengthening Oversight and Regulation of Shadow Banking Entities." Consultative Document, Financial Stability Board, Basel. http://www.financialstabilityboard.org/publications/r_130829c.htm.

Financial Stability Board (2014), "Global shadow banking monitoring report".

Financial Stability Board (2015), "Global shadow banking monitoring report".

Gola C., M. Burroni, F. Columba, A. Ilari, G. Nuzzo and O. Panzarino (2017), The Shadow Banking System and the Italian Regulatory Framework, *Quaderni di Economia e Finanza*, Banca d'Italia, n.372.

Gorton, G. and Metrick, A. (2012), "Securitized Banking and the Run on Repo", *Journal of Financial Economics* 104:425—51, June.

Grillet-Aubert L., J. Haguin, C. Jackson, N. Kileen and C. Weistroffer (2016), Assessing shadow banking – non-bank financial intermediation in Europe – *Occasional paper No 10* , European Systemic Risk Board.

McCulley, P. (2007), "Teton Reflections," *PIMCO Global Central Bank Focus*, August/September.

OECD (2016), "How to capture shadow banking in the system of National Accounts: A study on the delineation of shadow banking in national accounts, including a proposal for additional breakdowns".

Pozsar Z., T. Adrian, A.B. Ashcraft and H. Boesky (2010), Shadow banking, *Economic Policy Review*, Federal Reserve Bank of New York Staff Reports, pages 1-16.

Segura A. (2017), "Why did sponsor banks rescue their SIVs? A signaling model of rescue", *Discussion papers* 1110. Bank of Italy.

Appendix

In this appendix a brief and simplified description of the statistical treatment of securitization in banks' and FVCs' statistical balance sheets is provided. The reference is to European Central Bank (ECB) Regulations applied to euro-area countries (ECB/2013/33 concerning the balance sheet of the monetary financial institutions sector - recast; ECB/2013/40 concerning statistics on the assets and liabilities of financial vehicle corporations engaged in securitization transactions – recast).

Two examples are reported: one refers to self-securitizations (example A) and the other to disposals of bad loans with balance-sheet derecognition (example B). The appendix includes the calculation with alternative methods of the size of the securitization market using the data reported in the two examples.

The following main simplifications are used in the examples: a) banks finance their loans only through deposit accounts; b) loans by banks to FVCs are not reported.

Example A) Self-securitization

In the period between T-1 and T, a bank sells its loans to an FVC and acquires all the securities issued by the FVC backed by these loans issued by FVCs. In such cases loans are not derecognized from banks' balance sheets.[20]

The regulations on Monetary Financial Institutions (MFIs, hereafter banks to simplify) require the provision of off-balance-sheet information on loans securitized and not derecognized.

A- The bank's balance sheet.

Time T-1		Time T	
Assets	Liabilities	Assets	Liabilities
100 loans	100 deposit accounts	100 loans	100 deposit accounts
		100 Securities issued by FVCs	100 deposit with agree maturity over two years with FVCs[21]

Off-balance sheet information: 100 loans securitized and not derecognized.

A – The FVC's balance sheet

Time T-1		Time T	
Assets	Liabilities	Assets	Liabilities
0	0	100 loans securitized	100 securities issued

[20] Rules on derecognition are not harmonized among euro-area countries. In Italy the strict IAS 39 rules are also applied at individual bank level.

[21] According to ECB rules for the compilation of banks' statistics, a fictional deposit in the item "deposits with agreed maturity over 2 years" (not in broad money definition) must be compiled in banks' balance sheets in order to counterbalance FVCs' securities held by banks backed by their own non-derecognized loans.

Example B) Disposals with derecognition of bad loans from the bank's balance sheet

In the period between T-1 and T, bank B securitizes bad loans with derecognition (in other words it cancels them from its balance sheet). FVC B acquires the loans at a discount price (30 in the example, but according to FVC regulations it must report loans at their nominal value (100).

Usually FVCs issue securities of a value somewhat higher than 30 to have some gain; here, for the sake of simplicity, the FVC issues securities for a value of 30.

In this simplified example bank's losses during the period are not reported. In addition, banks do not have to hold a share of the securities issued by the FVC backed by their securitized loans, which instead they are required to do under the EU capital requirement regulation.

B -Bank's balance sheet

Time T-1		Time T	
Assets	Liabilities	Assets	Liabilities
100 loans	100 deposit accounts	0	0

B -FVC's balance sheet

Time T-1		Time T	
Assets	Liabilities	Assets	Liabilities
0	0	100 loans securitized	30 securities issued
			70 remaining liabilities[22]

The alternative calculation methods.

In this note a numerical example of the calculation of the size of shadow banking under different methods is performed considering only the two operations above (examples A and B). The reference is to FSB (2015).

FSB broad measure = 200 (total assets of FVC A + total assets of FVC B)

FSB narrow measure = 100 (only total assets of FVC B). FVC A is not counted since it is consolidated in banking groups (self-securitizations can be considered consolidated).

The proposed measure = 30 (130 securities issued by FVC A and FVC B minus 100 FVC securities bought back by bank A).

[22] The ECB Regulation on FVCs explicitly requires the difference between the nominal and the acquisition value of the securitized assets to be put under the item "remaining liabilities".

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A critical review of the statistics on the size and riskiness of the securitization market: evidence from Italy and other euro-area countries[1]

Giorgio Nuzzo,

Bank of Italy

[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.

A CRITICAL REVIEW OF THE STATISTICS ON THE SIZE AND RISKINESS OF THE SECURITIZATION MARKET: EVIDENCE FROM ITALY AND OTHER EURO-AREA COUNTRIES

Giorgio Nuzzo
(Bank of Italy- DG Economics, Statistics and Research)*
Bruxelles, 18 may 2017

* The views expressed in this note are my own and do not necessarily reflect those of the Bank of Italy.

Motivation

- This note is mainly a warning to a not appropriate use of Financial Vehicle Corporations (FVCS) data which are available for euro area countries under ECB/2013/40.
- The peculiarities of the securitizations are highlighted in order to criticize a “one size fits all” risks measurement of non bank financial entities.
- The note proposes an alternative measure of the size of the securitization market and two indicators to measure the risk dimension of complexity/opaqueness.

The reasons of over-evaluation

Entity-based measures of the securitization market, which use total assets of Financial Vehicle Corporations (FVCs), produce an over-evaluation mainly for two reasons:

1) the presence in the assets of FVCs also of retained securitizations ;

2) not considering adequately an accounting evaluation problem occurring when loans are securitized at a discount price

Over-evalution due to retained securitizations (1)

- In some euro area jurisdictions the loans connected to retained securitizations continue to be recorded also in the balance sheet of the originators in their statistical reports

- summing FVCs' and banks' assets for the calculation of total financial assets is not correct, since securitized assets non-derecognised are added twice

FSB (2014, 2015) all FVCs prudentially consolidated in banking groups are ruled out to calculate "narrow" shadow banking.

Statistical treatment of retained securitizations (example)

A- Bank's balance sheet.

Time T-1		Time T	
Assets	Liabilities	Assets	Liabilities
100 loans	100 deposit accounts	100 loans	100 deposit accounts
		100 Securities issued by FVCs	100 deposit with agree maturity over two years with FVCs

Off-balance sheet information: 100 loans securitized and not derecognized.

A - FVC's balance sheet

Time T-1		Time T	
Assets	Liabilities	Assets	Liabilities
0	0	100 loans securitized	100 securities issued

Over-evalution due to retained securitizations (2)

- What if loans are originated by other financial institutions (OFIs), especially by financial intermediaries engaged in lending (FCLs), and securitized but not derecognized in their statistical reports?

In the calculation of the size of shadow banking these securitized loans are counted twice: in FVCs and in FCLs balance sheets.

Therefore, there is room for further improvements in the treatment of retained securitizations. with respect to recent FSB reports in clearing out retained securitizations from the narrow shadow banking measure (FSB 2014, FSB 2015).

Assets securitized and not derecognized by FCLs should be filtered out.

This issue is material for FCLs not participating in banking groups.

Over-evaluation due to an accounting evalution problem

- In FVCs statistics securitized assets are evaluated at the nominal value. However originators can write down the assets before they are transferred to the vehicles so that FVCs purchase assets at a price below the nominal value. The issue is particularly significant in the case of securitization of non-performing loans.

- The item “other liabilities” in FVCs balance sheet may gauge the relevance of this mismatch as the item includes the difference between the nominal value and the purchase price of assets, according to the ECB regulation.

Over-evaluation due to an accounting evalution problem (example)

B -Bank's balance sheet

Time T-1		Time T	
Assets	Liabilities	Assets	Liabilities
100 Loans	100 Deposit accounts	0	0

B -FVC's balance sheet

Time T-1		Time T	
Assets	Liabilities	Assets	Liabilities
0	0	100 loans securitized	30 securities issued
			70 remaining liabilities

An alternative measure of the size of the market

A measure of the actual relevance of the securitization market may be obtained taking the difference between debt securities issued by domestic FVCs and those securities bought back by banks. However, this measure is accurate only for those euro-area countries, such as Italy, where securitization markets are self-contained at the domestic level; in addition, by definition, it is correct for the aggregate of the whole euro area.

But this measure is not applicable to synthetic securitizations <u>(total assets of synthetic securitizations should be added)</u>

A possible alternative measure may be obtained as the difference between debt securities issued by domestic FVCs and the securitized loans not derecognized by domestic banks. However, this measure is able to clear-out self-securitizations only for jurisdictions, such as Italy, that apply strict criteria for derecognizing loans (in Italy IAS 39 criteria are applied)

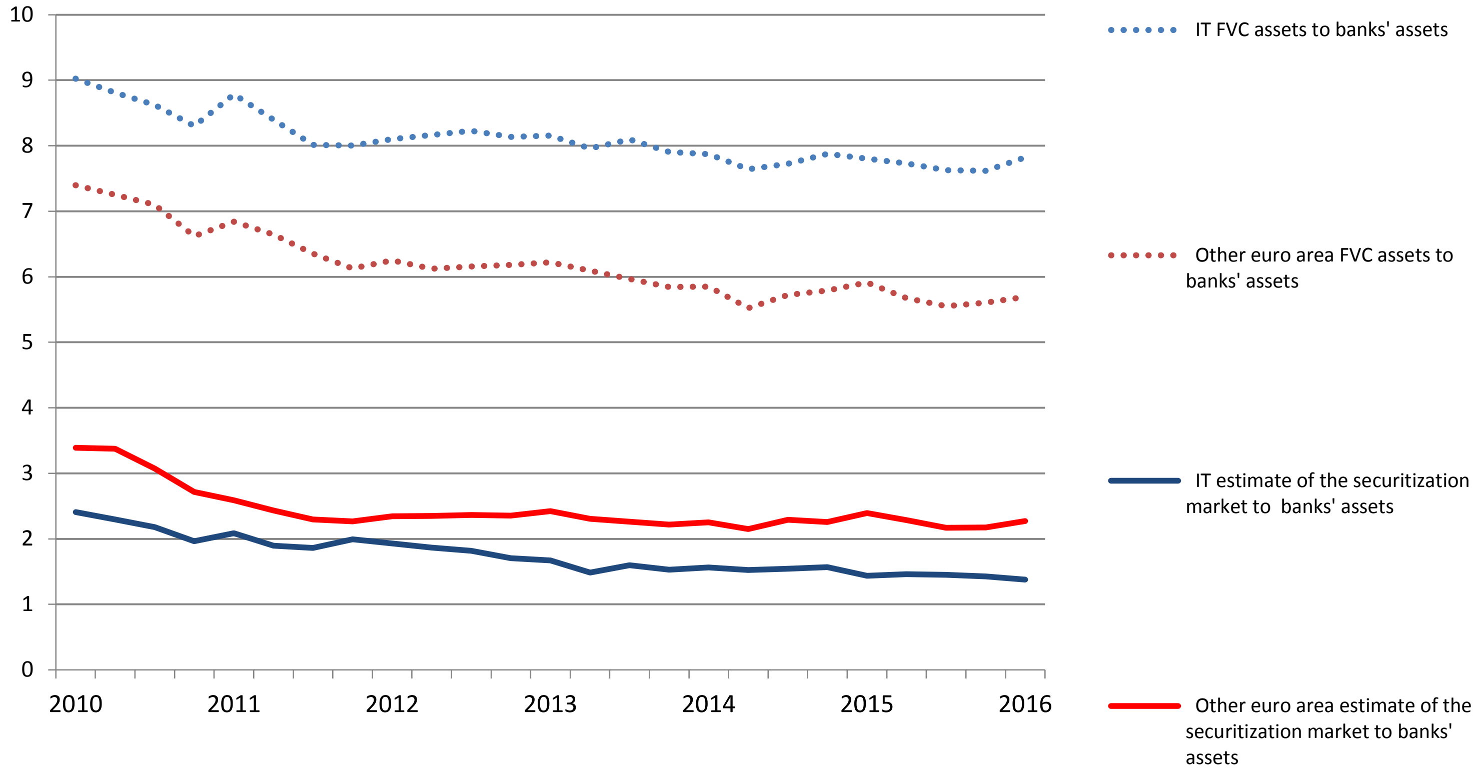
Alternative calculation methods of the size of the market (example)

FSB broad measure = 200 (total assets of FVC A + total assets of FVC B)

FSB narrow measure = 100 (only total assets of FVC B). FVC A is not counted since it is consolidated in banking groups (self-securitizations can be considered consolidated).

The proposed measure = 30 (130 securities issued by FVC A and FVC B minus 100 FVC securities bought back by bank A).
<u>Total assets of synthetic securitizations should be added.</u>

Figure 1 - Measures of the size of the securitization market (per cent)



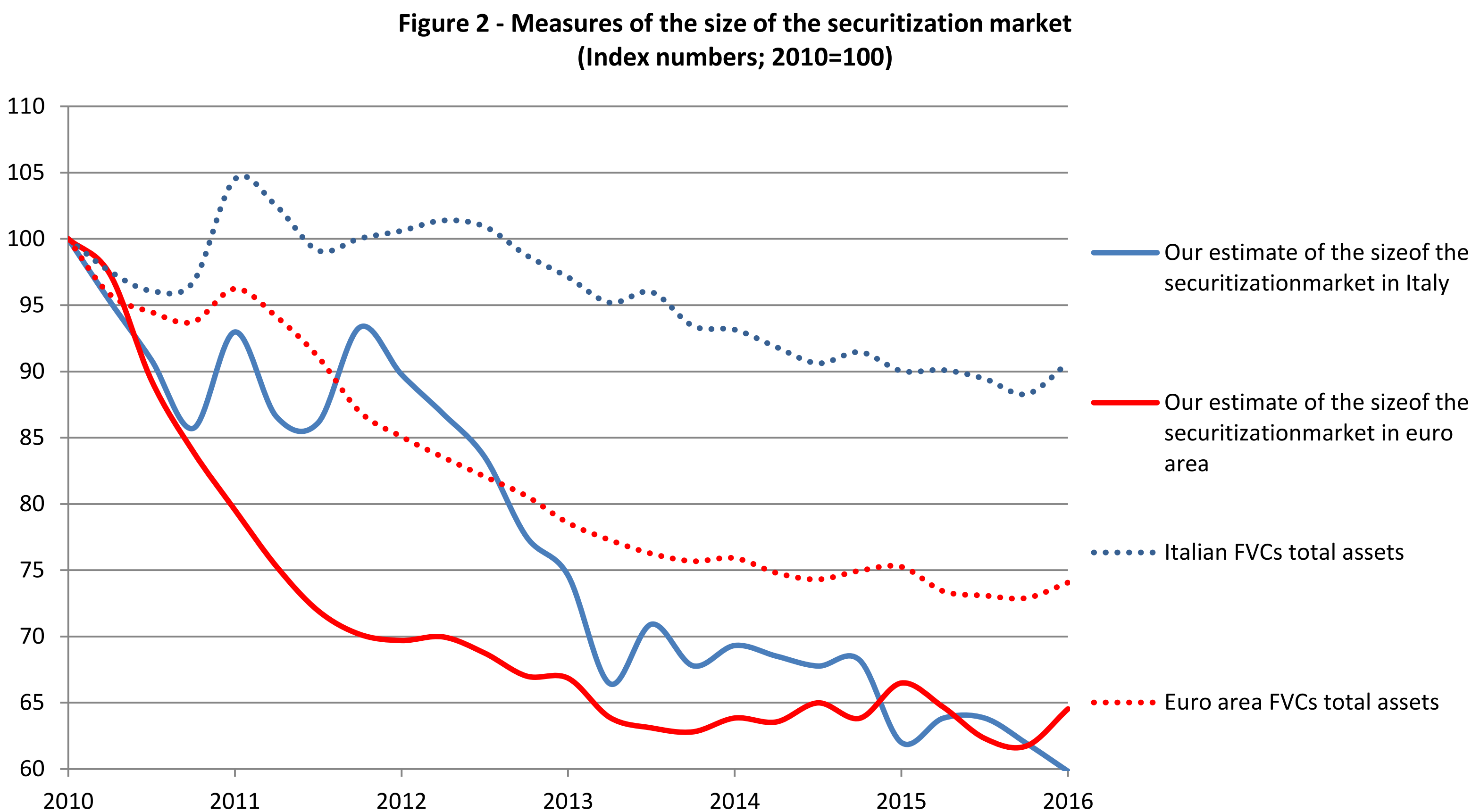


Figure 2 - Measures of the size of the securitization market
(Index numbers; 2010=100)
110
105
100
95
90
85
80
75
70
65
60
2010
2011
2012
2013
2014
2015
2016
Our estimate of the sizeof the securitizationmarket in Italy
Our estimate of the sizeof the securitizationmarket in euro area
Italian FVCs total assets
Euro area FVCs total assets

Risk profiles for securitizations

Risk areas such as leverage, credit intermediation and interconnectedness with the regular banking system are poorly significant if assessed through FVCs balance sheets (European Systemic Risk Board and FSB). Others risk area are pertinent: maturity missmatch and liquidity transformation.

However, the financial crisis showed that complexity and opaqueness in securitization structures are closely correlated and pose several risks. To fill this gap we propose two indicators calculated using FVCs' statistics. The first is the percentage ratio of debt securities issued by synthetic securitizations and other non-traditional FVCs to the total debt securities issued by all FVCs. The second indicator is the percentage ratio of securitized loans with a non-domestic counterparty to total securitized loans

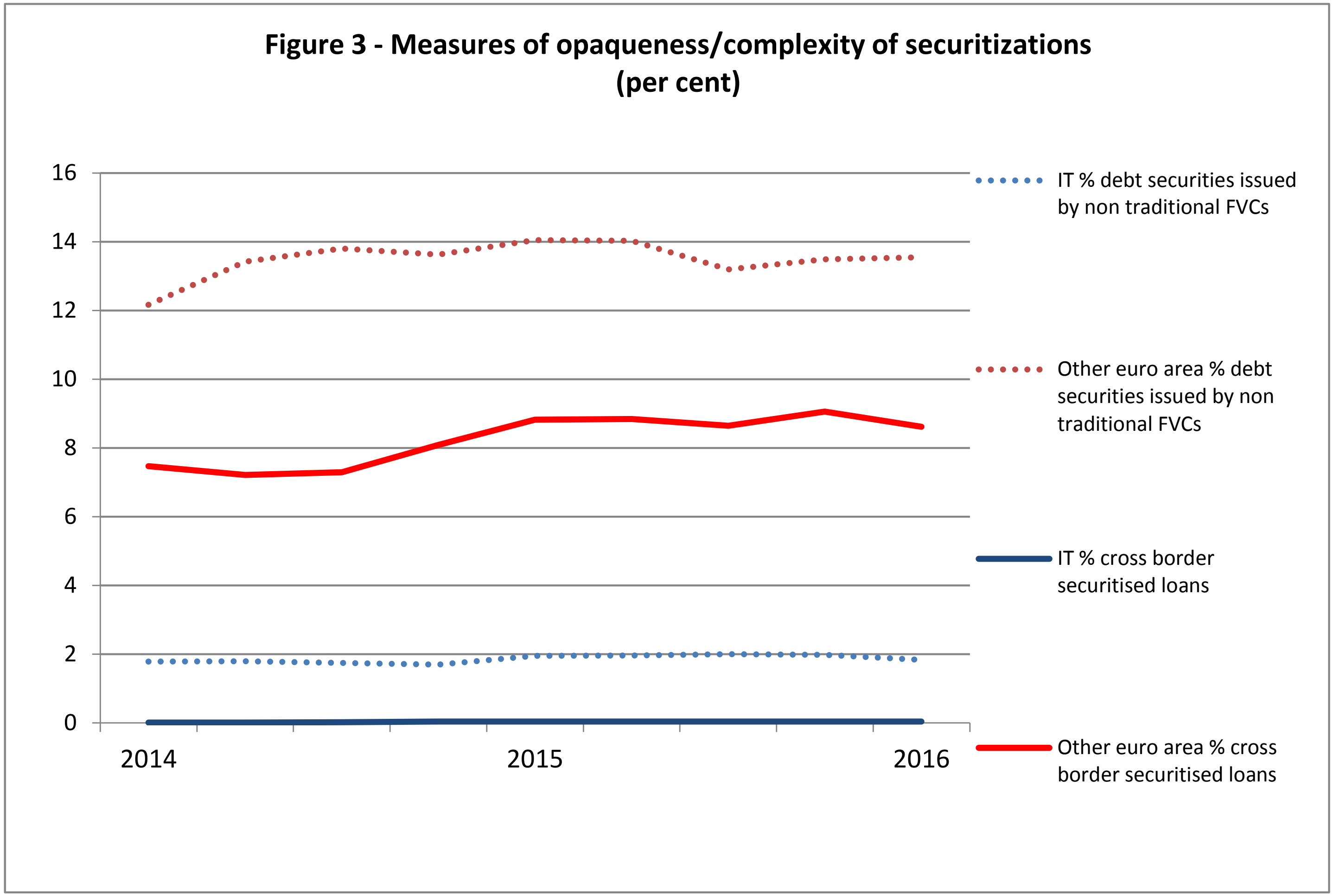


Figure 3 - Measures of opaqueness/complexity of securitizations
(per cent)
16
14
12
10
8
6
4
2
0
2014
2015
2016
IT % debt securities issued by non traditional FVCs
Other euro area % debt securities issued by non traditional FVCs
IT % cross border securitised loans
Other euro area % cross border securitised loans

Final remarks

There is room for further improvements in the FSB narrowing down process with reference to Economic Function 5 (in particular securitizations).
Given FVCs data peculiarities, it is better to focus on securities issued and rule out retained securitizations (included those originated by other OFIs).

Risk analysis should be more activity/entity specific. At least avoid use misleading data (e.g. leverage, credit intermediation and interconnectedness with the regular banking system using FVCs data).

Thanks for your attention!

giorgio.nuzzo@bancaditalia.it

Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

IFC-National Bank of Belgium Workshop on "*Data needs and Statistics compilation for macroprudential analysis*"

Brussels, Belgium, 18-19 May 2017

What 'special purposes' make Ireland attractive for debt funding by international banks?[1]

Brian Golden and Eduardo Maqui,
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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Central Bank of Ireland
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What 'special purposes' make Ireland attractive for debt funding by international banks?

Brian Golden[Ψ]
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brian.golden@centralbank.ie

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Outline

Context

Mapping

- The whole SPE reporting population
- Specific sponsor bank-linked SPEs
- Typical business models employed by sponsor banks

Initial research

- Motivation
- Research goal and data
- Empirical strategy I: Bivariate Probit model
- Empirical strategy II: Tobit model
- Empirical strategy III: OLS model

Conclusions

Context

- **Global market finance growth** $\longrightarrow$ Non-banks step up debt issuance as banks retrench (IMF, 2016);

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- Ireland $\longrightarrow$ Major **channel for global non-bank finance**: **€3.9 trillion** (mostly non-resident);

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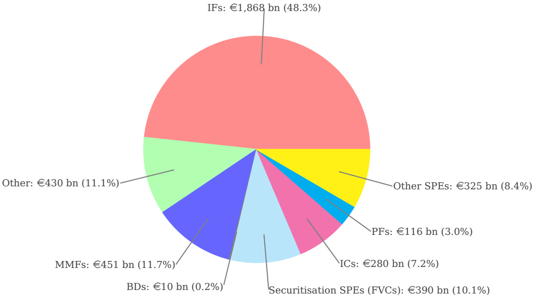

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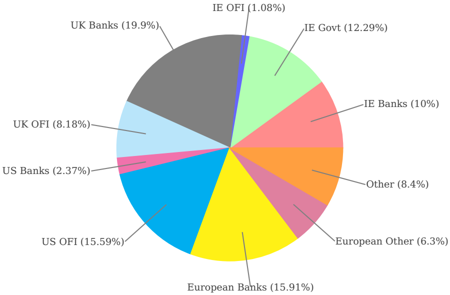
  1. Over 1,600 vehicles covering **total assets** of **€715 bn**;
  2. **Complex vehicle structures** with diverse activities, country and sector links;
  3. Potential for **original research**.

Mapping SPEs

- Sponsor profile of securitisation SPEs (FVCs)



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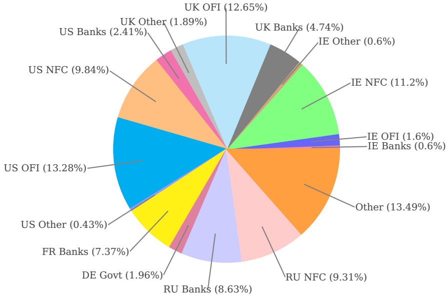

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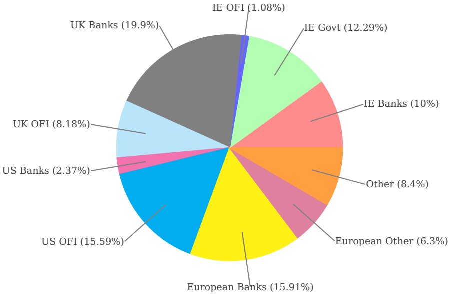

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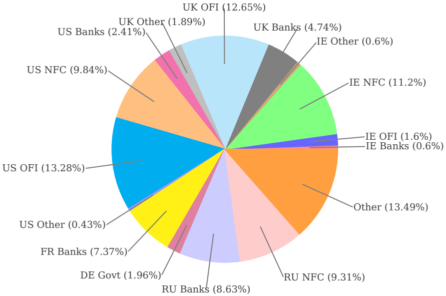

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Mapping SPEs

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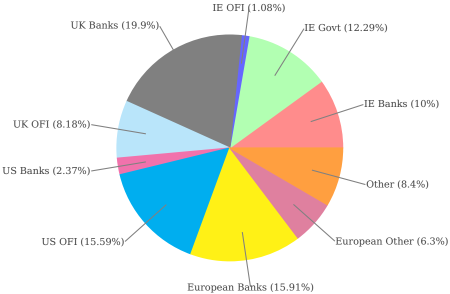

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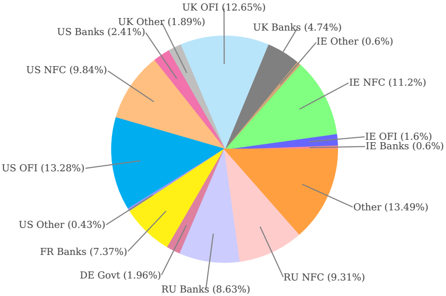

- Wide range of sector and country links, with cluster effects;
- **Other vehicles** $\rightarrow$ 14 different activity types (fund-linked investment, intra-group financing and external financing accounting for 70%).

Mapping bank-sponsored SPEs

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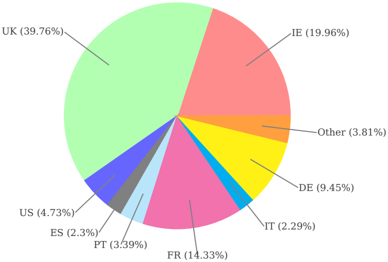
- Bank-sponsor profile of securitisation SPEs (FVCs)



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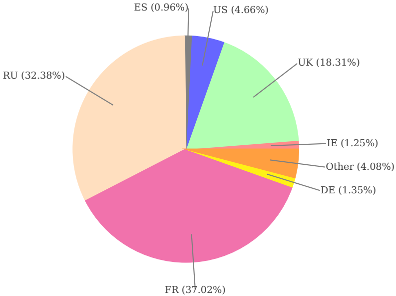

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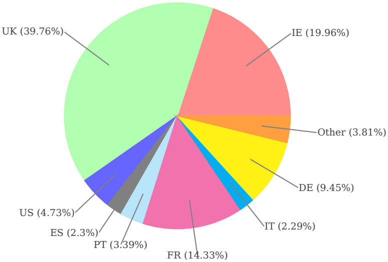

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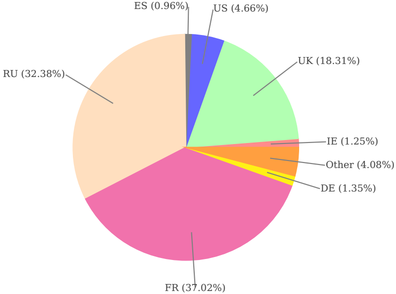

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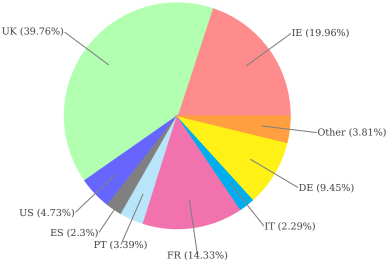

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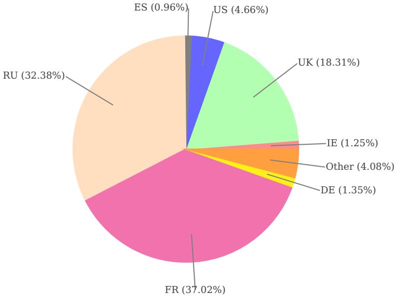

- **Securitisation vehicles** → Variety of links, with Western European cluster;
- **Other vehicles** → Less regional focus given the range of activities, but each country segment represents one to two activity types.

Standard securitisation model (1)

Turning cash flows from non-transferable debt into transferable debt securities

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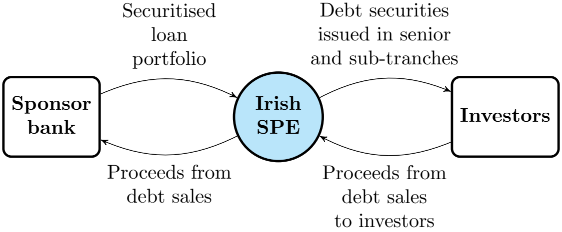

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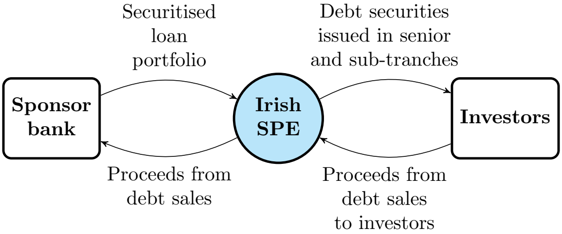

- Sponsor bank passes on the credit risk of loans to investors, reducing loans on the balance sheet while it earns servicing fee income.

Standard securitisation model (2)

Special case: Retained securitisation

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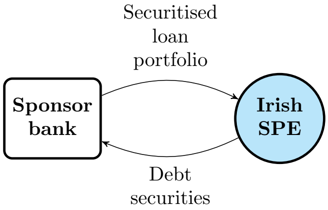

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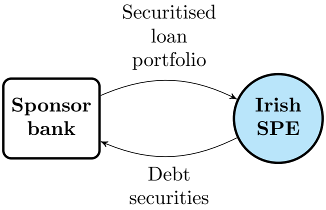

- Sponsor bank uses the debt securities as collateral to access central bank liquidity facilities.

Asset-backed debt issuance

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Debt securities held by SPE with returns split between sponsor bank and investors

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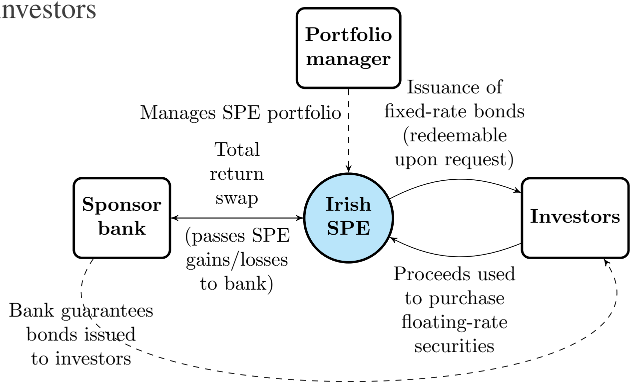

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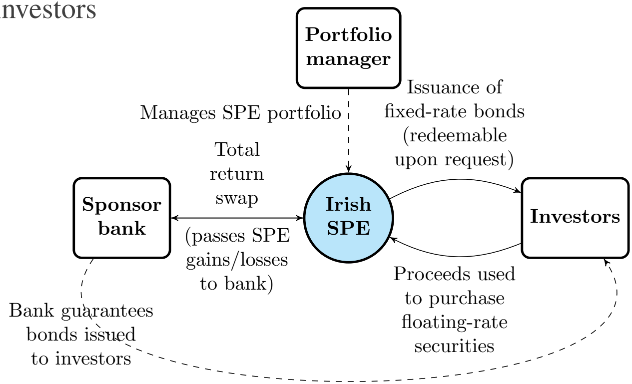

- Irish SPE holds debt securities and issues debt to investors based on portfolio cash flows;

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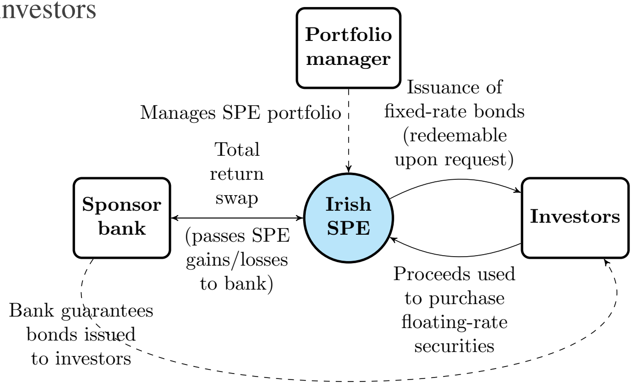

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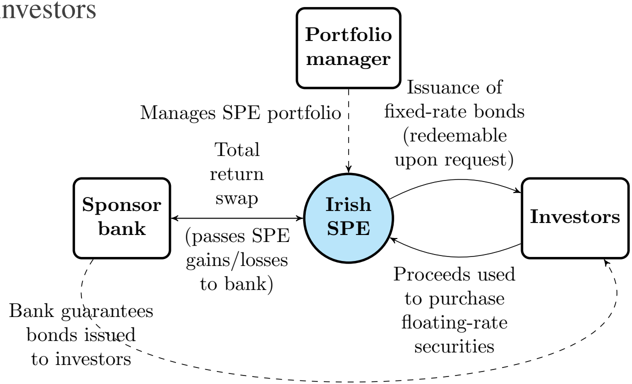

- Irish SPE holds debt securities and issues debt to investors based on portfolio cash flows;
- **Motivations**: Interest rate risk, maturity transformation and accessing cash flows to finance investments;
- **Open questions**: Where sponsor bank or investors run consistent losses and we do not see the full vehicle structure.

External financing

Sponsor bank places collateral into Irish SPE

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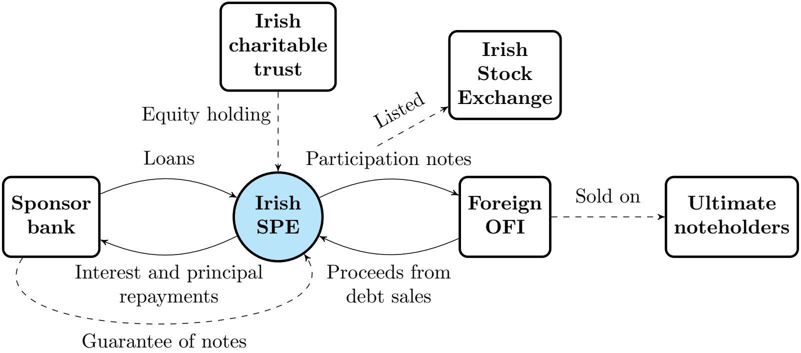

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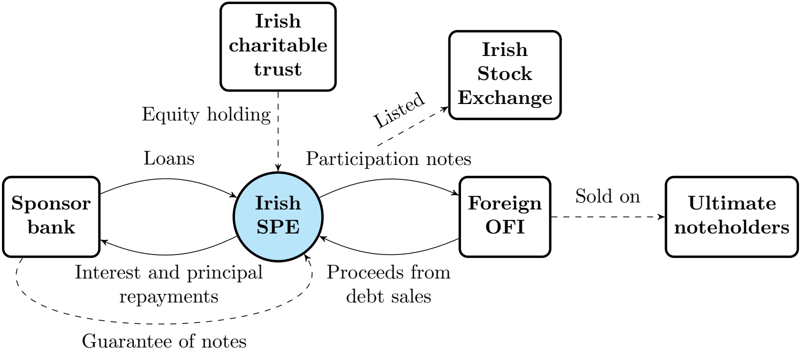

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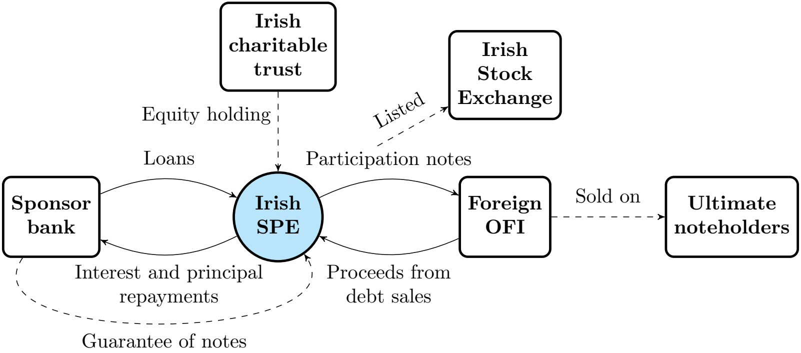

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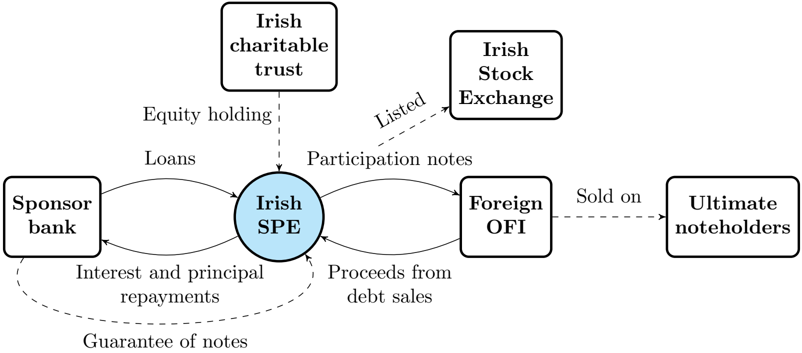

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- **Motivation**: Secure cheaper funding.

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- Cross-border bank-related debt flows (Lane, 2014):
  - Focus of attention since the financial crisis;
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- Global spillovers → Regulatory environment → Cross-border bank flows (Houston et al, 2012; Cerutti et al, 2015; Buch et al, 2016).

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- **Sample split analysis** → Sponsor banks from AE account for 85% of the sample observations → Analysis of full sample and this sub-sample.

Variables

Variable	Description	Source
DFB (Irish SPE)	Binary variable indicating 1 for debt funding issued through an Irish SPE, and 0 otherwise.	Central Bank of Ireland statistics.
DFR (Irish SPE)	Debt funding volume issued through an Irish SPE to total assets ratio.	Central Bank of Ireland statistics.
DFB (other)	Binary variable indicating 1 for senior and subordinated debt funding issuance other than through an Irish SPE, and 0 otherwise.	SNL Financial.
Size	Natural logarithm of total assets.	Bloomberg.
ROA	Return on assets ratio.	Bloomberg.
Tier 1 ratio	Regulatory Tier 1 capital to total assets ratio.	Bloomberg.
LLP/Loans ratio	Loan loss provisions to total loans ratio.	Bloomberg.
Funding constraint	Binary variable indicating 1 for sponsor banks with loan growth rates greater than the median level of all sponsor bank quarter observations and funding interest expenses greater than the median level of all sponsor bank quarter observations, and 0 otherwise.	Bloomberg.
Low Tier 1 ratio	Binary variable indicating 1 for sponsor banks with a Tier 1 ratio lower than the median level of all sponsor bank quarter observations, and 0 otherwise.	Bloomberg.
CFM	Overall index of capital flow controls (restrictions) including all asset categories.	Fernandez et al. (2015).
Tax	Country-level corporate income tax rate.	OECD and KPMG.
Macro-pru	Cumulative change in the aggregate sector-specific capital buffer instruments requiring banks to finance a larger fraction of these exposures with capital (including real estate credit, consumer credit and other sectors).	Cerrutti et al. (2015).
GDP growth	Growth rate of GDP per capita.	World Bank GFDD.
Population growth	Growth rate of population.	World Bank GFDD.

Bivariate Probit model

- Model international sponsor banks' binary debt issuance choice among two alternatives: debt and via Irish SPEs;
- Simultaneous estimation employing a 2-equation multivariate probit model:

$$DFB_{m,i,j,t} = I(DFB^{*}_{m,i,j,t} > 0), m = 1, 2$$
$$DFB^{*}_{m,i,j,t} = \beta' W_{m,i,j,(t-1)} + \gamma' Z_{m,j,(t-1)} + \sum_{t} \delta_t T_t + \epsilon_{i,j,t}$$

m represents the debt issuance choice among two alternatives. i, j, t denote sponsor bank, country and quarter, respectively. $W_{m,i,j,(t-1)}$ captures sponsor bank-specific characteristics, and $Z_{m,j,(t-1)}$ consists of country-level control variables.

Empirical results – full sample

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	Dependent variable: *DFB (Irish SPE)*				
	Baseline (1)	*CFM* (2)	*Tax* (3)	*Macro-pru* (4)	*Herding* (5)
Size	0.457***	0.876***	0.568***	0.490***	0.398***
	(0.035)	(0.085)	(0.063)	(0.034)	(0.033)
ROA	0.192**	0.294*	0.251	0.275***	0.105*
	(0.060)	(0.138)	(0.131)	(0.058)	(0.053)
Tier 1 ratio	0.007	0.041	0.022		0.021
	(0.016)	(0.031)	(0.029)		(0.016)
LLP/Loans ratio	0.137***	0.144*	0.185**	0.195***	0.132***
	(0.024)	(0.070)	(0.069)	(0.028)	(0.024)
GDP growth	0.051	-0.570**	0.022	0.148	0.054
	(0.110)	(0.200)	(0.179)	(0.104)	(0.111)
Population growth	-0.072	0.020	-0.030	0.020	-0.033
	(0.120)	(0.186)	(0.161)	(0.136)	(0.127)
Funding constraint		-0.917***	-0.311		
		(0.230)	(0.597)		
CFM		2.761***			
		(0.775)			
Funding constraint × *CFM*		5.855***			
		(1.300)			
Tax			-0.002		
			(0.011)		
Funding constraint × *Tax*			0.012		
			(0.018)		
Low Tier 1 ratio				0.209	
				(0.109)	
Macro-pru				0.152*	
				(0.073)	
Low Tier 1 ratio × *Macro-pru*				-0.060	
				(0.125)	
Country DFB (Irish SPE)					0.227***
					(0.026)
# Observations	1,882	871	871	1,969	1,882
Time fixed effects	YES	YES	YES	YES	YES
Robust clustered std. errors	YES	YES	YES	YES	YES
Pseudo R^2	0.614	0.840	0.836	0.587	0.624

Standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Empirical results – full sample

	Dependent variable: DFB (Irish SPE)				
	Baseline (1)	*CFM* (2)	*Tax* (3)	*Macro-pru* (4)	*Herding* (5)
Size	0.457***	0.876***	0.568***	0.490***	0.398***
	(0.035)	(0.085)	(0.063)	(0.034)	(0.033)
ROA	0.192**	0.294*	0.251	0.275***	0.105*
	(0.060)	(0.138)	(0.131)	(0.058)	(0.053)
Tier 1 ratio	0.007	0.041	0.022		0.021
	(0.016)	(0.031)	(0.029)		(0.016)
LLP/Loans ratio	0.137***	0.144*	0.185**	0.195***	0.132***
	(0.024)	(0.070)	(0.069)	(0.028)	(0.024)
GDP growth	0.051	-0.570**	0.022	0.148	0.054
	(0.110)	(0.200)	(0.179)	(0.104)	(0.111)
Population growth	-0.072	0.020	-0.030	0.020	-0.033
	(0.120)	(0.186)	(0.161)	(0.136)	(0.127)
Funding constraint		-0.917***	-0.311		
		(0.230)	(0.597)		
CFM		2.761***			
		(0.775)			
Funding constraint × *CFM*		5.855***			
		(1.300)			
Tax			-0.002		
			(0.011)		
Funding constraint × *Tax*			0.012		
			(0.018)		
Low Tier 1 ratio				0.209	
				(0.109)	
Macro-pru				0.152*	
				(0.073)	
Low Tier 1 ratio × *Macro-pru*				-0.060	
				(0.125)	
Country DFB (Irish SPE)					0.227***
					(0.026)
# Observations	1,882	871	871	1,969	1,882
Time fixed effects	YES	YES	YES	YES	YES
Robust clustered std. errors	YES	YES	YES	YES	YES
Pseudo R^2	0.614	0.840	0.836	0.587	0.624

Standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

- Sponsor banks more likely to issue debt through an Irish SPE:

Empirical results – full sample

	Dependent variable: *DFB (Irish SPE)*				
	Baseline (1)	*CFM* (2)	*Tax* (3)	*Macro-pru* (4)	*Herding* (5)
Size	0.457***	0.876***	0.568***	0.490***	0.398***
	(0.035)	(0.085)	(0.063)	(0.034)	(0.033)
ROA	0.192**	0.294*	0.251	0.275***	0.105*
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Standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

- Sponsor banks more likely to issue debt through an Irish SPE:
  - ↑ bank size
  - ↑ loan loss provisions ratio
  - ↑ profitability (FS only)
  - ↑ tier 1 (AE only)

Empirical results – full sample

Banc Ceannais na hÉireann
Central Bank of Ireland
Eurosystem

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  - ↑ profitability (FS only)
  - ↑ tier 1 (AE only)
- Country-level:

Empirical results – full sample

Banc Ceannais na hÉireann
Central Bank of Ireland
Eurosystem

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	(0.120)	(0.186)	(0.161)	(0.136)	(0.127)
Funding constraint		-0.917***	-0.311		
		(0.230)	(0.597)		
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Standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

- Sponsor banks more likely to issue debt through an Irish SPE:
  - ↑ bank size
  - ↑ loan loss provisions ratio
  - ↑ profitability (FS only)
  - ↑ tier 1 (AE only)
- Country-level:
  - ↑ CFM (particularly for funding constrained banks)
  - ↑ Macro-pru
  - ↑ Herding
  - ↑ Tax (only AE funding constrained banks)

Tobit model

- Model sponsor banks' debt issuance volumes;

- Tobit regression analysis for our dependent variable left-censored at zero :

$$DFR_{i,j,t} = \begin{cases} DFR^*_{i,j,t} & \text{if } DFR^*_{i,j,t} > 0 \\ 0 & \text{if } DFR^*_{i,j,t} \leq 0 \end{cases}$$

$$DFR^*_{i,j,t} = \beta' W_{i,j,(t-1)} + \gamma' Z_{j,(t-1)} + \sum_t \delta_t T_t + \epsilon_{i,j,t}$$

i, j and t denote the sponsor bank, country and quarter, respectively. The dependent variable $DFR_{i,j,t}$ is the ratio of total volume of debt issued to total assets, for sponsor bank i in country j in quarter t. $DFR^*_{i,j,t}$ is the latent variable in our Tobit regressions.

Empirical results – full sample

Banc Ceannais na hÉireann
Central Bank of Ireland
Eurosystem

	Dependent variable: *DFR (Irish SPE)*				
	Baseline (1)	*CFM* (2)	*Tax* (3)	*Macro-pru* (4)	*Herding* (5)
Size	0.237***	0.094***	0.067***	0.191***	0.193**
	(0.071)	(0.016)	(0.012)	(0.027)	(0.062)
ROA	0.219**	0.098**	0.108**	0.224***	0.160*
	(0.078)	(0.034)	(0.036)	(0.063)	(0.066)
Tier 1 ratio	0.005	0.005	-0.008		0.016
	(0.017)	(0.005)	(0.007)		(0.019)
LLP/Loans ratio	0.130*	0.035*	0.051**	0.124***	0.125*
	(0.063)	(0.014)	(0.017)	(0.025)	(0.063)
GDP growth	0.002	-0.076	0.018	0.134*	0.005
	(0.091)	(0.048)	(0.039)	(0.066)	(0.089)
Population growth	-0.147	-0.002	-0.022	-0.003	-0.116
	(0.106)	(0.035)	(0.033)	(0.067)	(0.103)
Funding constraint		-0.260**	0.047		
		(0.086)	(0.148)		
CFM		0.149			
		(0.159)			
Funding constraint × *CFM*		1.608***			
		(0.457)			
Tax			-0.005		
			(0.003)		
Funding constraint × *Tax*			-0.002		
			(0.004)		
Low Tier 1 ratio				0.170**	
				(0.061)	
Macro-pru				-0.015	
				(0.045)	
Low Tier 1 ratio × *Macro-pru*				-0.039	
				(0.099)	
Country DFB (Irish SPE)					0.123***
					(0.035)
# Observations	1,882	871	871	1,969	1,882
Time fixed effects	YES	YES	YES	YES	YES
Robust std. errors	YES	YES	YES	YES	YES
Pseudo R^2	0.492	0.888	0.869	0.555	0.503

Standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Empirical results – full sample

Banc Ceannais na hÉireann
Central Bank of Ireland
Eurosystem

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- Debt issuance volumes by sponsor banks through Irish SPEs increase with:

Empirical results – full sample

Banc Ceannais na hÉireann
Central Bank of Ireland
Eurosystem

	Dependent variable: *DFR (Irish SPE)*				
	Baseline (1)	*CFM* (2)	*Tax* (3)	*Macro-pru* (4)	*Herding* (5)
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- Debt issuance volumes by sponsor banks through Irish SPEs increase with:
  - ↑ bank size
  - ↑ loan loss provisions ratio
  - low Tier 1 ratio
  - ↑ profitability (FS only)

Empirical results – full sample

Banc Ceannais na hÉireann
Central Bank of Ireland
Eurosystem

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- Debt issuance volumes by sponsor banks through Irish SPEs increase with:
  - ↑ bank size
  - ↑ loan loss provisions ratio
  - low Tier 1 ratio
  - ↑ profitability (FS only)
- Less crucial role of regulatory capital;

Empirical results – full sample

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  - ↑ bank size
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  - low Tier 1 ratio
  - ↑ profitability (FS only)
- Less crucial role of regulatory capital;
- Country-level:

Empirical results – full sample

Banc Ceannais na hÉireann
Central Bank of Ireland
Eurosystem

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Low Tier 1 ratio				0.170**	
				(0.061)	
Macro-pru				-0.015	
				(0.045)	
Low Tier 1 ratio × Macro-pru				-0.039	
				(0.099)	
Country DFB (Irish SPE)					0.123***
					(0.035)
# Observations	1,882	871	871	1,969	1,882
Time fixed effects	YES	YES	YES	YES	YES
Robust std. errors	YES	YES	YES	YES	YES
Pseudo R^2	0.492	0.888	0.869	0.555	0.503

Standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

- Debt issuance volumes by sponsor banks through Irish SPEs increase with:
  - ↑ bank size
  - ↑ loan loss provisions ratio
  - low Tier 1 ratio
  - ↑ profitability (FS only)
- Less crucial role of regulatory capital;
- Country-level:
  - ↑ CFM (only FS funding constrained banks)
  - ↑ Herding
  - Tax insignificant

OLS model

- Model the impact of debt funding through Irish SPEs on sponsor bank characteristics:

$$\begin{aligned} W_{i,j,t} = {} & \lambda \mathit{Sponsor\ bank\ DFB\ (Irish\ SPE)\ past\ year}_{i,t-(1,\ldots,4)} \\ & + \omega \mathit{Sponsor\ bank\ DFB\ (other)\ past\ year}_{i,t-(1,\ldots,4)} \\ & + \beta' W_{i,j,(t-2)} + \gamma' Z_{j,(t-1)} + \sum_t \delta_t T_t + \epsilon_{i,j,t} \end{aligned}$$

i, j and t denote the sponsor bank, country and quarter, respectively. The dependent variable $W_{i,j,t}$ represents sponsor bank-specific characteristics, *Sponsor bank DFB (Irish SPE) past year*$_{i,t-(1,\ldots,4)}$ is a binary variable capturing debt issuance through an Irish SPE in the past four quarters and *Sponsor bank DFB (other) past year*$_{i,t-(1,\ldots,4)}$ is a binary variable capturing debt issuance other than through an Irish SPE in the past four quarters. $W_{i,j,(t-2)}$ is a vector sponsor bank-specific regressors, lagged by two periods. $Z_{j,(t-1)}$ consists of country-level control variables. $\epsilon_{i,j,t}$ is an i.i.d. error term which follows a normal distribution.

Empirical results – full sample

	Dependent variable:			
	Size	*ROA*	*LLP/Loans ratio*	*Tier 1 ratio*
	(1)	(2)	(3)	(4)
Sponsor bank DFB (Irish SPE) past year	1.245***	0.173	0.600*	-0.038
	(0.271)	(0.125)	(0.242)	(0.407)
Sponsor bank DFB (other) past year	0.900	0.182	-0.530	-0.886
	(0.472)	(0.165)	(0.364)	(0.645)
# Observations	1,866	1,866	1,869	1,885
Controls	YES	YES	YES	YES
Time fixed effects	YES	YES	YES	YES
Robust clustered std. errors	YES	YES	YES	YES
Adjusted R^2	0.379	0.224	0.284	0.363

Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Empirical results – full sample

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- Debt issuance through Irish SPEs has a particular impact on:

Empirical results – full sample

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  - ↑ bank size
  - ↑ loan loss provisions ratio

Empirical results – full sample

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Standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

- Debt issuance through Irish SPEs has a particular impact on:
  - ↑ bank size
  - ↑ loan loss provisions ratio
- No evidence of other debt issuance impacting sponsor bank characteristics.

Next steps

- **“Top down”** $\rightarrow$ Drill down further into why sponsor banks employ Irish SPEs for debt funding:

Next steps

- **"Top down"** $\rightarrow$ Drill down further into why sponsor banks employ Irish SPEs for debt funding:
  - Information at the security-level (current cost in sample size);

Next steps

- **"Top down"** $\rightarrow$ Drill down further into why sponsor banks employ Irish SPEs for debt funding:
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  - Alternative modelling techniques (REs, multilevel structure).

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- **“Bottom up”** $\rightarrow$ Further investigate SPE business models:
  - “Top-down” analysis helps to guide the focus;

Next steps

Banc Ceannais na hÉireann
Central Bank of Ireland
Eurosystem

- **“Top down”** $\rightarrow$ Drill down further into why sponsor banks employ Irish SPEs for debt funding:
  - Information at the security-level (current cost in sample size);
  - Alternative modelling techniques (REs, multilevel structure).
- **“Bottom up”** $\rightarrow$ Further investigate SPE business models:
  - “Top-down” analysis helps to guide the focus;
  - Co-operation across borders and data sharing capabilities.

Next steps

- **"Top down"** → Drill down further into why sponsor banks employ Irish SPEs for debt funding:
  - Information at the security-level (current cost in sample size);
  - Alternative modelling techniques (REs, multilevel structure).
- **"Bottom up"** → Further investigate SPE business models:
  - "Top-down" analysis helps to guide the focus;
  - Co-operation across borders and data sharing capabilities.
- Develop a comprehensive register of SPE activity types.

Thank you!

Outline

Context

Mapping

- The whole SPE reporting population
- Specific sponsor bank-linked SPEs
- Typical business models employed by sponsor banks

Initial research

- Motivation
- Research goal and data
- Empirical strategy I: Bivariate Probit model
- Empirical strategy II: Tobit model
- Empirical strategy III: OLS model

Conclusions

IFC-National Bank of Belgium Workshop on "*Data needs and Statistics compilation for macroprudential analysis*"

Brussels, Belgium, 18-19 May 2017

The Belgian shadow banking sector with a focus on other financial intermediaries (OFIs)[1]

Martine Druant and Steven Cappoen,
National Bank of Belgium

[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.

Belgian shadow banking sector with a focus on OFIs

Paper for the IFC-NBB Workshop
'Data needs and statistics compilation for macroprudential analysis'
(18-19 May 2017)

Martine Druant / Steven Cappoen

This paper delineates the Belgian shadow banking sector according to the FSB framework and explains the statistical information used. While remaining limited in size, a substantial share of the sector consists of other financial intermediaries (OFIs). OFIs include e.g. leasing and factoring companies, lenders in consumer and mortgage credit but also a large group of other entities. This diverse and sometimes variable composition can lead to volatile movements. A further split up into sub-sectors is done to distinguish the real shadow bank entities from entities that do not pose shadow banking risks and to exclude entities that are consolidated in the regulatory perimeter. This exercise enhances our understanding of the shadow banking sector and helps to downsize it to credit intermediation posing bank-like risks to the risks to the financial system.

Key words: shadow banking, other financial intermediaries, consolidation

Contents

1. Introduction

It is widely acknowledged that the shadow banking sector offers substantial benefits in leading to a diversification of funding sources for the economy, investment opportunities for investors and income sources for banks, as well as leading to an increased shock absorption capacity of the economy by sharing of the direct risks among multiple investors. However, the financial crisis demonstrated that if non-bank financial intermediation has characteristics comparable to banking activities, including maturity transformation and liquidity transformation, and leverage, it may become a source of risk. To be more specific, owing to connections with other financial institutions and with the real economy, adverse events in the shadow banking sector may lead to systemic risks.

In that context it is necessary to provide a comprehensive overview of the shadow banking system and the associated potential risks. The NBB subscribes to the international work done at European level, and from 2016 onwards it took part in the annual monitoring exercise concerning the shadow banking sector conducted by the Financial Stability Board (FSB). In the specific case of Belgium, besides the delineation of the shadow banking sector, the interconnections between shadow banking entities and the other financial and real sectors of the economy were studied. Subjects covered by the Bank's analyses include the contractual and non-contractual links between asset management vehicles and Belgian financial institutions, and the way in which they are treated for the purposes of risk management. Important efforts were made to enhance the monitoring framework on a continuous basis, but differences still exist between definitions of the shadow banking sector used and not all data gaps have been solved yet.

This paper describes, in a first section, the Belgian monitoring framework for shadow banks. It explains how the shadow banking sector is delineated, provides results for 2016 and puts them in an international perspective. This section reveals that important data gaps remain in the Other Financial Intermediaries (OFIs), more precisely with respect to the entities consolidated in the regulatory perimeter and to the composition of the other OFIs. These data gaps as well as a proposal to change the methodology will be dealt with in the second section of the paper. In this section a detailed analysis based on microdata breaks down the remaining OFIs into different categories. A third section summarizes the impact on the delineation of the Belgian shadow banking sector of the proposed changes in the methodology.

2. Framework for monitoring the Belgian shadow banking sector

How to delineate the shadow banking sector?

The delineation of the Belgian shadow banking sector is consistent with the framework developed by the FSB and is part of the 2016 FSB monitoring exercise[1].

[1] FSB, Global Shadow Banking Monitoring Report 2016.

The FSB has been conducting annual monitoring exercises since 2011 to assess global trends and risks in the shadow banking. The 2016 year's monitoring covers 28 jurisdictions[2]. This framework has been described in the NBB Annual Report 2016 and the NBB Macroprudential Report 2017.

The FSB defines shadow banking as credit intermediation that involves entities and activities outside the regular banking system, and therefore lacking a formal safety net. It should be stressed that this definition does not mean that the shadow banking sector escapes from regulatory requirements; the sector is regulated in a different manner than 'regular' banks, and a separate chapter of this report is devoted to describing the existing regulatory framework for shadow banks and to assessing if current regulation is sufficient to mitigate the risks detected.

This broad FSB definition starts from the monitoring universe of non-bank financial intermediation (MUNFI) which is the sum of financial assets of non-bank financial entities[3] , pension funds and insurance companies and is calculated using flow of funds data in financial accounts (established on a residential basis, meaning that only entities residing in the country are taken into account). Note that the financial accounts' data only cover on-balance sheet exposures (not off-balance sheet links).

In a second step, the FSB narrows down this concept towards non-bank credit intermediation that poses bank-like risks to the financial system. These bank-like risks are: maturity and liquidity transformation, leverage and credit risk transfer. This narrowing down was done for the first time in the 2015 monitoring exercise based on economic functions (EF), where authorities assess whether or not non-bank financial entities and activities are involved in shadow banking risks (e.g. maturity/liquidity transformation and leverage) and, if yes, are classified in an economic function.

For the 2016 monitoring exercise, five economic functions were defined:

1. EF1 Management of collective investment vehicles with features that make them susceptible to runs.
2. EF2 Loan provision that is dependent on short-term funding.
3. EF3 Intermediation of market activities that is dependent on short-term funding or on secured funding of client assets.
4. EF4 Facilitation of credit creation.
5. EF5 Securitisation-based credit intermediation and funding of financial entities.

Note that the FSB delineation framework is applied in seven Euro Area countries[4]. While the European institutions stick to the same broad definition for shadow

[2] AR = Argentina; AU = Australia; BE = Belgium; BR = Brazil; CA = Canada; CI = Cayman Islands; CH = Switzerland; CL = Chile; CN = China; DE = Germany; ES = Spain; FR = France; HK = Hong Kong; ID = Indonesia; IE = Ireland; IN = India; IT = Italy; JP = Japan; KR = Korea; MX = Mexico; NL = Netherlands; RU = Russia; SA = Saudi Arabia; SG = Singapore; TR = Turkey; UK = United Kingdom; US = United States; ZA = South Africa.

[3] Non-bank financial entities consist of money market funds (S123), non-money market funds (S124), other financial intermediaries (S125), financial auxiliaries (S126) and captive financial institutions (S127).

[4] Belgium, France, Germany, Ireland, Italy, Netherlands, Spain.

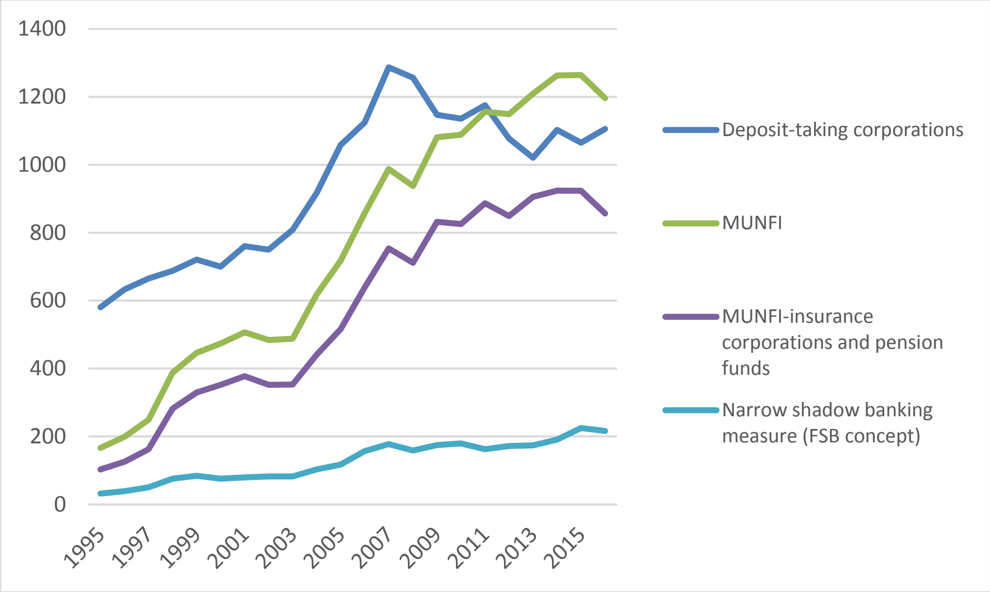
banking as the FSB, they use diverging approaches to further narrow down the sector.

Results for Belgium for 2016[5]

The Belgian MUNFI amounted to € 1,196 bn at the end of 2016 (283 % of GDP), compared to € 1,105 bn banking assets. It showed a steady increase and exceeded the banking sector in 2012. In order to calculate a narrow shadow banking measure that is consistent with the FSB methodology and includes non-bank credit intermediation that poses bank-like risks to the financial system, pension funds (€ 25 bn) and insurance companies (€ 314 bn) are disregarded in a first stage. The measure is further narrowed down by excluding equity funds (€ 39 bn), stockbroking firms and B-REITS (€ 8 bn), financial auxiliaries (€ 61 bn) and captive financial institutions (€ 471 bn). The main reason for excluding equity funds is that these entities have no credit intermediation function: the share of assets under management invested in credit-related assets is well below the 20% threshold set by the FSB. Stockbroking firms' assets as well as their liabilities are short term and only for the purpose of doing transactions with clients. They act as pure brokers for clients and are not engaged in credit intermediation. B - REITS mainly invest in income-generating (commercial) real estate and are all listed on a stock exchange, implying that they are not subject to run risk. They are furthermore legally limited in the provisioning of credit, and, hence remain below the 20% threshold mentioned above, and in the use of leverage. Financial auxiliaries (mainly consisting of financial head offices in Belgium) are excluded because they act on behalf of clients and do not own the assets or liabilities being transacted. The captive financial institutions, finally, mainly engage in intra-group transactions with very little engagement in investment or borrowing with entities external to the group. Their expansion was mainly linked to the attractiveness of the tax regime applied to them and has diminished from 2013 onwards because of the low interest rate environment, which lowered tax advantages.

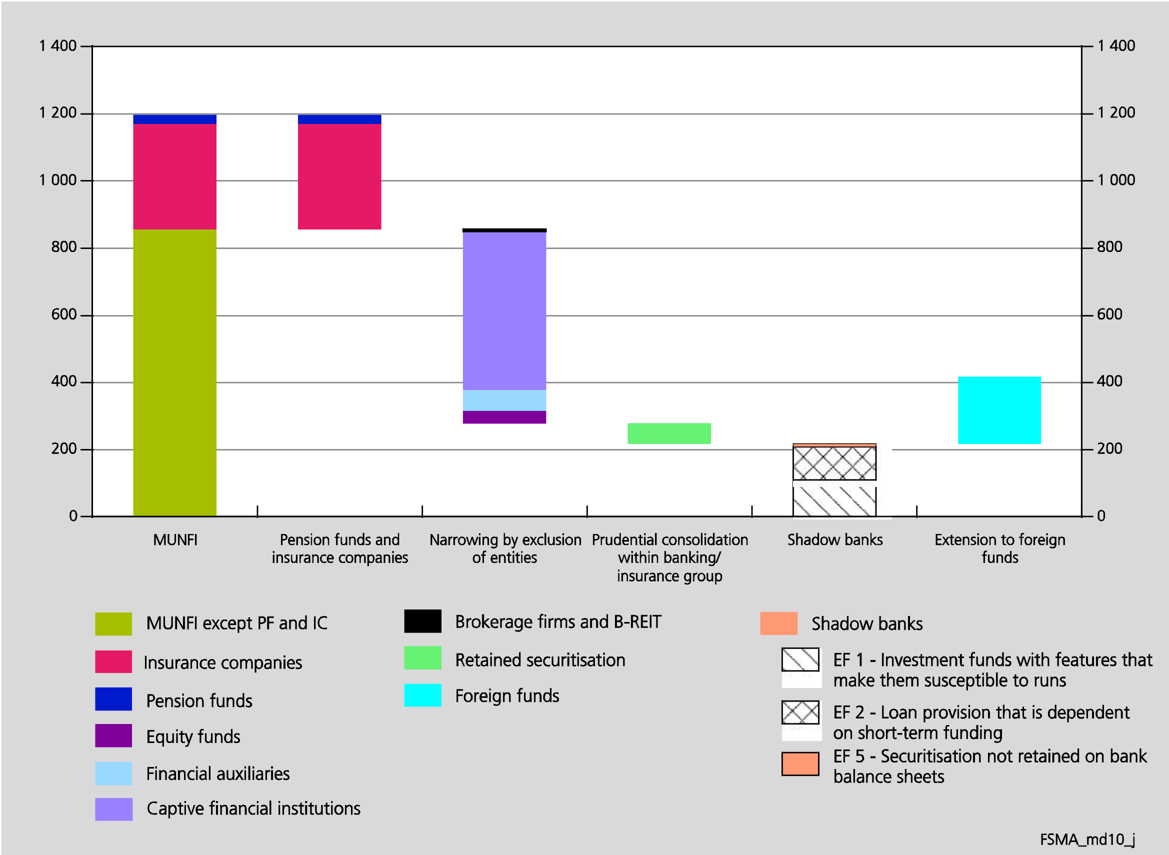
5 Note that the last FSB shadow banking exercise was conducted in 2016 for data up to 2015. Results have been published in the Global Shadow Banking Monitoring Report 2016. In this section we update the Belgian data to 2016.

Chart 1 – The Belgian financial sector
(in € billion)



Source: NBB calculations based on NAI-data.
MUNFI: monitoring universe of non-bank financial intermediation
PF: pension fund
IC: insurance company

Chart 2 – Delineating of the Belgian shadow banking sector according to the narrow FSB criterion
(at the end of 2016, in € billion)



Source: NBB calculations based on NAI-data.
MUNFI: monitoring universe of non-bank financial intermediation
PF: pension fund
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Entities consolidated into a banking group[6] for prudential purposes, should be excluded as much as possible from the shadow banking sector as they are already subject to appropriate regulation/supervision of shadow banking risks. In the same way, retained securitisation should be excluded. Retained securitisation vehicles take loans from a bank and turn these into debt securities which are given back to the same bank for use as collateral for accessing central bank funding. Data available at this stage, only permit to exclude the latter from the shadow banking definition, at the end of 2016 retained securitisation amounted to € 61 bn.

All in all, the Belgian narrow shadow banking sector, delineated according to the FSB methodology, amounted to € 217 bn at the end of 2016, representing 51 % of GDP. The bulk of the Belgian narrow shadow banking sector consists of investment funds, which are classified under EF1. EF1 includes the Belgian money market and non-money market non-equity investment funds (€ 111 bn at the end of 2016), which are almost all open-ended and hence susceptible to run risk. They can take

[6] The FSB currently only considers for exclusion consolidation into banking groups or entities subject to Basel-equivalent prudential regulation. Discussions are ongoing to consider consolidation into insurance companies and financial conglomerates as well.

the legal form of undertakings for collective investment in transferable securities (UCITS) or alternative investment funds (AIFs) and are offered to the public as well as to institutional investors.

The second largest category of shadow banks relates to EF2, consisting of loan provision that is dependent on short-term funding and which is done by other financial intermediaries as leasing and factoring companies, lenders in consumer and mortgage credit and other entities (€ 97 bn at the end of 2016). EF2 consists of all other OFI's with a view of taking a prudent approach because the available statistical information did not allow for a further split up. A further split up into sub-sectors is required to distinguish the real shadow bank entities (e.g. lenders in consumer credit) from entities that do not pose shadow banking risks (e.g. private equity companies). The diverse composition of the other OFIs also entails a lot of volatility in the data series. Moreover, they are to a large extent prudentially consolidated into banking/insurance groups. Section 2 of the paper deals with these issues. It proposes a refinement of the methodology which would, once applied, reduce the level of EF2 considerably. The impact on the delineation of the Belgian shadow banking sector of the proposed changes in the methodology will be summarized in section 3.

The third, and last category of shadow banks consists of securitization activities by financial vehicle corporations that are not retained on the balance sheets of Belgian banks. This small group of activities (€ 10 bn at the end of 2016) is categorized under EF5. The securitisation market peaked in 2011-2012, essentially due to the retained securitisation of mortgage loans. The securitisation vehicle turns these bank loans into debt securities and gives them back to the same bank that uses them as collateral for accessing central bank funding. Note that this part of the securitisation market is not considered as shadow banking. The important decline of the securitisation market at the global level also affected the Belgian market and the issuance lost momentum since 2013. Belgian banks instead placed more covered bonds in the market, as a less risky alternative.

Besides the Belgian entities mentioned so far, foreign investment funds play an important role in Belgium. These are to a large extent Luxemburg funds, but also include funds of German, French or Irish origin. As these foreign funds are not residing in Belgium, they are not automatically included in the shadow banking sector calculated by using flow of funds data established on a residential basis. They are neither under the supervision of Belgian authorities[7]; they have to follow a notification procedure with FSMA[8] in order to make an offer to the public. However, these funds are often commercialised and managed by Belgian banks and have close interconnections with the Belgian banking system. The FSB advices to consider funds that are domiciled abroad but managed/marketed domestically as 'offshore funds' and to report them in EF1[9]. From this perspective, they are included in the analysis of the Belgian shadow banking sector narrow measure, which is raised by the amount of investments by Belgian residents in foreign funds (€ 199 bn at the

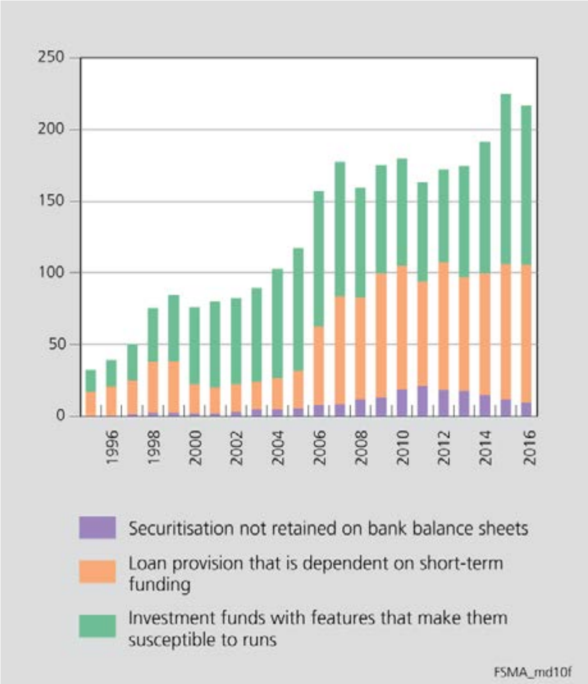
7 With the exception of foreign alternative public funds.

8 Foreign UCITS funds are notified in Belgium, foreign managers of AIF's notify their activities.

9 However, the FSB does not include these offshore funds in its global aggregate of shadow banking, in order to avoid double counting between countries.

end of 2016) and, hence, amounts to € 416 bn at the end of 2016, representing 99 % of GDP.

Chart 3 – Belgian shadow banking sector according to FSB narrow concept
(in € billion)



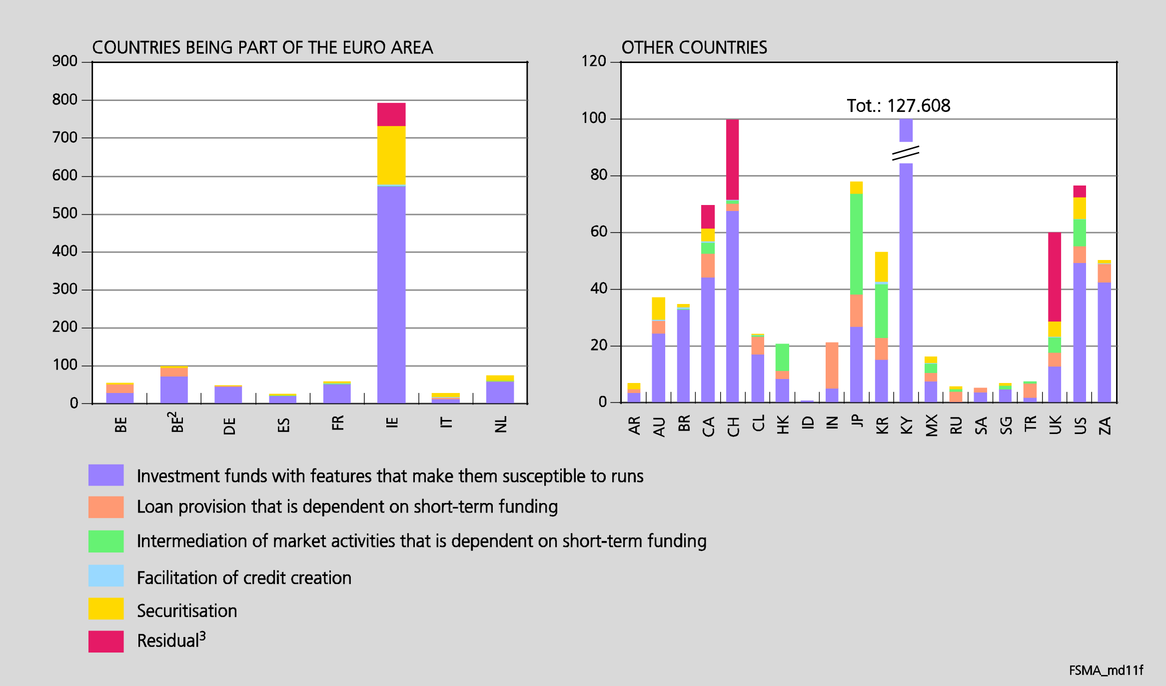
Source: NBB calculations based on NAI-data.

The shadow banking sector has almost continuously been growing since 1995, except for the years 2008 and 2011 and, recently, in 2016. Developments in the stock of investment funds are the result of net purchases/sales and valuation effects. The sector has gained importance from 1995 until the beginning of the financial crisis. After six years of decrease during and after the crisis, it regained momentum in the years 2013-2015. According to the most recent data of 2016, a new decrease was observed as a result of net sales of funds, valuation effects being slightly positive. The recent loss of interest for funds was mostly situated in the money market and bond funds, as well as in the funds offering capital protection, while net purchases were observed for mixed funds. The stock of money market funds returned to normal after the fast growth in 2015. This was explained by the investment strategy of funds with a floor-monitoring mechanism that temporarily switched from equity funds to money market funds to keep the floor. The developments in the second largest category of shadow banks, namely loan provisioning by other financial intermediaries, is subject to fluctuations caused by the changing composition of the sector. As to non-retained securitisation, the loss of interest observed since 2013 continued.

Belgian shadow banks in an international context (data 2015)

The share in GDP of the Belgian shadow banking sector is comparable to that of the Netherlands, Germany and France. Just like in Belgium, investment funds are the main component in these countries. The exceptional position of Ireland has to do with its role as a financial centre, more specifically the important presence on Irish territory of investment funds and securitisation vehicles that are often established by foreign financial institutions.

Chart 4 – International comparison of shadow banking sector: narrow FSB measure[1]
(at the end of 2015, in % gdp)



Sources: FSB, NBB.
[1] Entities consolidated in banking groups are excluded if these data are available. AR = Argentina; AU = Australia; BE = Belgium; BR = Brazil; CA = Canada; CI = Cayman Islands; CH = Switzerland; CL = Chile; CN = China; DE = Germany; ES = Spain; FR = France; HK = Hong Kong; ID = Indonesia; IE = Ireland; IN = India; IT = Italy; JP = Japan; KR = Korea; MX = Mexico; NL = Netherlands; RU = Russia; SA = Saudi Arabia; SG = Singapore; TR = Turkey; UK = United Kingdom; US = United States; ZA = South Africa.
[2] Narrow measure including investments by Belgians in foreign investment funds.
[3] Residual: part of shadow banking sector not classified in an economic function.

3. Focus on other Other Financial Intermediaries

To determine the size of the sector of the Other Financial Intermediaries (S125), data from the financial accounts statistics were used. In principle financial accounts are meant to describe the national economy as a whole, which means that all entities within the economy have to be covered. This is an important advantage compared to various other financial statistics which each cover only a specific part of the financial sector. Moreover, financial accounts are compiled in accordance with international standards (SNA 2008 / ESA 2010), so the definitions and methodologies are consistent across countries. On the other hand national (financial) accounts are drawn up to monitor the national economy by deriving (macro-)aggregates, so they are not primarily meant to analyse risks or measure shadow banking.

To achieve the 100% coverage in the financial accounts, multiple sources have to be integrated into one consistent framework. For the OFI-sector, there are two types of data sources available. First, some OFIs are obliged to provide a periodic (often quarterly) direct reporting of their activities and their balance sheets to a supervisory authority. This is the case for the Financial Vehicle Corporations, the stockbroking firms and the B-REITs. Based on the different direct reporting schemes, these companies can easily be isolated from the total OFI sector. For all the other OFIs direct comprehensive reporting schemes are not available. The main sources for these companies are indirect counterpart data and the annual accounts. In this section, annual accounts data are analysed on a micro level to further break down the other OFIs into different categories.

Which companies are classified as other OFIs?

The entities in the other OFI sector have no comprehensive reporting obligations to a supervising institution. This means no official lists of entities exist for the other OFI sector, unlike for many other financial sectors. The list of entities is therefore derived from the business register. In the business register NACE-codes are available, which provide already a good view on the activities of the entities. Moreover, some activities of the other OFIs require an initial licence. Companies wishing to develop leasing activities have to apply for a licence at the Federal Public Service Economy. Companies with consumer credit or mortgage credit activities need to be registered nowadays by the FSMA (Financial Services Market Authority). However, the available information on licences cannot be decisive as such for the sector allocation. For some companies the licenced activity is ancillary to the main activity (which is sometimes even non-financial).

Almost all legal entities in Belgium are required to report annual accounts to the Central Balance Sheet Office, which is a part of the National Bank of Belgium. They have to use standardised templates which contain the balance sheet, P&L statement, various additional tables and an annual report for the larger companies. Because the data are exhaustive, no oversampling is needed. However the annual accounts also have limitations. The data is only available on an annual basis and the time lag is at least seven months. In addition the templates follow an accounting framework which is not always consistent with the statistical requirements. To include the annual accounts data from the other OFIs in the financial accounts, various adjustments have to be made to obtain macroeconomic relevant results. The regular integration in the financial accounts is executed on a macro level. For this exercise the data for the years 2014 and 2015[10] from the other OFIs were analysed on a micro level and combined with the information in the business register and with other data sources to break down the aggregates into different functional categories in order to improve the delineation of the shadow banking in Belgium.

2 x 6 functional categories

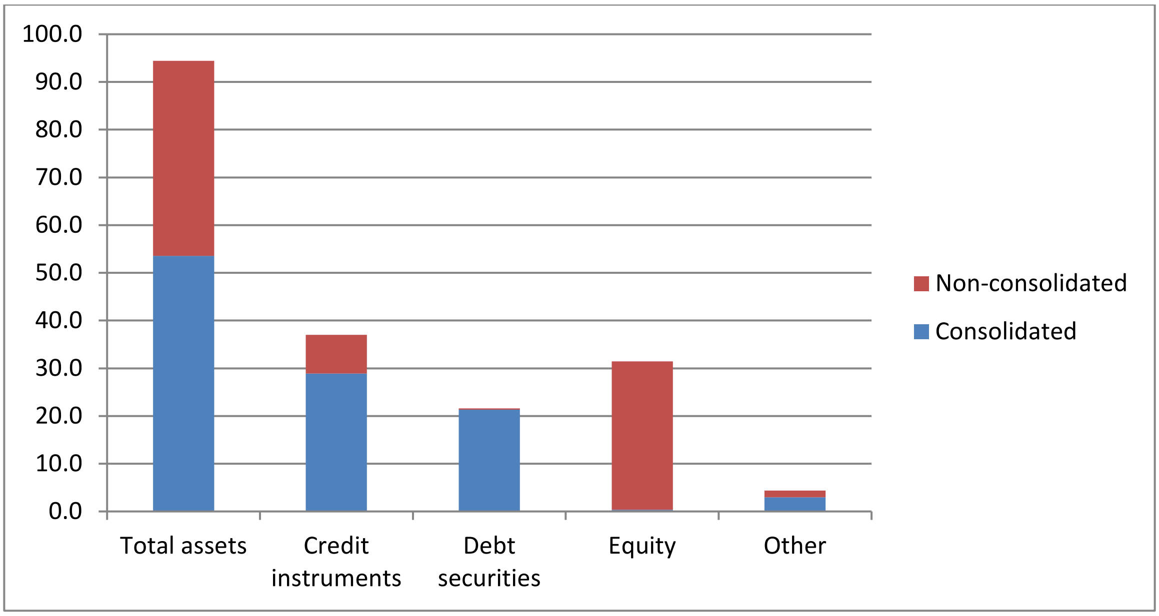
In all, 466 companies were analysed. The first part of the exercise consisted in breaking down the other OFIs into two groups. The first group contains the consolidated entities. These entities are part of a larger banking or insurance group, which means they are fully integrated in the consolidated balance sheets of a credit

[10] In this paper only the 2015 results will be presented. The 2014 data show a similar outcome.

institution or an insurance corporation. Although these entities have to be considered as separate institutional units according to the national accounting framework, they are included in the prudential supervision of the parent credit institution or insurance corporation. Hence, these entities might not be considered as a part of the shadow banking perimeter. The second group contains the non-consolidated entities; they are not subsidiaries of a larger banking group. The breakdown was performed by investigating the shareholder structure of the other OFIs. The main sources for this were on the one hand the information on the parent company in the annual accounts and on the other hand the tables on subsidiaries from the reports of the Belgian banks and insurance corporations. Of the 466 other OFIs, 50 companies are consolidated entities. The largest of these consolidated entities are all part of the four large financial groups in Belgium: Belfius, BNP Paribas Fortis, ING and KBC. In Belgium the financial sector is highly concentrated around these four institutions. Ten of the fifty consolidated entities are subsidiaries of foreign credit institutions.

The results of the breakdown are shown in chart 5. Of the € 94 bn of total assets of the other OFIs, € 54 bn arises from consolidated entities. Broken down by financial instruments, almost all of the debt securities and most part of the credit instruments belong to the consolidated entities. In contrast, the non-consolidated entities are almost entirely responsible for the equity held on the asset side of the other OFIs.

Chart 5 – Consolidated entities vs. non-consolidated entities
(at the end of 2015, in € billion)



Source: NBB.

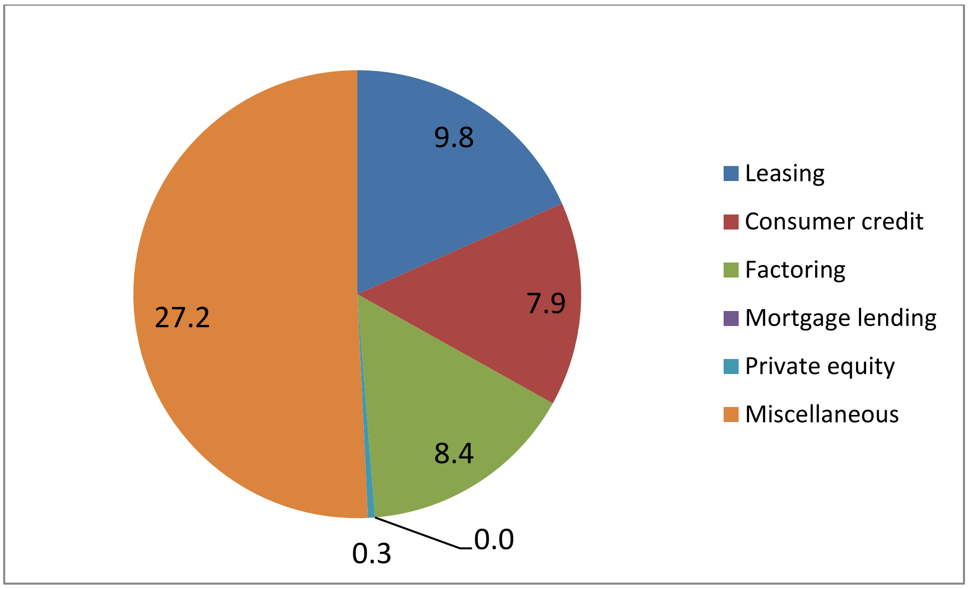
In the second part of the exercise the other OFIs were split into six functional categories based on the NACE-codes and enhanced with other data sources, such as the annual reports. A number of companies have developed activities in two or more categories. These cases were attributed to the category of the principal activity of the company. The six categories are:

- (Financial) leasing
- Consumer credit
- Factoring
- Mortgage lending
- Private equity
- Miscellaneous

The leasing category contains leasing companies which engage primarily in financial leasing. Many companies offer to their customers other types of leasing, like operational leasing, renting etc. Only those leasing companies with more than 50% financial leasing on the balance sheet are considered OFIs. If not, they are classified as non-financial corporations in the national accounts. The consumer credit companies are all registered as consumer credit companies and it is their main activity. The same reasoning is valid for the mortgage companies. The factoring companies are mainly identified by the NACE-code. The private equity companies are OFIs with most of their assets consisting of unlisted equity. Finally, the miscellaneous category contains all companies that cannot be classified in one of the five previous categories.

The two groups of consolidated and non-consolidated other OFIs were split into these six functional categories. The results for the consolidated entities are pictured in chart 6. Just over half of the total assets (27,2 of 53,6 € bn) of the consolidated entities are situated in the miscellaneous category. These entities are SPVs created by the credit institutions mainly for tax purposes, like the notional interest deduction. They are financed by their parent company (a bank) through equity and short term loans. They invest to a large extent in debt securities. The leasing category represents 9,8 € bn of the total assets. All large banks have subsidiaries involved in financial leasing. Moreover the consolidated leasing companies are substantially larger than the non-consolidated leasing companies where the total assets amount to 3,5 € bn. The same is even more valid for both the consolidated entities engaged in consumer credit and in factoring. The large consumer credit and factoring subsidiaries of the credit institutions account for over 90% of the market share: 7,9 € bn compared to 0,9 € bn for the non-consolidated entities in the consumer credit category, and 8,4 € bn compared to 0,7 € bn in the factoring category. Regarding the private equity category, the consolidated entities have very few activities. The credit institutions have no subsidiaries engaged in mortgage lending.

Chart 6 – Consolidated entities by category
(at the end of 2015, total assets in € billion)



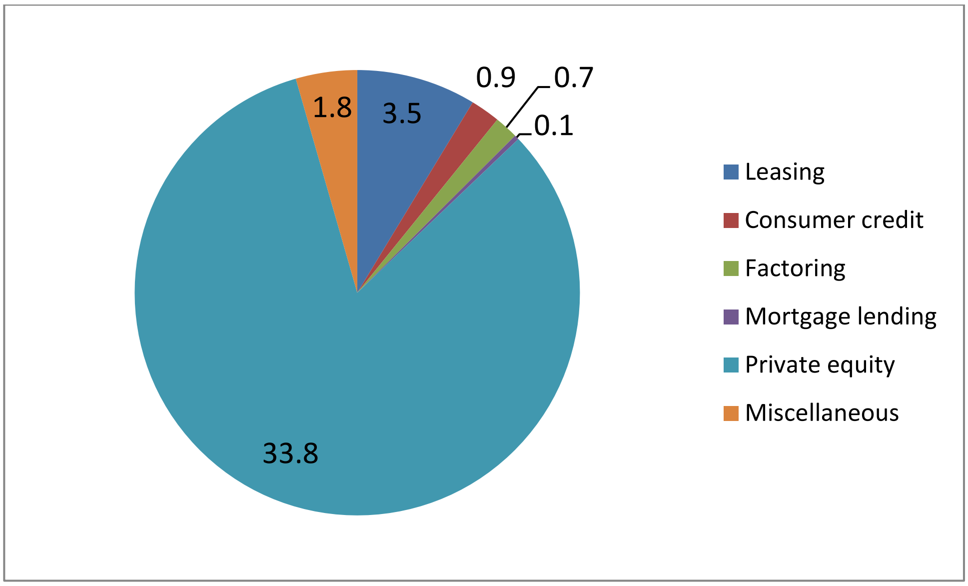
Source: NBB

The breakdown of the non-consolidated entities into the six categories is shown in chart 7. The largest category is formed by the private equity companies. They account for 33,8 € bn or 83% of the total assets of the non-consolidated entities. The private equity companies invest 90% of their assets in equity. Some very large listed investment companies are classified in this category. They hold a diversified portfolio of unlisted equity as well as some minority investments in listed companies. In addition a large number of smaller private equity companies are classified in this category. Some of them were created for tax incentives. These private equity companies, like investment fund shares invested in equity, might be considered to fall outside the scope of the shadow banking.

The leasing companies recorded in the non-consolidated entities are mainly subsidiaries of large car manufacturers which provide predominantly financial leasing – more than operational leasing – to their customers. Hence they are classified as financial leasing companies. The largest company classified in the consumer credit category is also a subsidiary of a car manufacturer, which main activity is providing consumer finance to its customers. These subsidiaries are mainly financed by affiliated companies within the multinational group. The other non-consolidated consumer finance companies and the non-consolidated factoring companies are rather small and limited in number. The mortgage lending category has decreased significantly in the last years to 0,1 € bn. The social credit providers, previously classified in this category, have been reclassified to the general government sector. Most of the remaining entities are in runoff. The miscellaneous category contains a diverse group of smaller companies. Some of them are created rather recently in the context of new financial innovations, such as crowd funding and providing micro credit. Lastly in this category were also recorded the entities, where after analysis of the annual accounts, one could conclude that they initially should not have been classified as OFIs. In all, the non-consolidated entities which are not classified in the private equity category, can still be considered as part of the shadow banking.

Chart 7 – Non-consolidated entities by category

(at the end of 2015, total assets in € billion)



Source: NBB.

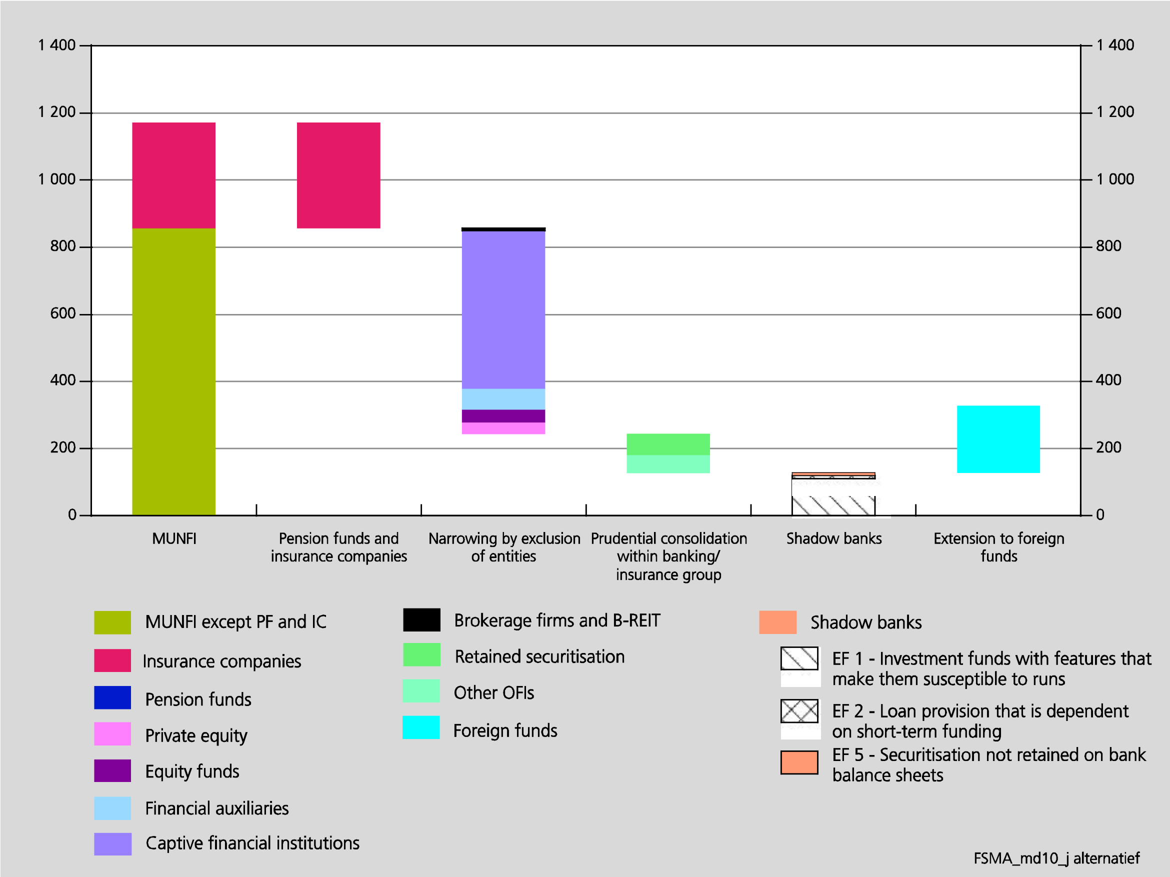
4. Conclusions

This paper investigated the important data gaps which remained in the Other Financial Intermediaries (OFIs), more precisely with respect to the entities consolidated in the regulatory perimeter and to the composition of the other OFIs. A new refinement of the methodology is proposed to enhance the measurement of the shadow banking sector according to the FSB narrow definition.

The impact of the proposal is considerable. If results for 2015 are extrapolated to 2016, only 8% of the other OFIs would be considered as shadow banks and included in EF2 – loan provision that is dependent on short-term funding. Of the € 97 bn formerly included in EF2, € 35 bn is private equity and € 55 bn consists of entities consolidated within a banking or insurance group. As there is no specific FSB guidance on the treatment of private equity so far, we follow the general guidance stating that entities that do not engage in credit intermediation with bank-like risks, are excluded from the shadow banking sector. Only the remaining € 7 bn can be considered as shadow banking. Hence, the narrow measure of shadow banking would fall from € 217 bn to € 128 bn.

Nevertheless, there remains room for improvement. This paper has shown that the entity classifications of the other OFIs can be further refined, which would enhance the shadow banking delineation as well as the financial statistics as a whole. Moreover there is a need to explore new data sources, besides the annual accounts data currently used, to better capture the more recent developments in the financial sector.

Chart 8 – New delineating of the Belgian shadow banking sector
(at the end of 2016, in € billion)



Source: NBB calculations based on NAI-data.
MUNFI: monitoring universe of non-bank financial intermediation
PF: pension fund
IC: insurance company

References

FSB, Global Shadow Banking Monitoring Report 2016.

NBB; Annual Report 2016.

NBB, Macroprudential Report 2017.

Annex1: Data tables.

Financial assets of the other OFIs by category and by financial instrument.
(at the end of 2015, in € millions)

		transferable deposits	other deposits	debt securities	short term loans	long term loans	equity	investment fund shares	other accounts receivable/payable	total
Consolidated entities	Leasing	79	76	0	2 305	7 252	59	41	24	9 836
	Consumer credit	87	227	15	2 648	4 901	2	-	13	7 893
	Factoring	90	-	-	8 285	1	0	-	1	8 376
	Mortgage credit	-	-	-	-	-	-	-	-	-
	Private equity	26	-	-	2	46	193	-	0	267
	Miscellaneous	126	2 132	21 318	940	2 508	57	9	93	27 183
	Total	409	2 435	21 334	14 180	14 709	311	50	130	53 556
Non-consolidated entities	Leasing	67	0	-	2 154	1 257	64	-	5	3 547
	Consumer credit	20	-	-	405	344	107	-	2	878
	Factoring	34	-	-	662	0	4	-	0	701
	Mortgage credit	15	-	-	36	83	4	-	0	137
	Private equity	352	648	180	1 041	1 042	30 364	150	5	33 783
	Miscellaneous	94	137	70	310	806	132	264	8	1 820
	Total	580	785	250	4 609	3 532	30 676	414	20	40 866
Total		989	3 220	21 584	18 789	18 241	30 986	464	150	94 422

Liabilities of the other OFIs by category and by financial instrument.
(at the end of 2015, in € millions)

		debt securities	short term loans	long term loans	listed shares	unlisted shares	other equity	other accounts receivable/payable	total
Consolidated entities	Leasing	-	1 121	11 718	-	405	-	22	13 266
	Consumer credit	-	1 009	5 898	-	823	186	6	7 922
	Factoring	-	8 717	-	-	114	-	2	8 833
	Mortgage credit	-	-	-	-	-	-	-	-
	Private equity	-	1	-	-	248	-	0	249
	Miscellaneous	-	13 109	162	-	13 368	127	16	26 782
	Total	-	23 957	17 777	-	14 957	314	45	57 051
Non-consolidated entities	Leasing	-	2 080	1 820	-	611	234	13	4 758
	Consumer credit	-	168	426	-	229	4	2	828
	Factoring	-	694	0	-	59	3	0	757
	Mortgage credit	4	30	64	-	41	2	0	143
	Private equity	601	6 378	866	22 580	3 415	2 912	14	36 765
	Miscellaneous	112	128	663	1	296	561	5	1 767
	Total	717	9 478	3 839	22 582	4 652	3 717	34	45 018
Total		717	33 435	21 617	22 582	19 609	4 030	79	102 069

Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

IFC-National Bank of Belgium Workshop on "*Data needs and Statistics compilation for macroprudential analysis*"

Brussels, Belgium, 18-19 May 2017

The Belgian shadow banking sector with a focus on other financial intermediaries (OFIs)[1]

Martine Druant and Steven Cappoen,

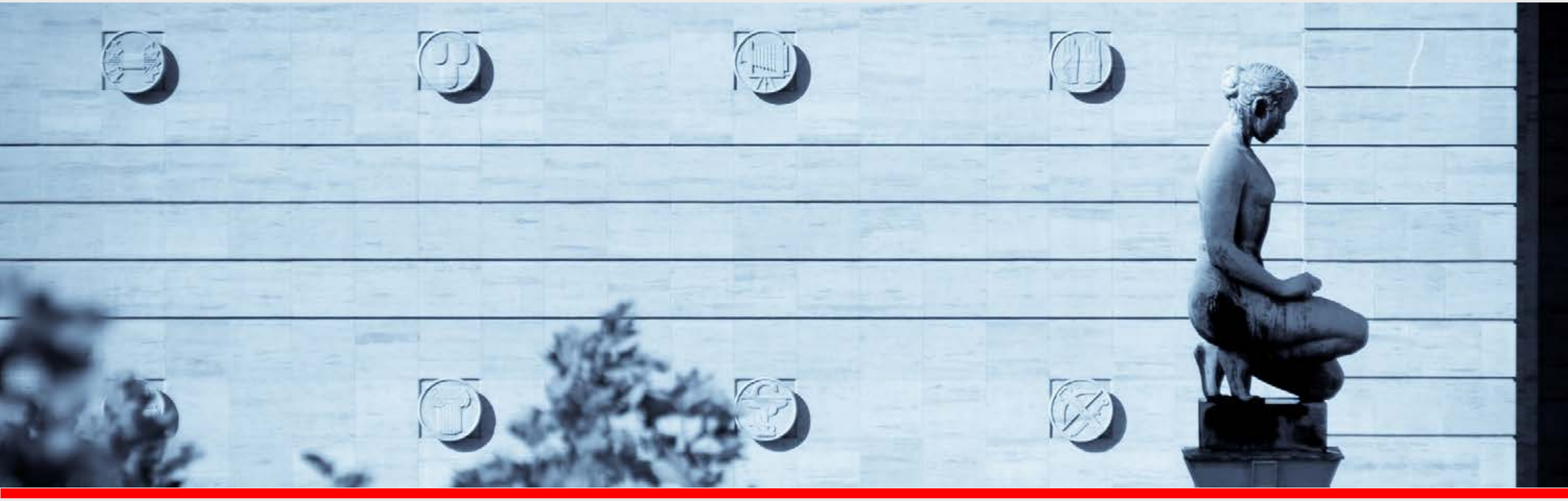
National Bank of Belgium

[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.

Belgian shadow banking sector with a focus on OFIs

IFC-NBB Workshop, 18-19 May 2017

Financial Statistics - Prudential Policy and Financial Stability
Steven Cappoen - Martine Druant



BanqueNationaleBank DE BELGIQUE VAN BELGIË
Eurosystem
Filename

Overview

1. **Monitoring framework**
2. **Focus on other 'Other Financial Intermediaries' (other OFIs)**

Belgian shadow banking sector: monitoring framework

- Consistent with FSB framework:
  - **credit intermediation** that involves **entities** and **activities** outside the regular banking system, and therefore lacking a formal safety net
  - from broad to narrow measure: from assets based on financial accounts towards non-bank credit intermediation with bank-like risks
- European framework:
  - ESRB (EU Shadow Banking Monitor): follows FSB approach for broad definition, not for narrow definition
  - EBA: slightly different definition (excl. non money market investment funds)

Financial sector overview based on financial accounts

		Financial assets 2016 (billions of euro)
Financial corporations	**S12**	**2424**
Central bank	S121	123
Deposit-taking corporations	S122	1105
Money market funds (MMFs)	S123	2
Non-MMF investment funds	S124	148
Other financial intermediaries (OFIs)	S125	175
Financial auxiliairies	S126	62
Captive financial institutions and money lenders	S127	471
Insurance corporations and pension funds	S128+S129	339

1196

MUNFI: Monitoring Universe of Non-bank Financial Intermediation

- Important note: based on residential concept

Sources: NAI, NBB.

Shadow banking: broad and narrow measure

		Financial assets 2016 (bn of euro)
Financial corporations	**S12**	**2424**
Central bank	S121	123
Deposit-taking corporations	S122	1105
Money market funds (MMFs)	S123	2
Non-MMF investment funds	S124	148
Other financial intermediaries (OFIs)	S125	175
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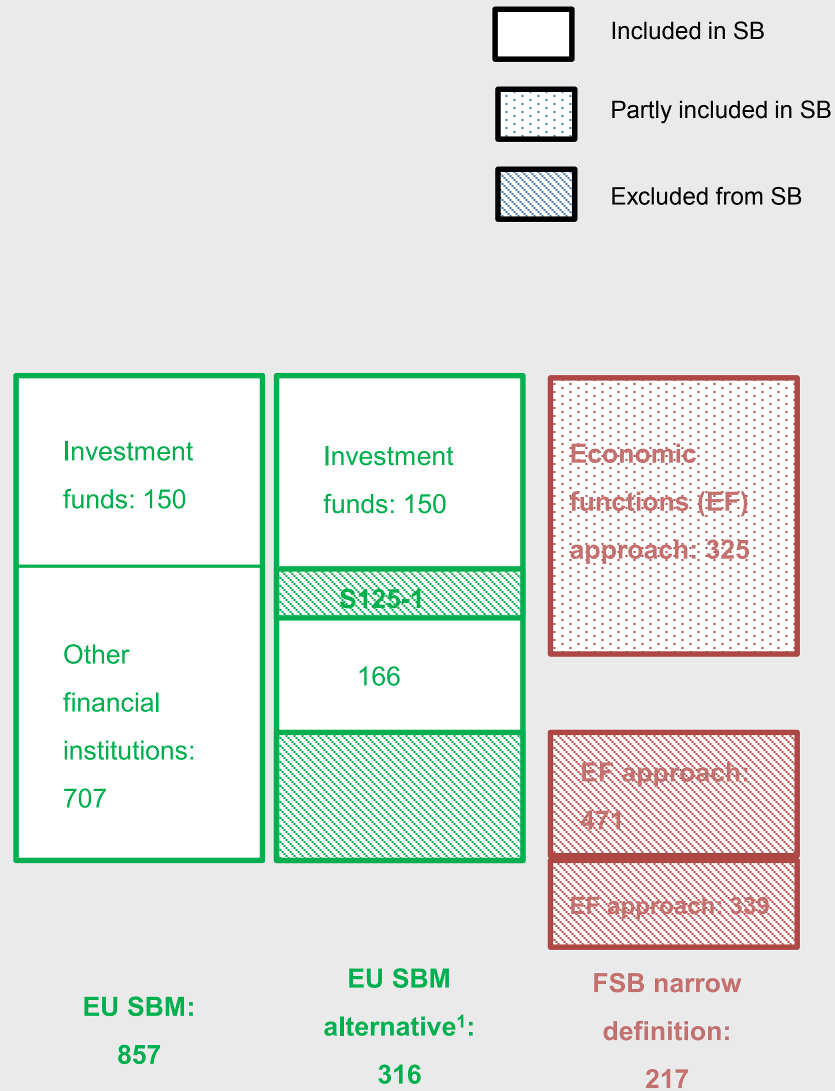
MUNFI: 1196



[1] Some countries provide more detailed data to exclude the known sub-sectors that should not be considered as shadow banks, and, hence , to calculate the residual other financial institutions to be included in the shadow banking definition.

 Sources: NAI, NBB.

Towards the FSB narrow concept – economic functions

FSB FINANCIAL STABILITY BOARD

Five Economic Functions (EFs)

Economic Function (EF)	Definitions	Examples of classified entity types[1]
EF1	Management of collective investment vehicles with features that make them susceptible to runs	Fixed income mutual funds, Credit hedge funds, Real estate funds mixed funds, ETFs, other funds
EF2	Loan provision that is dependent on short-term funding	Finance companies, leasing companies, Real estate credit companies, Factoring companies, Consumer credit companies
EF3	Intermediation of market activities that is dependent on short-term funding or on secured funding of client assets	Broker-dealers
EF4	Facilitation of credit creation	Insurance companies (including monolines), Mortgage guarantee insurers
EF5	Securitisation-based credit intermediation and funding of financial entities	Securitisations, ABCP, Synthetic ETFs, Mortgage-backed securities

[1] From the 2014 information-sharing exercise.

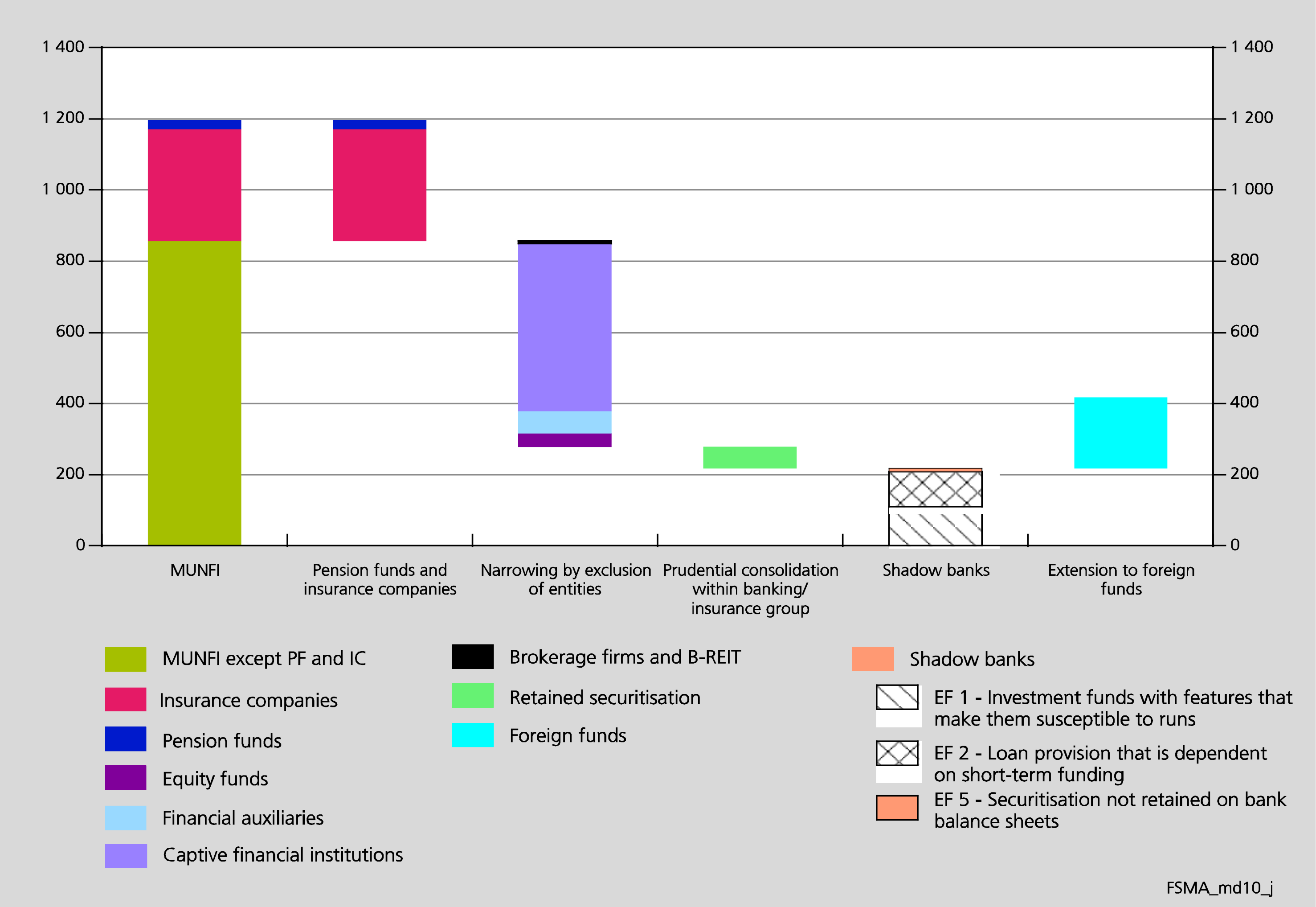
Classifying entities according to economic functions approach

(billions of euro)

Sector		Include	Why not	EF1	EF2	EF3	EF4	EF5	No EF
S123	MMFs	Y		2					
S124	Non MM Investment funds	Y except equity funds	Equity funds: no credit intermediation	109					
	Investment by BE in foreign funds	*Report as offshore*		*199*					
S125	1. FVCs	Y except retained securitisation						10	
	2.Stockbroking firms	N	Act as pure brokers for clients, no credit intermediation						
	3.B-REITs	N	No run risk, no credit intermediation						
	4.Other OFIs	Y			97				
S126	Financial auxiliaries	N	Act on behalve of clients						
S127	Captive fin. institutions	N	Intragroup transactions						

Current FSB narrow concept – results 2016

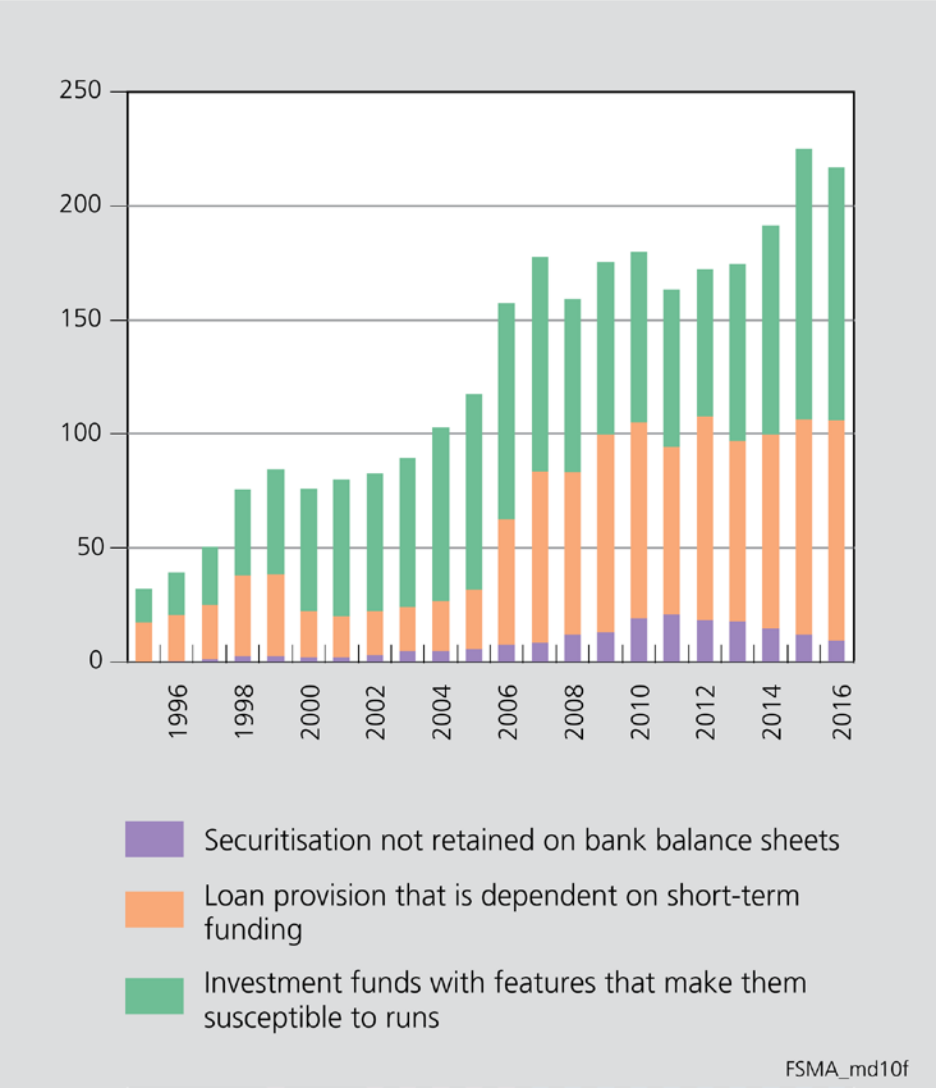
(billions of euro)



Source: NBB.

Evolution of Belgian narrow shadow banking

(billions of euro)



Sources: NAI, NBB.

Focus on EF2: loan provision that is dependent on short-term funding

- Consists of other 'Other Financial Intermediaries' (other OFIs) : 97 bn euro, almost half of narrow shadow banking sector
- Prudent approach
- Heterogeneous group (volatility)
- To a large extent prudentially consolidated into banking/insurance group
- Better knowledge necessary: first results in next section **(2015)**

Breaking down the other OFI-sector

- **Framework of the data: national financial accounts**

Main goal is not shadow banking or risk measurement, yet a statistical framework providing an overview of the national economy and its institutional sectors (applying ESA 2010).

- **Financial accounts OFI-sector (S.125): two types of data sources**
  - **Reports to supervisory authorities:**
    - FVC
    - Stockbroking firms
    - B-REIT – GVV/SIR
  - **Annual accounts and counterpart data:**
    - Other OFIs
- Aim is using **micro-data** to classify all companies of the other OFIs in different categories based on their main activity and whether or not they are part of a larger banking group

Methodology for breaking down the other OFI-sector

- **What entities are included in the other OFIs?**
  - List of entities is set by the business register
  - No supervisory obligations for these entities. Some activities do require an initial licence:

    e.g. leasing, consumer credit, mortgage lending
- **Classification into different categories based on:**
  - NACE-codes in the business register
  - List of licenced activities
  - Annual accounts analysis
  - Annual report, website, etc
- **Data sources:**
  - Mainly the **annual accounts**
  - Additionally NBB Financial Statistics, Euronext, FSMA, Credit Register, Ministery of Finance, etc

Methodology for breaking down the other OFI-sector

- **Annual Accounts?**
  - Mandatory reporting for almost all companies in Belgium (more than 400,000 companies)
  - Standardised templates
  - Collected by the Central Balance Sheet Office at the NBB
  - Contains balance sheet, P&L, additional tables, annual report

  Limitations:
  - Annual data, not quarterly
  - Time lag of at least 7 months
  - Accounting framework, not statistical
- This analysis will be conducted annually. There is no intention to integrate the data in the quarterly financial accounts.

Breaking down the other OFI-sector: results

- Total number of entities analysed: **466**
- First analysis on the parent company and/or the shareholdership of the entities.
- **50 entities are part of a larger banking or insurance group**, which means they are fully integrated in the consolidated balance sheets of a credit institution or insurance corporation.

  10 of the 50 entities are subsidiaries of foreign credit institutions.
- Highly concentrated market in Belgium : 4 large financial groups.

  Belfius, BNP Paribas Fortis, ING, KBC.

Breaking down the other OFI-sector: results

- **6 categories** were identified based on NACE-codes and enhanced with other data sources.

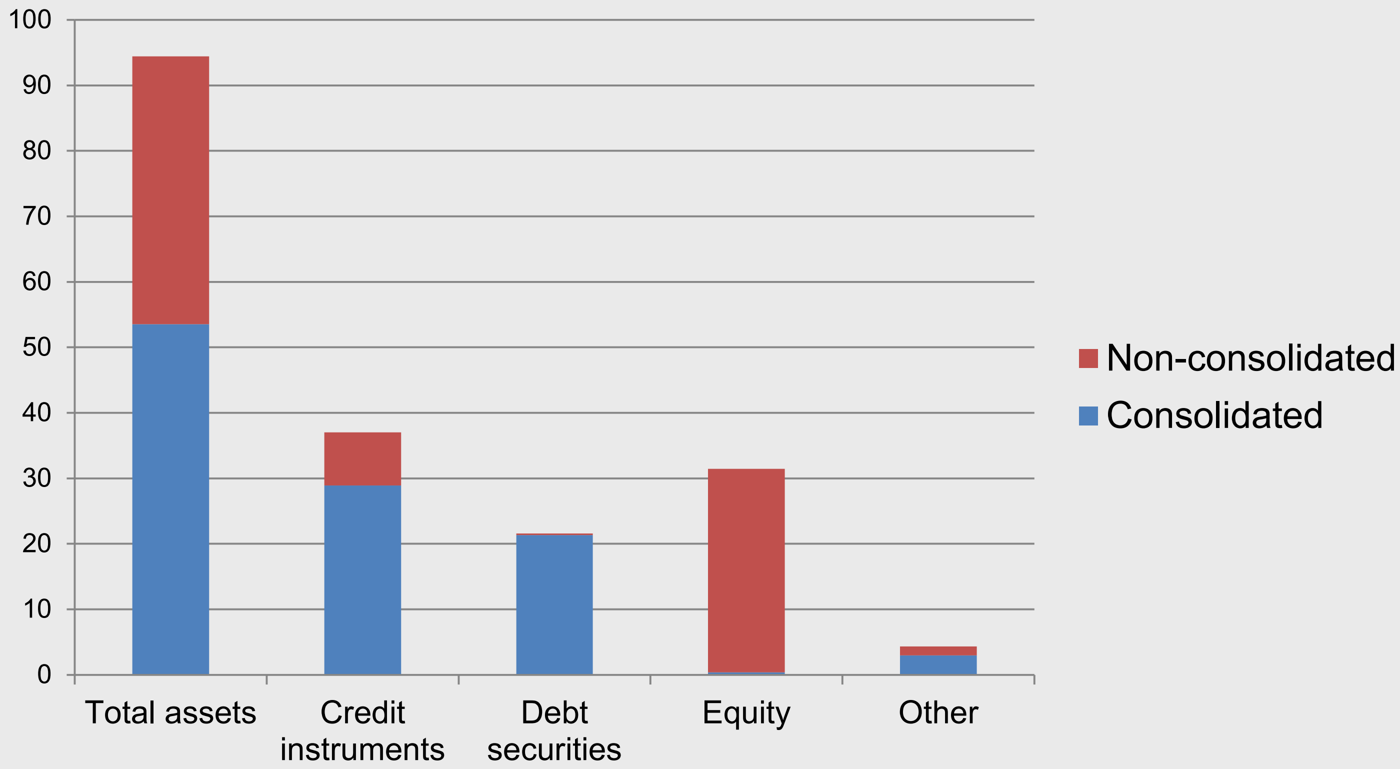
  - **(Financial) Leasing**
  - **Consumer credit**
  - **Factoring**
  - **Mortgage lending**
  - **Private Equity**
  - **Miscellaneous**

- Some companies are active in two or more categories: classification according to the principal activity.

Breaking down the other OFI-sector: results

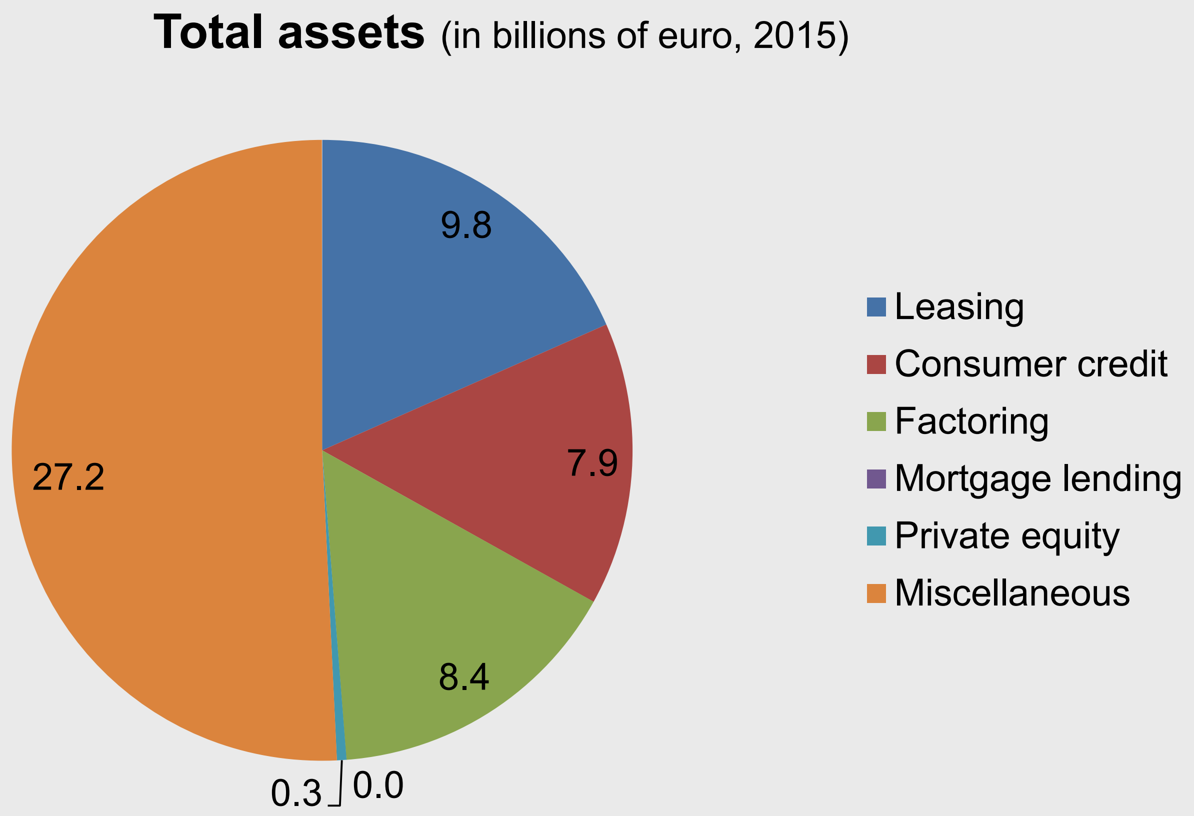
Consolidated entities vs. non-consolidated entities

(in billions of euro, 2015)



Breaking down the other OFI-sector: results

Consolidated entities by category



Breaking down the other OFI-sector: results

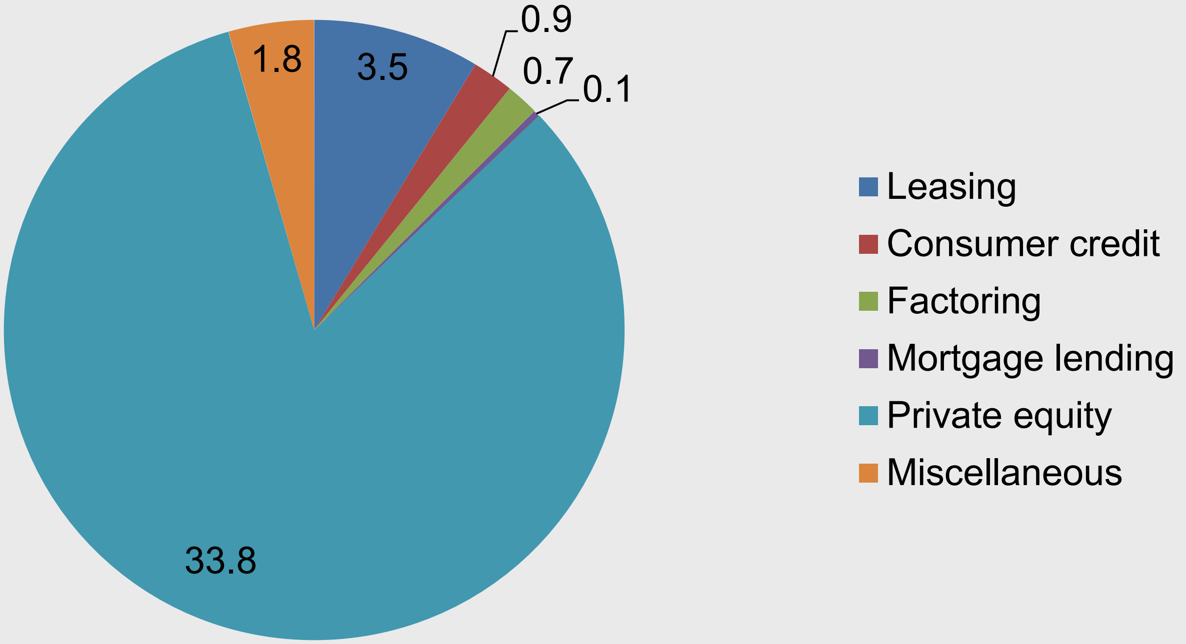
Consolidated entities by category

- **Miscellaneous:** these are SPVs created by banks for tax purposes (notional interest deduction). They are financed by the banks through equity and short term loans. The SPVs mainly invest in debt securities
- **Leasing:** all large banks have subsidiaries involved in (financial) leasing activities
- **Consumer credit** and **Factoring:** Subsidiaries established by the banks. Very high market share (90%+) for both consumer finance and factoring.
- **Mortgage lending** and **Private Equity:** zero or marginal

Breaking down the other OFI-sector: results

Non-consolidated entities by category

Total assets (in billions of euro, 2015)



Breaking down the other OFI-sector: results

Non-consolidated entities by category (1)

- **Private Equity:**
  - Some very large listed investment companies are classified in this category (GBL, Ackermans & Van Haaren, GIMV). They hold a diversified portfolio of private equity and minority investments in listed companies.
  - A large number of smaller private equity companies, some created for tax incentives (Arkimedes funds).
- **Leasing:** mainly subsidiaries of large car manufacturers which provide leasing solutions for their customers. Predominantly financial leasing (vs. operational leasing), hence classified as a financial company (OFI).

Breaking down the other OFI-sector: results

Non-consolidated entities by category (2)

- **Consumer credit:** largest entity is a subsidiary of a car manufacturer, which main activity is consumer finance. Some smaller entities.
- **Factoring:** limited number of small companies.
- **Mortgage lending:** some small entities, most of them in runoff. Mortgage lending in Belgium nowadays is provided by banks (and to some extent by the government).
- **Miscellaneous:**
  - some recent developments: microcredit providers, crowd funding companies
  - various SPVs
  - some misclassified entities

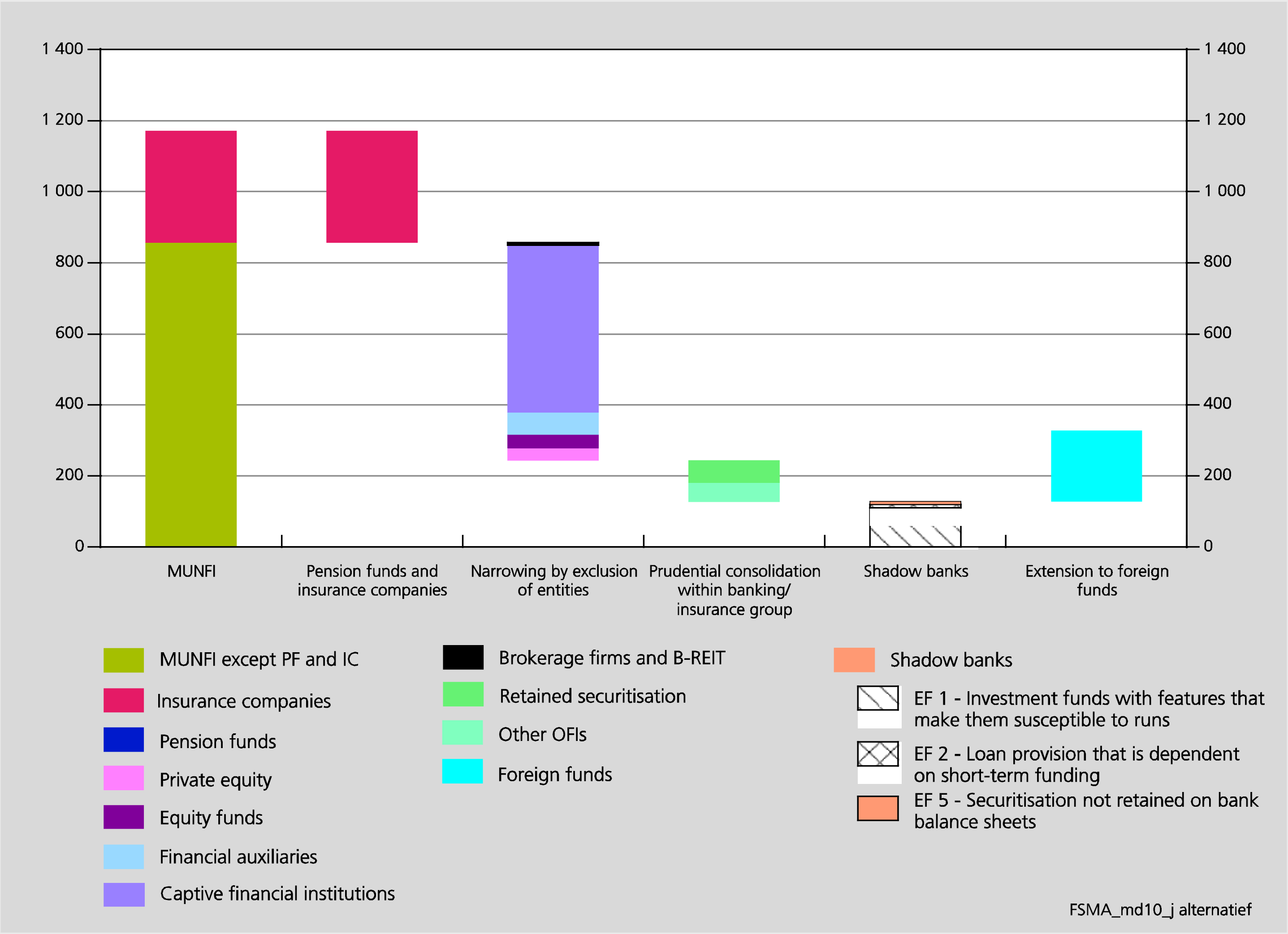
Breaking down the other OFI-sector in 2015: conclusions

- **57%** of total assets of the other OFIs (53,5 bn) are held by entities which are part of a larger banking group. They are separate institutional units according to national accounts, yet **integrated in the consolidated accounts of credit institutions**. Hence, these entities are already under prudential supervision.
- **36%** of total assets of the other OFIs (33,8 bn) are held by **private equity** companies (not consolidated in a banking group). These activities might not be considered as shadow banking.
- **8%** of total assets of the other OFIs (7,1 bn) might be identified as **shadow banking** (EF2: loan provision) → **Extrapolate to 2016**

- **Data gaps?** Room for improvement:
  - Enhancing of entity classifications
  - Exploring new data sources for recent developments

New FSB narrow concept – results 2016

(billions of euro)



Source: NBB.

IFC-National Bank of Belgium Workshop on "*Data needs and Statistics compilation for macroprudential analysis*"

Brussels, Belgium, 18-19 May 2017

Improving data quality and closing data gaps with machine learning[1]

Tobias Cagala,
Deutsche Bundesbank

[1] This paper 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.

Improving Data Quality and Closing Data Gaps with Machine Learning

Tobias Cagala*

July 14, 2017

Abstract

The identification and correction of measurement errors often involves labour intensive case-by-case evaluations by statisticians. We show how machine learning can increase the efficiency and effectiveness of these evaluations. Our approach proceeds in two steps. In the first step, a supervised learning algorithm exploits data on decisions to flag data points as erroneous to approximate the results of the human decision making process. In the second step, the algorithm applies the first-step knowledge to predict the probability of measurement errors for newly reported data points. We show that, for data on securities holdings of German banks, the algorithm yields accurate out-of-sample predictions and increases the efficiency of data quality management. While the main focus of our analysis is on an application of machine learning to data quality management, we demonstrate that the potential of machine learning for official statistics is not limited to the prediction of measurement errors. Another important problem that machine learning can help to overcome is missing data. Using simulations, we show that out-of-sample predictions of missing values with machine learning algorithms can help to close data gaps in a wide range of datasets.

Keywords: Data Quality Management, Measurement Errors, Data Gaps, Machine Learning, Supervised Learning

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Further improving and maintaining high data quality is a central goal of official statistics. In the field of data quality management (DQM), the collection of data on human decisions in the DQM process creates an opportunity to increase the efficiency and effectiveness of DQM with machine learning. This paper shows how computers can learn to predict measurement errors on the basis of data on human decisions to flag data points as erroneous. These predicted probabilities of measurement errors facilitate the work of statisticians and form the basis for a novel machine-learning-based approach to automating checks.

While the main focus of our analysis is on an application of machine learning to DQM, we demonstrate that the potential of machine learning for official statistics is not limited to the prediction of measurement errors. Another important problem that machine learning can help to overcome are data gaps. In both applications, we fill in missing information with predictions. To support DQM, the machine learning algorithms predict if a human decision maker would flag data points. In the application to data gaps, the algorithms predict missing values. Using simulations, we establish the algorithms' ability to successfully close data gaps in a wide range of datasets, illustrating their potential beyond an application to DQM.

In this paper, our goal is not to isolate causal effects of data points' features on the probability of measurement errors but, to accurately predict the probability of a measurement error for each data point with machine learning algorithms.[1] Machine learning algorithms fall into two categories: *Supervised* and *unsupervised* learning algorithms. In supervised learning, we provide the algorithm with an outcome and features, in our case, with decisions to flag data points (outcome) and the information that is stored in the data point (features). The task of the algorithm is to learn how to approximate the result of the human decision making process to predict the probability that a data point has to be flagged as erroneous.

In unsupervised learning, we provide the algorithm with unlabelled data, i.e. a dataset without feature and outcome labels. The task of the algorithm is to structure the data, by clustering data points with similar characteristics. Because these clusters are not labelled, they do not necessarily allow us to differentiate between accepted and flagged data points, which is why we focus on supervised learning.[2]

This paper aims to provide an intuitive introduction to the application of machine learning methods to improve data quality. We focus on two types of supervised learning algorithms. The first type of algorithm builds upon assumptions on the functional form of the relationship between features and the outcome. Popular examples for these algorithms are *Linear regressions* and *Logistic regressions*. We demonstrate the application of the structural algorithms with the Logit model. The second type of algorithms is more flexible and does not require structural assumptions. Examples are *decision trees*, *random forests*, and the *K-nearest-neighbors* algorithm. In this paper, we illustrate the premise of these algorithms with the decision tree and the random forest algorithm. Whereas the Logistic regression is applied in econometrics, random forests are "machine learning natives". The comparison of the approaches therefore also hints at advantages and disadvantages of machine learning in comparison to an econometric approach to data analysis.

To illustrate how machine learning can improve data quality, we apply the algorithms to securities holdings data that is reported by German banks to the German central bank (Deutsche Bundesbank). For each reported security, the dataset shows whether a compiler decided to flag the security as erroneous. We begin by splitting the data into a *training dataset* and a *validation dataset*. The application of the algorithms proceeds in two steps. In the first step, the algorithms use the training dataset to learn about the relationship between features of securities and human decisions to flag securities as erroneous. In the second step, the algorithms apply what they have learned in the first step to the validation dataset and make predictions of the probability that securities have to be flagged as erroneous. Importantly, securities in the validation dataset were not used

[1]The machine learning approach to data analysis differs from the econometric approach. In econometrics, causal inference is the name of the game (Angrist and Pischke, 2009). In contrast, the goal in machine learning is to make accurate predictions (Friedman *et al.*, 2001; Varian, 2014; Mullainathan and Spiess, 2017). For a discussion of the application of machine learning to economic problems see, e.g., Mullainathan and Spiess (2017).

[2]Because data on human decisions to flag data points are not always available, supervised learning is not applicable in some contexts. In these cases, unsupervised learning algorithms can provide a viable alternative. In this paper, we do not further discuss unsupervised learning algorithms.

for learning in the first step. Therefore, predictions of measurement errors in the validation dataset are *out-of-sample* and allow us to judge the accuracy of predictions for newly reported securities holdings for which compiler decisions are still unknown.

On the basis of the out-of-sample accuracy of predictions, we compare the performance of the Logit and the random forest algorithm. We find that the random forest algorithm yields a large improvement in accuracy. Building on our findings, we outline possibilities to implement the algorithms and highlight their potential for increasing the efficiency of the DQM process.

The good performance of the algorithms in predicting measurement errors provides the basis for extending the analysis to data gaps. Using simulated data, we show that our findings are not limited to an application of machine learning to DQM. The same methods can be applied to the imputation of missing data with predictions in a wide range of datasets.

Our contributions to the literature are twofold. First, with the application of machine learning to DQM, we introduce a novel approach to the literature on methodologies for the improvement of data quality.[3] Second, our application to data gaps contributes to a literature that discusses the use of machine learning algorithms for the imputation of missing data. Our findings complement earlier work that has mainly focused on closing data gaps in medical databases (see, e.g., Batista and Monard, 2003; Jerez *et al.*, 2010).

The remainder of the paper is organized as follows. Section 1 outlines the background of the Bundesbank's data quality management process for securities holdings data. Section 2 describes the data. Section 3 details the machine learning models. Section 4 presents the results in terms of prediction accuracy and assesses the external validity of the findings. Section 5 describes the implementation of the algorithms in the DQM process. Section 6 discusses the application of machine learning algorithms to close data gaps. Section 7 concludes.

1 Background

German Banks report securities holdings security-by-security to the German central bank (Deutsche Bundesbank) on a monthly basis (Amann *et al.*, 2012).[4] Besides their own securities portfolios, banks report holdings of domestic and foreign depositors, broken down by the depositors' economic sector and country of origin. The reported securities are identified by their International Securities Identification Number (ISIN) and are linked to data about their issuer and market price.

To guarantee high data quality, three types of quality checks are in place. If a security does not pass a check, the reporting bank is asked to explain the reasons for not passing the check and to correct the reported data if necessary. The first type of checks evaluates the consistency of the data and ensures compliance with data format requirements. The second type of checks assesses the plausibility of the data. The third type of checks makes comparisons with other data sources.

In this paper, we focus on a plausibility check of securities that were reported after the expiration of their maturity date. When the maturity date has expired, a security typically has been redeemed and is no longer in the holder's portfolio. In this case, the security should not be reported by the bank. However, if an issuer of a security has financial problems, securities are sometimes redeemed after their maturity date. In this case, the security is still in the holder's portfolio and should be reported. Because of this ambiguity, there is no simple deterministic rule that allows the central bank to automate the check. Instead, compilers make security-by-security evaluations to determine whether a security was erroneously reported after the security's maturity date or not.

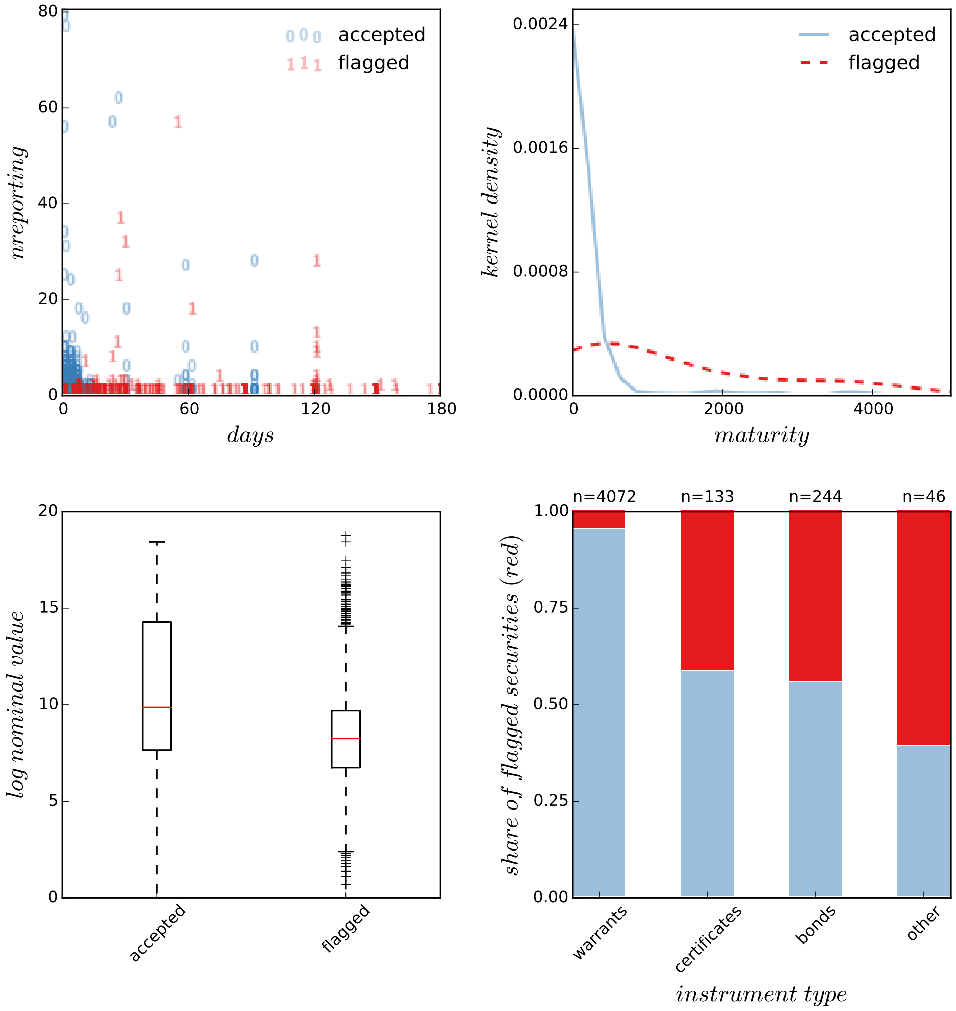
[3] For a literature review, see Batini *et al.* (2009).

[4] The reported securities comprise negotiable bonds and debt securities, negotiable money market papers, shares, participating certificates and investment fund certificates.

2 Data

The algorithms exploit two data sources. The first data source consists of the reported securities' characteristics. The data comprises information on: the number of banks that reported the security (*nreporting*), the number of days that have passed since the maturity date (*days*), the maturity of the security (*maturity*), the type of the security (*stype*), and the nominal value of the security (*nvalue*). The second data source consists of security-by-security compiler decisions. For each security, we use information on a compiler decision to accept the security or to flag the security. There are three types of flags: *"bankrupt"* (12% of flagged securities) if information on a default of the issuer is available, *"erroneous"* (44% of flagged securities) if the maturity date is incorrect, and *"implausible"* (44% of flagged securities) if there is suspicion of an issuer default or an error from the reporting bank. In the following, we differentiate between flagged and accepted securities but do not further distinguish between the three types of flags.

Figure 1: Descriptive Statistics of Features for Accepted and Flagged Securities



Note: The figure shows descriptive statistics of features for accepted and flagged securities. The upper left panel shows a scatter plot of accepted (blue) and flagged (red) securities. The upper right panel shows kernel density plots of the distribution of the securities's maturity dates (in days) for accepted and flagged securities. The lower left panel shows box-plots of the log-normalized nominal values of securities. The lower right panel shows the ratio of accepted and flagged securities by security type. For illustrative purposes, we exclude securities in the top one percentile of days and reporting banks in the upper left panel and the top one percentile of maturity in the upper right panel of this figure.

After linking the data on securities' characteristics to the compiler decisions, we end up with a dataset of $N = 4\,495$ securities that were reported after the expiration of their maturity date between February and September of 2016. Out of the securities in this dataset, 385 securities (9%) were flagged by compilers.

Figure 1 shows descriptive statistics for securities that were flagged and securities that were accepted. Overall, the figure indicates that characteristics of flagged securities differ in a number of ways from accepted securities.

On their own, these descriptive statistics hint at a possibility to predict which securities are flagged on the basis of securities' features. However, the relationships between the characteristics of a security and the probability of a flag is likely complex. Therefore, in the next section, we fit models that can capture complex relationships to the data and make predictions on the basis of these models.

3 Models

Our goal is to support the compiler by providing the probability that a reported security has to be flagged, conditional on the features of the security:

$$P\big(y_i = 1|x_i\big). \tag{1}$$

The outcome y_i is a dummy variable that takes the value one if security $i \in \{1, 2, \dots, N\}$ is flagged and zero otherwise. The vector x_i consists of the features of security i. We compare two types of models that provide a prediction of the conditional probability in eq. (1): Models that base predictions on structural assumptions and data-driven models without structural assumptions.

3.1 Models with Structural Assumptions

To predict the probability in eq. (1), we start by making assumptions on the relationship between features of the reported security and the probability of compilers flagging the security. A common assumption is that the data-generating process can adequately be described by a transformation function that maps a *single linear index* z_i to the probability $P(y_i = 1) \in [0, 1]$. We construct the index from the security's features under the assumptions of linearity and additive separability. We get:

$$z_i = \alpha + x_i^T \beta, \tag{2}$$

where α is a constant and β is a parameter vector that captures separable effects of the security's features on the index and ultimately the compiler decision.[5] The sigmoid function $\Lambda(\cdot)$ transforms the index z_i in the domain $[-\infty, \infty]$ into a probability in the domain $[0, 1]$:

$$\Lambda(z_i) = (1 + e^{-z_i})^{-1}. \tag{3}$$

Equipped with these assumptions, we can express the conditional probability in eq. (1) as:

$$P\big(y_i = 1|x_i\big) = \Lambda\big(z_i\big) = \Lambda\big(\alpha + x_i^T \beta\big). \tag{4}$$

This is the *Logit* model.[6]

[5]For a bivariate model, with the features $days_i$ and $nreporting_i$, we get $z_i = \alpha + \beta_1 days_i + \beta_2 nreporting_i$. In this example, the linearity assumption implies that the index increases by a constant value β_1 for each additional day that has passed since the maturity date and by a constant value β_2 for each additional bank that reports the security. The separability assumption implies that there is no interaction between the features, i.e. the marginal effect of an additional day on the index is independent of the number of reporting banks.

[6]From an econometric perspective, we can derive the Logit model from a decision model, if we interpret the index function (2) as a latent score that the compiler uses to decide whether to flag security i (see Section B of the Appendix). In Machine Learning, we put no

An important difference to an econometric application of the Logit model is that our goal is not to interpret estimated parameters causally but to make a prediction of the probability with high out-of-sample accuracy. Therefore, we do not discuss potential endogeneity problems of the model in our application.

An alternative to the Logit model that follows a similar approach, i.e. starting with assumptions on the structural relationship between features and the outcome, is the *linear regression model*. In contrast to the Logit model, the linear regression model lacks the transformation function (3) and models the conditional probability in eq. (1) as a linear combination of the features: $P(y_i = 1|x_1) = \alpha + x_i^T \beta$. Comparing the Logit and the linear regression model, the linear regression model has the attractive property of providing the best (minimum mean squared error) linear approximation to the data. The Logit model does not have this property but can provide a better fit to binary dependent variables by restricting the domain of $\widehat{P}$ to $[0, 1]$ (Angrist and Pischke, 2009). In the following, we focus on the Logit model.

Fitting the Logit Model to the Data To fit the Logit model to the data, we estimate the sample equivalents of the population parameters in (4) under the assumption that compilers evaluate securities independent from one another.[7] The estimation maximizes the log likelihood function with the Broyden-Fletcher-Goldfarb-Shanno algorithm.[8] With the estimated parameters, we can predict the probability of a flag, $\widehat{P}$, for any representation x of the feature vector x_i as:

$$\widehat{P}\big(y_i = 1|x_i = x\big) = \Lambda\big(\widehat{\alpha} + x^T \widehat{\beta}\big), \tag{5}$$

where $\widehat{\alpha}$ and $\widehat{\beta}$ are the estimates of the intercept and slope parameters.

Figure 2 shows a stylized illustration of a Logit model that includes the number of days that have passed since the maturity date as a single feature. For this univariate model, the estimation with Maximum Likelihood yields the estimates $\widehat{a}$ (intercept) and $\widehat{b}$ (slope). With these parameter estimates, we construct the linear index function $\widehat{z}(x)$ in the lower panel. By plugging the index into the transformation function in the upper panel, we map from the index to a probability. The grey dashed lines illustrate how we make a prediction for an exemplary security that has been reported $x = 75$ days past its maturity date.[9] In the example, the predicted probability of a flag is $\widehat{P}\big(y_i = 1|days_i = 75\big) = \Lambda\big(-1.22 + 0.03 * 75\big) = 72\%$. The Figure also illustrates the restrictions that our assumptions impose on the model: By assumption, the index function is a linear combination of our features (lower panel) and the transformation function yields a continuous S-shaped curve (upper panel).

emphasis on the decision model underlying the Logit and focus on the ability of the model to provide a good fit to the data.

[7] For human decisions to flag data points, the independence assumption is likely violated. This is because a compiler might flag clusters of data points as erroneous on the basis of information that is not part of the dataset. Then, in terms of our model, the unobserved element in decisions is correlated within these clusters of data points. To evaluate the influence of these correlations on the performance of the algorithms, we simulate datasets with correlated data points. Because we find that in our application, the negative effect of a violation of the independence assumption on prediction accuracy is negligible for a moderate cluster size, we do not further discuss the independence assumption. For detailed simulation results, see section C.5 in the appendix.

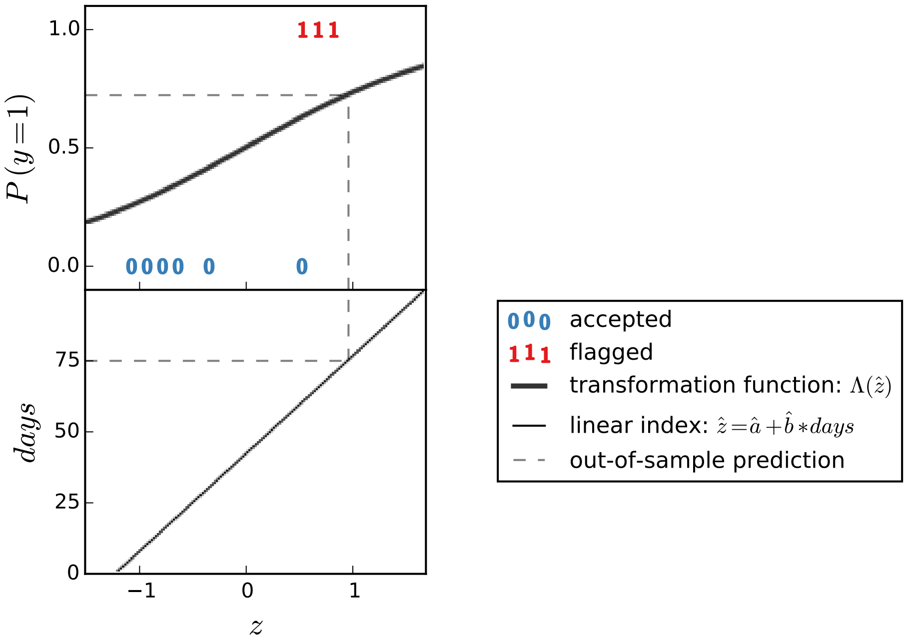
[8] The "individual" likelihood function L_i describes the likelihood of observing the outcome y_i for a security i with features x_i, given the parameter α and the parameter vector β. For our model, we get:

$$L_i = \begin{cases} \Lambda\big(\alpha + x_i^T \beta\big) & for \;\; y_i = 1 \\ 1 - \Lambda\big(\alpha + x_i^T \beta\big) & for \;\; y_i = 0 \end{cases} .$$

We can summarize this piecewise function as $L_i = \Lambda\big(\alpha + x_i^T \beta\big)^{y_i}\big(1 - \Lambda\big(\alpha + x_i^T \beta\big)^{y_i - 1}\big)$. If we are willing to assume independence across securities, the likelihood of observing the different feature-outcome combinations in our sample is simply the product of the individual likelihood functions $L = \prod_{i=1}^{N} L_i$. A model provides a good fit to the data if it results in a high value of L, i.e. a high likelihood of observing the feature-outcome combinations in the sample, given the parameter values of α and β. Maximum Likelihood is a method that allows us to choose the optimal values of α and β, i.e. the values that provide the best fit to the data, by maximizing the logarithm of L. The iterative numerical optimization routine that we use to maximize L is the BFGS algorithm.

[9] For the illustrative example, we first construct the index in the lower panel and then use the sigmoid function to map to a probability in the upper panel.

Figure 2: Logit Model and Predictions



Note: The figure shows an exemplary illustration of the Logit model (solid lines) and a prediction with the model (grey dashed lines). The blue (red) data points represent accepted (flagged) securities.

Decision Boundary of the Logit Model So far, we have predicted the probability of a flag. To move from the predicted probabilities to a prediction of the binary outcome, we follow the rule:

$$\widehat{y}_i = \begin{cases} 0 & for \quad \widehat{P}\left(y_i = 1 | x_i = x\right) < 50\% \\ 1 & for \quad \widehat{P}\left(y_i = 1 | x_i = x\right) \geq 50\% \end{cases}, \tag{6}$$

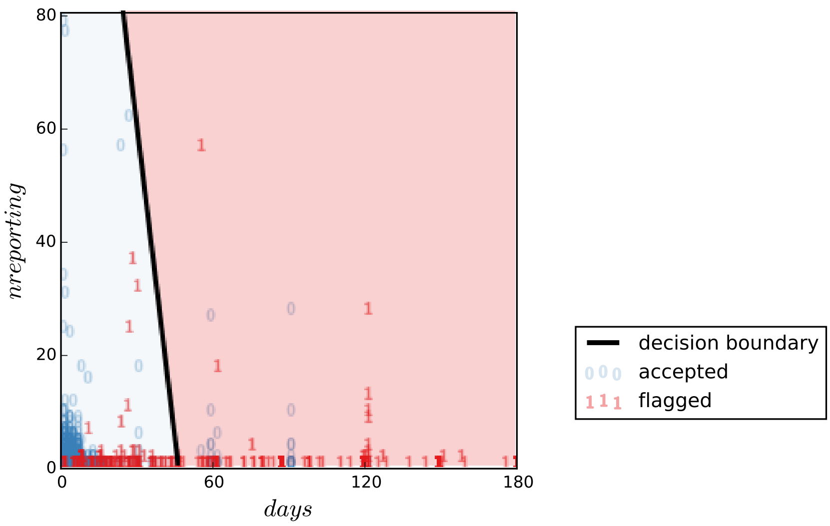
predicting a flag for securities with $\widehat{P}$ equal or greater than 50%. From eq. (6), we can derive a decision boundary that separates securities for which we predict a flag from securities for which we predict acceptance.

Figure 3 shows the decision boundary for a bivariate model with days and the number of reporting institutions as features. In the figure, we predict acceptance for securities with nreporting-days feature combinations in the blue area and flags for securities with nreporting-days feature combinations in the red area. Because the index is a linear combination of the features, the decision boundary is linear.[10]

Strengths and Weaknesses of Models With Structural Assumptions A strength of the approach are accurate out-of-sample predictions for observations outside the sample's feature-space if our assumptions yield a good representation of the data-generating process. Intuitively, for Figure 2, we use the sample to estimate a and b. Once we have estimated these parameter values, we can make a prediction for a security that has longer passed the maturity date than the securities in the sample by extrapolating the index curve and the transformation function. Another strength is transparency due to the structural underpinning of the model and the limited number of parameters.

[10] At the decision boundary, the probability of a flag is 50%. With the sigmoid transformation function, we get a predicted probability of 50% for securities with an index function value of zero: $\Lambda(z=0) = 50\%$. Consequently, to depict the index function in a two dimensional *nreporting-days* diagram, we first set the index function to zero: $0 = a + b_1 days + b_2 \text{nreporting}$. By solving for *nreporting*, we get the boundary: $nreporting = \frac{-a}{b_2} + \frac{b_1}{b_2} days$.

Figure 3: Logit Model and Decision Boundary



Note: The figure shows an illustration of the bivariate Logit model's decision boundary (solid line). The blue (red) data points represent accepted (flagged) securities. For securities with a days-nreporting combination in the light red (blue) area, we predict a flag (acceptance).

The main weakness of the approach is that the modelling assumptions restrict how flexibly we can fit the model to the data. If the assumptions result in a bad fit of the model to the true data-generating process, the model yields inaccurate predictions. In Figure 3, the linear decision boundary that follows from the assumption of linearity and separability of the features in the index function of the Logit model does not provide a close fit to the data.

One way to increase the flexibility of the Logit model and to allow for non-linearities in the decision boundary is to expand the index function by polynomials of the features and interactions between the features.[11] However, the method described in section 3.2 provides a more direct approach to flexibly capture non-linearities and might therefore be preferable to the expansion of the index function.

3.2 Models without Structural Assumptions

In the model with structural assumptions, we described the relationship between features and the probability of a flag with the linear index function and the transformation function in eq. (4). In contrast, we now make no assumptions on the functional form of the relationship. We only assume that securities with the same characteristics have the same probability of being flagged. With this assumption, our prediction is a very direct representation of the conditional probability:

$$\widehat{P}\big(y_i = 1 | x_i = x\big) = Ave\big(y_i | x_i = x\big). \tag{7}$$

Following eq. (7), to predict the conditional probability of a flag for a security with the feature vector x, we simply take the average over the binary outcome in the group of securities with characteristics $x_i = x$.[12]

There is usually not a large enough number of securities with the exact feature values in x to allow for a precise prediction of the conditional probability with eq. (7). Therefore, we estimate the probability by considering securities with *similar* characteristics. To this end, we define non-overlapping regions $N_r(x)$ with

[11] *Support vector machines* with nonlinear kernels are another popular model that allows us to classify securities as flagged or accepted by fitting a nonlinear decision boundary to the data.

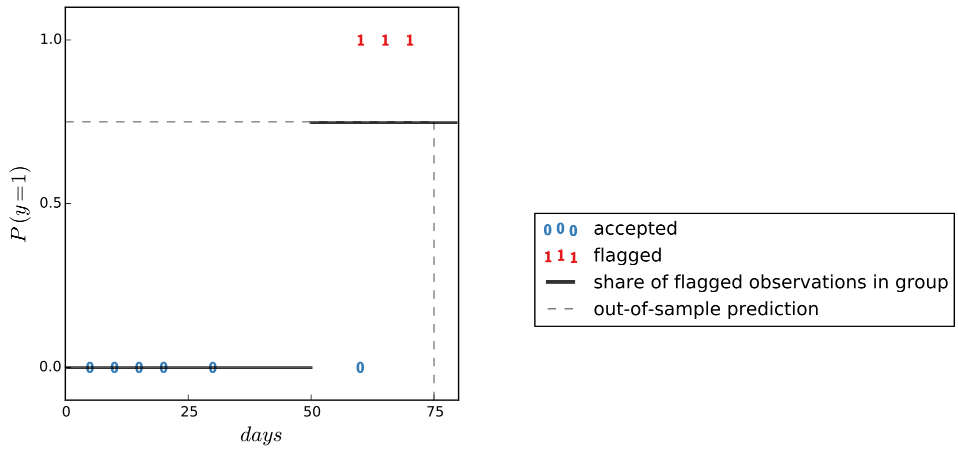
[12] The average over the binary outcome is simply the share of flagged securities with characteristics $x_i = x$.

$r \in \{1, 2, \ldots, R\}$ of securities with similar feature values. Formally, we get:

$$\widehat{P}\big(y_i = 1 | x_i = x\big) = Ave\big(y_i | x_i \in N_r(x)\big). \tag{8}$$

The estimation of the conditional probability boils down to calculating the average over the outcomes of flagged securities in a reference group with characteristics x_i that are similar to x, i.e. securities that are part of the same region N_r like x. For our binary outcome, this average is simply the share of flagged securities in the region.

Figure 4: Model without Structural Assumptions and Predictions

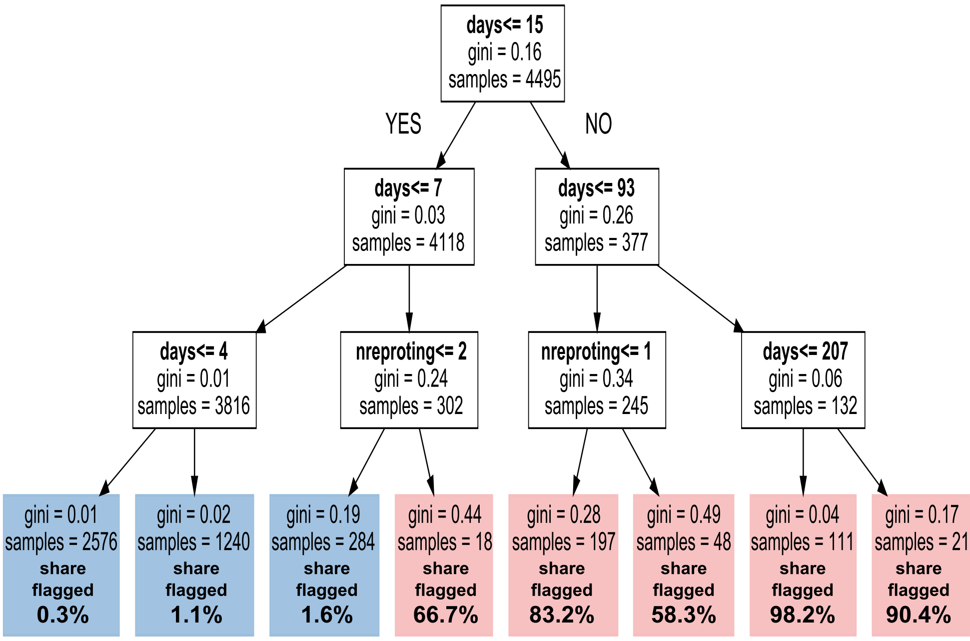


Note: The figure shows an illustration of a model without structural assumptions(solid lines) and a prediction with the model (grey dashed lines). The blue (red) data points represent accepted (flagged) securities.

Figure 4 illustrates the conceptual idea of the approach for a bivariate model with the features *days* and *nreporting*. We first separate the securities by region, according to the number of days that have passed since the maturity date. In the figure, one region comprises securities for which more than 50 days have passed since the maturity date and the other region comprises securities for which 50 days or less have passed since the maturity date. In a second step, we calculate the share of flagged securities in both regions. For the first region, the share is zero. For the second region, the share is 0.75. Conditional on knowing the number of days that have passed since the maturity date, these shares correspond to our prediction of the probability that a security in the region has to be flagged. The grey dashed lines provide an exemplary prediction for a security that was reported $x = 75$ days past its maturity date. In the example, the predicted probability of a flag is 75%, the share of flagged securities for which more than 75 days have passed since the maturity date.

The conceptual idea is representative for a larger class of algorithms: decision trees, random forests, and the K-nearest-neighbors algorithm. All of these algorithms follow the premise of eq. (8). They make predictions of the probability of a flag, conditional on the feature values in x in two steps. In the first step, they define a reference group that comprises observations with feature values that are similar to x. In the second step, they make a prediction of the outcome by averaging over the outcomes in this reference group. The algorithms differ in the way in which they define the reference groups. Decision trees and random forests define reference groups by sequentially splitting the feature-space into regions. The reference group of a security with feature values x are the observations that fall into the same region as the security. In the K-nearest-neighbors algorithm, the reference group of a security with the feature values x are the K observations whose feature vector has the smallest Euclidean distance to x. In the following, we focus on random forests, starting with a description of the decision tree algorithm on which the random forest algorithm rests.

Figure 5: Decision Tree for Bivariate Model



Note: The figure shows the result of an algorithm that determines the optimal decision tree for the bivariate model with days and nreporting ass features. The algorithm operated under the restrictions of a maximal depth of three and a minimal number of samples in a leaf of 18.

Decision Trees Because we do not have data that allows us to construct a separate region for every possible feature combination, the task for our algorithm is to optimally divide the theoretical feature space into regions. Finding optimal splitting rules on the basis of the training data is equivalent to fitting the Logit model to the data.

An optimal region is homogeneous, i.e. securities in the region all are of the same type (flagged or accepted). In such a homogeneous regions, our predictions are perfectly aligned with the actual decisions of the compilers. We either predict a conditional probability of a flag of 100% for all securities in the region and all securities are actually flagged, or we predict a probability of 0% for all securities in the region and none of the securities is actually flagged. Put differently, in homogeneous regions we get all predictions exactly right which is why homogeneity intuitively is an adequate target for our algorithm. To measure the homogeneity within a region, we use the *gini index*:

$$G = 2\mu_r(1-\mu_r) \quad \in \quad [0,0.5], \tag{9}$$

where μ_r is the share of flagged securities in region r. If all securities in a region are flagged $\mu_r = 1$ and $G = 0$.[13] G increases with the heterogeneity of the region up to a maximum of 0.5.[14]

To divide the feature-space, we sequentially split the dataset into ever smaller, more homogeneous regions. A split allocates each observation to one out of two regions on the basis of a feature k and a cutpoint s, so that securities in one region satisfy $x_k \leq s$ and securities in the other region satisfy $x_k > s$. The approach is *top-down greedy*. We start with the full dataset and compare splits for all features at all potential cutpoints. We then select the feature and cutpoint that maximizes the resulting regions' homogeneity. In the following steps, we repeat the process and successively split the regions, optimizing for homogeneity with each split. By sequentially splitting the dataset, the regions become smaller and increasingly homogeneous. We stop splitting a region either when all observations in the region are of the same type (flagged or accepted), when

[13] Likewise, we get $G = 0$ if none of the securities in the region is flagged, i.e. if $\mu_r = 0$.
[14] For our binary outcome, we get maximum heterogeneity ($G = 0.5$) if 50% of the securities in the region are flagged.

the region contains a pre-defined minimal number of securities, or after a pre-defined number of steps.[15]

Figure 5 shows the optimal decision tree for the feature set $J = \{days, nreporting\}$, a maximal splitting depth of three and a minimal number of securities in a region of 18. The first split separates securities for which 15 or less days have passed since the maturity date from securities for which more than 15 days have passed since the maturity date. After a second and third split, we end up with eight regions (leafs). To make a prediction, we calculate the share of flagged securities in a leaf which equals the predicted probability that a security is flagged. To make a prediction of the binary outcome, we predict a flag for securities for which the predicted probability of a flag is equal to or greater than 50% (see, eq. (6)). This corresponds to majority voting, where each security casts a vote according to its own type.[16]

Random Forests A disadvantage of decision trees is that the division into regions strongly depends on the random draw from the population that our sample represents. If we draw different samples from the population and compute decision trees, the trees look very different from one another. Ideally, we would like to have a stable prediction that is not affected by the random selection from the population, the sample represents.[17]

We can overcome this problem by computing a decision tree on the basis of the entire population or by making repeated, independent draws from the population and averaging over the corresponding decision trees. Usually, both of these approaches are not viable because we do not have the population data. However, we can still approximate random draws of samples from the population by using *bootstrapping*. To construct a bootstrap sample, we draw N observations with replacement from the original sample of size N. We then compute a decision tree for the bootstrap sample. We repeat this many times and end up with a large number of decision trees, a forest, which allows us to average over estimated probabilities. In a nutshell, we approximate repeated draws from the population by drawing repeatedly with replacement from the sample.

A caveat of the approach is that often, predictions are correlated across trees. The reason is that if there is a particular feature that has a strong effect on predictions, all trees likely use this feature. The resulting correlations between trees are problematic for the prediction accuracy if they reflect relationships between features and the outcome that are characteristic of the sample but not the population. To overcome this problem, random forests use a different subset of randomly selected features for each bootstrap sample. This is referred to as *decorrelation* of the trees.

Decision Boundary of Random Forests Figure 6 shows the decision boundary for a random forest of 300 trees, a minimum number of securities in a leaf of seven and the feature set $\{nreporting, days\}$. As for the Logit model, we flag securities with a predicted probability equal or greater to 50%. Accordingly, we predict flag for securities with nreporting-days feature combinations in the red area and acceptance for securities with nreporting-days feature combinations in the blue area. In contrast to the Logit model's decision boundary in Figure 3, we did not impose any functional form restrictions or distributional assumptions on the model. This flexibility is reflected in the nonlinear decision boundary.

Strengths and Weaknesses of Models Without Structural Assumptions Conceptually, the approach is very different from starting with structural assumptions on the relationship between the features and the outcome. Because there are no functional form restrictions that constrain the relationship between features and the probability of a flag, the algorithm can flexibly portray interdependencies and non-linearities in the data. Nonlinear and complex links between features and the outcome do not clash with rigid assumptions on linearity, separability and the shape of the transformation function. Because of this flexibility, the approach is

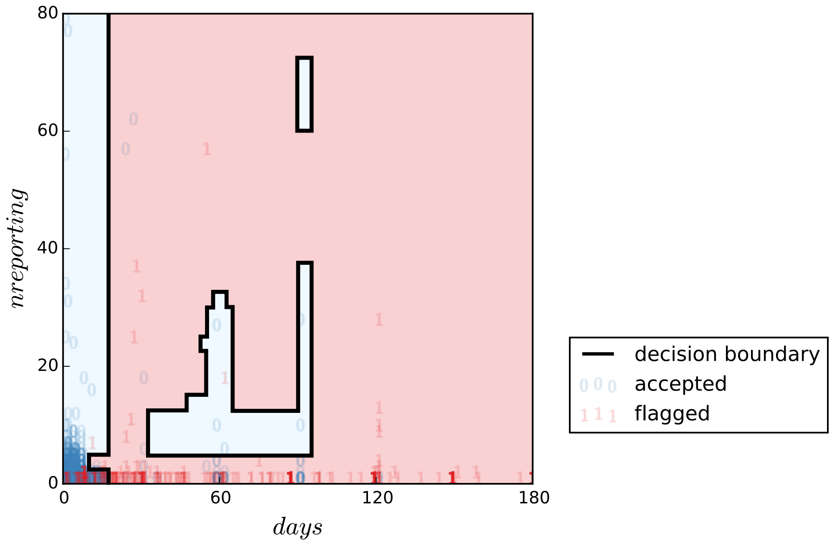
[15] The depth is the maximal number of successive splits.

[16] Figure A.1 in the appendix shows the corresponding decision boundary.

[17] Another way of framing this is in terms of variance. Varying predictions for different random samples imply that estimates with decision trees have a high variance. In terms of the estimator's properties, this implies that decision trees are inefficient estimators.

a very direct representation of the conditional probability in eq. (1). The nonlinear decision boundary that results from the random forest in Figure 3 illustrates this flexibility.

Figure 6: Random Forest and Decision Boundary



Note: The figure shows an illustration of the decision boundary (solid line) resulting from bivariate classification with a random forest. The blue (red) data points represent accepted (flagged) securities. For securities with a days-nreporting combination in the light red (blue) area, we predict a flag (acceptance).

The weaknesses of the approach are twofold. First, there is a tradeoff between the gain in flexibility and the accuracy of predictions when we apply models without structural assumptions to high dimensional (large number of features) data. Following the law of large numbers (LLN), sample averages converge to expected values with an increasing number of observations in the sample. Because we get convergence to population parameters only if the number of observations underlying the prediction tends to infinity (LLN), the accuracy of predictions based on the premise of non-structural models (eq. (8)) decreases exponentially with an increasing number of features. This is because in eq. (8), the number of observations underlying a prediction is the number of observations with similar feature values. If the number of features increases, the number of observations with similar feature values decreases exponentially. Intuitively, whereas we might find securities with the same number of days since the maturity date, it is unlikely that we find a security with the same number of days, number of reporting banks, maturity, and security type. This is often called the *curse of dimensionality*. In contrast, in the structural Logit model, our assumptions on the functional form of the relationship between features and the outcome allow us to use the *entire* sample to estimate model parameters. Because we do not rely on a subset with the same feature values, our estimates allow for accurate predictions even if a particular combination of feature values in x is not common in the sample.

Second, with higher flexibility, we run the risk of fitting the model too closely to the data, i.e. overfitting the model. In case of overfitting, our model picks up relationships between features and the outcome that are characteristic of the random sample but not the population. Picking up such sample-specific relationships makes for low accuracy in out-of-sample predictions.[18]

[18] Overfitting can affect both, the Logit model and the random forest. However, due to its higher flexibility, there is more potential for overfitting of the random forest algorithm. For both models, there are ways to prevent overfitting. A first line of defence against the risk of overfitting is to judge the models with respect to the accuracy of out-of-sample predictions. For the Logit, a second line of defence is *regularization*. In a nutshell, with regularization, we add a penalty term to the Likelihood function. The term penalizes large parameter estimates and thereby provides a counter weight to the increase in the likelihood function, we achieve by overfitting (e.g., by adding additional features to the model or overestimating the size of coefficients). To include a penalty term in the individual Likelihood function in Footnote 8, we expand L by adding $-\lambda\beta'\beta$, the sum of squared parameter estimates. By choosing λ, we can calibrate the size

4 Results and External Validity

To compare the Logit model to the random forest, we evaluate the accuracy of both models' out-of-sample predictions.[19] A simple and straightforward method to assess out-of-sample prediction accuracy is cross-validation with the *validation set approach*. In the first step, we randomly split the securities into a training dataset and a validation dataset and fit the models to the training data. In the second step, we make out-of-sample predictions for securities in the validation dataset on the basis of the first-stage estimates. We then compare the accuracy of both models' predictions in terms of two metrics: *recall* and *precision*. Recall is formally defined as:

$$R = \frac{T_p}{T_p + F_n}, \tag{10}$$

where T_p is the number of true positives (the number of flagged securities for which we correctly predicted flags) and F_n is the number of false negatives (the number of flagged securities for which we incorrectly predicted acceptance). The nominator of eq. (10) equals the number of correctly predicted flags and the denominator equals the actual number of flags in the validation dataset. Taken together, R is the share of flags in the validation dataset that were correctly predicted. Precision is formally defined as:

$$P = \frac{T_p}{T_p + F_p}, \tag{11}$$

where F_p is the number of false positives (the number of accepted securities for which we incorrectly predicted a flag). The nominator of eq. (11) equals the number of correctly predicted flags, whereas the denominator equals the overall number of predicted flags. Intuitively, P measures the share of securities for which we predicted a flag that were actually flagged.

The results of the validation set approach rest on a single random split of the data into a training dataset and a validation dataset. Therefore, the values of our performance metrics depend on the random nature of the split. To overcome this problem, we implement *stratified k-fold* cross-validation. In stratified k-fold cross-validation, we randomly split the data into k equal sized datasets. To make sure that the number of flags is the same in each of these datasets, we stratify the sample by our outcome variable. We then, in turn, use each of the k datasets as training data, computing the recall and precision metric for out-of-sample predictions in the other $k-1$ datasets. This provides us with k values for recall and precision, each representing an estimation with a different randomly selected training dataset. By averaging over these k-values, we get average values for recall and precision that are stable in the sense of not depending on a single random split.

Table 1: Prediction accuracy

	Logit Regression	Random Forest Algorithm
Recall	0.63	0.86
Precision	0.85	0.89

Note: The table shows average recall and precision with stratified five-fold cross-validation for the Logistic regression and the random forest algorithm. Each of the algorithms uses the feature set that minimizes average recall.

of the penalty. For the random forest, a strategy that is equivalent to regularization is limiting the maximum number of splits (depth of decision trees). This prevents the algorithm from producing regions with few observations and low out-of-sample prediction accuracy.

[19] We implement both models with the *sklearn* package in *python*.

Table 1 shows average recall and precision with stratified five-fold cross-validation for the Logistic regression and the random forest algorithm. For each method, we use the feature set that maximizes the model's performance in terms of recall.[20]

We find that both models have a similar performance in terms of precision. In terms of recall, the random forest algorithm ($R = 0.86$) yields a 37% percent improvement over the Logistic regression ($R = 0.63$). Predicting flags with the random forest algorithm, we correctly identify 86% of the securities that were flagged by compilers.

So far, we have treated human decisions as the benchmark for the algorithms. However, there is a margin for decision errors by compilers. If the compilers make random errors in their assessment, an ideal algorithm should produce a non-zero share of false positives and negatives. Following this line of reasoning, the algorithms can yield results that are superior to a human decision maker by filtering out random decision errors.[21]

In order to establish the external validity of our results, we predict two further types of measurement errors using Logit regressions and random forests. The first type of errors concerns erroneous reporting of securities before the emission date. The second type of errors concerns missing reference data. In both cases, we get results that are similar to our findings in Section 4.[22]

Figure 7: Result of additional out-of-sample predictions

isin	...	prob
DE000...	...	82
DE000...		81
DE000...		80
DE000...		80
DE000...		73
DE000...		60
DE000...		43
DE000...	...	42
DE000...		39
DE000...		35
DE000...		2
DE000...		2
DE000...		1
DE000...	...	1

Note: The figure shows the data table after an implementation of the random forest algorithm. The predicted probabilities are shown in the last column. The other columns show the isin that identifies the security and the features of the security (not in the figure).

5 Implementation

Because of its higher out-of-sample accuracy, we focus on the implementation of the random forest algorithm. To implement the algorithm, we use all 4.495 reported securities and compiler decisions as training data. We then predict the probabilities of flags for newly reported securities and add the predictions to the data table, compilers use to evaluate securities for measurement errors. Figure 7 shows an illustration of the data table with predicted probabilities for securities that were reported in October, 2016. Securities with a high predicted probability of a flag appear on the top of the table. The conditional formatting allows compilers to

[20] For the random forest, we use the feature set {*days, nreporting, mvalue, stype*}, where *stype* is a set of dummy variables for the instrument type. The Logistic regression uses the same set of features except for the nominal value. For the random forest algorithm, we compute 300 trees and implement a maximum depth of six, again to maximize recall.

[21] Of course, if decision errors are structural, the algorithm might learn to make the same mistakes as the compiler.

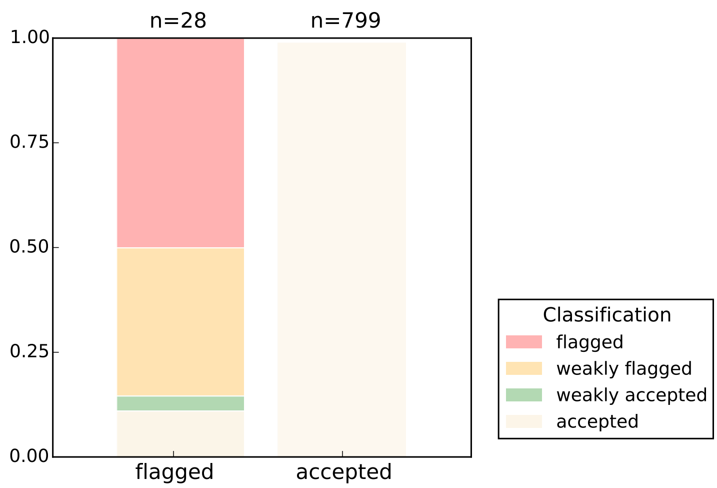
[22] For securities that were reported before their emission date, predictions of flags with the random forest algorithm achieve a recall of 77% and a precision of 88%. Predictions with Logit regression yield a recall of 50% and a precision of 86%. Regarding the attribution of a lack of reference data to a measurement error, predictions with the random forest algorithm have a recall of 96% and a precision of 97%. The Logit regression produces predictions with a recall of 39% and a precision of 97%.

easily spot potentially problematic securities. By providing compilers with the predicted probability instead of making binary predictions of flags, we take advantage of all the information, the machine learning algorithm provides.

The sorting of securities by predicted probabilities of measurement errors increases the efficiency of the DQM process. Because compilers know which securities are likely subject to a measurement error, they can allocate their time more efficiently to these securities. The ordering furthermore leads to a higher effectiveness of the evaluation process. Because the attention of compilers and their ability to evaluate a security correctly decreases with each security they review, checking securities with a high probability of a measurement error first increases the success of compilers' efforts to identify measurement errors in the data.

Figure 8 shows the results of out-of-sample predictions for the securities that were reported in October, 2016 and were not part of the training dataset.[23] The left (right) bar shows securities that were flagged (accepted) by compilers. We find that the algorithm classifies more than 85% of securities that were flagged by compilers as weakly flagged or flagged. If we had informed compilers about the classification, they would have found all of the 28 flagged securities in the top-35 of the list of 827 securities which they received for evaluation.

Figure 8: Result of additional out-of-sample predictions



Note: The figure shows the result of additional out-of-sample predictions for securities reported in October, 2016. The left (right) bar shows securities that were flagged (accepted) by compilers. The colours correspond to the predicted probabilities.

6 Using Machine Learning to Close Data Gaps

To illustrate that the potential of machine learning for official statistics is not limited to DQM, we evaluate the possibility of using predictions with machine learning algorithms to close data gaps. Essentially, there are two prerequisites for the algorithms' ability to close data gaps with out-of-sample predictions of the missing values. First, there have to be dependencies between the outcome variable that suffers from data gaps and other features of a data point. Second, we have to observe some data points for which the outcome is not missing. In a nutshell, by learning about the dependencies between features and the outcome from data points where the outcome values are not missing, the algorithm can predict the missing values.

[23] If manual checks by compilers are replaced by predictions with a machine learning algorithm, problems can arise when structural changes in the data occur. Because the algorithm draws on historic training data, there might be no possibility to learn about new ways in which a human decision maker would evaluate the data. To investigate whether this is a problem in our implementation, we evaluate whether predictions for October, 2016 on the basis of training data from more recent months are superior to predictions using older training data. We find no systematic difference in performance and conclude that the relationships between the outcome and features in our application are stable over time. Figure A.2 in the Appendix summarizes the results of the analysis.

To evaluate the success of the algorithms in closing data gaps, we use simulated data. By simulating data, we can vary the environments in which we evaluate the algorithms' performance in a controlled fashion. For simplicity, we simulate a binary outcome variable $y_i \in \{0, 1\}$ with data gaps. The binary variable allows us to use the same performance metrics as in the DQM application. Intuitively, recall and precision measure the success of the algorithm in predicting the missing values, i.e. the share of observations with data gaps for which the prediction equals the unobserved value. While recall measures our success in predicting the missing outcome $y_i = 1$, precisions shows the performance of the algorithms in predicting the missing outcome $y_i = 0$.

In our simulations, we cover predictions in a wide range of datasets with different: binomial distributions (shares of data points with $y_i = 1$), numbers of data points, data quality, degrees of correlation between data points, and nonlinear feature-outcome relationships. The simulations show that the application of machine learning to close data gaps has a large potential in many environments.[24] If the outcome variable measures occurrences of a rare event, the performance of the models suffers but can be improved by collecting larger datasets. Whereas correlated observations have a minor effect on performance, data quality has a large positive effect on recall and precision. When we introduce nonlinear feature-outcome relationships, the random forest algorithm is clearly superior to the Logit model. Taken together, the results show that machine learning algorithms have applications beyond DQM. In particular, they can be tested against other algorithms for the imputation of missing values to close data gaps.

7 Conclusion

There is a large potential to improve Data Quality Management if data on human decisions to flag observations as erroneous is available. With data on decisions, supervised learning algorithms can approximate the result of the human decision making process and predict probabilities of measurement errors. We showed that, for data on German securities holdings, out-of-sample predictions using a random forest algorithm are superior to predictions with the Logit model. The predicted probabilities allow for a prioritization in the DQM process and an increase in the effectiveness and efficiency of the search for measurement errors.

The application of machine learning to close data gaps illustrates that the potential of the methods for officieal statistics is not limited to DQM. Simulations show that the Logit model and the Random Forest accurately predict missing data over a wide range of datasets, with a superior performance of the random forest algorithm in datasets with complex feature-outcome relationships. These findings suggest that machine learning algorithms provide a powerful alternative to established imputation methods.

Future research on the application of machine learning to DQM could discuss unsupervised learning algorithms. Unsupervised learning algorithms can help to identify measurement errors if no information on human classifications of observations as erroneous is available.

[24]For a detailed description of the simulation results, see section C of the Appendix.

References

AMANN, M., BALTZER, M. and SCHRAPE, M. (2012). Microdatabase: Securities holdings statistics a flexible multi-dimensional approach for providing user-targeted securities holdings data. *Bundesbank technical documentation*.

ANGRIST, J. and PISCHKE, J.-S. (2009). *Mostly Harmless Econometrics: An Empiricist's Companion*. 1st edn.

BATINI, C., CAPPIELLO, C., FRANCALANCI, C. and MAURINO, A. (2009). Methodologies for data quality assessment and improvement. *ACM computing surveys (CSUR)*, **41** (3), 16.

BATISTA, G. E. and MONARD, M. C. (2003). An analysis of four missing data treatment methods for supervised learning. *Applied Artificial Intelligence*, **17** (5-6), 519–533.

FRIEDMAN, J., HASTIE, T. and TIBSHIRANI, R. (2001). *The Elements of Statistical Learning*, vol. 1. Springer Series in Statistics, Berlin.

JEREZ, J. M., MOLINA, I., GARCÍA-LAENCINA, P. J., ALBA, E., RIBELLES, N., MARTÍN, M. and FRANCO, L. (2010). Missing data imputation using statistical and machine learning methods in a real breast cancer problem. *Artificial Intelligence in Medicine*, **50** (2), 105–115.

MULLAINATHAN, S. and SPIESS, J. (2017). Machine learning: An applied econometric approach. *Journal of Economic Perspectives*, **31** (2), 87–106.

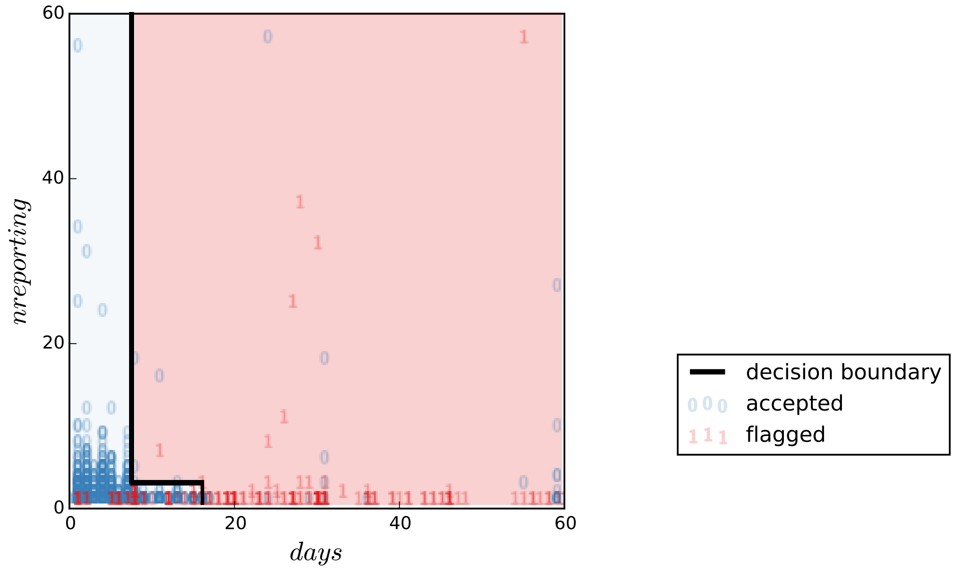
TOMZ, M., KING, G. and ZENG, L. (2003). Relogit: Rare events logistic regression. *Journal of Statistical Software*, **8** (i02).

VARIAN, H. R. (2014). Big data: New tricks for econometrics. *Journal of Economic Perspectives*, **28** (2), 3–28.

Appendix

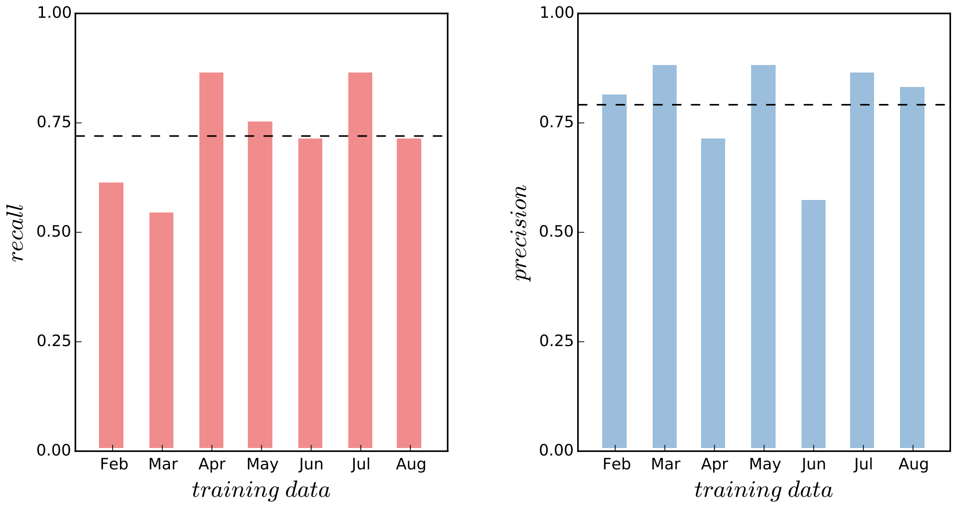
A Figures

Figure A.1: Decision Tree and Decision Boundary



Note: The figure shows an illustration of the bivariate decision tree's decision boundary (solid line). The blue (red) data points represent accepted (flagged) securities. For securities with a days-nreporting combination in the red (blue) area, we predict a flag (acceptance).

Figure A.2: Decision Tree and Decision Boundary



Note: The figure shows the performance of the random forest algorithm in terms of recall (left panel) and precision (right panel) for out-of-sample predictions of measurement errors in securities data, reported in October, 2016. To evaluate a potential influence of the time lag between the collection of the training data and the reporting date of the data for which we make predictions, we use training data from different months. For the first bar of each panel, for example, we only use data from February, 2016 as training data. The figure shows no indication of a systematic negative relationship between the time lag and performance. The dashed lines show the mean recall and precision.

B Derivation of the Logit Model

From an econometric perspective, we can derive the Logit model from a decision model, if we interpret the index function (2) as a latent score that the compiler uses to decide whether to flag security i. We start by assuming that there is an additive, logistically distributed decision error u_i. Then, we get the latent score:

$$z_i^* = \alpha + x_i^T \beta + u_i.$$

If the compiler flags security i for $z_i^* > 0$ and accepts the security otherwise, we get:

$$\begin{aligned} P\big(y_i = 1|x_i\big) &= P\big(z_i^* > 0|x_i\big) \\ &= P\big(u_i > -x_i^T \beta|x_i\big) \\ &= 1 - P\big(u_i \leq -x_i^T \beta|x_i\big) \end{aligned}$$

Because we assumed that u_i is logistically distributed, the conditional probability $P\big(u_i \leq -x_i^T \beta|x_i\big)$ is the density of the cumulative logistic distribution function $\Lambda(\cdot)$ (sigmoid function) at $-x_i^T \beta$. Hence, we get:

$$1 - P\big(u_i \leq -x_i^T \beta|x_i\big) = 1 - \Lambda\big(-x_i^T \beta\big).$$

Because of the symmetry of the sigmoid function, this reduces to:

$$\begin{aligned} 1 - \Lambda\big(-x_i^T \beta\big) &= \Lambda\big(x_i^T \beta\big) \\ &= \Lambda\big(z_i\big). \end{aligned}$$

In sum, we have shown that $P\big(y_i = 1|x_i\big) = \Lambda\big(z_i\big)$ if decisions are based on a latent score with an additive decision error that is drawn from the logistic distribution. In Machine Learning, we put no emphasis on the decision model underlying the Logit but focus on the ability of the model to provide a good fit to the data.

C Using Machine Learning to Close Data Gaps: Simulations

We proceed in two steps to simulate a dataset. First, for each of N data points, we randomly draw a feature value x_i from the normal distribution $\mathcal{N}(\mu, \sigma^2)$ and an unobserved element e_i from the logistic distribution $\mathcal{L}(\mu, s)$. Second, we determine the outcome for each data point with the univariate model:

$$y_i = \begin{cases} 0 & for \quad \alpha + \gamma x_i + e_i < 0 \\ 1 & for \quad \alpha + \gamma x_i + e_i \geq 0 \end{cases} \quad . \tag{1}$$

We end up with a simulated dataset with data points for which $y_i = 1$ and data points for which $y_i = 0$. By constructing the outcome with eq. (1), we implement a structure in the data that the algorithms can learn to predict the outcome.

After constructing a simulated dataset, we evaluate the algorithms' performance in terms of precision and recall using stratified five-fold cross-validation. In the cross-validation procedure, we make out-of-sample predictions for a randomly chosen subset of observations. Essentially, we treat the outcome of the subset as a data gap and fill this gap with the algorithm's predictions. In constructing the performance metrics, we evaluate the success of the algorithms in predicting the missing values, i.e. the share of observations with data gaps for which the prediction equals the unobserved value.

Because the performance metrics also depend on our random draws of x and e, we repeatedly: draw features and unobserved elements, construct a simulated dataset, implement the algorithms, and calculate the performance metrics. This provides us with distributions of the precision and the recall metric.

C.1 Benchmark: Linking the Simulation Results for Data Gaps to the Prediction of Measurement Errors

Simulating a binary variable with data gaps allows us to draw additional conclusions about the performance of machine learning algorithms in the application to measurement errors. This is because we can interpret simulated data points with $y_i = 1$ as "flagged" and simulated data points with $y_i = 0$ as "accepted" observations.

To facilitate drawing conclusions about the performance of machine learning in DQM from the simulation results, we include a simulated dataset with characteristics that are common in the DQM application as a benchmark and show performance in the benchmark (grey dotted lines) in the Figures C.2, C.3, C.4, and C.6.[25] To mirror the fact that measurement errors are a relatively rare event in most datasets, we choose the distributions of x and e and the parameter values in eq. (1) in the benchmark such that the average share of flagged data points is small (15%).[26] Furthermore, human evaluations are usually contingent on a pre-selection of data points from the original dataset. We conjecture that because of this pre-selection, the number of data points is likely in the lower four-digit range and choose $N = 2\,000$ as the number of data points in our benchmark.[27]

Figure C.1 illustrates the recall and precision of predictions for the benchmark simulations. The left panel shows that the median recall is similar for both models. The right panel indicates that the Logit model is slightly superior in terms of precision. Overall, the random forests' performance is more disperse.

The improvement of the Logit model's performance for the simulated data compared to the application to

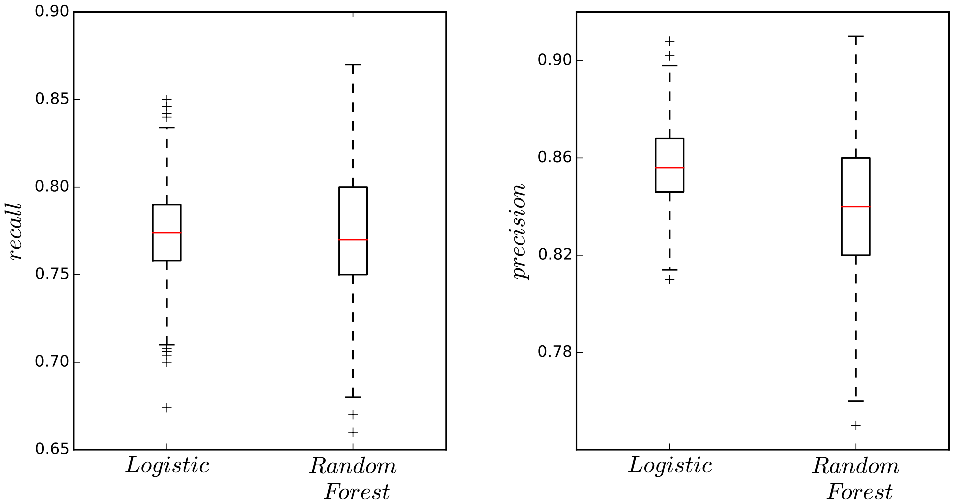
[25] In Figure C.6, the benchmark performance is the performance at the intercept.

[26] In eq. (1), we set alpha to -1.09 and γ to one. For the distributions, we choose $x \sim \mathcal{N}(\mu = 0, \sigma^2 = 1)$ and $e \sim \mathcal{L}(\mu = 0, s = 0.17)$. The scale parameter of $s = 0.17$ corresponds to a variance of 0.1. We implement a lower variance for the unobservable element than for the feature in order to give the algorithms a better chance to approximate the result of the simulated decision making process. For a detailed discussion of the performance of the algorithms in environments with a higher variance of the unobservable element, see Section C.4.

[27] We provide an evaluation of the algorithms for different numbers of data points in Section C.3.

German securities holdings data is due to the simulated data generating process closely following the Logit's modelling assumptions.

Figure C.1: Monte Carlo Simulation – Benchmark



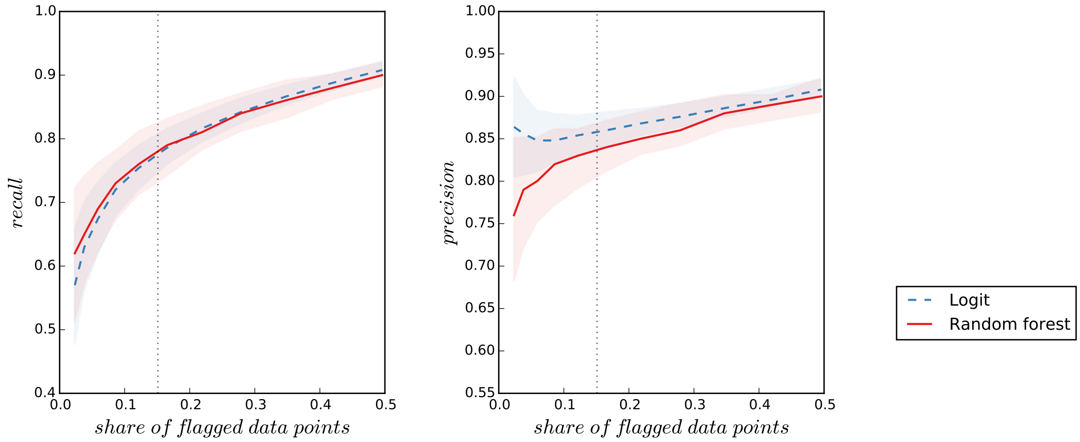
Note: The figure shows the distribution of the recall (left panel) and the precision metric (right panel) for the Logistic regression and the random forest algorithm. Underlying the figure are 1 000 randomly drawn datasets.

C.2 Rare Events (Distribution of Outcome)

To evaluate the performance of the algorithms for different shares of observations with $y_i = 1$, we vary the size of the constant α in eq. (1). Figure C.2 shows the results of the simulations. With an increasing share of observations with $y_i = 1$, i.e. $y_i = 1$ becoming less *rare* as an event, there are gains in recall and precision for both models.

To explain this increase in performance, note that datasets with a small share of observations with $y_i = 1$ contain little information on data points with $y_i = 1$ and lot of information on data points with $y_i = 0$. In terms of the overall information content of a dataset, we can not fully substitute for a lack of information in the first group of data points with additional information on data points in the second group. Therefore, in datasets with a small share of data points with $y_i = 1$, an increase in the share of this group of data points increases the overall information content of the dataset and makes it easier for the algorithm to make predictions. This explains the improvement in the performance metrics illustrated by Figure C.2.

Figure C.2: Monte Carlo Simulations – Share of Flagged Data Points

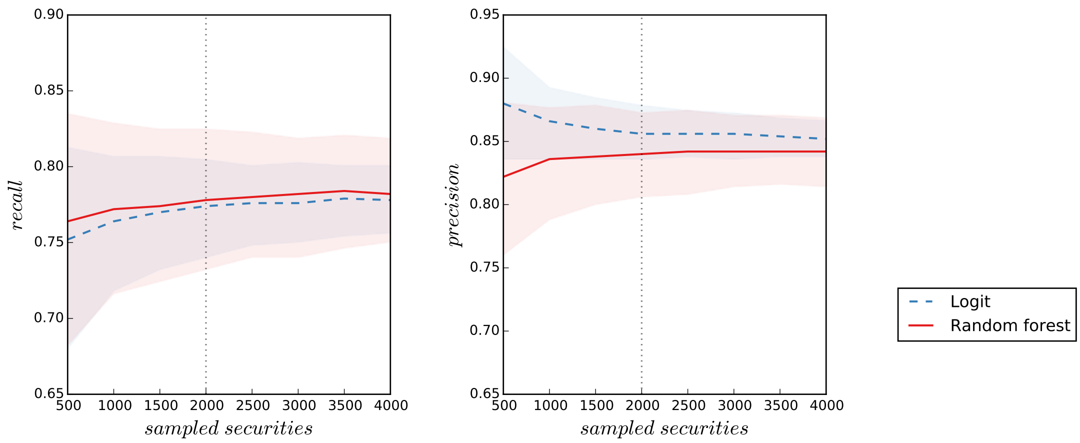


Note: The figure shows the median recall (left panel) and precision (right panel) for the random forest algorithm (red solid lines) and the Logistic regression (blue dashed lines) for 1 000 randomly drawn datasets for each of the shares of data points with $y_i = 1$. The light red and blue areas depict 90% confidence intervals. The grey dotted lines show the benchmark.

C.3 Number of Data Points

One way to increase the accuracy of predictions in datasets with a small share of data points with $y_i = 1$ is to collect more data. Figure C.3 shows the influence of the sample size on the performance metrics. The random forest algorithm shows an improvement in recall and precision over an increase in the number of data points. This is consistent with the idea that the accuracy of estimates increases with a rising number of data points. In contrast, precision decreases with sample size in the Logit model. An explanation for this finding is that in small samples, Logit models underestimate the probability of rare events (Tomz *et al.*, 2003). In our simulated data, this implies a lower probability of false positives in smaller samples and a higher precision at the cost of a lower recall.

Figure C.3: Monte Carlo Simulation – Number of Data Points



Note: The figure shows the median recall (left panel) and precision (right panel) for the random forest algorithm (red solid lines) and the Logistic regression (blue dashed lines) for 1 000 randomly drawn datasets for each of the sample sizes. The light red and blue areas depict 90% confidence intervals based on the normal distribution. The grey dotted lines show the benchmark.

C.4 Data Quality

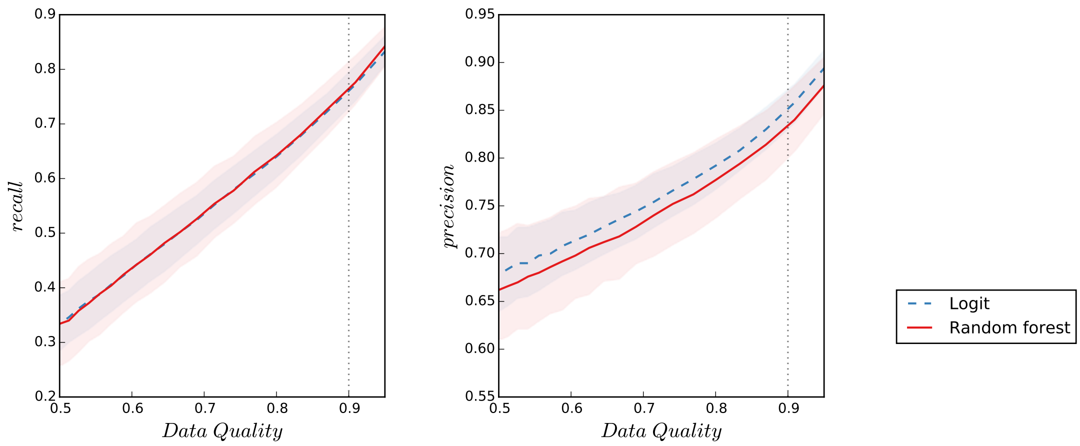
In the model underlying our simulations, we construct the outcome from a feature x and an unobserved element e. The feature is an observable characteristic of a data point that affects the probability that $y_i = 1$. Our algorithms can use this information to make predictions. The unobserved element, on the other hand, represents characteristics of the data point that affect the propensity of y_i taking the value one but are not observable to us. Because these influences are not observable, the algorithms can not exploit them to make predictions. Consequently, data quality increases with observable feature variation and decreases with variation in the unobservable element. Following this notion, we define:

$$DQ = \frac{\sigma_x^2}{\sigma_x^2 + \sigma_e^2} \tag{2}$$

as our measure of data quality, where σ_x^2 is the variance of the observable feature and σ_e^2 is the variance of the unobservable element.[28]

To implement different data qualities in our simulations, we alter the variance of the $\mathscr{L}$-distribution from which we draw the unobserved element.[29] Figure C.4 shows the simulation results. For both, the Logit regression and the random forest algorithm, data quality has a strong positive effect on performance in terms of recall and precision.

Figure C.4: Monte Carlo Simulation – Data Quality



Note: The figure shows the median recall (left panel) and precision (right panel) for the random forest algorithm (red solid lines) and the Logistic regression (blue dashed lines) for 1 000 randomly drawn datasets for each of the different degrees of data quality. The light red and blue areas depict 90% confidence intervals. The grey dotted lines show the benchmark.

The effect of data quality on the accuracy of predictions is smaller if the observable features and the unobserved element are positively correlated. This is because a positive correlation implies that some of the unobserved variation is reflected in the observable feature variation and can be exploited to make accurate predictions.[30]

[28]The nominator measures observable feature variation and the denominator measures overall variation. Our measure of data quality is similar to the coefficient of determination.

[29]Because tempering with the variance of the unobservable element affects the share of observations with $y_i = 1$, which in turn has an effect on performance (see Figure C.2), we fix the share of observations with $y_i = 1$ at 15% by adjusting the constant parameter α.

[30]For inference in an econometric applications of regression models, such correlations with omitted variables are a problem because they bias parameter estimates.

C.5 Correlated Data Points

One of the assumptions in the derivation of the Logit model is that the data points are uncorrelated. In many applications, this assumptions is likely violated. Therefore, we evaluate the robustness of our results if the unobserved element in eq. (1) is correlated within clusters of data points.

To assess the influence of intra-cluster correlations on the performance of the algorithms, we simulate datasets with correlated data points. To simulate correlated observations, we first set up a block diagonal correlation matrix (C) that captures the correlations within clusters of data points. For clusters comprising two-data points ($n = 2$), for example, we use the block-diagonal correlation matrix:

$$C = \begin{bmatrix} \begin{bmatrix} 1 & \rho_c \\ \rho_c & 1 \end{bmatrix} & & \mathbf{0} \\ & \ddots & \\ \mathbf{0} & & \begin{bmatrix} 1 & \rho_c \\ \rho_c & 1 \end{bmatrix} \end{bmatrix},$$

where ρ_c is the intra-cluster correlation. We then use the Cholesky decomposition and get:

$$C = LL^T,$$

where L is a lower triangular matrix. With L, we can finally use a simple transformation to turn the vector of independent unobserved elements $\mathbf{e}$ into a vector of correlated elements $\mathbf{e_c}$ with correlation structure C:

$$\mathbf{e_c} = L * \mathbf{e}.$$

We find that the effects of the intra-cluster correlations on prediction accuracy are negligible for the Logit regression and the random forest algorithm. From the baseline with independent unobserved elements, a high intra-cluster correlation in the unobserved elements of $\rho_e = 0.9$ decreases recall and precision by less than one percent. The negative impact increases with cluster size but remains below the one percent mark for a moderate cluster size of ten data points.

C.6 Nonlinear Feature-Outcome Relationships

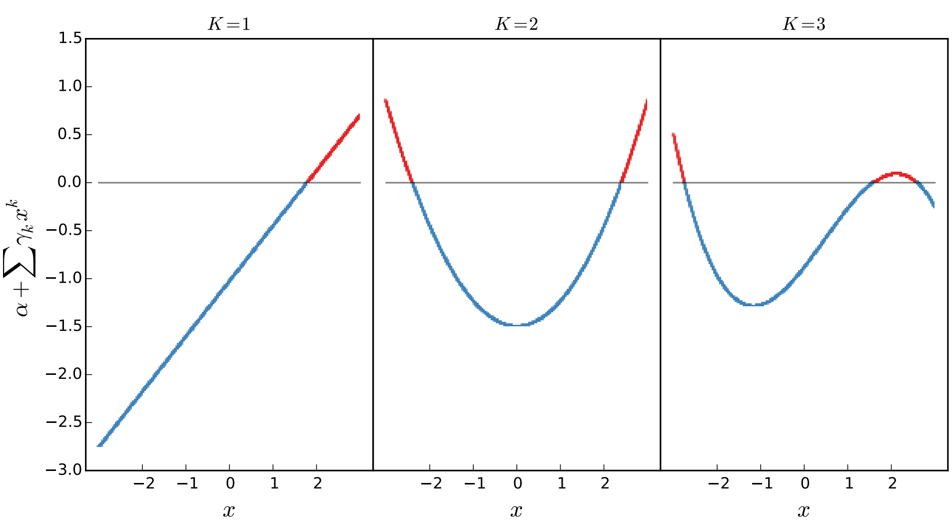
So far, the simulations indicated that the Logit model's performance is similar to the performance of the random forest in most applications. This assessment changes, once we introduce datasets with complex structures. To model nonlinear feature-outcome relationships, we use a power-series of order K:

$$y_i = \begin{cases} 0 & \textit{for} \quad \alpha + \sum_{k=1}^{K} \gamma_k x_i^k + e_i < 0 \\ 1 & \textit{for} \quad \alpha + \sum_{k=1}^{K} \gamma_k x_i^k + e_i \geq 0 \end{cases}, \tag{3}$$

where we draw the γ coefficients from the normal distribution $\mathcal{N}(0, 1)$.[31] For a power series of order $K = 1$, we get the benchmark model in eq. (1). With an increase in K, the relationship between feature and outcome becomes nonlinear and increasingly complex.

[31] We adjust α so that the share of observations with $y_i = 1$ is not affected by the transformations with the power-series.

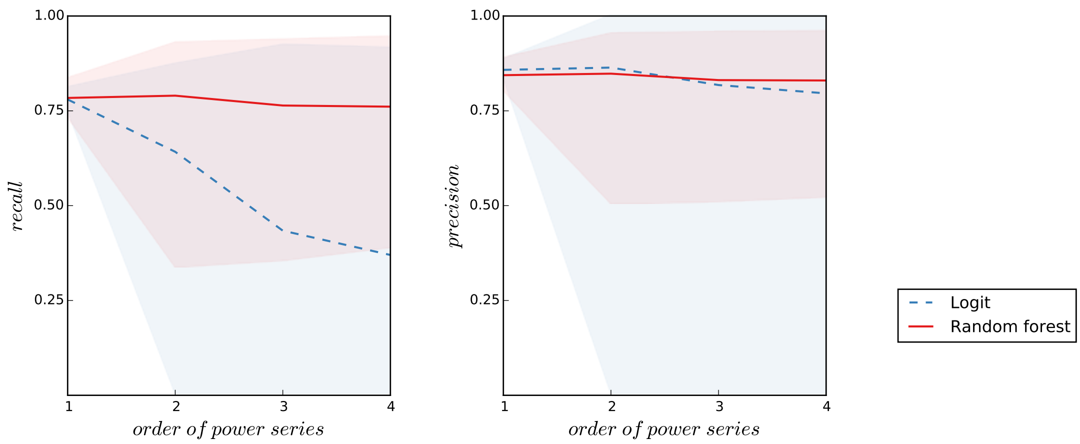
Figure C.5: Decision Tree and Decision Boundary



Note: The figure shows an illustration of nonlinear feature-outcome relationships that result from the models with power-series of order K, outlined in eq. (3).

Figure C.5 shows an illustration of nonlinear feature-outcome relationships that result from the models with power-series of order K, outlined in eq. (3). Data points with values below zero (blue) get the outcome zero and data points with values above zero get the outcome one (red). The figure shows that with an increasing order of the power-series, classification into outcome-groups becomes more difficult. Whereas for power-series of order $K = 1$, there is a single critical value of x that separates the groups, for power-series of order $K = 2$ there are two critical values, and for power-series of order $K = 3$ there are three critical values. The higher complexity of the data structure that is reflected in the number of critical values increases the difficulty of classifying data points for the algorithms.

Figure C.6: Monte Carlo Simulation – Nonlinear Feature-outcome Relationships



Note: The figure shows the median recall (left panel) and precision (right panel) for the random forest algorithm (red solid lines) and the Logistic regression (blue dashed lines) for 1 000 randomly drawn datasets for each of the orders of the power series. The light red and blue areas depict 90% confidence intervals. The grey dotted lines show the benchmark.

Figure C.6 shows the performance of the Logit model and the random forest in datasets with nonlinear feature-outcome relationships. We find that the good performance of the Logit model deteriorates, once we introduce a nonlinear structure. In contrast, the random forest algorithm seems well equipped to capture the nonlinear relationship. For data generating processes described by high order power series, there is only a small decrease in recall and precision of predictions with the random forest algorithm. At the same time, the accuracy of predictions with the Logit model is very unstable over different random draws of datasets. Taking this instability which is illustrated by the broad confidence bands into account, the random forest algorithm has a clearly superior performance in datasets with nonlinear feature-outcome relationships.

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Brussels, Belgium, 18-19 May 2017

Improving data quality and closing data gaps with machine learning[1]

Tobias Cagala,

Deutsche Bundesbank

[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.

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Improving Data Quality and Closing Data Gaps with Machine Learning

Tobias Cagala / Deutsche Bundesbank

May 18, 2017

Background

Machine Learning

Provides computers with the ability to:

(1) *learn about patterns* in the data and

(2) use this knowledge to make *predictions*.

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Econometrics v Machine Learning

Econometrics:	Identify causal effects $\Rightarrow \widehat{\beta}$
Machine Learning:	Make accurate predictions $\Rightarrow \widehat{y}$

Background

"... Applying machine learning to economics requires finding relevant $\widehat{y}$ cases."

Mullainathan and Spiess, 2017

Background

We discuss two $\widehat{\mathbf{y}}$ cases in official statistics

Use out-of-sample predictions with machine learning algorithms for...

1. DQM (identify and correct measurement errors)
2. Closing data gaps (impute missing values)

Application to DQM

Securities Holdings Statistics

- German banks provide monthly reports of securities holdings (security-by-security)
- DQM with labor intensive manual case-by-case evaluations

Application to DQM

Securities Holdings Statistics

- German banks provide monthly reports of securities holdings (security-by-security)
- DQM with labor intensive manual case-by-case evaluations

Goal

Support compilers by providing predictions of the result of manual checks with machine learning methods.

Data

Plausibility check

Securities reported after the maturity date

Two data sources

(I) **Outcome** of evaluation by compiler: Acceptance v Flag

(II) **Features** of the security

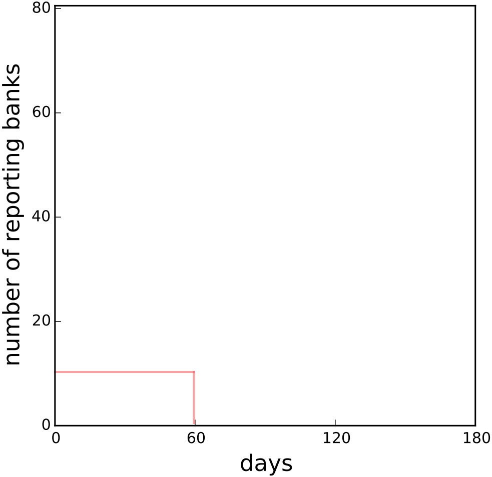
$\Rightarrow$ Linkage of securities data with data on compiler decisions

Data

Dataset

- Reported securities: 4 495
- Accepted: 4 110
- Flagged: 385

Descriptive Analysis of Patterns
Number of Reporting Banks, Days since Maturity



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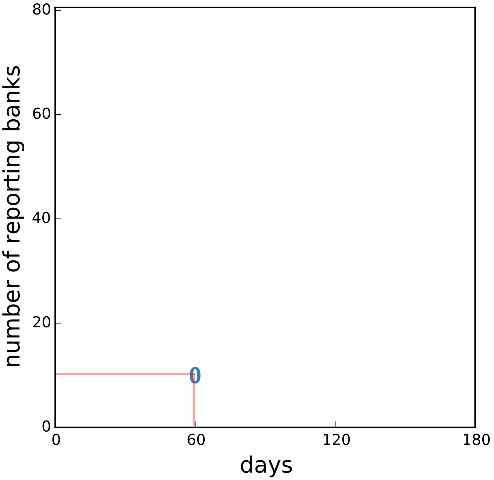

Descriptive Analysis of Patterns

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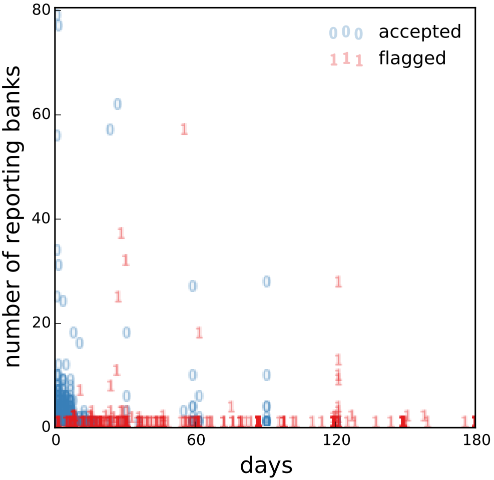

Idea

Goal

1. **Learn** human decision making process: **feature vector (x)** determines **decision (y)**

$$P(y_i = 1 | x_i)$$

2. **Predict** decision for newly reported securities (only feature vector is known)

$$\widehat{P}(y_i = 1 | x_i = x)$$

3. **Use** these predictions to improve DQM

Idea

Two ways to achieve our goal (prediction of decision)

1. Model with structural assumptions
2. Model without structural assumptions

Idea

Two ways to achieve our goal (prediction of decision)

1. **Model with structural assumptions**
2. Model without structural assumptions

Model with structural assumptions

- Assumptions on the structure of the relationship between **features** and **decision**
- Typical assumptions:
  - Linear relationship between feature x_i and index z_i
  - Effects of features on index are additively separable
  - Transformation of index into probability with sigmoid function
- Model (Logit):

$$P\big(y_i = 1 | days_i, nreporting\big) = \Lambda(z_i) = \Lambda\big(\alpha + \beta days_i + \gamma nreporting_i\big)$$

Model with structural assumptions

- Assumptions on the structure of the relationship between **features** and **decision**
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$$P\left(y_i = 1 | days_i, nreporting\right) = \Lambda(z_i) = \Lambda\left(\alpha + \beta days_i + \gamma nreporting_i\right)$$

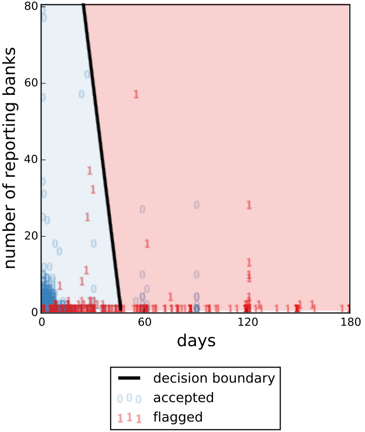
Task for Algorithm
Find optimal values of $\widehat{\alpha}$, $\widehat{\beta}$, and $\widehat{\gamma}$
$\rightarrow$ Maximum Likelihood

▸ Model

Model with Structural Assumptions

Prediction: $\widehat{P}(y_i | \cdot) = \Lambda(\widehat{\alpha} + \widehat{\beta}_1 days_i + \widehat{\beta}_2 nreporting_i)$

Binary prediction: $\widehat{P} \geq 50\% \quad \Rightarrow \quad \widehat{y}_i = 1$



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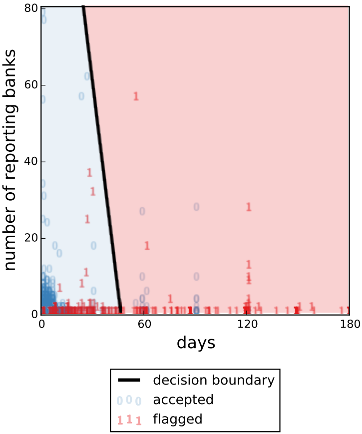


Strengths

- Data-driven
- Transparency
- Stable out-of-sample predictions

Weaknesses

- Requires (strong) assumptions
- Limited flexibility

Idee

Two ways to achieve our goal (prediction of decision)

1. Model with structural assumptions
2. **Model without structural assumptions**

Model without Structural Assumptions

– Prediction by evaluating decisions on securities with the same characteristics:

$$\widehat{P}\big(y_i|x_i = x\big) = Ave\big(y_i|x_i = x\big)$$

– Because of small number of securities with identical characteristics, we evaluate decisions on similar securities in regions $N_r(x)$:

$$\widehat{P}\big(y_i|x_i = x\big) = Ave\big(y_i|x_i \in N_r(x)\big)$$

Random Forest

Task for Algorithm

Optimal division of feature space into regions (N_r)

$\Rightarrow$ **Random forest (in a nutshell):**

- **Decision tree:** Split dataset to maximize homogeneity of regions; prediction is share of flagged securities in region
- **Forest:** Compute decision trees for Bootstrap samples; prediction is average over decision trees' predictions

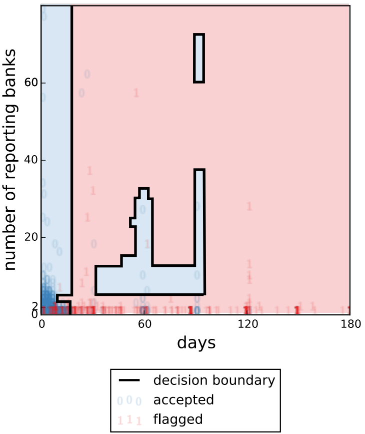
▸ Model ▸ Decicion Tree

Model without Structural Assumptions

Predicitions with the Random Forest

Prediction: $\widehat{P}(y_i|\cdot) = Ave(y_i|days_i, nreporting_i \in N_r(days, nreporting))$

Binary prediction: $\widehat{P} \geq 50\% \quad \Rightarrow \quad \widehat{y}_i = 1$



Model without Structural Assumptions
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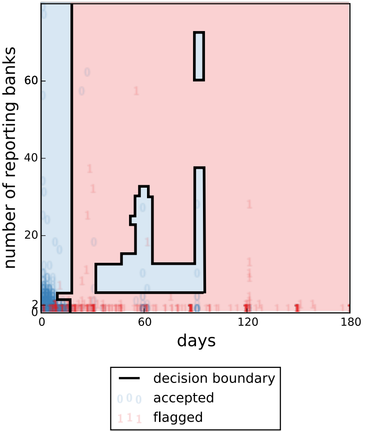


Strengths

- Data-driven
- Complex decision boundaries
- No structural assumptions

Weaknesses

- Potential overfitting
- "Curse of Dimensionality"

Performance

Accuracy of out-of-sample predicitions

- Random forest (86% of flags correctly identified) with higher accuracy than Logit (63% of flags correctly identified)
- Optimal accuracy < 1 if compilers make random decision errors

▸ Stratified 5-fold Cross-validation

Taking Advantage of the Probability

Prediction allows for sorting

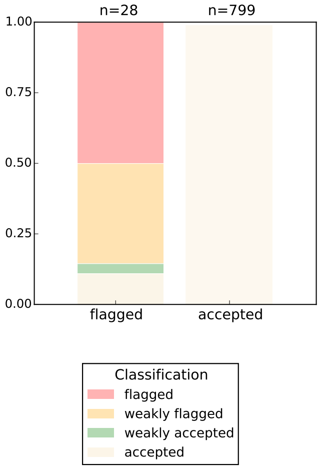
Taking Advantage of the Probability

Prediction allows for sorting

isin	...	prob
DE000...	...	82
DE000...		81
DE000...		80
DE000...		80
DE000...		73
DE000...		60
DE000...		43
DE000...	...	42
DE000...		39
DE000...		35
DE000...		2
DE000...		2
DE000...		1
DE000...	...	1

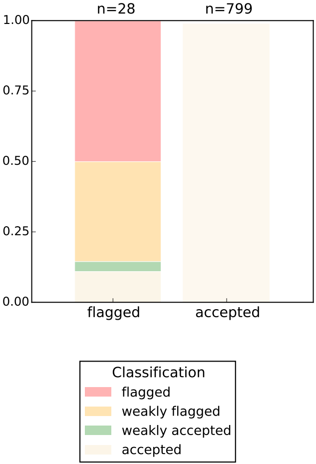
Taking Advantage of the Probability

Out-of-sample prediction for October 2016



Taking Advantage of the Probability

Out-of-sample prediction for October 2016

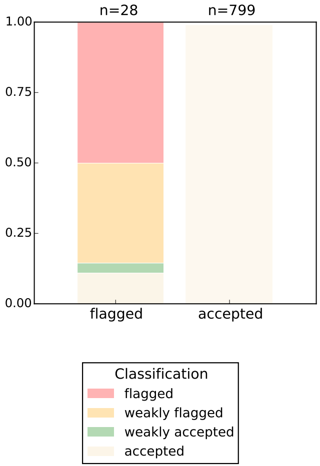


Advantages

- All of the 28 out of 827 securities in Top-35
- Improvement in efficiency and effectiveness

Taking Advantage of the Probability

Out-of-sample prediction for October 2016



Advantages

- All of the 28 out of 827 securities in Top-35
- Improvement in efficiency and effectiveness

Experience

- 50% reduction in time for check and increased effectiveness of evaluations

Application to Data Gaps

Potential of Machine Learning is not Limited to DQM

- Data gaps are a common problem in micro-data
- Machine learning algorithms can close data gaps by imputation with predictions if $E\left(y_i|x_i\right) \neq E\left(y_i\right)$

Application to Data Gaps

Goal

1. **Learn** about structure: **feature vector (x)** determines **variable with data gaps (y)**

$$E\left(y_i | x_i\right)$$

2. **Predict** missing values (only feature vector is known)

$$\widehat{y}_i = E\left(y_i = 1 | x_i = x\right)$$

Performance

Simulated Data

– Binary outcome

– Structural relationship between outcome and features

– Idiosyncratic unobservable noise

Algorithms

– Logit

– Random Forest

Performance

– Evaluate out-of-sample predictions

– 5-fold cross validation

Simulation Results

Main Results

1. Random forest outperforms structural models in datasets with complex feature-outcome relationships
2. Rare events are hard to predict in small datasets
3. Performance increases if unobserved variables are correlated with missing features

Conclusion

Application of Machine Learning to DQM

- Application to DQM is feasible and straightforward
- Large potential for improvements of efficiency if data on compiler decisions is available

Application of Machine Learning to Data Gaps

- Large benefits of Random Forest compared to more conventional methods in datasets with complex feature-outcome relationships

Performance

Performance Metrics

$$\textbf{Recall} = \frac{\textit{Number of Correctly Predicted Flags}}{\textit{Number of Flags}}$$

$$\textbf{Precision} = \frac{\textit{Number of Correctly Predicted Flags}}{\textit{Number of}\ \text{Predicted}\ \textit{Flags}}$$

Underlying Idea (Stratified 5-fold Cross-validation)

1. Randomly split dataset into 5 parts
2. Use 4 parts to train the dataset
3. Evaluate predictions for the fifth part

Back

Performance

Result (Average over Recall and Precision)

	Logit	Random Forest
Recall	0.63	0.86
Precision	0.85	0.89

- $\Rightarrow$ Random Forsest with superior performance
- $\Rightarrow$ If compilers make random decision errors, algorithm can outperform compiler. Optimal recall and precision should be < 1

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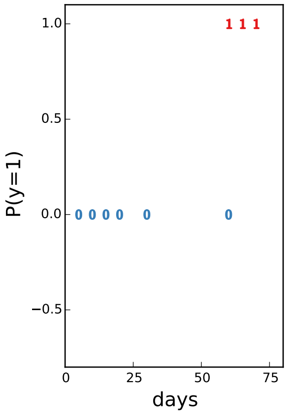
Model with Structural Assumptions

Model (Example): $P\left(y_i = 1 | days_i\right) = \Lambda(z_i) = \Lambda\left(\alpha + \beta days_i\right)$



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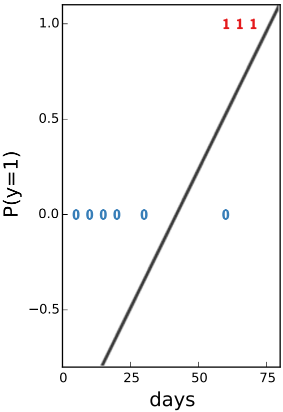

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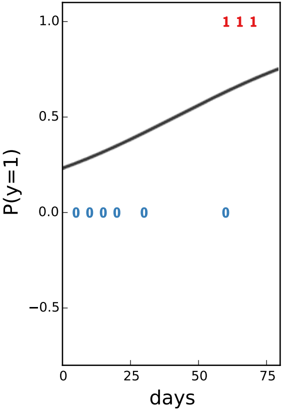

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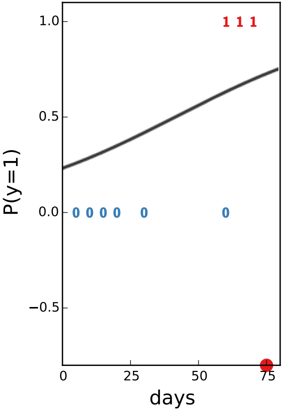
Model with Structural Assumptions

Model (Example): $\widehat{P}\big(y_i = 1 | days_i = 75\big) = \Lambda(\widehat{z}_i) = \Lambda\big(\widehat{\alpha} + \widehat{\beta}75\big)$



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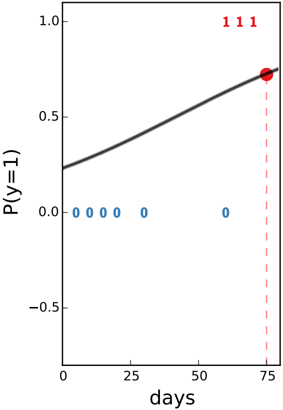

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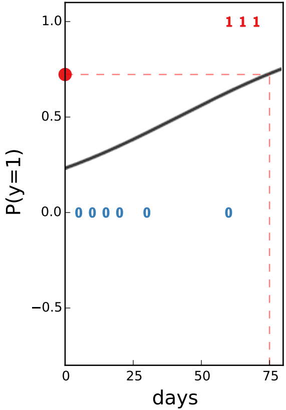

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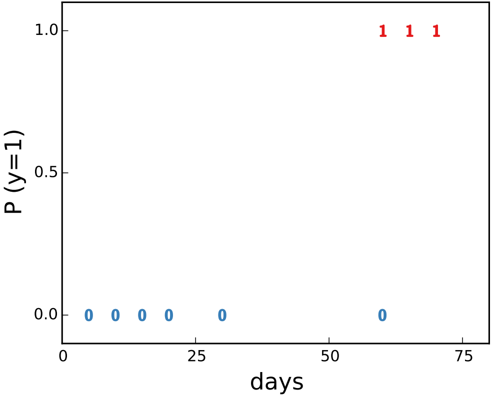
Model without Structural Assumptions

Model (Example): $\widehat{P}\big(y_i | days_i = days\big) = Ave\big(y_i | days_i \in N_r(days)\big)$



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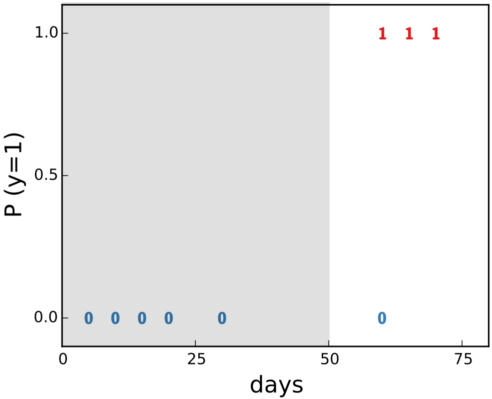

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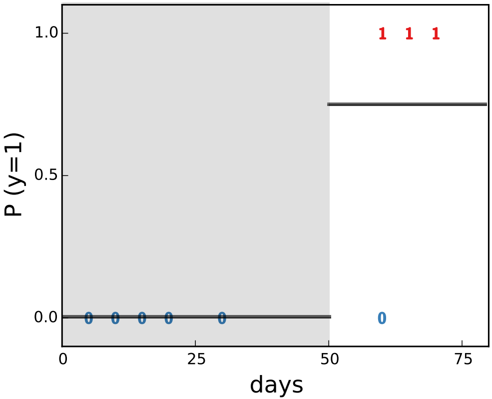
Model without Structural Assumptions

Model (Example): $\widehat{P}\big(y_i | days_i = days\big) = \color{red}{Ave}\big(y_i | days_i \in N_r(days)\big)$



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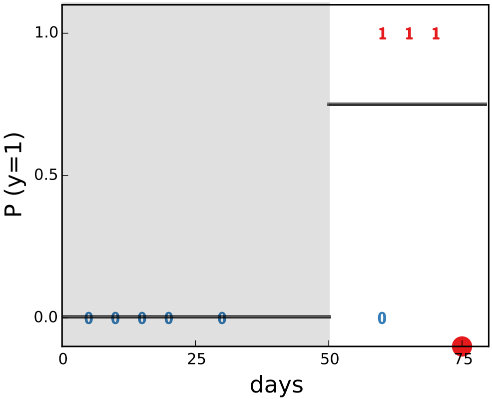
Model (Example): $\widehat{P}\left(y_i | days_i = 75\right) = Ave\left(y_i | days_i \in N_r(75)\right)$



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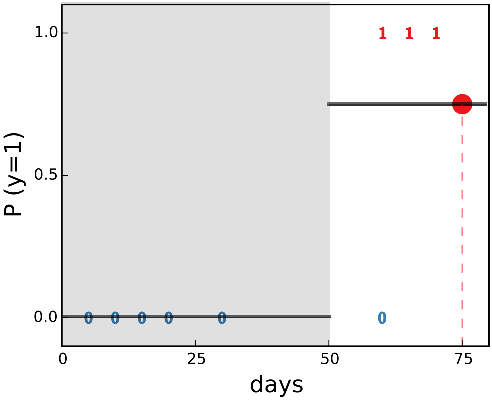

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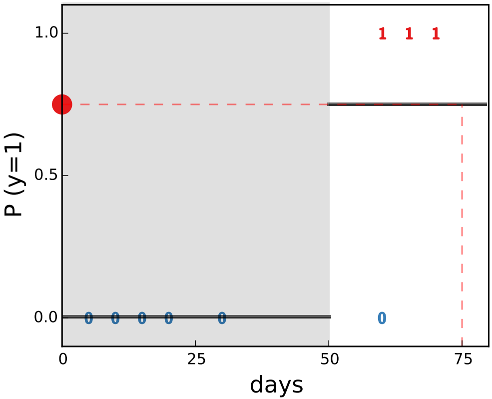

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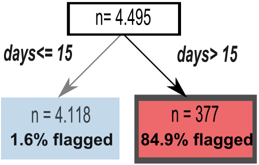
Random Forest
Example for a decision tree

Prediction: Decision tree with features *nreporting* and *days*

Binary Prediction: $\widehat{P} \geq 50\% \quad \Rightarrow \quad \widehat{y}_i = 1$



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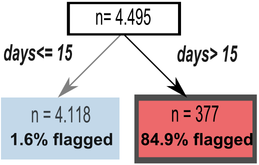

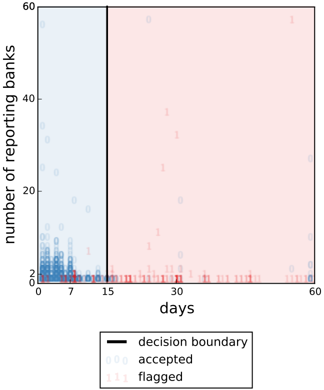

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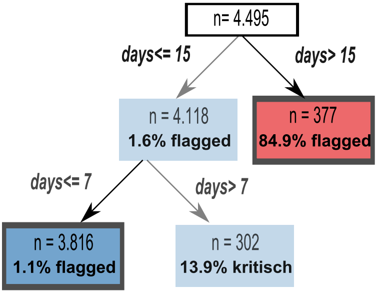

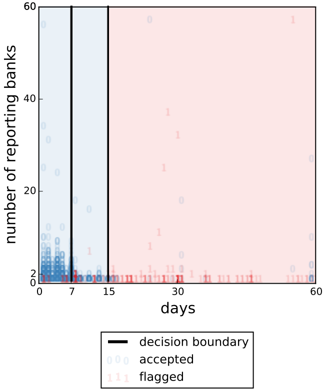

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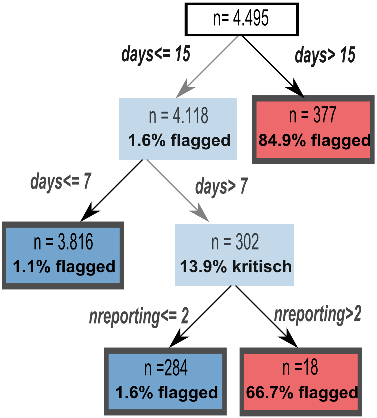

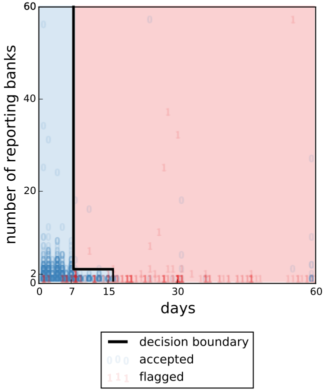

Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

IFC-National Bank of Belgium Workshop on "*Data needs and Statistics compilation for macroprudential analysis*"

Brussels, Belgium, 18-19 May 2017

Using microdata from monetary statistics to understand intra-group transactions and their implication in financial stability issues[1]

Graziella Morandi and Giulio Nicoletti,
European Central Bank

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Using Microdata from Monetary Statistics to Understand Intra-group Transactions and their Implication in Financial Stability Issues

Graziella Morandi[1] and Giulio Nicoletti[2]

Abstract

Recent research has shown that intra-group lending may be large – often comparable in size to interbank flows – and hence form an important aspect of international banking and financial stability. Interbank transactions have implications on the conduct of monetary policy since banking groups can fund themselves from, or move resources to, their foreign subsidiaries located in different jurisdictions. This affects the transmission channel of monetary policy as highlighted by Cetorelli and Goldberg (2012) and Bruno and Shin (2015). From a macroprudential policy perspective, it helps understand how local economic conditions for a parent company may impact its subsidiaries. Very little is known as yet, even in the literature, about the systemic factors driving intra-group funding over time.

The paper investigates the pattern of intra-group transactions by looking at the intra-group loans contained in the ESCB statistics on individual MFI Balance Sheet Items and Interest Rates. To better exploit these indicators about the interconnectedness between sibling financial institutions, the ESCB 'Register of Institutions and Affiliates Database' is used to retrieve information on group consolidation and geographical counterparts.

JEL code: F34, G21, G28, G38

Keywords: Macro-Prudential Analysis, Interbank funding, Bank consolidation

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2 Giulio Nicoletti (Giulio.Nicoletti@ecb.europa.eu) is Expert at the Macro-Financial Policies Division at the ECB.

Contents

Introduction

In the post-crisis setting where financial research still stands, there is a lot literature showing that cross-border banking activity declined sharply during distressed periods on the financial markets.

A specific aspect of cross-border banking activity regards the existence of internal capital markets in international banking groups, also documented in several publications. The case of internal markets in the euro area and more generally within the European Union is of particular interest due to the efforts put into place by European institutions to achieve a better integration of the European banking industry. This has materialised in recent years by an acceleration of bank mergers across borders with the total number of credit institutions based in the euro area dropping from 8,320 in December 1998 to 4,988 entities in March 2017 (see ECB website – list of financial institutions). At the same time, the number of branches of euro area based credit institutions rose from 321 at end December 2005 to 406 entities in 2016.

If market integration allows overall for higher efficiency and diversification in funding the private sector across the European Union, it raises the risk, as indicated by Popov and Udell (2012), that a shock to the capital of an international banking group propagates across borders to the countries where the group operates by means of a branch or subsidiary. Such a risk has implications for the macro-financial stability of the Eurozone due to the unbalanced structure of the banking sector across Member States. In the new Member States (Eastern Europe and Baltic countries), a large part of credit institutions are foreign-owned whereas the banking sector is mostly held by domestic credit institutions in the western part of Europe (Germany, France, Spain, Italy). Besides, in terms of economic activity and revenue, foreign banks (branches or subsidiaries) are often of relatively small importance from the parent's bank perspective whereas they may be of systemic importance for host countries, thus leading to contradictory interests or supervisory views between the home and the host countries. Therefore, cross-border activities may be seen by governments and regulators as a threat to control and financial stability. What if foreign-owned credit institutions stop lending in countries where they represent a large proportions of the loans granted?

In more concrete terms, the work carried out on internal capital markets often assumes that lending by foreign-owned banks is affected by the financial conditions of a parent bank. This is confirmed by Popov and Udell in their research paper. Cetorelli and Goldberg (2009) also show that the existence of internal capital markets with foreign bank affiliates contributes to an international propagation of domestic liquidity shocks to lending by affiliated banks abroad.

There are actually several internal bank channels used to transfer assets and income from a parent bank to its subsidiary and the other way round. In this paper, we focus on intra-group loans and deposits as these correspond to the data made available on the topic of intra-group transfers by the latest update of the EU Regulation of MFI Balance Sheet Statistics (ECB/2013/33) (hereafter "the Regulation"). We use two inter-connected data sources to look at loan and deposit transfers within banking groups, both based on the Regulation: the Balance Sheet Items (BSI) dataset containing national balance sheet aggregates and the corresponding individual BSI (IBSI) data, i.e. the BSI aggregates broken down by individual banks for a sample of approximately 300 MFIs across the euro area. For reasons of confidentiality the data have all been aggregated or anonymised.

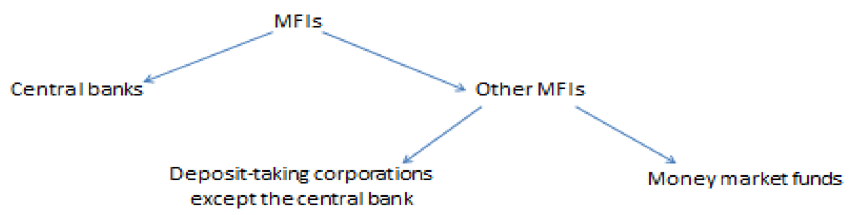
Macro-picture of inter-MFI lending in the Eurozone

Aggregate statistics and key features retrieved

Since December 2014 and the entry into force of Regulation (EU) No 1071/2013 of the European Central Bank of 24 September 2013 concerning the balance sheet of the monetary financial institutions sector (ECB/2013/33), the ECB collects monthly information on inter-MFI ("deposit-taking corporations except the central bank") loans and deposits as well as the corresponding intra-group positions as an "of which" of these items. The decomposition of the MFI counterpart sector as established by the statistical Regulation and ECB Guideline on Monetary and Financial Statistics is illustrated in Figure 1.

The inter-MFI sector in the MFI statistical balance sheet

Figure 1



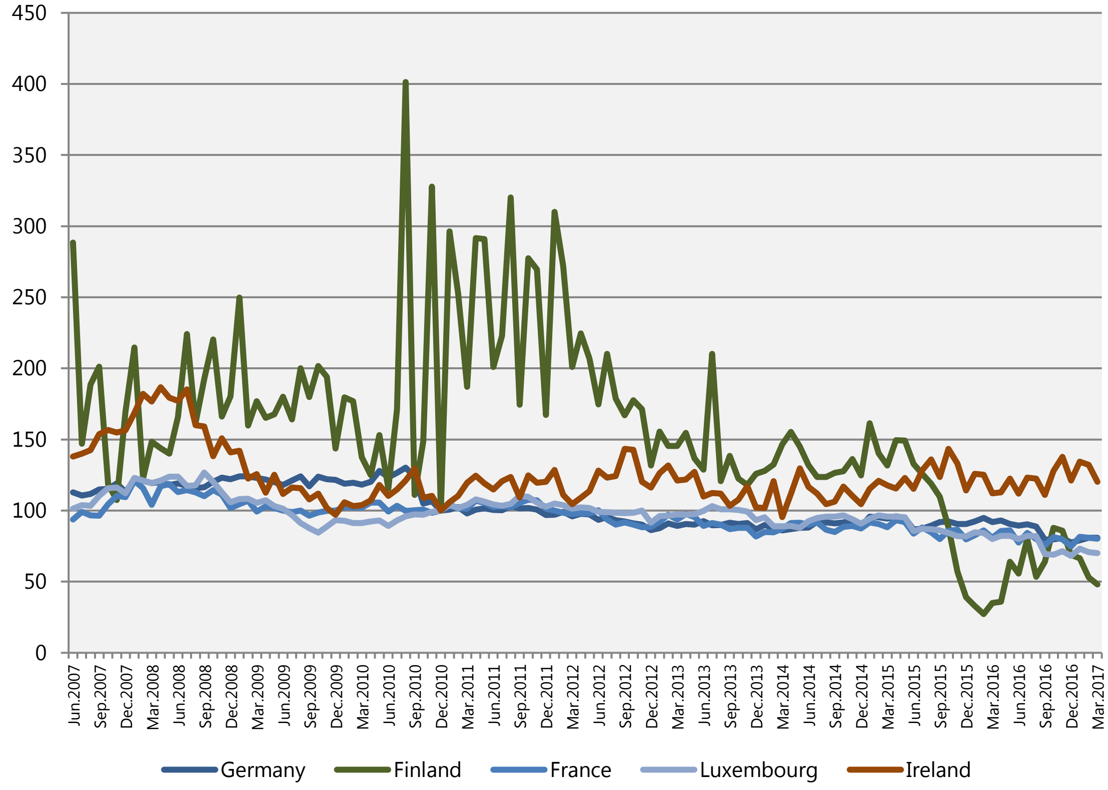
Source: ECB.

At aggregate level, the size of the inter-MFI market shows high disparity between countries. Euro area Member States in Table 1 were classified according to the share of their inter-MFI loans within the total outstanding amount of loans granted to euro area counterparts at end December 2016. For Luxembourg, Ireland, France and Germany, the inter-MFI market approximately represents a third of the total lending to euro area counterparts. With the exception of Luxembourg for which the increase in loans to the Eurosystem since mid-2015 explains the decline in the inter-MFI loans ratio, this proportion has remained fairly stable over the last three years (see Figure 11 in Annex).

Euro area countries also differ from one another with respect to the dynamics of cross-border banking activity. Figure 2 shows the monthly index of notional stocks for inter-MFI loans vis-à-vis "other euro area Member States" since June 2007. Although not as heavily represented as in France, Germany, Luxembourg or Ireland, the cross-border inter-MFI market in Finland shows a much higher volatility than in these countries. Thus the dynamics behind the inter-MFI market prove to be complex, and especially not necessarily correlated neither to the relative size of interbank activities at national level nor to the number of legally incorporated credit institutions in the respective country and as illustrated on Figure 3.

Index of notional stocks for cross-border inter-MFI loans
Based on financial transactions; position vis-à-vis euro area only

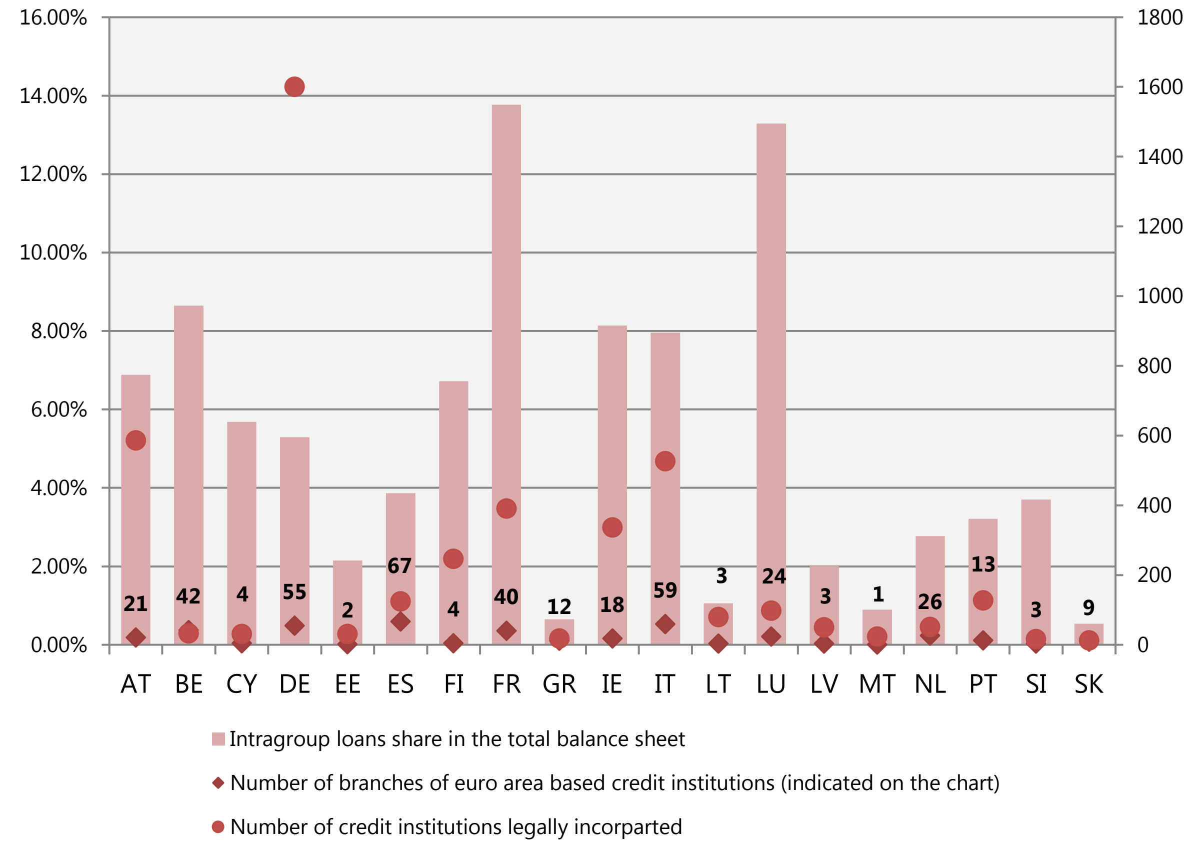
Figure 2



Source: ECB.

Share of inter-MFI loans in the total loans granted by MFI to euro area counterparts

Figure 3



Source: ECB. BSI dataset and lists of financial institutions.

Inter-MFI market in the Eurozone (assets)

Share of inter-MFI loans within the total outstanding amounts of loans granted by MFIs to euro area counterparts (data in %)

Table 1

Country	December 2014	December 2015	December 2016
LU	61.5	52.3	45.1
IE	37.6	41.0	40.7
FR	43.0	40.6	37.6
DE	31.8	30.1	27.0
AT	28.5	26.6	24.5
BE	25.4	24.1	20.9
IT	18.7	19.2	18.3
CY	12.8	10.9	13.1
ES	13.1	14.2	12.9
SI	14.7	13.3	12.0
PT	9.4	9.8	10.4
FI	12.1	11.4	12.6
NL	7.4	7.5	7.8
MT	20.7	16.4	9.6
LV	21.0	9.9	6.4
EE	4.2	7.6	4.1
GR	3.2	2.4	2.0
LT	1.9	2.4	1.6
SK	3.9	2.0	1.5

Source: ECB. BSI dataset.

Inter-MFI market in the Eurozone (liabilities)

Share of inter-MFI deposits within the total outstanding amounts of deposits placed by euro area counterparts (data in %)

Table 2

Country	December 2014	December 2015	December 2016
FR	44.5	42.7	40.8
LU	42.9	40.1	34.9
IE	35.5	32.9	31.6
AT	29.6	27.9	25.4
DE	27.7	26.3	24.5
IT	23.2	23.8	21.7
MT	31.3	28.3	21.5
FI	17.7	19.2	19.5
NL	12.2	13.5	14.3
ES	15.8	15.8	14.2
CY	12.5	11.9	13.5

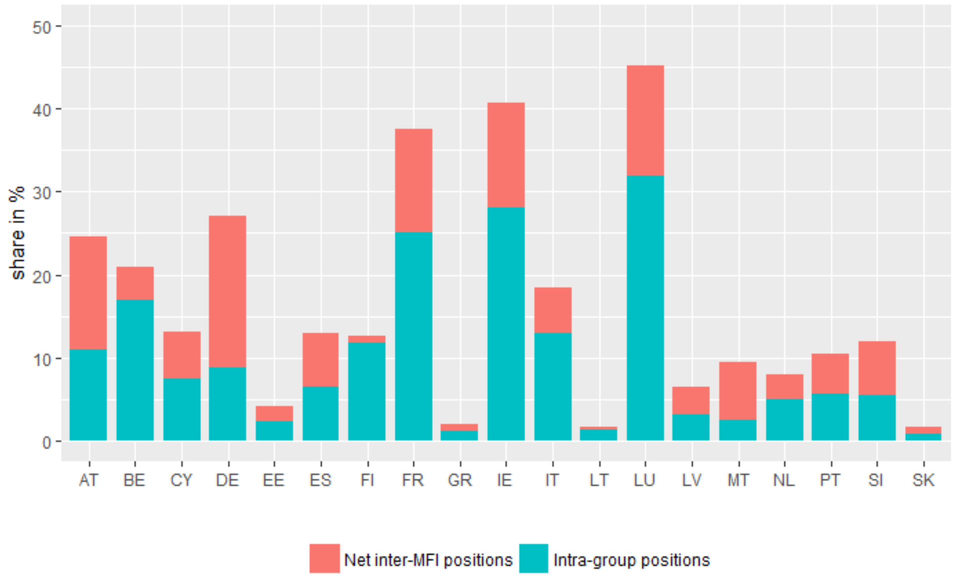
BE	13.2	11.5	12.3
PT	10.7	10.9	11.7
SI	16.4	12.1	9.6
GR	5.1	2.8	5.0
LT	10.7	3.8	4.9
SK	4.0	3.3	4.2
EE	13.4	3.1	3.8
LV	13.3	5.8	3.0

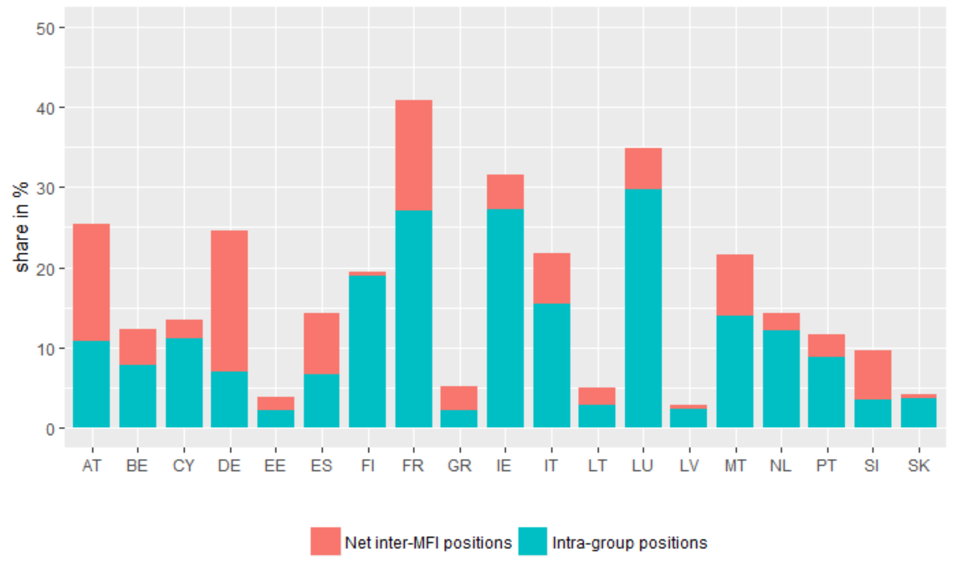
Source: ECB. BSI dataset.

Finally, and of specific interest for this paper, inter-MFI loans structurally differ across Member States. This is illustrated in Figure 4. Some countries are characterised by a high proportion of intra-group positions within their total inter-MFI lending: a relevant case is again represented by Finland where 94% of inter-MFI loans correspond to intra-group lending. On the other hand, Germany, where the inter-MFI market is more significant as compared to Finland, intra-group lending accounts for only 33% of the whole inter-MFI loans and similarly for deposits. However, looking at the aggregate figures for intra-group loans and deposits says very little about the dynamics driving these transactions. In Finland, a third of the financial market (loans to households and non-MFI deposits) is held by the former subsidiary of the Swedish bank Nordea, recently turned into a branch (see also paper from L. G. Goldberg, R. J. Sweeney and C. Wihlborg). One may therefore assume that most of intra-group transactions are driven by this single entity. What about the other countries? Are intra-group transactions the result of a strategy followed by specific MFIs in a given jurisdiction? Are they on the contrary a usual practise for parent bank to fund their subsidiaries or branches? Are foreign-owned banks equally involved in such transactions across the monetary union? This information can only be retrieved from data collected at the level of individual MFIs. These are presented in the next section.

Structure of inter-MFI loans (upper chart) and deposits (lower chart) in the total corresponding position vis-a-vis euro area counterparts

Data with reference December 2016 Figure 4





Source: ECB. BSI dataset.
Note: Positions vis-à-vis the NCB are excluded.

The micro view: the individual MFI statistics

As main data source for the work presented in this paper, this section aims at briefly presenting the microdata collected under the ECB monetary statistics.

In 2012, the ECB started to receive on a regular basis from the euro area NCBs individual BSI data. The exchange, which was set up for monetary policy and financial stability purposes, was also supplemented with the one-off transmission of individual BSI and MIR data for historical periods to better support Eurosystem users. These data were intended and still are treated as strictly confidential so that their access is restricted to a limited number of named Eurosystem users. In 2014 the data transmission became permanent and started to also include the regular exchange of individual MIR data.

Another review of the IBSI and IMIR datasets was undertaken mid-2015 in order to address new Eurosystem users' request to expand the sample of MFIs covered in the data exchange and enhance the reporting scheme with higher granularity. The review also included data requirements formulated by the ECB Banking Supervision.

The IBSI statistics encompass information on the balance sheet of MFIs, both on the assets and liabilities side. The asset side indicators include cash, loans to households, NFCs and governments, debt securities, money market fund (MMF) shares/units, equity and non-MMF investment fund shares/units, non-financial assets (including fixed assets) and remaining assets. On the liabilities side, time series are collected for deposits included and not included in the broad money aggregate M3, debt securities issued, capital and reserves and remaining liabilities. The granularity of series allows the analysis by loan purposes for households' loans, e.g. loans for house purchase, and by maturity. Regarding banks deposits, information is collected broken down by type (overnight, with agreed maturity, redeemable at notice, repos), maturity and reference area of depositors (domestic versus other Monetary Union Members) with a focus on deposits placed by NFCs and households – granularity is higher for these two sectors. Finally, and of particular interest for this study, the IBSI reporting template includes since the 2015 review additional indicators on the inter-MFI business: (1) on the asset side, series on loans granted to the whole MFI sector are available broken down by counterpart area (domestic MFI versus MFI located in other euro are countries) together with the respective "of which" positions for intra-group lending - besides, the domestic counterpart sector breakdown "national central bank" is also collected; (2) on the liabilities side, the same five series on outstanding amounts are collected for deposits.

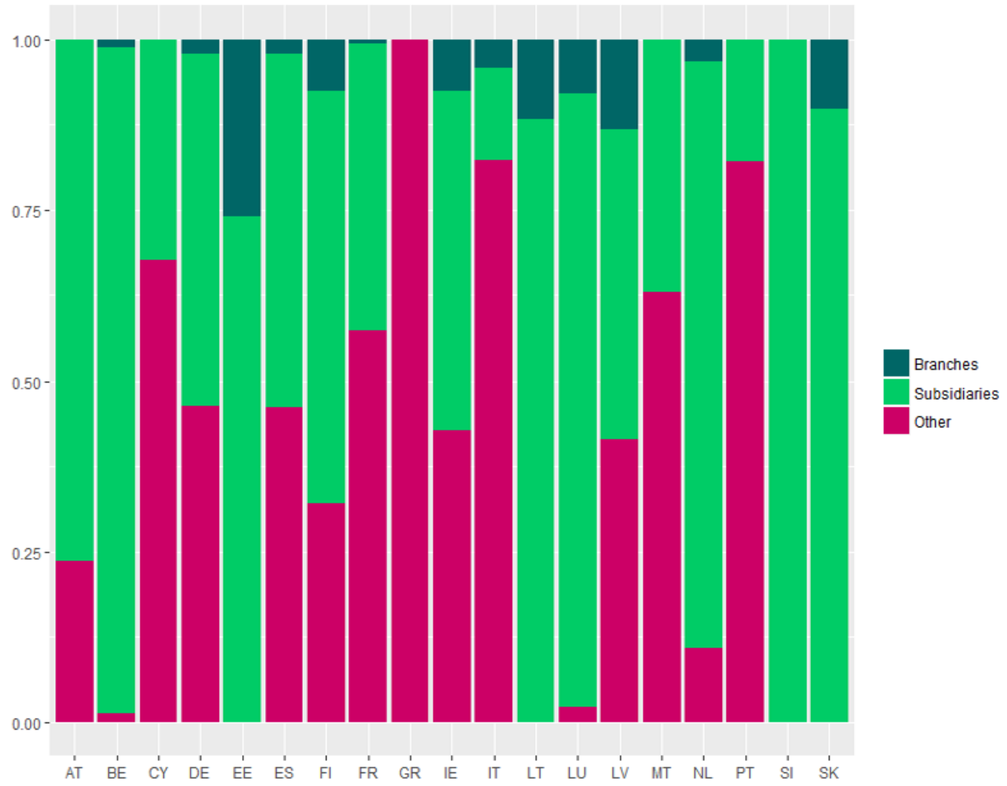
Following the remarks made in the previous section about inter-MFI lending such as captured by the aggregate dataset (BSI), it is worth looking at the representativeness of the corresponding figures calculated from the statistical balance sheet of individual MFI covered by the IBSI and IMIR reporting framework.

Figure 12 in Annex displays the representativeness of the IBSI sample with respect to the BSI aggregates for intra-group loans (Figure 12a) and the respective deposits (Figure 12b). An important aspect of intra-group positions is undoubtedly their volatility when compared to other balance sheet positions. Figure 12 also illustrates the disparity between countries as regards the representativeness of their national sample for intra-group banking activity. Cyprus for instance shows above 90% coverage for intra-group loans and deposits whereas countries such as Malta, Slovenia, Slovakia, etc. are for certain time periods far below 50%. Countries with a high coverage across time show to have credit institutions continuously involved in intra-group transfers. Other countries seem to be represented under the IBSI dataset by banks more sporadically engaged in intra-group banking activity. The interest of looking at individual MFI is therefore and precisely to be able to identify different behaviours across banks and countries and distinguish between intra-group activity as part of the banking groups' business model in funding the different entities of the group or intra-group transfers arising from specific events and aimed at covering specific risks or liquidity shortages.

To conclude this section and to the aim of broadly picturing the structure of the IBSI sample at national level, Figure 5 displays the distribution of assets according to the three legal forms of entities included in each panel. It should be noted that the chart does not reflect the actual ownership of the national banking sectors as it does not distinguish between domestic and foreign-owned subsidiaries or branches. However, the intuition is that intra-group transfers should be of greater relevance in proportion to the total inter-MFI lending in Member States where a significant part of the banking sector is held by subsidiaries and branches.

Structure of the banking sector as represented by the IBSI national samples

Data with reference December 2016 Figure 5



Source: ECB. IBSI dataset and RIAD (lists of financial institutions).
Note: The distribution of the different legal forms across samples is a proxy due to the reporting of aggregated groups by some countries, i.e. group of MFIs centrally reported under an entity playing the role of "central MFI" for the purpose of compiling individual MFI statistics.

Correlation indicators

A. Correlation between national aggregates and individual MFI data

This section looks at net flows of lending for the whole inter-MFI sector and at the level of banking groups i.e. it analyses the difference between loan and deposit transactions on the balance sheet of MFIs.

In MFI statistics, transaction flows are normally corrected for "non-transactional factors" such as revaluations, reclassifications, loans write-offs, write-downs and exchange rate changes. However, in the particular case of intra-group loans and deposits, the information on adjustments ("ancillary series") to the differences in stocks is not available under the reporting framework applying to the individual MFI statistics. This information is only collected at the level of the whole MFI counterpart sector, i.e. including the central bank as well as money market funds. Net intra-group liquidity flows are therefore calculated as simple differences in stock. Nevertheless and based on the aggregated adjustments for the whole MFI sector, one may observe that more than 50% of the MFIs covered by the whole euro area sample from July 2007 to February 2017 (namely 304 credit institutions in total) report above 99 percent of observations for these ancillary series with zero values. Although sometimes significant in magnitude, empirically, adjustments therefore only affect a very small number of data points so that for the purpose of this analysis, differences in stocks are deemed a reasonable proxy to assess the dynamics of intra-group liquidity flows.

Assessing the level of correlation between (a) the national aggregates of net lending flows based on the BSI dataset, i.e. covering almost 100% of the MFI sector – "BSI aggregates" – and (b) the corresponding aggregates compiled from a subset of MFI reported under the IBSI dataset – "IBSI aggregates" – allows to assess the representativeness of the IBSI panel as regards the inter-MFI market which an indicator of data quality for the analysis we wish to carry out at "micro level". Simple correlation coefficients have been used between the relevant time series and results are displayed in Table 3.

For most of countries, correlation coefficients between BSI and IBSI are satisfying. For Estonia, the MFIs included in the IBSI panel do not have intra-group transfers despite their aggregated representativeness in the total balance sheet of the country (more than 80% on average across the relevant time period). For Cyprus, the low correlation for net intra-group lending is only due to a couple of observations which are outliers. For Ireland, Luxembourg and Malta, the lower correlation as compared to the other countries results from the lower coverage of the IBSI panel (respectively around 40%, 35% and 40%).

Correlation between BSI national aggregates and the corresponding IBSI series *)

Table 3

Country	Inter-MFI net lending	Intra-group net lending (*of which* of inter-MFI)
AT	0.78	0.56
BE	0.96	0.81
CY	0.92	0.15
DE	0.93	0.79
EE	0.98	0.00
ES	0.90	0.85
FI	0.94	0.76
FR	-0.06	0.83
GR	0.99	0.93
IE	0.10	0.64
IT	0.67	0.72
LT	0.95	0.96
LU	0.73	-0.11
LV	0.86	0.86
MT	0.42	0.38
NL	0.95	0.97
PT	0.53	0.67
SI	0.82	0.84
SK	0.93	0.91

Source: ECB and authors' calculations. BSI and IBSI datasets.

*) IBSI series were compiled as national aggregates over the latest version of the IBSI sample (reference date March 2017).

B. Cross-sector correlation

This section looks at the correlation between intra-group loans and deposits and the corresponding inter-MFI positions. Results are displayed in Table 4. The level of correlation between the total inter-MFI transactions and the sub-breakdown for intra-group transfers provides an idea of the structure of the interbank market for the different euro area countries. In most of cases, the trend of intra-group transfers follows the trend of the whole inter-MFI market (positive correlation coefficient). In theory there are three exceptions for Latvia, Slovenia and Slovakia which show a slight decorrelation of their domestic intra-group transfers within the total domestic inter-MFI. However, in practise, these countries have a very small domestic inter-MFI market (respectively about 10%, 20% and 30% - see also Figure 7). For comparison, French and Finnish MFIs carry out more than 80% of their inter-MFI transactions for loans and deposits within each other, i.e. within the domestic market. On the other hand, intra-group transactions with institutions located in other Member States are very much correlated to the total inter-MFI for these same countries, suggesting that their domestic credit institutions are strongly connected on the interbank market with cross-border parent institutions. This in fact corresponds to the structure of the banking sector in these jurisdictions, mostly foreign-owned. We see that cross-border intra-group transfers closely follow the total inter-MFI activity also in countries such as Luxembourg and the Netherlands, where the interbank market is at the same time well developed and many foreign-owned banks operate (see Figures 6 and 7).

On the contrary, countries with a more active domestic interbank market show significantly higher correlation for the domestic sector as regards intra-group transfers within the total inter-MFI. This is the case for Finland, France and Italy.

Correlation between total inter-MFI positions and intra-group positions
Linear correlation coefficient based on transaction flows;
time range January 2015 – March 2017

Table 4

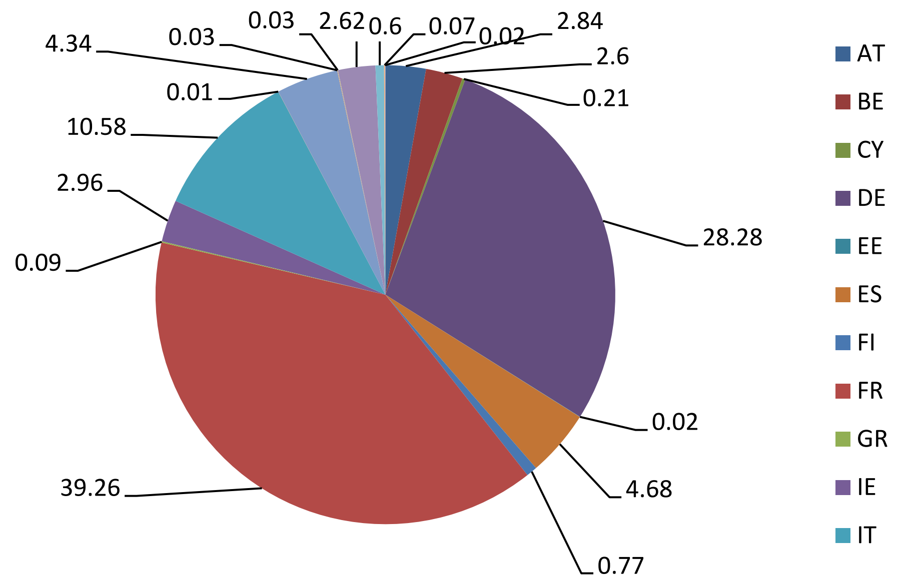
Country	Loans		Deposits	
	domestic	other MUMs	domestic	other MUMs
AT	0.65	0.39	-0.06	-0.06
BE	0.87	0.52	0.88	0.82
CY	0.96	0.40	0.96	0.27
DE	0.22	0.74	0.23	0.76
EE	0.00	-0.09	0.00	0.10
ES	0.15	0.44	0.33	0.28
FI	0.92	0.49	0.98	0.55
FR	0.76	0.17	0.66	0.40
GR	0.30	0.45	0.29	0.87
IE	0.67	0.31	0.95	0.90
IT	0.76	0.36	0.74	0.29
LT	0.28	0.98	0.12	0.95
LU	0.47	0.80	0.53	0.96
LV	-0.31	0.74	-0.29	0.96
MT	0.11	0.84	0.18	0.57
NL	0.21	0.70	0.08	0.86
PT	0.53	0.68	0.76	0.66
SI	-0.14	0.89	-0.13	0.61
SK	-0.07	0.74	-0.06	0.99

Source: ECB and authors' calculations.
Note: Low correlation coefficients were high-lighted in red. High correlation coefficients were high-lighted in green.

Distribution of inter-MFI loans across euro area countries

Data in percentage; reference date March 2017

Figure 6

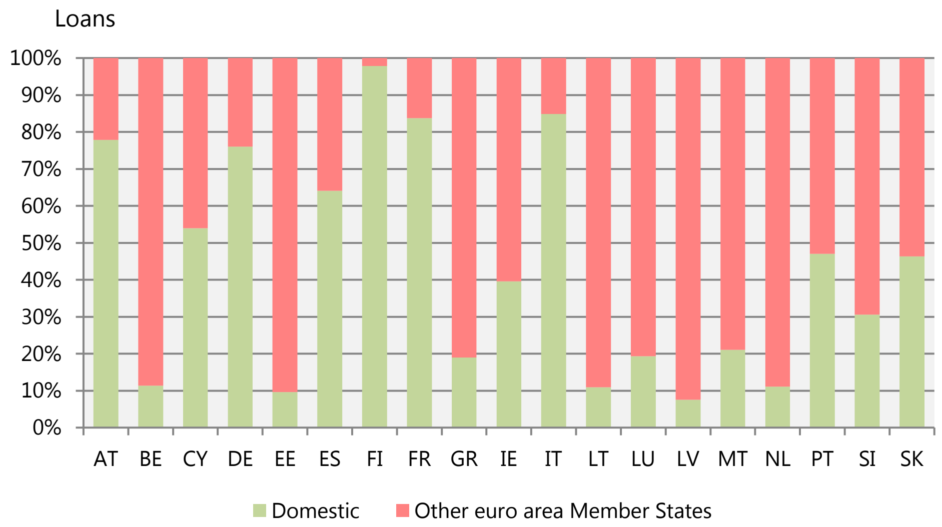


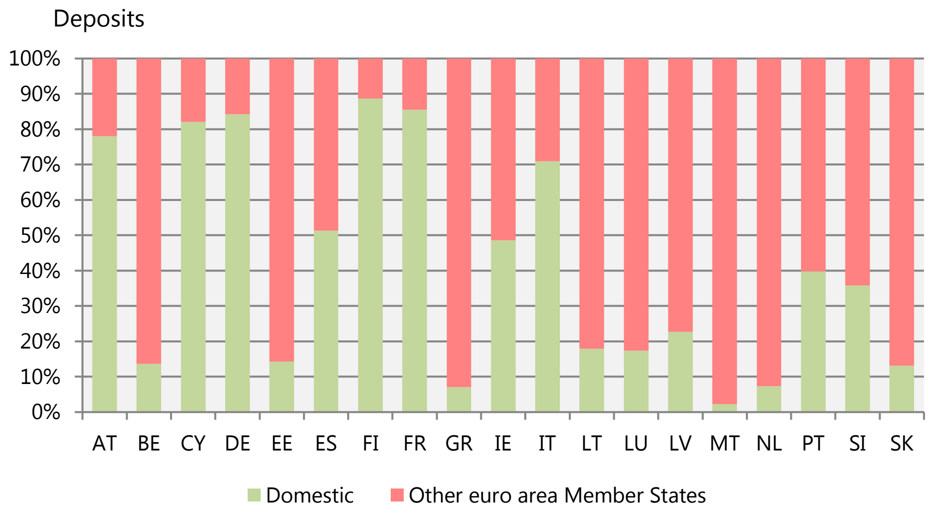
Source: ECB. BSI dataset.

Geographical distribution of inter-MFI positions within euro area countries

Data in percentage; reference date March 2017

Figure 7





Source: ECB. BSI dataset.

Intra-group liquidity – an alternative to credit institutions' funding?

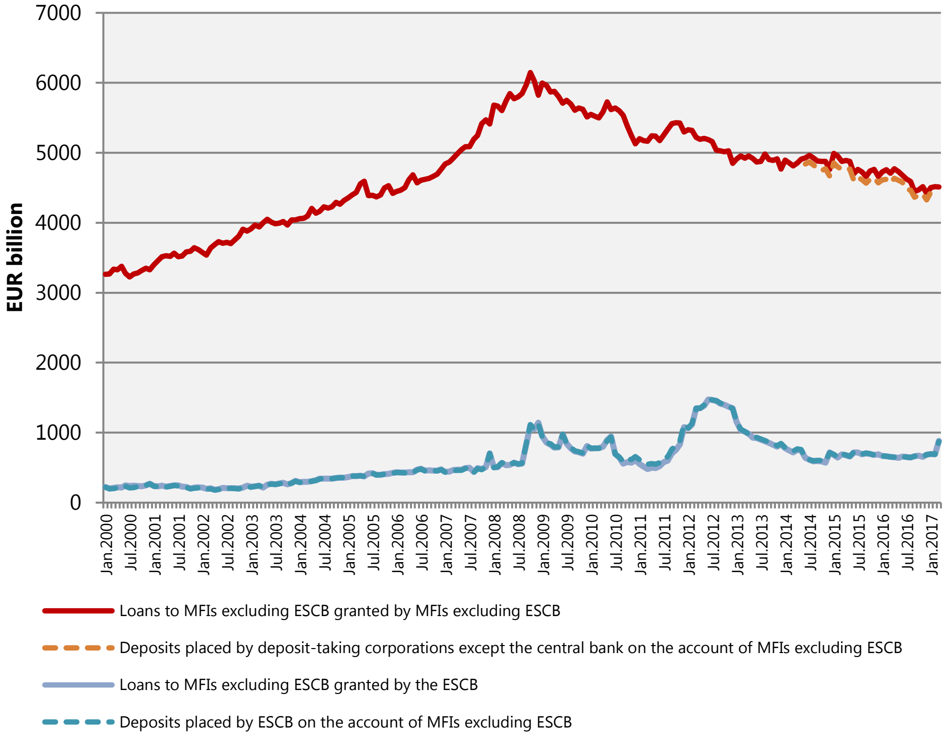
Intra-group liquidity transfers – a key factor in shaping interbank markets

The basic business of credit institutions is to provide credit to the real economy by granting loans. To this aim, credit institutions may obtain funding on the interbank market or by reverting to their national central bank. The use of the interbank market used to prevail in the euro area before the financial crisis. Today in the euro area many credit institutions only have access to the central bank money. The liquidity of the interbank market did not recover its pre-crisis level (see Figure 8): credit institutions do not trust each other as they used to. National central banks are *a priori* the obvious alternative to interbank funding when the confidence between banks on financial markets is impaired. However, with the development of cross-border banking groups in the Eurozone, favoured by the increasing market integration of the monetary union, intra-group transfers may also constitute a source of funding for banks. Logically enough, from the lender's perspective, the perception of counterpart risk is not the same whether the counterpart is part of the same banking group or whether it is an entity out of its scope of governance.

Overview of the inter-MFI market in the euro area since 2000

Outstanding amounts; euro area geographical counterpart only

Figure 8

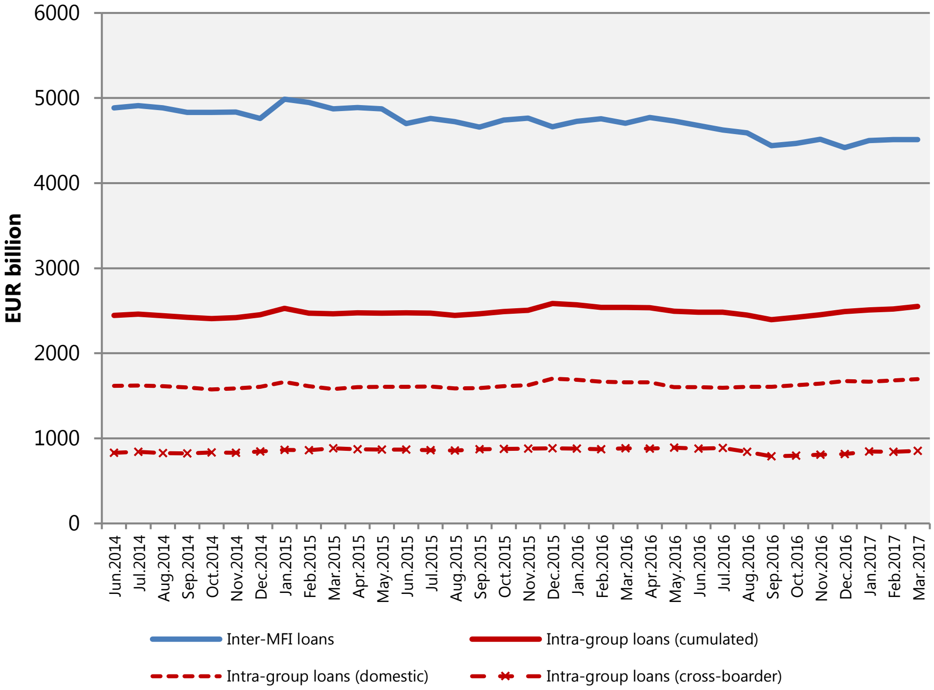


Source: ECB. BSI dataset.

As a matter of fact, and for the time span permitted by the available history of the BSI data on intra-group positions (reported as of June 2014 only as a result of the entry into force of Regulation ECB/2013/33), *intra-group loans* (and equally on the liability side *intra-group deposits*) are far from being negligible in the total inter-MFI balance, representing across time approximately 50% of the outstanding amounts on the total euro area MFI balance sheet (see Figure 9). This may also be observed on Figure 10 showing that intra-group flows contribute to the total inter-MFI lending along two aspects: (1) in terms of absolute magnitude (see for instance transactions for the third quarter of 2016 and the first quarter of 2017); (2) in terms of influencing the sign of the total lending at certain periods in time (see for instance observations for 15Q4 and 16Q4). This suggests that there exist, on the one hand, active internal capital markets within banking groups operating in the Eurozone and, on the other hand, that such markets are not only driven by the economic factors traditionally influencing the “net interbank” market. This is the object of the next section.

Intra-group loans in the euro area
Outstanding amounts; euro area geographical counterpart only

Figure 9

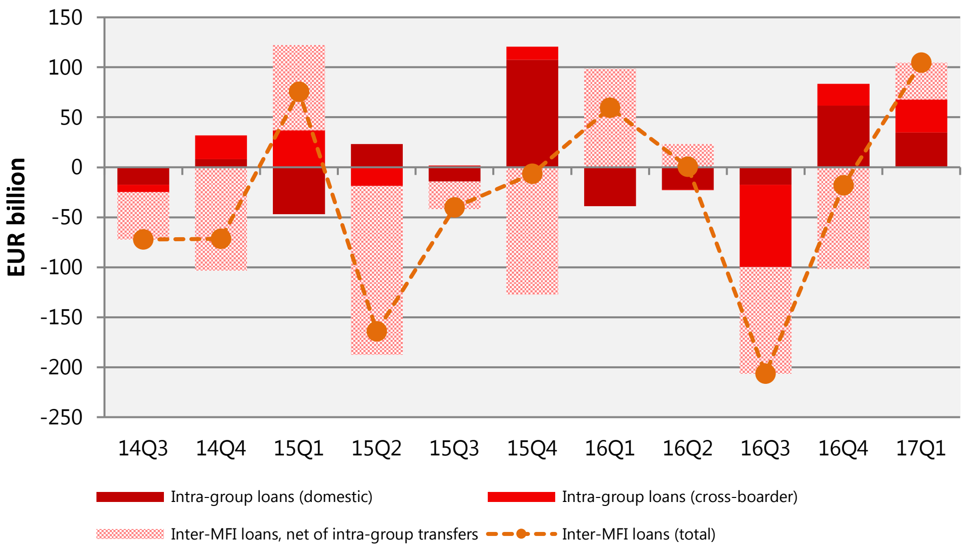


Source: ECB. BSI dataset.

Note: Here the scope of institutions as counterpart for intra-group and inter-MFI loans only covers deposit-taking corporations excluding the central bank.

Intra-group loans in the euro area
Quarterly financial transaction flows; euro area geographical counterpart only

Figure 10



Source: ECB and authors' calculations. BSI dataset.

Note: Here the scope of institutions as counterpart for intra-group and inter-MFI loans only covers deposit-taking corporations excluding the central bank.

Investigating possible drivers of intra-group lending in the euro area

This section describes the panel data model used to analyse intra-group transfers in the balance sheet of euro area MFIs. Our panel data covers all euro area countries (categories) over the time span December 2014 – March 2017 corresponding to the availability of the data on intra-group loans and deposits under the BSI and IBSI dataset.

A. Panel analysis using the BSI aggregates

- The variable to explain at country level $\boldsymbol{Y_{i,t}}$ is the **net intra-group lending** at country level within the euro area, i.e. the difference between the national aggregated flow of loans granted to domestic and euro area cross-border MFIs within the banking group and the corresponding deposit flow.
- The first predictor variable $\boldsymbol{X^1_{i,t}}$ is the **concentration** of national markets compiled from the IBSI dataset as the Herfindahl-Hirschmann index of the share of loans granted to the non-MFI sector. Figure 13 in Annex illustrates, for information, the concentration level at end December 2016.
- The second predictor variable $\boldsymbol{X^2_{i,t}}$ corresponds to the **size of national banking sectors** calculated as the respective share of loans granted to the non-MFI sector over the total euro area aggregate.
- The third predictor variable $\boldsymbol{X^3_{i,t}}$ is a structural indicator on the **ownership of the banking system** based on the individual BSI dataset, i.e. for each country the total assets share of foreign-owned credit institutions over the whole

sample. It should be stressed that is a very broad indicator of which the coefficient, as a result of the panel analysis, must be interpreted cautiously. There are several reasons for that, amongst which: (a) the IBSI dataset only provides partial coverage of the reporting population underlying the aggregate MFI balance sheet statistics – between 33% and 96% depending on countries at end March 2017 (latest available reference date - average coverage: 73% - median coverage: 78%); (b) the definition of ownership is, according to the rules applied in RIAD, based on the major share-holder of the bank, leading sometimes to border-line cases where the bank is "almost" domestic or foreign-owned; (c) the reporting panel for IBSI includes aggregate groups for which the ownership is difficult to assess (some group includes hundreds of MFIs) – for the purpose of this analysis, these were set to "domestic".

- The fourth predictor variable $\boldsymbol{X_{i,t}^4}$ is a measure of the "**net Eurosystem funding**" compiled again from the balance sheet of MFIs, i.e. using the difference between monthly changes in deposits placed by the domestic NCB (intermediary for the ECB money) and the corresponding loans (i.e. deposits replaced by the borrowers on its account at the NCB).
- The fifth predictor variable $\boldsymbol{X_{i,t}^5}$ corresponds to **the issuance of debt securities** held by euro area counterparts (all maturities included) compiled from the MFI Balance Sheet Statistics. The assumption is that parent banks may issue bonds in order to finance their subsidiairies and branches which would be reflected in the intra-group deposits on the balance sheet of the entities of the group.
- Finally, the last predictor variable plugged into the panel data model $\boldsymbol{X_{i,t}^6}$ is the **leverage ratio** of the euro area consolidated national banking sectors taken from the ECB Consolidated Banking Data. It corresponds to the ratio of total consolidated assets over total equity (commonly referred to in the litterature as "banks' capital"). This indicator being reported on a quarterly basis, we use linear interpolation in order to fill in the missing observations for the monthly time series. For the sake of clarity, we here remind that the interpretation of the leverage ratio is the following: the higher the ratio the more capital the bank has under the liability side of its balance sheet to finance its assets relative to its total amount of borrowed funds; hence the safer it is.

We test both a fixed effects and a random effects model for the panel data analysis. The model describes as follows:

$$Y_{i,t} = \beta X_{i,t} + \alpha + u_{i,t} + \varepsilon_{i,t}$$

Taking into account all variables for the regression leads to regression coefficients which are not significant. See Table 7 in Annex. However, the p-values obtained indicate that the size of the banking sector together with the Eurosystem funding may be the best regressor candidates to determine a valid model. We restrict the regression to these two variables and obtain the results displayed in Table 5. They are not fully satisfying in terms of significance – certainly we do not interpret them as causal. They confirm however the existence of a correlation between intra-group activity and the effect of the size of the banking sector together with the Eurosystem funding channelled through the Eurozone by means of transfers between parent banks and their subsidiaries and branches: the smaller the banking sector, the higher the intra-group activity; the higher the level of Eurosystem funding, the higher the magnitude of intra-group transactions.

Results of the restricted panel regression

Table 5

Variables	Fixed effects model	Random effects model	p-value
X_2 – Size of the banking sector	-2,293*	-47.89*	**0.083**
Standard Error	(1,348)	(26.51)	
X_4 – Eurosystem funding	0.000637*	0.000587	**0.090**
Standard Error	(0.000367)	(0.000364)	
Constant	11,807*	-6.941	**0.097**
Standard Error	(7,099)	(242.8)	
Observations	513	513	
R-squared	0.011		
Number of countries	19	19	
Log likelihood	-5036	.	
Pseudo R2	.	.	

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

In the above regression, we use at dependent variable the net lending taking therefore negative values. To give us an idea of the dependence in magnitude of intra-group flows with the size of banking sector, we also run the regression with net intra-group lending flows in absolute value as dependent variable. We use a fixed effects model as the random effects model lead to a negative variance of the time effect. We also allow in the estimation to test for residual cross-sectional dependence after the introduction of time fixed effects to account for common shocks. The estimated coefficient is fairly significant which we can interpret as the largest banking sector being responsible for the largest intra-group transactions. This follows the intuition that large jurisdictions have on their territory large banking groups operating and being involved in internal capital markets with their cross-border subsidiaries or branches. The reversal cannot be observed since, basically, banking group *X* in "large country" *A* will provide funding to subsidiaries/branches X_1, X_2, X_3, etc. in smaller jurisdictions. On the balance sheet of X_1, X_2 or X_3, the final flow is of course smaller than the aggregated one recorded by *X*. And most likely, subsidiary X_1 will not be involved in intra-group transactions beyond the ones with its parent bank.

Results of the restricted panel regression
Dependent variable: absolute net intra-group lending flows

Table 6

	Estimate	Standard Error	t-value	Pr(>|t|)
X2_size_banking_sector	2266.1	938.29	2.4151	0.01611*

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

B. Panel analysis carried out at bank-level

We showed earlier in this paper that intra-group lending is highly correlated with the overall interbank lending in the IBSI sample. We now provide some bank-level evidence on the correlation between intra-group lending and other sources of financing for MFIs.

The second column in Table 7 presents the results of a panel regression using changes in net intra-group lending – loans minus deposits – outside the domestic economy (dependent variable *Y*) against the changes in holdings of domestic sovereign bonds (regressor *X*). The economic idea behind the model is that MFIs reducing their holdings of domestic sovereign bonds, i.e. going short on the sovereign bonds market, use the liquidity retrieved to provide funding to other entities of the same banking group when these are cross-border.

Columns three and four present separate evidence that changes in intra-group loans and deposits are related to the issuance of debt securities. While net intra-group inflows of the issuing subsidiaries are not significantly related to bond issuance, both loans and deposits are found to be significantly related to changes in bonds issued. This might suggest that once bonds are issued by some subsidiary in a country, funding is redirected elsewhere outside that jurisdiction.

All regression exercises here control for time and random effects at MFI level. We do not interpret them as causal but we use the regressions to document correlations. In particular, the Haussmann test carried out the fixed versus random effects models favour the results obtained from the random effects model.

Finally, we only obtain some significance between (net) flows going or coming from outside the jurisdiction, while movements within the same jurisdiction do not seem to be related to other specific sources of funding for MFIs. This supports the view that intra-group lending is mostly relevant as a cross-border phenomenon.

Results of the regression at individual MFI level

Table 7

Variables	**Change in net intra-group lending**	**Change in intra-group loans**	**Change in intra-group deposits**
Change in holdings of domestic government debt	-0.0402**		
Standard Error	(0.0196)		
Newly issued debt securities		0.0360***	
Standard Error		(0.00578)	
Newly issued debt securities			0.0397***
Standard Error			(0.00692)
Random effects by MFI	YES	YES	YES
Time dummies	YES	YES	YES
Observations	12,201		
Number of Banks	290		
Standard errors in parentheses			
*** p<0.01, ** p<0.05, * p<0.1			

Conclusion

The liquidity management of central bank money within the banking sector is a key aspect of monetary policy. As stressed by Cetorelli and Goldberg (2011), internal capital markets plays a role in it by allowing managing cross-border liquidity, substituting this way banks' funding via the domestic central bank or the "traditional" interbank market.

This paper aims at exploring the information about liquidity redistribution within the euro area domestic market through two relatively new data sources: the new balance sheet items on intra-group positions provided by Regulation ECB/2013/33 and the ECB micro-dataset on individual MFI Balance Sheet Statistics.

The statistical information provided by intra-group loans and deposits allows for a segmentation of the interbank market which proves to be useful in an economic context where the interbank market remains fragile and trust between credit institutions is still to be rebuilt to reach again its pre-crisis level. At the same time, the increasing market integration in the Monetary Union, and to some extent, within the whole European Union, favour the development of large cross-border banking groups. These two phenomena on the European market makes the analysis of intra-group lending a relevant work to understand how liquidity, and in particular, from an ECB perspective, the central bank money is channelled through euro area countries.

The national aggregates allow building structural indicators in order to assess the size and nature (domestic or cross-border) on intra-group lending within the euro area. We show that for certain countries, intra-group lending is a large part of the inter-bank market. We also show that banking sectors in new euro area Member States, very much foreign-owned, is quite dependent on funding from parent banks in other jurisdictions.

The use of national aggregates for panel data analysis is on the other limited by the low number of observations for the items newly collected under Regulation ECB/2013/33 and reported for most of countries since December 2014 only. We are therefore aware that the results of the regression estimated in this work can only give a broad indication on possible correlations between net intra-group lending and macro-financial variables such as the local size of national banking sectors or the Eurosystem funding. In a nutshell, our paper indicates that the Eurosystem funding plays a role in intra-group transactions by enhancing the funding of smaller institutions by the parent bank within a banking group.

The individual MFI statistics are a precious input for econometrical analysis on balance sheet data owing to the granularity of the dataset: with approximately 300 individuals, results of the regression are more likely to lead to significant coefficients allowing a proper interpretation of the correlation between variables. However, due to the partial coverage of the sample at national level, conclusions should be rather drawn at the level of the euro area as a whole with a general distinction between the domestic and euro area cross-border sectors. This is the approach we followed in Section B when identifying possible linkages between the issuance of debt securities and intra-group transfers to cross-border institutions.

The work initiated in this paper must be further enhanced in order to fine-tune the panel data analysis following for instance the approach of Affinito (2013) who carries out his regression using an endogenous covariate. Besides, the individual MFI Balance Sheet Statistics, thanks to the meta-information on institutional reporters contained in the ESCB Register of Institutions and Affiliates Database, can allow network analysis to better understand how credit insitutions, based on some of their key characteristics (structure of the balance sheet or cross-border presence) interact with each other.

References

Cetorelli N., Goldberg L. "Liquidity management of U.S. global banks: internal capital markets in the great recession", National Bureau of Economic Research, *Working paper 17355*, August 2011.

Allen F., Gu X., Kowalewski O. "Corporate governance and intra-group transactions in European bank holding companies during the crisis". *Research paper*, The Wharton School University of Pennsylvania, February 2011.

Bojaruniec P., Morandi G., "Setting-up the transmission of individual MFI statistics on balance sheet items and interest rates across the Eurosystem", IFC-NBP Workshop in Warsaw, publication available on the BIS website (www.bis.org), December 2015.

Popov A., Udell G. F., "Cross-border banking, credit access, and the financial crisis", Journal of International Economics, publication available at the link https://doi.org/10.1016/j.jinteco.2012.01.008, May 2012.

Affinito M. "Central bank refinancing, interbank markets, and the hypothesis of liquidity hoarding - evidence from a euro-area banking system", ECB publication, Working Paper Series N. 1607, November 2013.

Darracq Paries M., Moccero D., Krylova E. and Marchini C. (2014), "The retail Bank interest rate pass-through the case of the euro area during the financial and sovereign debt crisis". *Occasional Paper Series*, No. 155, European Central Bank, September 2014.

Torres-Reyna O., "Data Analysis Fixed and Random Effects using Stata". *Lecture notes*, Princeton University, December 2007.

ECB (1998), Regulation (EC) No 2819/98 of the ECB of 1 December 1998 concerning the consolidated balance sheet of the monetary financial institutions

ECB (2001), Regulation (EC) No 63/2002 of the ECB of 20 December 2001 concerning statistics on interest rates applied by monetary financial institutions to deposits and loans vis-à-vis households and non-financial corporations (ECB/2001/18)

ECB (2008), Regulation (EC) No 25/2009 of the ECB of 19 December 2008 concerning the balance sheet of the monetary financial institutions sector (Recast) (ECB/2008/32)

ECB (2013), Regulation (EU) No 1071/2013 of the ECB of 24 September 2013 concerning the balance sheet of the monetary financial institutions sector (recast) (ECB/2013/33)

ECB (2011), "The ECB's non-standard measures – impact and phasing-out". *ECB Monthly Bulletin*, July 2011.

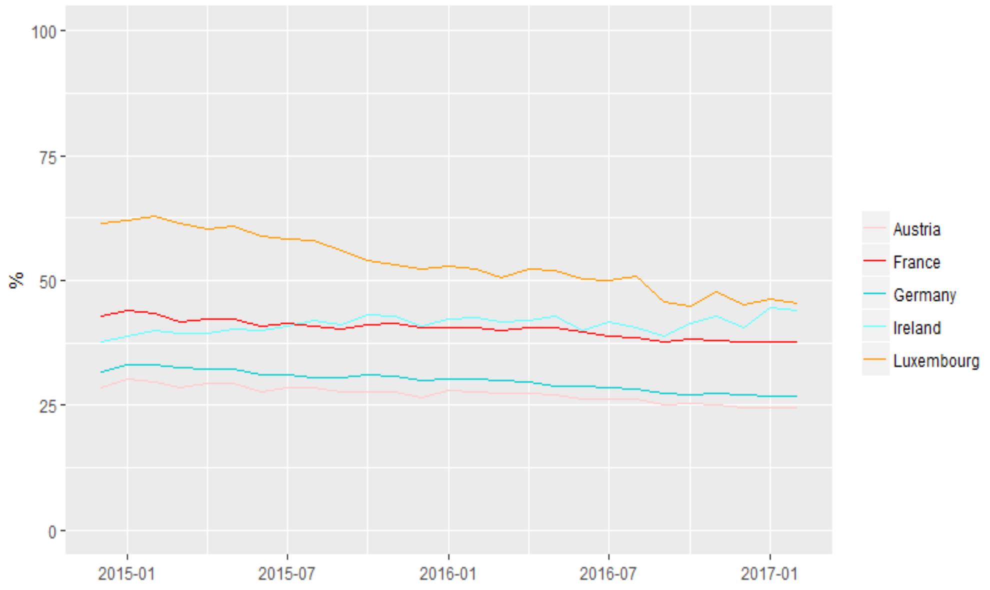
ECB (2014), "Exploiting the cross-sectional dimension for monetary analysis: the use of individual MFI data". *ECB Monthly Bulletin*, February 2014.

ECB (2015) "Economic Bulletin Issue 1". *ECB Economic Bulletin*, February 2015.

Annex

Share of inter-MFI loans in the total loans granted by MFI to euro area counterparts

Figure 11

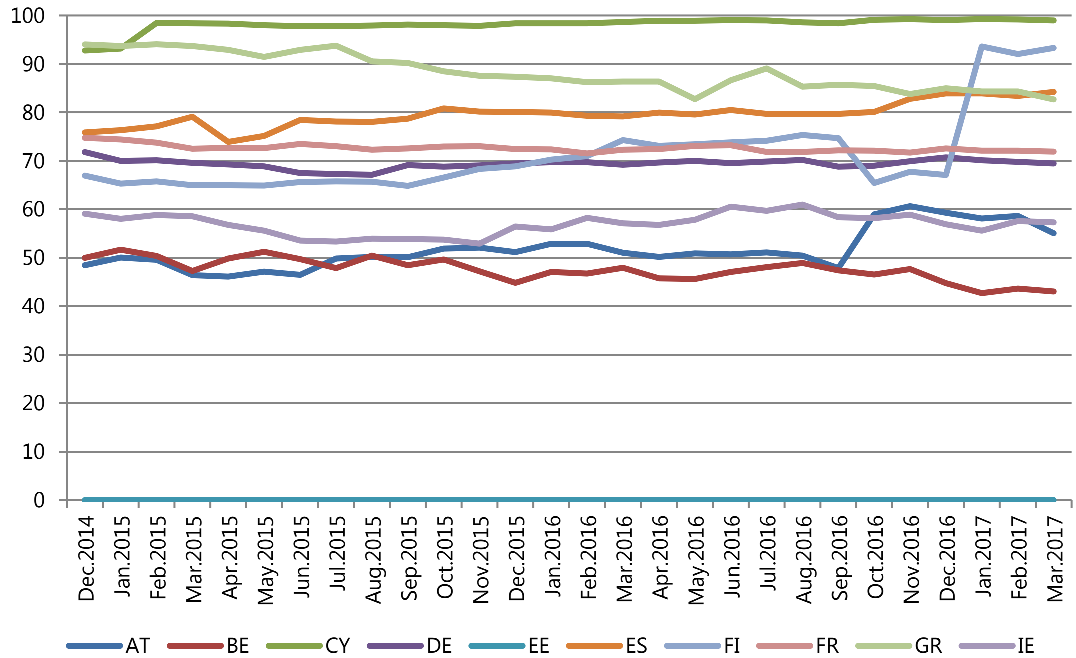


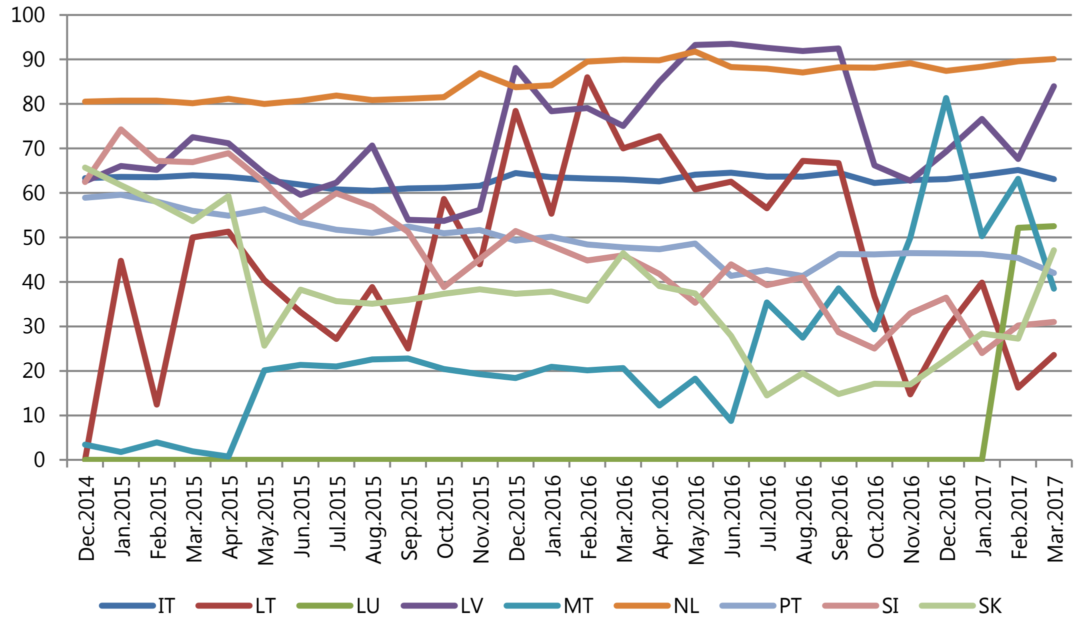
Source: ECB.

Representativeness of the IBSI sample in the national BSI aggregates

Intra-group loans; values in percentage

Figure 12a





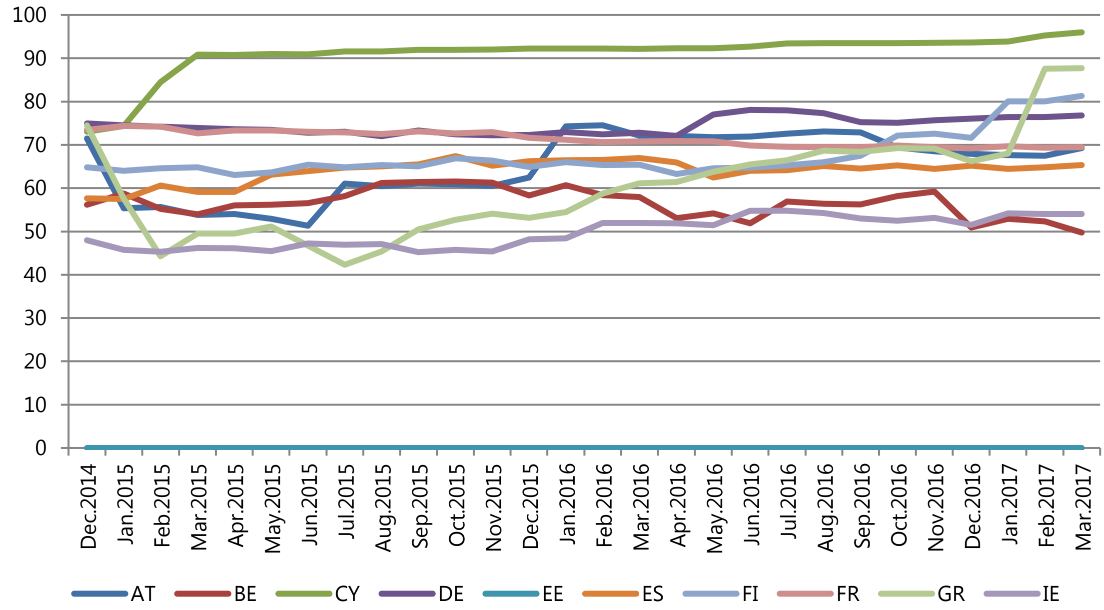
Source: ECB.

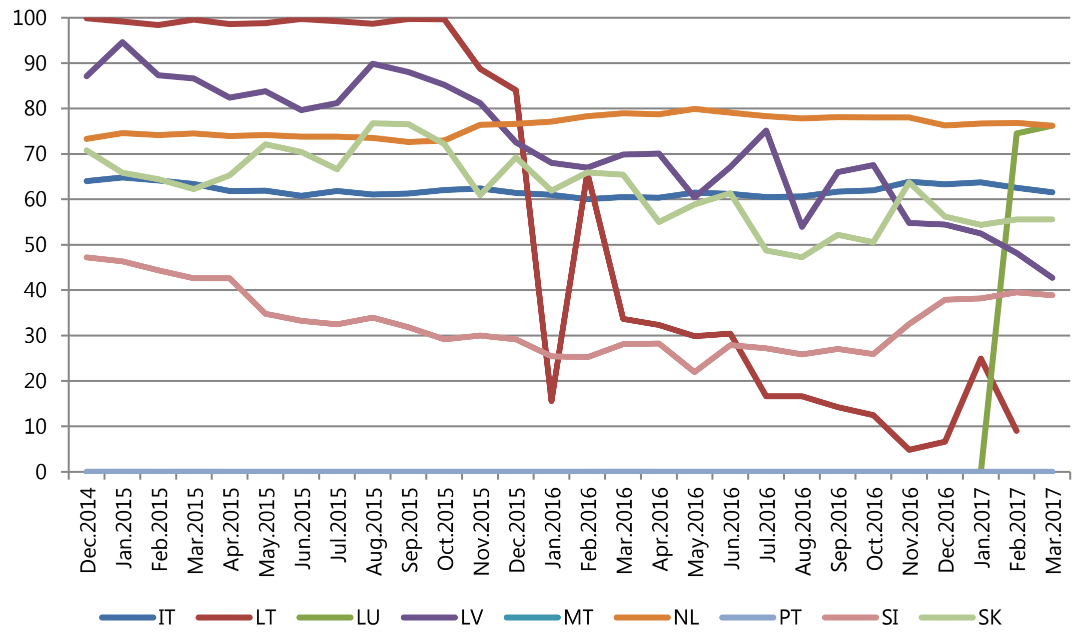
Note: MFIs included in the IBSI sample for Estonia do not hold intra-group loans from euro area MFIs.

Representativeness of the IBSI sample in the national BSI aggregates

Intra-group deposits; values in percentage

Figure 12b





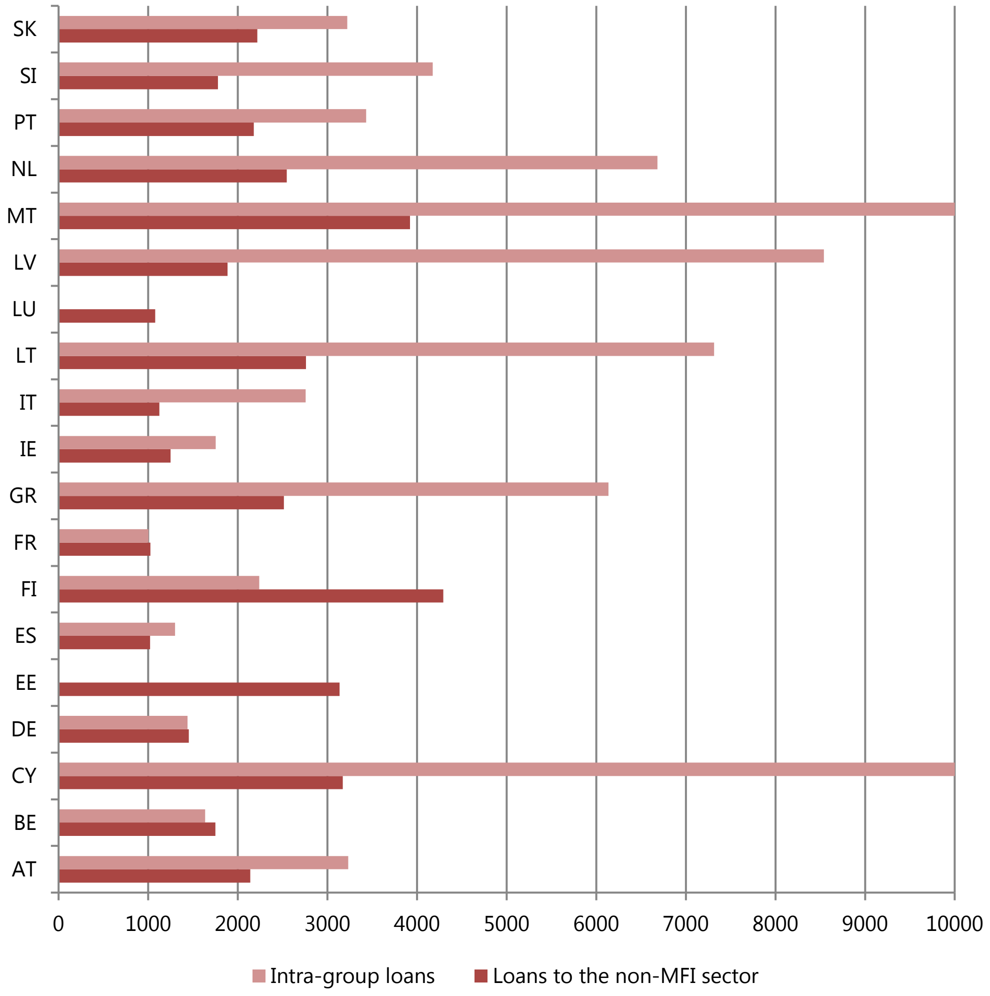
Source: ECB.

Note: MFIs included in the IBSI sample for Estonia, Malta and Portugal do not hold intra-group deposits from euro area MFIs.

Herfindahl-Hirschman index

Based on outstanding amounts at end of period; data with reference December 2016

Figure 13



Source: ECB. IBSI dataset and authors' calculations.

Note: 1) Data on intra-group loans for Luxembourg are not available. 2) The non-MFI sector comprises general government, OFIs, NFCs and households.

Results of the panel regression including all variables described in Section 2.1

Table 7

Variables	Fixed effects model	Random effects model	p-value
X_1 – Concentration index of banking business	-93.66	10.97	**0.708**
	(429.8)	(29.31)	
X_2 – Size of the banking sector	-2,217	-50.10	**0.253**
	(1,368)	(43.84)	
X_3 – Foreign ownership of the banking sector	-57.25	-3.070	**0.676**
	(132.1)	(7.337)	
X_4 – Eurosystem funding	0.000624*	0.000586	**0.109**
	(0.000371)	(0.000365)	
X_5 – Issuance of debt securities held by the euro area	-0.0196	-0.00961	**0.844**
	(0.0516)	(0.0489)	
X_6 – Leverage ratio	-115.0	-0.786	**0.992**
	(289.1)	(78.95)	
Constant	16,894	-108.2	**0.930**
	(14,525)	(1,227)	
Observations	513	513	
R-squared	0.012		
Number of countries	19	19	
Log likelihood	-5036	.	
Pseudo R2	.	.	

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

IFC-National Bank of Belgium Workshop on "*Data needs and Statistics compilation for macroprudential analysis*"

Brussels, Belgium, 18-19 May 2017

Using microdata from monetary statistics to understand intra-group transactions and their implication in financial stability issues[1]

Graziella Morandi and Giulio Nicoletti,
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

Using Microdata from Monetary Statistics to Understand Intra-group Transactions and their Implication for Financial Stability

Graziella Morandi
ECB – Research analyst
Author and speaker

Giulio Nicoletti
ECB – Financial stability expert
Co-author

Working Paper (May 2017)

Disclaimer

- This presentation **should not** be reported as representing the views of the European Central Bank (ECB).
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- To protect data confidentiality, data have been aggregated or anonymised.

Overview

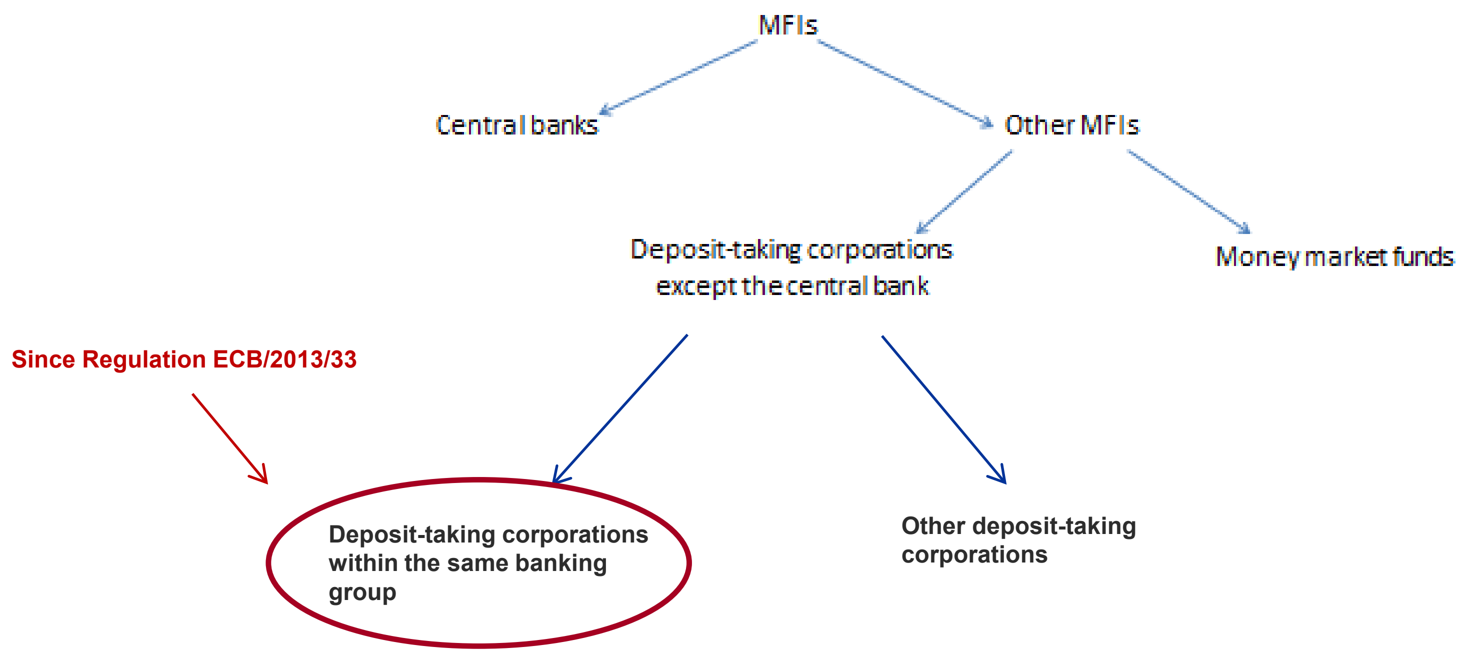
1. Macro-picture of inter-MFI lending in the Eurozone
2. The individual MFI statistics
3. Intra-group liquidity – an alternative to credit institutions' funding?
4. Investigating possible drivers of intra-group lending in the euro area
5. Conclusion and way forward

Roadmap

1	**Macro-picture of inter-MFI lending in the Eurozone**
2	The individual MFI statistics
3	Intra-group liquidity – an alternative to credit institutions' funding?
4	Investigating possible drivers of intra-group lending in the euro area
5	Conclusion and way forward

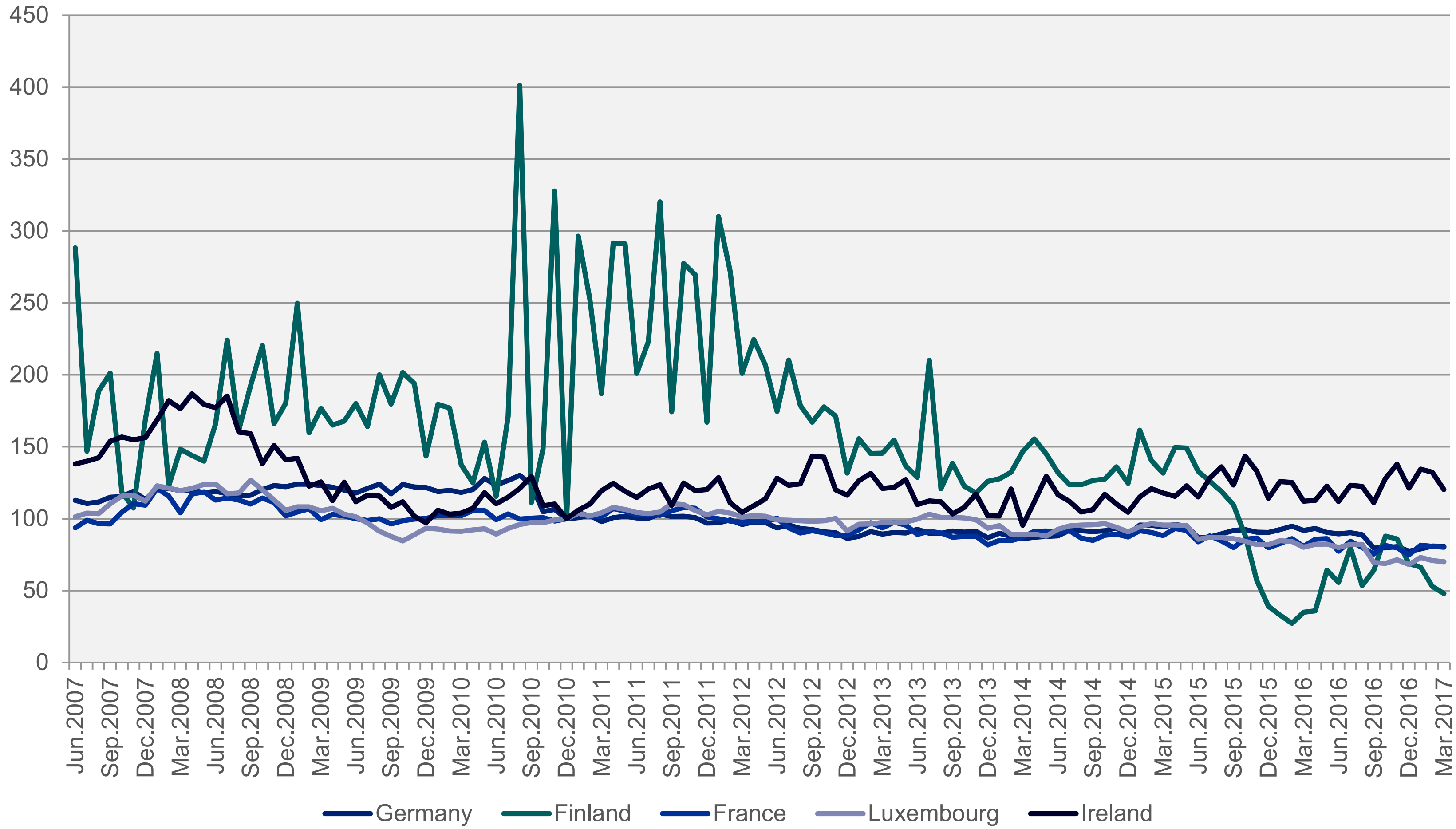
The "MFI sector" in the euro area MFI statistical balance sheet

- MFI Balance Sheet Statistics collected under an EU Regulation (four since the beginning of the Monetary Union) + ECB Guideline on Monetary and Financial Statistics.
- The latest regulation into place is Regulation (EU) No 1071/2013 of the ECB of 24 September 2



Cross-border inter-MFI loans

→ Monthly index of notional stocks reported for cross-border inter-MFI loans

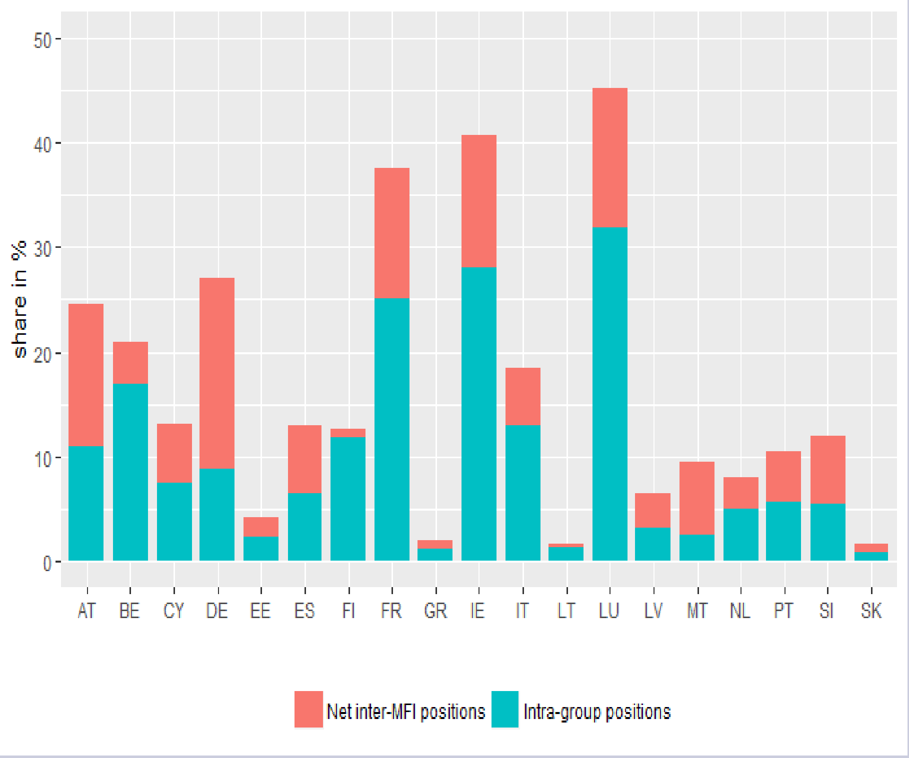


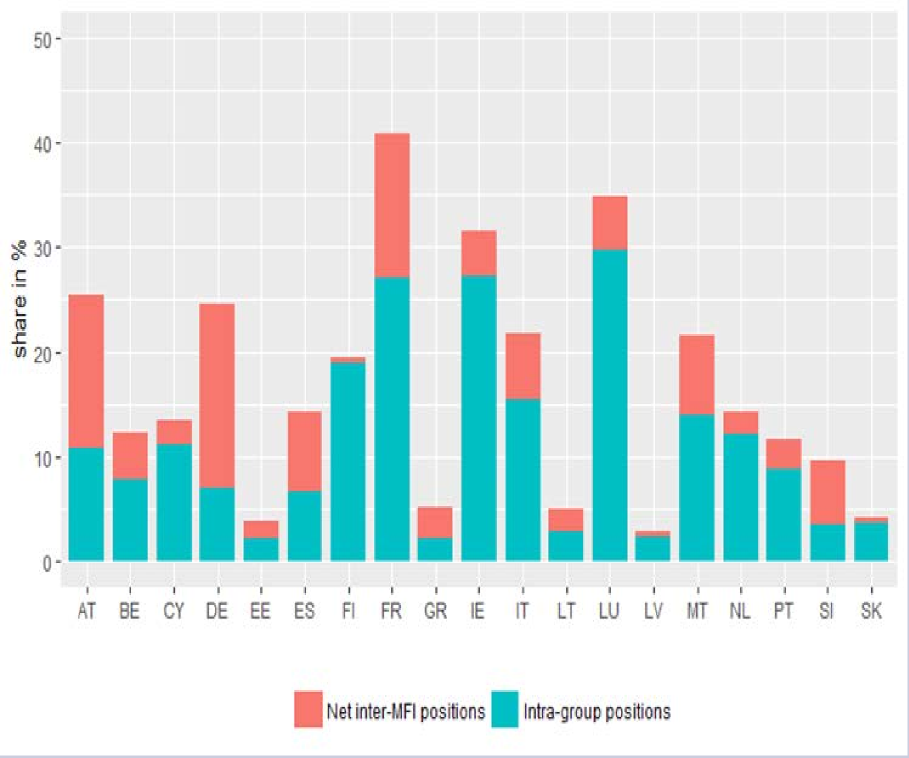
How are inter-MFI lending positions structured?

→ Intra-group positions are a relevant share of total inter-MFI lending

(*data with reference end December 2016*)

Loans	Deposits





Roadmap

1	Macro-picture of inter-MFI lending in the Eurozone
2	**The individual MFI statistics**
3	Intra-group liquidity – an alternative to credit institutions' funding?
4	Investigating possible drivers of intra-group lending in the euro area
5	Conclusion and way forward

Two data sources for intra-group lending:

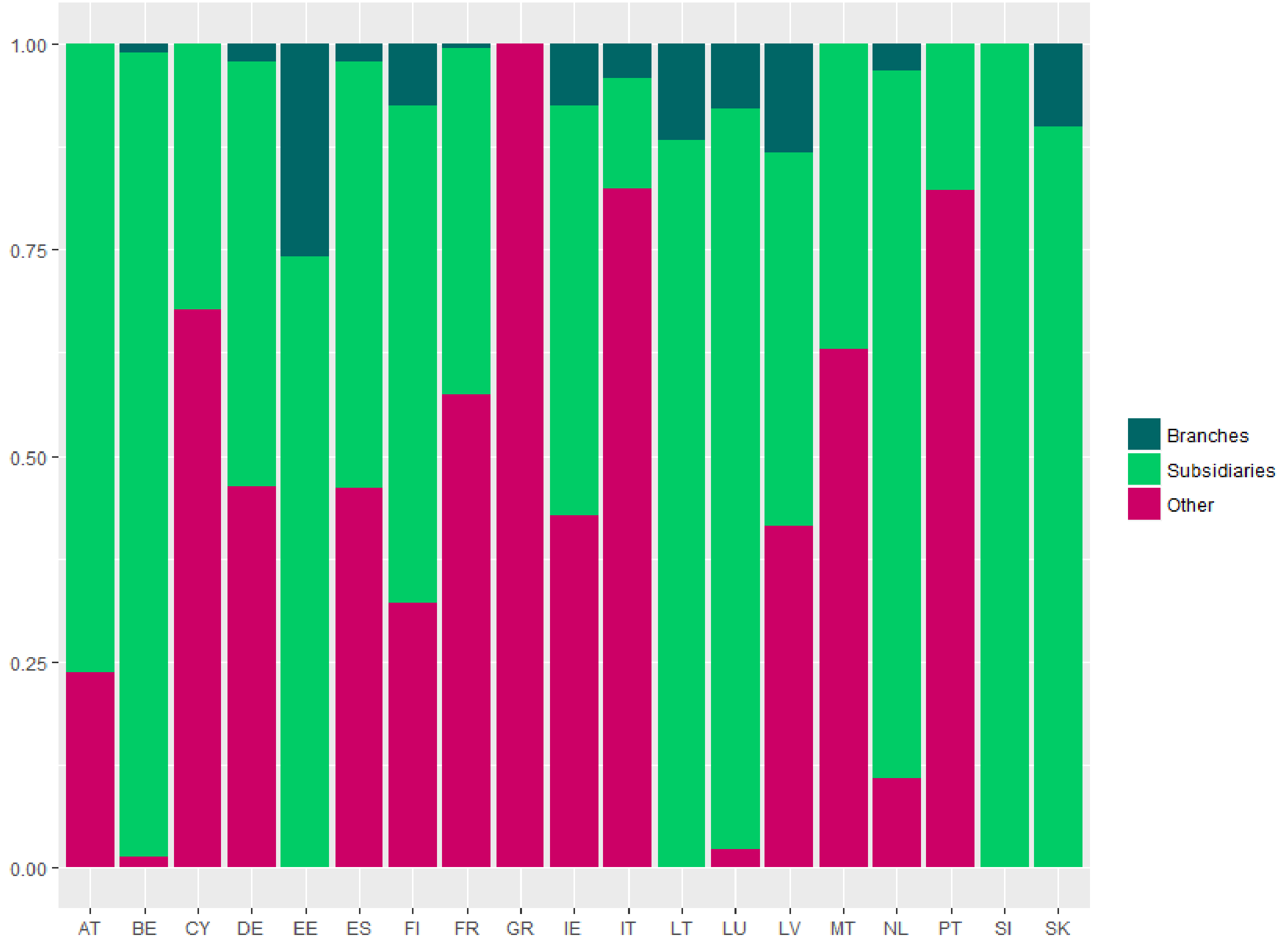
- **National aggregate MFI statistics (BSI)** → key country characteristics and dispersion across euro area countries
- **Individual MFI statistics (IBSI)** → same BSI items but reported at the level of individual MFI → panel data analysis with higher granularity → better identification of countries' national specificities

The IBSI panel:

- **Selection criteria:**
  – Bank size
  – Active participation in monetary policy operations
  – Representativeness
- Role of non deposit-taking or credit-granting specialised credit institutions in the sector of savings and cooperative banks as a channel of liquidity injection
- Selected agents are notified by their NCBs; data are first collected by NCBs
- Initial selection of approximately **300 MFIs** belonging to **115** headquarters: parent heads, some branches and some subsidiaries included

Structure of the banking sector as represented by the IBSI national samples

Data with reference December 2016

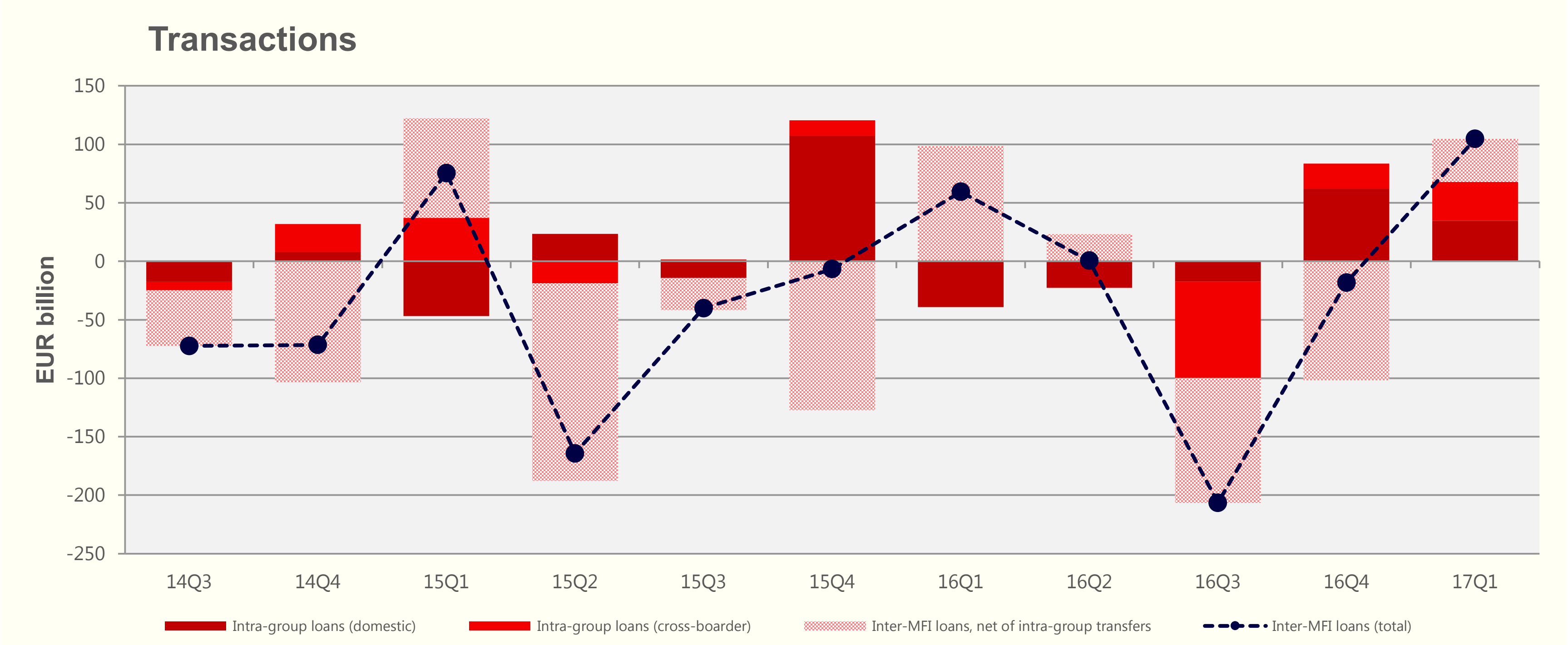


Roadmap

1	Macro-picture of inter-MFI lending in the Eurozone
2	The individual MFI statistics
3	**Intra-group liquidity – an alternative to credit institutions' funding?**
4	Investigating possible drivers of intra-group lending in the euro area
5	Conclusion and way forward

Intra-group liquidity – an alternative to credit institutions' funding?

- Basic business of credit institutions → providing credit to the real economy by granting loans.
- Two ways to obtain short-term funding:
  ✓ interbank market; *pre-crisis setting*
  ✓ national central bank; *post-crisis habit* + some banks cannot access the interbank market anymore
- The liquidity of the interbank market did not recover its pre-crisis level.
- In this context, what should we expect from intra-group lending?



Roadmap

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4	**Investigating possible drivers of intra-group lending in the euro area**
5	Conclusion and way forward

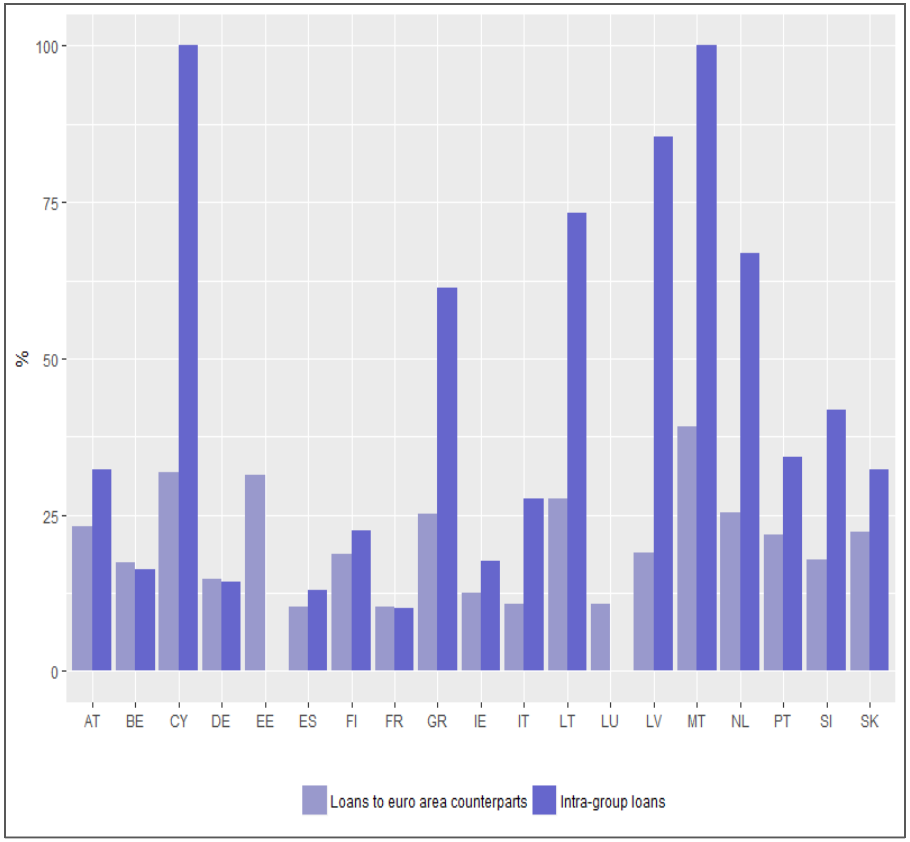
Explaining net intra-group lending compiled from MFI statistics:

- **Concentration of national markets?**
  - ➲ "predictor variable" compiled from IBSI dataset - Herfindahl-Hirschmann index of the share of loans granted to the non-MFI sector

- **Relative size of national banking sectors** as regards the lending business to the euro area non-MFI sector?

- **Ownership of the banking system?**
  - ➲ structural indicator based on the individual BSI dataset + information in RIAD "Register of Institutions and Affiliates Database"

Herfindahl-Hirschmann index at December 2016



Explaining net intra-group lending compiled from MFI statistics:

- “**Net Eurosystem funding**”? Seen as difference between monthly changes in deposits placed by the domestic NCB and the corresponding loans, i.e. deposits replaced by the borrowers on its account at the NCB
- **Issuance of debt securities** held by euro area counterparts - do parent banks issue bonds in order to finance their subsidiaries and branches?
- **Leverage ratio** (compiled from the ECB Consolidated Banking Data) – Does the level of solvency of a banking sector impact the dynamics of intra-group transactions?

Roadmap

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5	**Conclusion and way forward**

Three variables show to be significantly correlated to intra-group lending at individual MFI level

- **Size of the banking sector** → structural dimension – "big" parent banks finance many smaller cross-border credit institutions
- **Eurosystem funding** → liquidity redistribution through internal banking channels ("micro financial system") – to be better quantified!
- **Issuance of debt securities** → countries with a better integrated and developed financial sector may provide funding to entities having less access to financial markets

→ participates to market integration in the euro area

Way forward

- **Network analysis** making more extensive use of banking group information in RIAD
- **Fine-tuning of the panel data analysis** by better specifying entities solo banks versus subsidiaries versus branches - *clustering*

Thank you

for your attention

Questions?

Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

IFC-National Bank of Belgium Workshop on "*Data needs and Statistics compilation for macroprudential analysis*"

Brussels, Belgium, 18-19 May 2017

Euro-area derivatives markets: structure, dynamics and challenges[1]

Mario Ascolese, Annalisa Molino, Grzegorz Skrzypczynski,
Julius Cerniauskas and Sébastien Pérez-Duarte,
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.

Euro area derivatives markets: structure, dynamics and challenges

Mario Ascolese, Annalisa Molino, Grzegorz Skrzypczynski, Julius Cerniauskas, Sébastien Pérez-Duarte (European Central Bank)

Abstract

Thanks to the reporting obligation established by the European Market Infrastructure Regulation (EMIR), EU regulators have now access to an unprecedented amount of data on derivatives markets through authorised trade repositories (TRs). EMIR data are a precious information source to monitor financial stability; after more than 2 years, however, a number of challenges still prevent their wide-spread use for macro-prudential policy purposes. First, as they reflect an intrinsically complex and fast-changing market, EMIR data are difficult to analyse; second, the data collection process established by EMIR and the significant data volume pose a number of technical challenges; finally, data quality concerns still discourage users from working with the dataset. As a result, there is so far relatively little empirical research in this field.

The objective of this paper is twofold. First, it aims at investigating the evolution of the structure and the dynamics of the euro area derivatives market between 2014 and 2017. The analysis focuses on the effect of the implementation of EMIR obligations, such as those on clearing and risk mitigation, as well as the impact of other institutional and economic developments in the EU. Furthermore, it relies on techniques from network theory to monitor the connectivity and stability of the market over time. The results lay the ground for further work, aimed at monitoring the network of main market participants and developing early warning indicators for supervisory purposes. Second, the paper reviews and analyses the main challenges linked to the use of EMIR data – from data quality to data volume and data integration – that, once overcome, will allow financial stability authorities to fully and systematically use this dataset in the implementation of their respective mandates.

Keywords: derivatives, EMIR, network analysis, financial stability

This paper should not be reported as representing the views of the European Central Bank. The views expressed in this paper are those of the authors and do not necessarily reflect those of the European Central Bank. The authors would like to thank Yohan Theatre for excellent research assistance.

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Introduction

Crises are often regarded as a powerful trigger for non-incremental public policy change.[1] From this viewpoint, it is easy to recognise in the far-reaching reform program of the over-the-counter (OTC) derivatives trading and post-trading rules a "child" of the 2008 economic crisis. Starting from the commitment taken by G20 leaders in Pittsburgh in 2009, regulators at global and national level have developed – and are still in the process of developing – a new framework to ensure a more transparent and resilient functioning of OTC derivatives markets.[2]

The Pittsburgh commitment encompassed five elements: (1) reporting of all OTC derivatives contracts to trade repositories; (2) moving of all standardised OTC contracts on exchanges; (3) clearing obligation through central counterparties (CCPs); (4) introduction of margin requirements for non-cleared trades and (5) periodic assessment of the reforms' implementation.[3] Almost eight years later, according to the Financial Stability Board (FSB),[4] progress has been substantial in all areas, with legislation on trade reporting, central clearing and margin requirements for non-cleared trades now in force in most G20 countries.

In the European Union, 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) established the contours of the new EU regime for OTC trading and post-trading. EMIR established a clearing obligation for most trades and risk-mitigation techniques for non-cleared trades and introduced, since 2014, the obligation to report all OTC and exchange-traded derivatives transactions. As correctly pointed by Abad et al. (2016), what used to be one of the most opaque markets suddenly became one of the most transparent: to date, over 60 authorities across the EU have access to granular data on derivatives transactions according to the policy and geographical scope of their mandates.

Through EMIR, the European Central Bank (ECB) is entitled to access transactional-level EMIR 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.[5] The objective of this paper is to assess, almost three years after the entry into force of the EMIR reporting obligation, how and to which extent EMIR data can be used to monitor euro area OTC derivative markets, and to take stock of the challenges linked to this uniquely complex and large dataset. In a first section, we review the state of play and the challenges of the data collection. In a second step we walk through the data cleaning process, which allows us in a third section to briefly describe the characteristics of three derivatives asset classes. The fourth section is a short analysis of the state of the clearing obligation as viewed from the data, while the fifth and final section presents some first results of the network analysis of EMIR data.

1 See among the others Nohrstedt and Weible (2010).

2 See ECB (2016) for more information on the background of the post-crisis reforms of OTC derivatives markets.

3 "All standardized OTC derivative contracts should be traded on exchanges or electronic trading platforms, where appropriate, and cleared through central counterparties by end-2012 at the latest. OTC derivative contracts should be reported to trade repositories. Non-centrally cleared contracts should be subject to higher capital requirements. We ask the FSB and its relevant members to assess regularly implementation and whether it is sufficient to improve transparency in the derivatives markets, mitigate systemic risk, and protect against market abuse." Pittsburgh Summit Leader's Statement, 2009, pp. 8-9.

4 See FSB (2017).

5 The ECB is also entitled to access position-level data for euro-denominated derivative contracts. However, due to the lack of clear guidance on position definition, these data are so far de facto unavailable.

1. The EMIR data: state of play and challenges

1.1 The EMIR reporting framework

After the entry into force of the EMIR reporting obligation in February 2014, EU competent authorities gained access to an unprecedented amount of granular data mapping the derivatives trade activity of all counterparties established in the EU.

The information to be reported in compliance to 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.[6] The EMIR reporting template in force before 1 November 2017 is summarised in Table 1.

Overview of EMIR reporting fields — Table 1

Counterparty data	
Timestamps (reporting, execution, clearing…)	Counterparty side (buy or sell)
Counterparty ID/name	Broker, reporting entity, beneficiary ID
Counterparty nature (financial or non-financial) and sector	Valuation and collateral information
Contract (or common) data	
Contract type	Product and underlying IDs, notional/deliverable currencies
Details on the transaction	Trade ID[7], execution venue, maturity/settlement/termination date, price, notional, delivery type etc.
Risk mitigation/reporting	Confirmation means and timestamp.
Clearing	Clearing status/obligation/timestamp, CCP identifier, intragroup transaction.
Interest rates	Interest rates, payment frequencies, day count conventions, reset frequencies for both trade legs.
FX	Exchange rate, exchange rate basis, forward exchange rate.
Commodities	Commodity base, further details on energy derivatives.
Options	Option type/style, strike price.
Modification to the contract (life-cycle)	Action type (e.g. new, modify, error, cancel, compression, valuation).

Source: ECB, based on Regulation (EU) 1247/2012 and Regulation (EU) 148/2013

When both counterparties are subject to the reporting obligation, EMIR establishes a "double-reporting" regime, by which both of them are bound to individually report the same transaction after agreeing on the content of common fields.[8]

6 Regulation (EU) 1247/2012, Regulation (EU) 148/2013 and the respective amendment acts, Regulation (EU) 105/2017 and Regulation (EU) 104/2017.

7 Trade and Product IDs are expected to be replaced by uniform global unique transaction identifier (UTI) and unique product identifier (UPI), once developed. See below Section 1.2.1.

Information is currently collected by six authorised trade repositories (TRs) that validate and stock the data submitted by market participants and share it with competent authorities.[9] Furthermore, alongside the confidential dataset accessible by competent authorities, TRs also have to publish weekly aggregate data on their websites, with the objective to increase transparency also towards the general public.

Therefore, together with the traditional BIS semi-annual and triannual surveys, researchers and authorities investigating the European derivatives markets obtained access to two new data sources, the EMIR "confidential" data and the EMIR "public" data (see Table 2).

Comparison of main existing data sources on OTC derivatives markets

Table 2

Data source	Subject scope	Content scope	Frequency
BIS semi-annual and triannual survey on OCT derivatives	c. 400 banks and other derivatives dealers based in 13 countries (incl. 8 EU Member States and 6 euro-area countries) and 33 countries (incl. 18 EU Member States and 11 euro-area countries).	Notional and market value of OTC derivatives of all 5 asset classes	Semi-annual and triennial
EMIR confidential TR data	All euro area residents. All euro area reference entities. All reference obligations being sovereign debt of euro area member countries.	85 (129 as of November 2017) data fields for OTC and ETD contracts of all 5 asset classes	Daily
EMIR public data	All EU-residents.	Transaction volumes, outstanding notional values and market values of OTC and ETD contracts of all 5 asset classes	Weekly

Source: BIS (2016) and Osiewicz et al. (2015)

Thanks to the depth and breadth of their coverage, EMIR data offer a unique and unprecedented viewpoint on European derivatives markets that allow monitoring the accumulation of risks at market and counterparty level, to follow developments in market structure, and to develop tools for macro-prudential policies.[10]

At the same time, three years after the entry into force of the reporting obligation, the usability of EMIR data by competent authority is still hindered by a number of challenges, which we review and analyse in the rest of this section.

1.2 EMIR data: challenges and way forward

1.2.1 Data quality and comparability across TRs

One of the distinguishing features of EMIR data is surely their complexity and the variety and intricacy of the quality issues they pose to researchers.

8 While this provision increases the volume of data and poses some reconciliation issues, especially when counterparties report their trade to two different TRs, it is still regarded by regulators as a useful tool to validate and complement information.

9 These are (i) CME Trade Repository Ltd. (CME), (ii) DTCC Derivatives Repository Ltd. (DDRL), (iii) ICE Trade Vault Europe Ltd. (ICE), (iv) Krajowy Depozyt Papierów Wartościowych S.A. (KDPW), (v) Regis-TR S.A. (Regis-TR), and (vi) UnaVista Limited (UnaVista). A new TR, Bloomberg Trade Repository Ltd, was authorised by ESMA with effect from 7 June 2017 but at the time of writing does not report any transaction.

10 See Abad et al. (2016).

The detailed content and format of EMIR reports was established by delegated regulations and implementing acts (e.g. Regulation (EU) 1247/2012 and Regulation (EU) 149/2013). The provisions included in these pieces of legislation, however, did not prove entirely effective in guaranteeing a sufficient level of standardisation in the main data elements (i.e. counterparty and product ID, trade ID and valuation information) to ensure comparability within and across TRs. Furthermore, the lack of sufficiently stringent data validation procedures by TRs resulted in a significant volume of missing or misreported information, especially at the earliest stages of the reporting obligation.[11]

While current data still suffer from these “original sins”, regulators have been working to gradually overcome the abovementioned problems both by amending EU legislation and guidelines and by supporting international work on OTC derivatives data standardisation.

In fact, a multilateral process coordinated by the Committee on Payments and Market Infrastructures (CPMI) and the International Organisation of Securities Commission (IOSCO) is set to deliver detailed guidelines for unique trade and product identifiers.[12] Once implemented, these standards are expected to substantially improve data quality at national level and, in the medium term, allow for global aggregation of OTC derivatives data. The further diffusion of other internationally agreed standards – most prominently the legal entity identifier (LEI) and the international security identification numbers (ISIN) – will also substantially contribute to increase the robustness and facilitate the use of EMIR data.

Furthermore, the adoption of the revised delegated and implementing acts (Regulation (EU) 104/2017 and Regulation (EU) 105/2017) laid the ground for data quality improvements from 1 November 2017, also by making sure that the EU reporting regime incorporates global standards (such as LEI or ISIN codes) to the maximum extent practicable and as timely as possible. Table 3 summarises the content of Regulation (EU) 104/2017 and Regulation (EU) 104/2017 and their impact on data quality.

11 In order to improve the quality of reporting, ESMA published two sets of validation rules to be performed by TRs. See https://www.esma.europa.eu/policy-rules/post-trading/trade-reporting.

12 This work is being coordinated by the CPMI-IOSCO Harmonisation Group (HG), under the auspices of the FSB. The HG is working to enhance the use of open standards, including the UPI (unique product identifier) and the UTI (unique transaction identifier), by drafting recommendations in each of these areas. UTI and UPI Technical Guidance documents have been recently published. Subsequently, the group will also develop a proposal for a governance framework of these standards. See http://www.bis.org/cpmi/index.htm.

Summary of the main new features of EMIR reporting standards

Table 3

Reporting field	Change in reporting standards	Expected result
Counterparty ID	Mandatory use of LEI. Introduction of a LEI/client code flag for the other counterparty.	Significant improvement in counterparty identification.
Corporate sector	Introduction of dedicated taxonomies for financial and non-financial corporation.	Significant improvement in identification of sectors.
Counterparty nature	Introduction of "CCP" and "Other", alongside "financial" and "non-financial" types.	Possibility to easily and clearly identify CCPs.
Counterparty side	Introduction of specific criteria to identify buyer/seller according to the instrument type.	Fundamental improvement as mandatory criteria for the buyer/seller identification are currently lacking.
Value of contract	Format specification (negative sign, decimal mark), and introduction of a distinctive tag for CCP valuation.	Significant improvement in the interpretation of contract value. However, heterogeneous valuation practices among counterparties may still result in conflicting information.
Margin and collateral	Detailed indication of initial, variation margin (received and posted) as well as of excess collateral.	Significant improvements to ensure correct and robust margin calculation.
Contract type	Establishment of a unique taxonomy.	Significant facilitation vis-à-vis current situation, where contract and product information are reported in the same field.
Product classification and identification (incl. underlying)	Restriction of taxonomies to CFI and UPI for classification and ISIN and AII for identification.	Significant clarification. Further standardisation expected with implementation of the UPI guidance.
Trade ID	Mandatory use of UTI. In the meantime, unique code.	Implementation of UTI guidance to facilitate trades pairing and matching.
Venue of execution	Introduction of mandatory use of MIC codes.	Significant improvement.
Price (incl. for options)	Introduction of mandatory indication of price notation (units, percentage or yield).	Significant improvement to ensure correct interpretation of reported values.
Notional	Format specification (negative sign, decimal mark).	Useful improvements to avoid misreporting and decrease the number of outliers.
Timestamps	In general, clarification of the timestamp format to be used.	Useful improvements linked to format standardisation.
Rates	Clarification of rate format (percentage, negative sign, decimal mark).	Crucial improvement for interest rate derivatives analysis.
Rate payment and reset frequency	Specification of the time period (year, month, week, day).	Significant improvement to obtain correct tenor data.
Floating rate	Introduction of a non-exhaustive list of the most common indexes.	Facilitation of floating rate identification.
Exchange rates	Clarification of rate formats (decimal mark, negative sign).	Crucial improvement to increase usability of rates data for FX derivatives.
Option type	Clarification of criteria to report swaptions.	Useful complement to the existing rules.
Credit derivatives	Introduction of dedicated data fields to identify contract seniority, underlying, payment frequency…	Significant improvement that will allow better understanding of credit derivatives data.
Action types	Introduction of specific action types for correction and early termination of trades. Introduction of specific indication on the trade vs. position level of the contract modification.	Significant improvement that will allow more robust analysis of trade activity reports.

Source: ECB, based on Regulation (EU) 104/2017 and Regulation (EU) 105/2017.

Finally, it can also be assumed that some "economies of learning" will come into play both on the side of authorities and on the one of reporting entities and TRs: in this regard, a well-structured and coordinated feedback process involving all EMIR data users seems crucial to ensure coordination and address the most widespread data quality issues in a timely and efficient manner.

1.2.2 Data volume and accessibility

Another issue that still prevents a widespread use of EMIR data by competent authorities is the very large size of datasets. The ECB, for instance, receives reports including tens of millions of observations on a daily basis, which is far beyond the size of other datasets traditionally processed and utilized by regulators. Due to the amounts of data, most of the authorities have so far embarked mostly on ad hoc analyses, limited to specific asset classes and limited periods. Only by building state-of-the-art infrastructures and using appropriate big-data techniques that allow for distributed storing and computing it will be possible to use EMIR data to monitor markets and counterparties on a regular basis, e.g. through real-time indicators.

Another technical challenge to the use of EMIR data is the one of accessibility. Currently, data are shared by TRs with competent authorities on an individual basis. In practice, this means that each authority needs to establish connection with six TRs, sometimes operating on different systems with different technical specifications. As a result, the margins to improve efficiency by avoiding duplication of work within and across authorities that have access to different subsets of the EU EMIR dataset are very high. The revised technical standards under Article 81 of EMIR offer some solutions to this suboptimal state of play,[13] in particular by introducing uniform XML templates and specifying the technical requirements for data transmission from TRs to authorities.

[13] The amended technical standards were adopted by the European Commission as Commission Delegated Regulation (EU) No 2017/1800 on 29 June 2017.

2. Putting EMIR data to the test

Notwithstanding the significant challenges outlined in Section 1, EMIR confidential data have attracted significant interest and European authorities have started explorative research work to test their potential.

In this section, we first present the euro area dataset accessible to the ECB, and show concretely through our analysis how the complexity of the EMIR reporting framework impacts on the usability of EMIR data. Subsequently, we describe in detail the cleaning and filtering process that, starting from the voluminous and intricate files provided by TRs, leads to a subset of data, fit for analytical purposes. The result of this process will be the analysed in Sections 3 to 5.

2.1 Narrowing the scope of the analysis

We focus our analysis on OTC trades for the three largest derivatives asset classes: interest rate, credit, and currency derivatives.[14] Figures 1.1 and 1.2 show the breakdown of the trades collected by TRs between April 2015 and March 2017, as resulting from the data published online by the six EU TRs.[15] When considering the total notional outstanding, interest rate derivatives are the largest asset class, followed by currency and credit derivatives. It is interesting to note a jump in the notional value of currency derivatives from the second half to the end of 2015 and in the first quarter of 2017: the increase, as highlighted below in Figure 2, is generated by two specific TRs and seems likely to be due to outlier values rather than to actual changes in market structure. In this regard, it is useful to recall that concerns on the quality of EMIR public data are well known[16] and were the object of the ESMA consultation on a proposal for new technical standards.[17]

Figure 1 also shows that, although interest rate derivatives account on average for the largest share of the total OTC derivatives outstanding notional, currency derivatives are traded in higher volumes: this confirms previous findings that the currency market is more fragmented and characterised by high number of contracts of relatively low value.[18]

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14 See BIS (2016). EMIR also mandated ETD transactions' reporting; however, this analysis only focuses on OTC data.

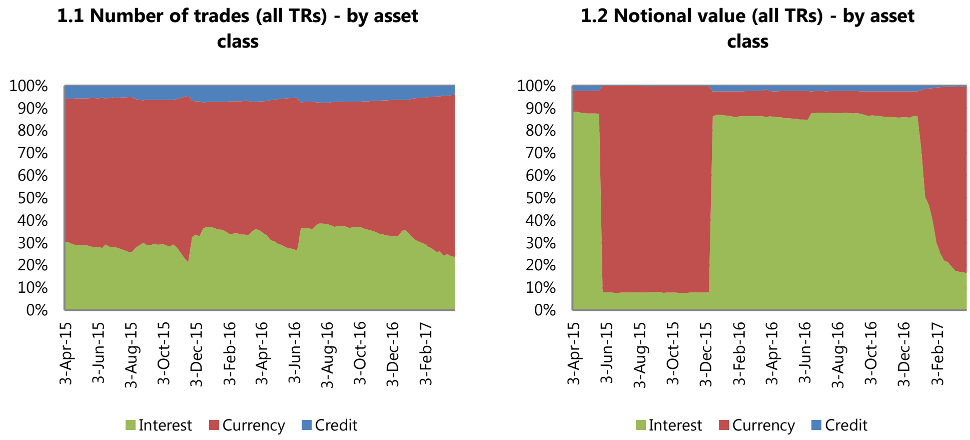
15 The obligation for TRs to publish weekly aggregates entered into force in April 2015.

16 As highlighted by Osiewicz et al. (2015), TR public data present a number of data quality concerns. In the case of currency derivatives, in particular, the series of one of the TRs (UnaVista) seems to include a number of disproportionately high notional values that may need to be treated as outliers.

17 See ESMA Final Report on the draft technical standards on data to be made publicly available by TRs under Art. 81 of EMIR, available at https://www.esma.europa.eu/sites/default/files/library/esma70-151-370_final_report_tr_public_data_under_emir.pdf.

18 See Abad et al. (2016)

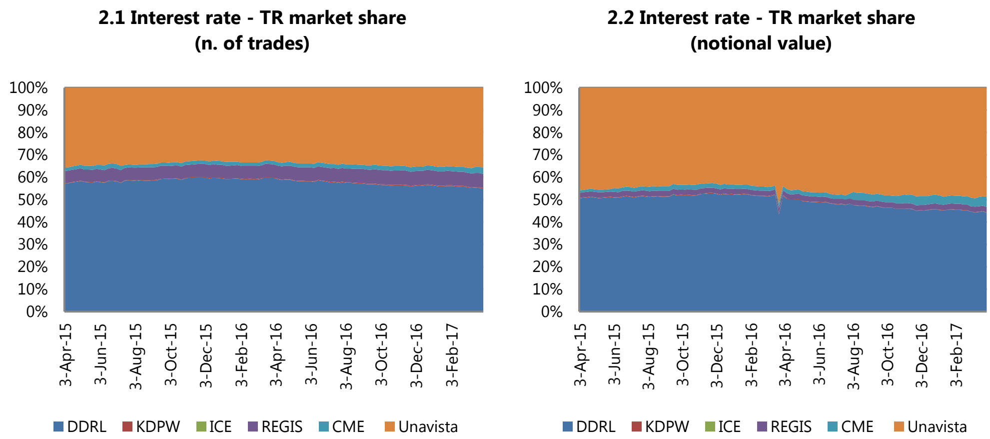
Figure 1: Breakdown of the dataset by asset class.



Source: ECB calculations based on weekly data published by the six authorised EU TRs.

The lack of standardisation in reporting standards among TRs makes inter-TR analysis complex and subject to potential mistakes in aggregation and misinterpretations. With a view to selecting a representative TR, we plot in Figures 2 to 4 the relative share of each of the six authorised EU TRs in the three asset classes under consideration.[19]

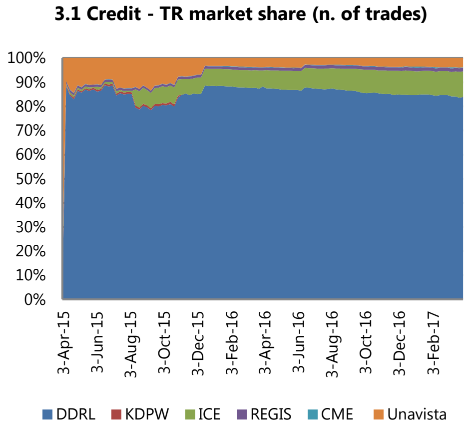
Figure 2: TR shares in the interest rate derivatives reporting market.

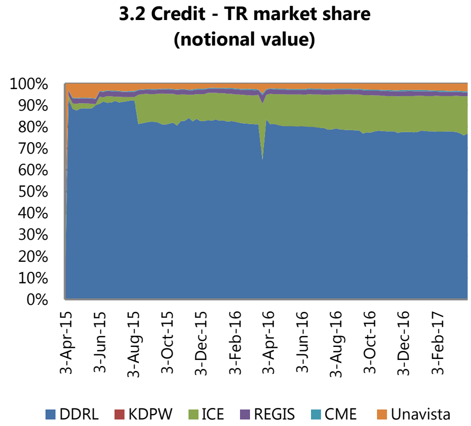


Source: ECB calculations based on weekly data published by the six authorised EU TRs.

19 The methodology followed in computing the data presented in Figures 2 to 4 is the following: (1) we keep all trades labelled by TRs as "double-sided", as TRs are expected to pair the two legs and report the net value themselves; (2) we count half of the "single-sided" trades between EEA counterparties, assuming that they are duplicate because of unsuccessful pairing and thus their inclusion would lead to double-counting; (3) we keep all trades labelled as "single-sided" when one of the counterparties is non-EEA, as the reporting obligation only covers EEA-based counterparties.

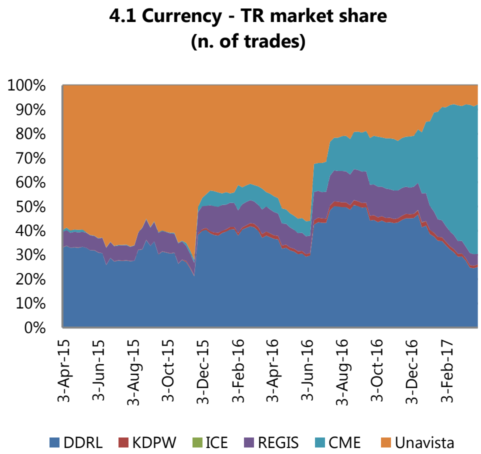
Figure 3: TR shares in the credit derivatives reporting market.

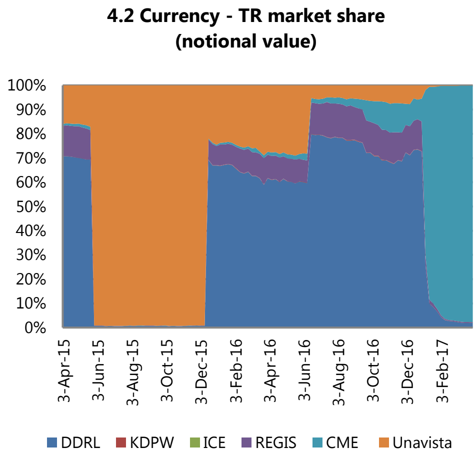




Source: ECB calculations based on weekly data published by the six authorised EU TRs.

Figure 4: TR shares in the currency derivatives reporting market.





Source: ECB calculations based on weekly data published by the six authorised EU TRs.

DDRL appears as the TR with the largest share across the three markets, although UnaVista has a comparable weight in the currency trades. Focusing on DDRL data also allows for comparability with previous works that have followed the same approach.[20]

DDRL provides different trade reports, the main ones being the “trade-state”, a snapshot of all outstanding transactions at a given moment (usually at the end of the day), and the “trade-activity”, that records all new transactions as well as modification of existing transactions (e.g. through compression, termination etc.).

As our objective is to sketch and analyse the euro-area OTC derivatives market structure, we concentrate on trade state data, which seem better fit for purpose. In particular, we use end-of-month trade state reports issued between October 2014 and March 2017.[21]

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20 See among the others Abad et al. (2016), Kenny et al. (2015) and Cielinska et al. (2017).

21 The ECB started collecting TR data in April 2014. However, in light of the low data quality of early reports – where, in particular, data on market value are almost completely missing – we restrict the scope of our analysis to a shorter period, starting from October 2014.

2.2 The de-duplication procedure

One of the distinguishing features of the EU reporting regime is the obligation for *both* counterparties to a trade to report it to TRs. Also in the context of a single-TR analysis, it is therefore necessary to account for the double-reporting and "de-duplicate" the dataset so that each trade appears only once in the dataset.

In a context of improving data quality, the double-sided reporting obligation has proven effective for regulators to match and validate reported information. At the same time, however, it poses some analytical complications, especially as – due to the lack of a global UTI – it is sometimes difficult to reconcile the information on the two sides of the trades within and across different TRs. It is therefore important to establish some consistent criteria in de-duplicating data. In this regard, we assume that the most recent reports, which should include modification or correction of previous reports, shall be more reliable and therefore retained in case of conflicts and inconsistencies.

Based on this assumption, we proceed first to drop the duplicates where a same trade identifier is associated to two trades with the same common data. In cases when different common data are associated to the same trade identifier, we retain the information provided by the latest report. We also find some occurrences when the same trade is reported more than twice: in this cases, if the report in excess is generated by the same counterparty, all but the latest report from that counterparty are dropped; if, on the other hand, the multiple reports are issued by multiple counterparties, the most recent reports from the buyer and the seller are retained.

2.3 Dataset overview

Our de-duplicated dataset includes a total of 90 end-of-month trade state reports, 30 for each asset class. Table 4 compares the total notional outstanding for the three asset classes resulting from our dataset with the corresponding data from the BIS semi-annual OTC derivatives dataset.[22] While the comparison is methodologically somewhat inaccurate due to the differences in product and subject scope, this raw comparison highlights the implausibility of the content of some EMIR reports, especially the oldest ones. In fact, EMIR data would seem to have a substantially higher aggregate notional value than the global aggregate collected by the BIS.

Comparison between BIS global aggregates and EMIR notional outstanding

Notional value before cleaning – ratio of EMIR to BIS semi-annual survey total — Table 4

	Dec-14	Jun-15	Dec-15	Jun-16
Credit derivatives	521%	628%	810%	818%
Interest derivatives	10,829%	1,623%	1,590%	1,202%
FX derivatives	2,002%	44%	38%	46%

Source: ECB calculations, based on DDRL EMIR confidential data and BIS semi-annual survey on OTC derivatives (global aggregate).

22 As outlined in Fache Rousová et al. (2015), the comparison between EMIR and BIS OTC derivatives data is subject to a series of caveats due to the different product (e.g. BIS only collects information for CDS and not for other credit derivatives) and subject scope (e.g. BIS collects data from large dealers on a global scale, while EMIR gathers data from EU counterparties).

2.4 Cleaning process

Based on the contribution by Abad et al. (2016), we design a two-stage cleaning procedure for the three asset classes: first, we apply some general cleaning rules, valid across different asset classes; subsequently, we clean the three datasets based on further asset-specific features.

2.4.1 First stage: general cleaning across asset classes

The first stage of the cleaning process focuses on four elements: the value of contract, the notional value, the counterparty identifier and the execution timestamp. For each of them, based on existing regulatory provision and following Abad et al. (2016), we develop a number of cleaning rules.

Value of contract

Under EMIR, financial counterparties and non-financial counterparties above the clearing threshold are obliged to report the mark to market or, when appropriate, mark to model value of outstanding contracts on a daily basis. As outlined in ESMA's EMIR Q&A,[23] the mark to market value should be based on the end of day settlement price of the market (or CCP) from which the prices are taken as reference. For transactions cleared by a CCP, the CCP shall make the results of its valuation available to the counterparties, who shall individually report it.

In light of the heterogeneity of needs and practices across the market, no further valuation guidance is in force; as a result, when both counterparties are bound to report the contract value, their valuation can be different, especially when contracts are marked-to-model. Furthermore, some ambiguity persists on the format, with some counterparties reporting the contract value as an absolute value and others, more appropriately, as a positive or negative value depending on their role in the contract.

In order to account for inconsistencies in double reports, we compute a relative difference measure to capture the spread between the two counterparties' valuations.[24] As differences stemming from different valuation techniques, valuation times and exchange rates fluctuations are legitimate, we set a tolerance threshold and drop only observations where the relative difference between the two absolute values is higher than 5%.

Most importantly, we find a high number of missing values in the value of contract fields; ECB (2016) reports that the issue is mainly due to counterparties' failure to notify the cancellation of cancelled trades, and TRs failing to incorporate cancellation in the repository. Therefore, we drop those trades where no valuation is available from neither of the counterparties.

Notional value

All counterparties covered by EMIR are bound to report the notional value of the contracts they trade. In the context of the EMIR reporting framework, the notional is a common variable that counterparties should agree upon and report consistently.

Further to being used as the main indicators of derivatives' markets size, the notional is also important from a regulatory point of view, as in accordance with Article 11 of Regulation (EU) 149/2013 the clearing thresholds – that define the scope of the clearing obligation for non-financial counterparties – are computed on the basis of notional values.

Based on these considerations, we drop the contracts where the notional value is missing or, in case of double-sided reports, mismatching. Figures 1 and 2 highlight the presence of

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[23] See https://www.esma.europa.eu/questions-and-answers

[24] The relative difference measure is computed as: (counterparty 1 valuation – counterparty 2 valuation)/average valuation. All values are converted in EUR using the exchange rates published by the ECB at the last day of each month.

outliers in the notional fields; we therefore follow Abad et al. (2016) and set a lower bound (EUR 1,000) and an upper bound (EUR 10 billion) to discard contracts with implausible notional values, including negative and zero values.[25]

Counterparty ID

The adoption of Commission Implementing Regulation (EU) 105/2017 established the mandatory use of the LEI in EMIR reporting starting from November 2017. The LEI allows a punctual identification of counterparties and, via the integration with commercial datasets, of their characteristics (including sector, country of establishment etc.). Furthermore, the LEI allows to track an entity's belonging to a group or holding, an important information to obtain an accurate picture of large and systemic counterparties' activities and exposure.

However, not all counterparties have – or used to have – an LEI, and are therefore partially or completely unidentifiable. After dropping observations where the counterparty ID is not an LEI, in order to gather the information on sector, country and – if applicable – of the group that has ultimate ownership of the counterparty, we merge the remaining observations with the Global Ultimate Ownership information of the ORBIS dataset.[26]

Timestamps

When they report their trade to TRs, counterparties must indicate the exact time and date when the transaction was executed. In some cases, the reported execution date is later than the report date or unrealistic. Therefore, we drop all observations with unrealistic execution timestamp (i.e. later than the report date or earlier than 1990) and those where the execution timestamp is missing, suggesting possible cancellation or termination of the trade.

Results

As highlighted by Figure 5, the monthly number of observations after the implementation of the cleaning procedure is relatively stable over time across the three asset classes. We still observe, however, a drastic increase in the number of credit derivatives trades in 2015 accompanied by a peak in notional value, probably due to outlier values. It is difficult to link the movements observed in the dataset to specific market events, due to concerns over data quality, especially at the earliest stages of the reporting obligation. At the same time, the stability of the dataset both in terms of notional value and in terms of number of reported trades since 2016 points to an overall improvement in data quality that may allow for more robust analyses.

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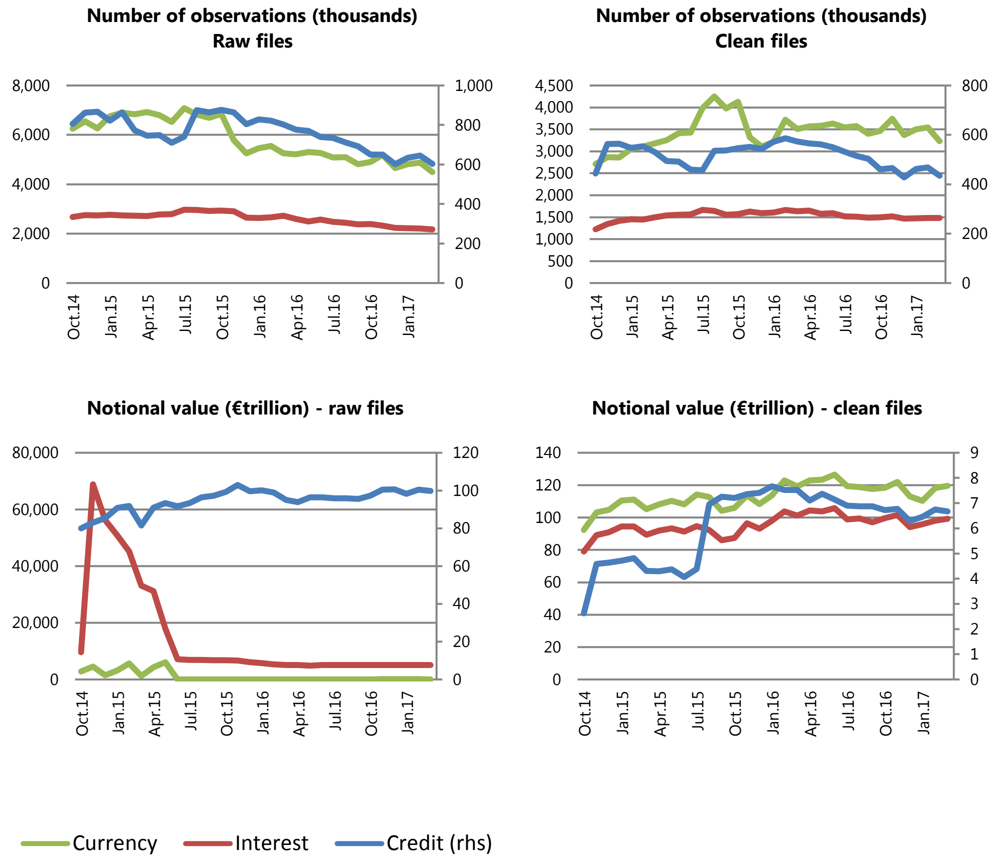
[25] All values are converted in EUR using the exchange rates published by the ECB at the last day of each month.

[26] See https://www.bvdinfo.com/en-gb/our-products/company-information/international-products/orbis

Figure 5: Raw vs. clean files comparison, all asset classes.



Source: ECB calculations, based on DDRL EMIR confidential data.

Figure 6 digs further into the composition of misreported trades, i.e. the shares of observations dropped at each step of the cleaning process.

In terms of number of trades, misreporting of contract values seems responsible for the largest part of data quality concerns. This finding is consistent with previous literature.[27] Interestingly, we find that those trades have an extremely high notional value, suggesting that they also account for a significant share of observations with outlier notionals. Another interesting feature emerging from Figure 6 is the significant number of outlier notional values in 2014 and early 2015 interest rate and currency derivatives reports. The jump in the time series after June 2015 maybe explained by the introduction of new TR validation rules or to the correction of previously misreported trades by reporting entities.

Figure 6 and Table 7 also show a gradual but steady improvement in the quality of EMIR data over time. In the case of interest rate and credit derivatives, this trend seems to result from broader use of LEIs as counterparty IDs, a practice that will become mandatory as of November 2017.[28] The number of outlier notional values has also decreased sensibly both for interest rate and currency derivatives. On the other hand, while the number of missing or misreported market value has declined for all asset classes, it still remains high: stricter TR validation rules as well as further regulatory clarifications aimed at ensuring harmonised valuation and reporting practices will be key to improve the quality and reliability of the EMIR data in the coming months and years.

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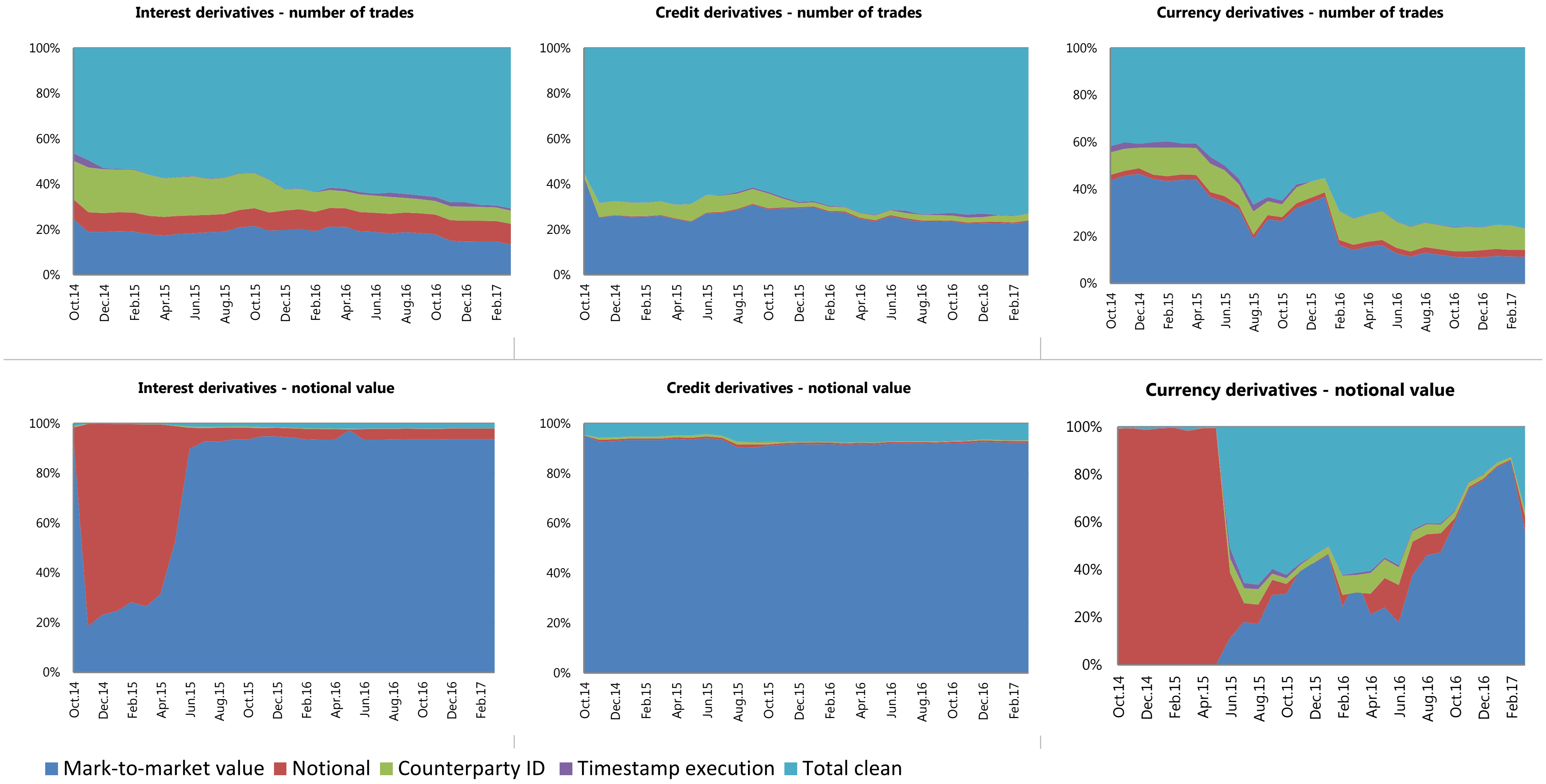
[27] See e.g. Abad et al. (2016), ECB (2016).

[28] See Art. 1 of Regulation (EU) 105/2017.

Figure 6: Observations (number and notional value) dropped at each step of the first stage of the cleaning procedure.



Source: ECB calculations, based on DDRL EMIR confidential data.

Maximum, minimum and average number of observations and notional value dropped at each step of the first stage of the cleaning procedure

Table 5

	2014 4Q						2015						2016						2017 1Q						Overview					
Interest	N.of observations			Notional outst.			N.of observations			Notional outst.			N.of observations			Notional outst.			N.of observations			Notional outst.			Clean number of observations			Clean notional outstanding		
	Min	Avg	Max	Min	Avg	Max	Min	Avg	Max	Min	Avg	Max	Min	Avg	Max	Min	Avg	Max	Min	Avg	Max	Min	Avg	Max	Min	Avg	Max	Min	Avg	Max
Starting value	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%						
Mark-to-market value	18.8%	20.7%	24.5%	17.1%	44.8%	94.8%	17.3%	19.1%	21.5%	24.6%	67.9%	94.8%	14.6%	18.6%	21.3%	93.4%	93.7%	95.3%	13.4%	14.2%	14.7%	93.6%	93.7%	93.7%						
Notional	8.4%	8.6%	8.8%	3.6%	54.6%	82.7%	7.7%	8.1%	8.6%	3.3%	30.8%	75.1%	8.2%	8.7%	9.2%	3.7%	4.2%	4.3%	9.1%	9.1%	9.2%	4.2%	4.2%	4.2%						
Counterparty ID	16.9%	18.7%	19.7%	0.1%	0.2%	0.4%	9.3%	16.1%	18.9%	0.1%	0.3%	0.5%	6.0%	7.2%	9.1%	0.1%	0.1%	0.2%	5.9%	6.0%	6.1%	0.1%	0.1%	0.1%						
Timestamp execution	0.4%	2.3%	3.3%	0.0%	0.0%	0.1%	0.2%	0.2%	0.4%	0.0%	0.0%	0.0%	0.2%	1.3%	1.9%	0.0%	0.1%	0.1%	0.9%	0.9%	1.0%	0.0%	0.0%	0.0%						
Total clean	**46.4%**	**49.6%**	**53.1%**	**0.1%**	**0.5%**	**1.2%**	**53.2%**	**56.5%**	**62.1%**	**0.2%**	**1.0%**	**1.6%**	**61.6%**	**64.3%**	**68.0%**	**0.2%**	**1.9%**	**2.1%**	**69.1%**	**69.7%**	**70.7%**	**2.0%**	**2.0%**	**2.0%**						
Credit	N.of observations			Notional outst.			N.of observations			Notional outst.			N.of observations			Notional outst.			N.of observations			Notional outst.			Clean number of observations			Clean notional outstanding		
	Min	Avg	Max	Min	Avg	Max	Min	Avg	Max	Min	Avg	Max	Min	Avg	Max	Min	Avg	Max	Min	Avg	Max	Min	Avg	Max	Min	Avg	Max	Min	Avg	Max
Starting value	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%						
Mark-to-market value	25.2%	31.5%	43.1%	92.8%	93.7%	95.3%	23.3%	27.2%	30.9%	90.4%	92.5%	94.1%	22.5%	24.9%	29.7%	91.4%	91.8%	92.6%	22.5%	22.9%	23.4%	92.2%	92.3%	92.4%						
Notional	0.2%	0.2%	0.2%	0.0%	0.4%	0.6%	0.2%	0.4%	0.5%	0.6%	0.7%	1.2%	0.5%	0.5%	0.6%	0.6%	0.6%	0.7%	0.6%	0.6%	0.6%	0.6%	0.7%	0.7%						
Counterparty ID	1.5%	4.6%	6.2%	0.1%	0.6%	0.9%	1.8%	6.0%	7.6%	0.2%	0.8%	1.0%	1.8%	2.2%	2.6%	0.2%	0.2%	0.2%	2.7%	2.8%	2.9%	0.3%	0.3%	0.3%						
Timestamp execution	0.1%	0.1%	0.1%	0.0%	0.0%	0.0%	0.1%	0.3%	0.7%	0.0%	0.1%	0.1%	0.2%	0.7%	1.5%	0.0%	0.1%	0.1%	0.2%	0.2%	0.2%	0.0%	0.0%	0.0%						
Total clean	**55.0%**	**63.6%**	**68.3%**	**4.6%**	**5.3%**	**5.7%**	**61.4%**	**66.1%**	**69.0%**	**4.4%**	**5.9%**	**7.4%**	**67.5%**	**71.8%**	**73.5%**	**6.4%**	**7.2%**	**7.7%**	**72.9%**	**73.5%**	**73.9%**	**6.7%**	**6.8%**	**6.8%**						
Currency	N.of observations			Notional outst.			N.of observations			Notional outst.			N.of observations			Notional outst.			N.of observations			Notional outst.			Clean number of observations			Clean notional outstanding		
	Min	Avg	Max	Min	Avg	Max	Min	Avg	Max	Min	Avg	Max	Min	Avg	Max	Min	Avg	Max	Min	Avg	Max	Min	Avg	Max	Min	Avg	Max	Min	Avg	Max
Starting value	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%						
Mark-to-market value	43.7%	45.3%	46.5%	0.1%	0.2%	0.3%	18.8%	34.7%	44.2%	0.1%	15.8%	43.0%	10.9%	15.1%	36.7%	17.8%	42.7%	77.3%	11.2%	11.4%	11.6%	56.0%	74.9%	85.7%						
Notional	2.2%	2.3%	2.4%	98.5%	98.9%	99.3%	1.6%	2.0%	2.4%	0.6%	45.7%	99.4%	2.0%	2.4%	3.1%	5.4%	5.9%	15.8%	2.8%	2.9%	3.0%	0.5%	2.4%	6.2%						
Counterparty ID	8.7%	9.2%	9.7%	0.0%	0.1%	0.1%	5.5%	9.4%	12.1%	0.0%	2.5%	6.5%	6.0%	10.4%	12.3%	1.6%	5.1%	8.7%	9.0%	9.8%	10.3%	1.0%	1.6%	2.5%						
Timestamp execution	1.7%	2.4%	2.7%	0.2%	0.2%	0.2%	0.1%	2.0%	3.0%	0.2%	1.2%	4.4%	0.1%	0.2%	0.3%	0.2%	0.5%	0.9%	0.1%	0.1%	0.1%	0.1%	0.1%	0.2%						
Total clean	**40.2%**	**40.8%**	**41.6%**	**0.3%**	**0.6%**	**1.0%**	**39.8%**	**51.8%**	**66.5%**	**0.3%**	**34.9%**	**66.3%**	**55.3%**	**71.9%**	**76.0%**	**20.0%**	**45.8%**	**62.2%**	**75.1%**	**75.7%**	**76.7%**	**12.6%**	**20.9%**	**35.2%**						

Source: ECB calculations, based on DDRL EMIR confidential data.

Table 6 compares the datasets resulting from the stage-one cleaning procedure with the corresponding ones from the BIS semi-annual survey. As highlighted in Table 6, the dimension of our dataset seems now realistic in relation to the global BIS aggregates; at the same time, the significant jump experienced by credit and currency derivatives data, in 2014 and 2015 respectively, suggests that the quality level of EMIR data may have reached a satisfactory level only starting from the second part of 2015.[29]

Comparison between BIS global aggregates and EMIR notional outstanding after cleaning

Table 6

Notional value after cleaning - EMIR/BIS semi-annual survey	Dec-14	Jun-15	Dec-15	Jun-16
Credit derivatives	28%	28%	60%	61%
Interest derivatives	18%	21%	24%	25%
Currency derivatives	18%	23%	22%	28%

Source: ECB calculations, based on DDRL EMIR confidential data and BIS semi-annual survey on OTC derivatives (global aggregate).

2.4.2 Second stage: asset class specific cleaning

After implementing the general cleaning rules based on the main reporting fields, we move further and, following Abad et al. (2016), we develop asset class-specific cleaning procedures.

Interest rate derivatives

One of the defining elements of interest rate derivatives is the underlying benchmark. The lack of a detailed benchmark taxonomy in current reporting rules results in a series of ambiguities and mistakes due to trivial typos or abbreviations.[30] Following Abad et al. (2016), we attempt to overcome such misreporting issues through manual cleaning for the major benchmarks (EURIBOR, EONIA, LIBOR, inflation, etc.).

After that, we identify all non-standard contracts, including forward-starting swaps, swaps with embedded options, contracts with spread on the floating leg, contracts with upfront payment, float-to-float and fixed-to-fixed contracts. At this stage, we also compute the contract tenors, as the difference between the maturity date and the date in which the contractual obligation became effective, both part of the EMIR reporting template. Finally, based on the global ultimate ownership identifier, we flag intra-group trades.

We then proceed to filter out all non-EURIBOR, non-fixed to float interest rate swaps, and intragroup trades. In order to facilitate the analysis, we focus on the four most frequent tenors: one, six, nine and twelve months. Table 7 summarises the cleaning and filtering process for interest rate derivatives for a sample trade state report (September 2016).

[29] The comparison between BIS and EMIR data is subject to a series of caveats. See footnote 22.

[30] A detailed taxonomy will be implemented in November 2017. See Annex to Regulation (EU) 105/2017.

Cleaning and filtering of interest rate derivatives

Table 7

Interest derivatives - Sept 2016	N. of obs.	%	Notional (€ bn)	%
Original number of observations	2,374,904	100.0%	5,004,686	100.0%
Value of contract				
Missing value of contract	382,162	16.1%	4,680,000	93.5%
Mis-matching value of contract (buyer/seller relative difference > 5%)	109,371	4.6%	2,540	0.1%
Notional				
Different notionals	202,292	8.5%	13,000	0.3%
Missing notional	775	0.0%	0	0.0%
Outliers	6,984	0.3%	202,000	4.0%
Counterparty ID				
Buyer or Seller or both ID are non LEI	146,173	6.2%	4,280	0.1%
Timestamp execution				
Execution date missing	22,482	0.9%	2,460	0.0%
Execution date after trade state report date	70	0.0%	2	0.0%
Execution year before 1990	17,802	0.7%	1,140	0.0%
Subtotal (clean dataset)	**1,486,793**	**62.6%**	**99,264**	**2.0%**
Filter				
Non-swap	205,343	8.6%	23,500	0.5%
Float-to-float	121,327	5.1%	8,500	0.2%
Fix-to-fix	10,670	0.4%	272	0.0%
Forward starting	254,584	10.7%	20,000	0.4%
Cross-currency	1,975	0.1%	29	0.0%
Upfront payment	2,173	0.1%	60	0.0%
Spread floating	96,082	4.0%	5,290	0.1%
Embedded option	723	0.0%	21	0.0%
Intragroup	69,479	2.9%	3,750	0.1%
Non-EURIBOR	559,748	23.6%	25,900	0.5%
Tenor different from 1M, 3M, 6M, 12M	1,202	0.1%	42	0.0%
Total (filtered dataset for network analysis)	**163,487**	**6.9%**	**11,900**	**0.2%**

Source: ECB calculations, based on DDRL EMIR confidential data.

Credit derivatives

Current rules allow for some flexibility in the choice of the underlying identifiers. As a result, it is sometimes difficult to identify the underlying to a credit derivative and, subsequently, the issuer of the underlying security.[31]

In this context, it seems wise to drop all observations where the underlying reference entity is not univocally identifiable (i.e. not identified by an ISIN code) or missing. Following Abad et al. (2016), we also filter out contracts written on index or baskets as they do not include information on the underlying index or basket content.[32] As in the case of interest rate derivatives, we also filter out intra-group trades. Table 8 summarises the cleaning and filtering process for credit derivatives for a sample trade state report (September 2016).

[31] See Regulation (EU) 1247/2012 and Regulation (EU) 148/2013.

[32] Regulation (EU) 105/2017 will introduce the obligation to report an index product code, that will allow to identify this increasingly popular type of credit derivatives.

Cleaning and filtering of credit derivatives

Table 8

Credit derivatives - Sept 2016	N. of obs.	%	Notional (€ bn)	%
Original number of observations	692,696	100.00%	95,495	100.00%
Value of contract				
Missing value of contract	114,976	16.60%	87,200	91.31%
Mis-matching value of contract (buyer/seller relative difference > 5%)	49,292	7.12%	429	0.45%
Notional				
Different notionals	13	0.00%	0	0.00%
Missing notional	1	0.00%	0	0.00%
Outliers	3,399	0.49%	626	0.66%
Counterparty ID				
Buyer or Seller or both ID are non LEI	17,991	2.60%	225	0.24%
Timestamp execution				
Execution date missing	2,907	0.42%	72	0.08%
Execution date after trade state report date	2	0.00%	0	0.00%
Execution year before 1990	1,021	0.15%	15	0.02%
Subtotal (clean dataset)	503094	**72.63%**	**6,928**	**7.26%**
Filter				
Non-swap	7,403	1.07%	239	0.25%
Intra-group transactions	51,989	7.51%	1,060	1.11%
Missing reference entity	2,695	0.39%	38	0.04%
Index or basket	103,909	15.00%	3,540	3.71%
Non-ISIN	13,870	2.00%	97	0.10%
Problematic ISINs	24,190	3.49%	105	0.11%
Total (filtered dataset for network analysis)	**299,038**	**43.17%**	**1,850**	**1.94%**

Source: ECB calculations, based on DDRL EMIR confidential data.

Currency derivatives

The key variable of interest for currency derivatives analysis is the currency pair. As in the case of interest rate derivatives benchmarks, we proceed to manually clean and correct reporting mistakes in this field. In particular, we drop observations where currency pairs that are missing, numerical or composed by the same identical currency. Also here, we filter out intra-group trades. Table 9 summarises the cleaning and filtering process for currency rate derivatives for a sample trade state report (September 2016).

Cleaning and filtering of currency derivatives

Table 9

Currency derivatives - Sept 2016	N. of obs.	%	Notional (€ bn)	%
Original number of observations	2,442,662	100.0%	47,230	100.0%
Currency pair clean				
Wrong currency pair	28,813	1.2%	444	0.9%
Missing currency pair	93,027	3.8%	2,997	6.3%
Value of contract				
Missing value of contract	158,566	6.5%	19,900	42.1%
Mis-matching value of contract (buyer/seller relative difference > 5%)	137,091	5.6%	2,470	5.2%
Notional				
Missing notional	432	0.0%	0	0.0%
Outliers	57,802	2.4%	3,740	7.9%
Counterparty ID				
Buyer or Seller or both ID are non LEI	250,692	10.3%	1,730	3.7%
Timestamp execution				
Execution date missing	70	0.0%	1	0.0%
Execution date after trade state report date	70	0.0%	0	0.0%
Execution year before 1990	6,310	0.3%	236	0.5%
Subtotal (clean dataset)	**1,709,789**	**70.0%**	**18,190**	**38.5%**
Filter				
Intragroup	303,461	12.4%	1,400	3.0%
Non-fwd	155,405	6.4%	2,560	5.4%
Non-EUR/USD	925,497	37.9%	9,700	20.5%
Total (filtered dataset for network analysis)	**325,426**	**13.3%**	**4,530**	**9.6%**

Source: ECB calculations, based on DDRL EMIR confidential data.

2.4.3 Summary of the results

The application of relatively basic cleaning procedures considerably reduces the size of EMIR confidential datasets. In particular, missing contract valuations, outlier notional values and wrong counterparty IDs account for the largest share of misreported observations.

Alongside the reporting mistakes and the missing values, it is interesting to note the weight of insufficient or incorrect use of global standards such as LEI and, in the case of credit instruments, ISIN codes. This finding suggests that the finalisation of the work for the implementation of new global identifiers (UPI and UTI) coupled with stricter validation rules and a wider use of LEI and ISIN codes would have the potential to dramatically improve the quality of EMIR data.

While data quality continues being an obstacle to the full use of EMIR data, we also observe a considerable improvement over time: the average “survival” rate (i.e. the share of observation retained after the cleaning procedure) in the last year went from c.50% in 2014 up to almost 70% in the first quarter of 2017. Reporting agents’ increasing knowledge and compliance with reporting obligations, the implementation of stricter TR validation rules, as well as the adoption and implementation of new ESMA regulatory and implementing standards or guidelines surely all contributed to this positive trend.

In conclusion, subject to the quality caveats outlined above, EMIR data are a unique information source, that will continue to be improved and will be used more and more often in the years to come.

In the following sections, we will zoom into the datasets we have obtained and outline some interesting insights on the structure of euro area OTC derivatives markets.

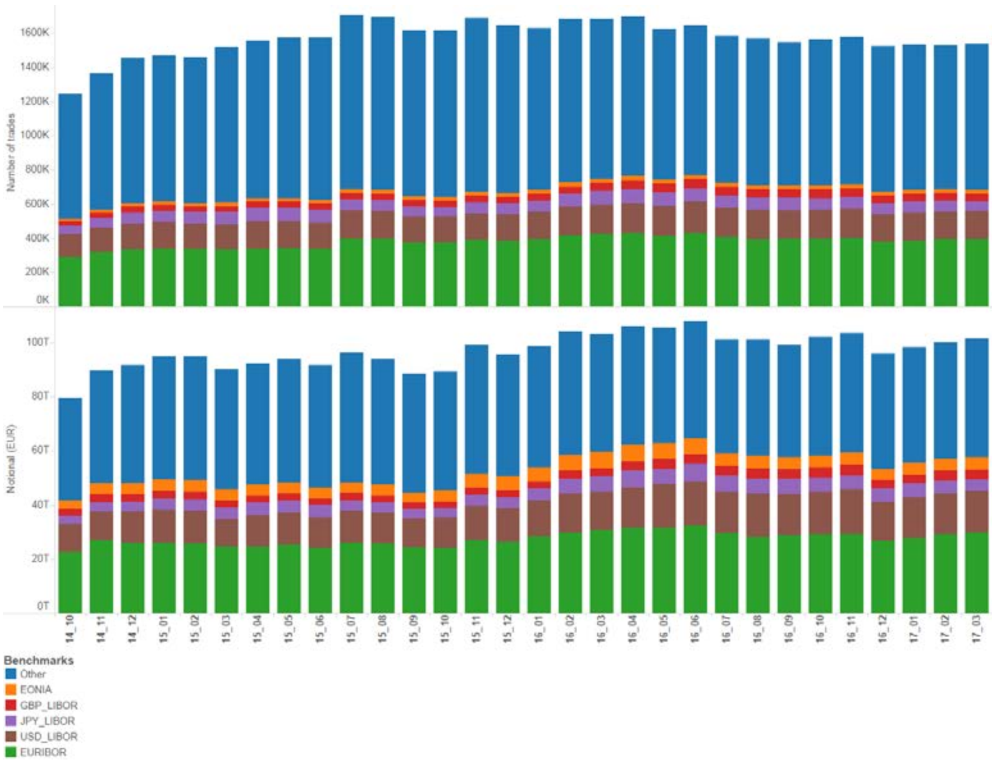
3. Dataset overview

3.1 Interest rate derivatives

Figure 7 below depicts the evolution of the composition of benchmarks in the interest rate derivatives market. In line with Abad et al. (2016), we group benchmarks that account for less than 1% of total notional or number of trades into the category "Other".

In March 2017, euro area OTC interest rate derivatives market was worth almost EUR 100 trillion in terms of notional value, approximatively a quarter of the global aggregate.[33] As highlighted by Figure 7, EURIBOR is the benchmark accounting for the greatest market share (up to 25%), followed by USD LIBOR (10.8%), JPY LIBOR (3.9%), GBP LIBOR (2.9%), and EONIA (1.5%). Other benchmarks account for the remaining 55% of the market, suggesting that – apart from the few "blockbusters" – the market for interest rate derivatives is very heterogeneous. This result seems stable over time and valid not only when measured in relation to the number of outstanding trades, but also to the total outstanding notional.

Figure 7: Interest rate derivatives - breakdown by floating leg benchmark.



Source: ECB calculations, based on DDRL EMIR confidential data.

Figure 8 shows the breakdown of interest rate derivatives on EURIBOR by tenor at the latest available date (end-March 2017). The 6 month tenor is the most prevalent, both in terms of number of trades and of notional value. This confirms the finding by Abad et al. (2016) also for the euro area market.

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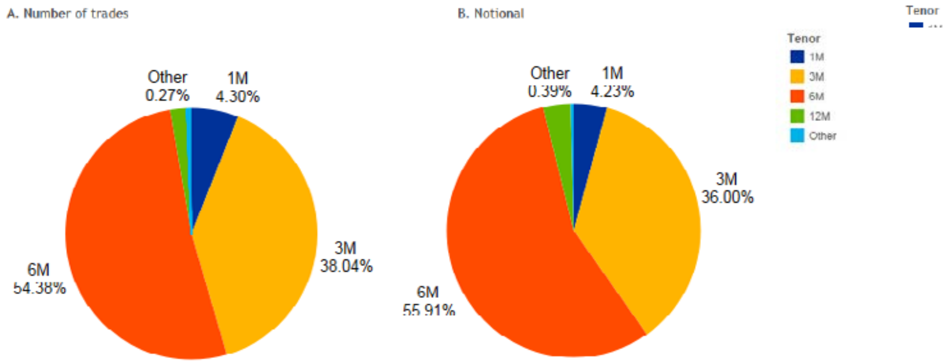
[33] According to BIS (2016), the aggregate global notional outstanding of OTC interest derivatives at the end of June 2016 was c.418 trillion USD.

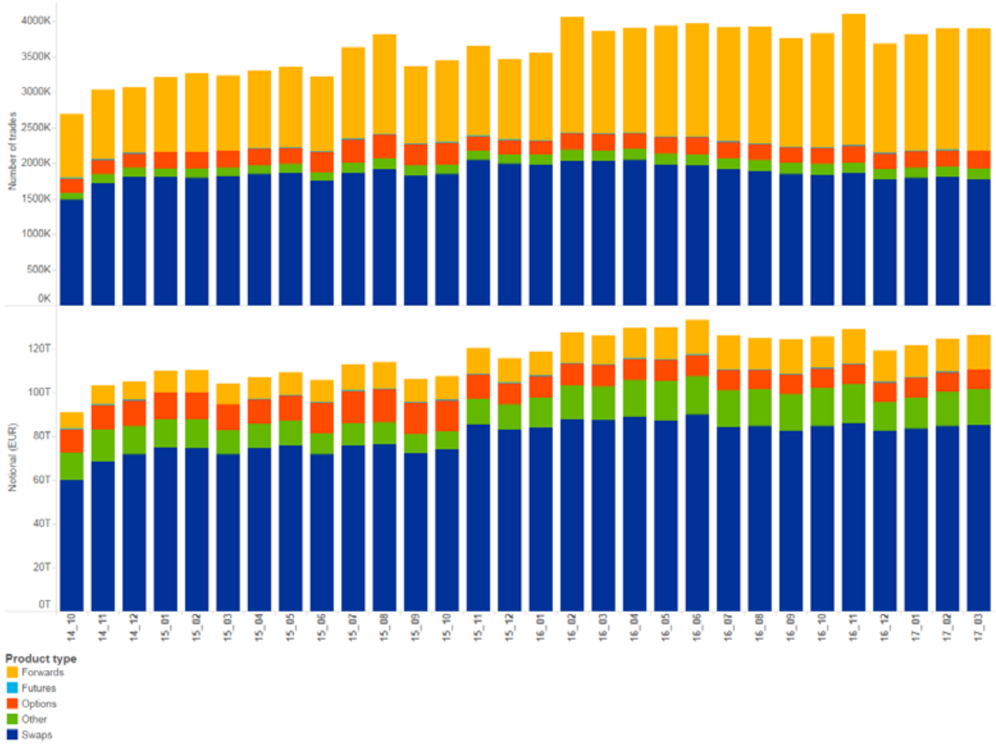
Figure 8: Breakdown of EURIBOR interest rate derivatives by tenor (March 2017).



Source: ECB calculations, based on DDRL EMIR confidential data.

Figure 9 presents the breakdown of the interest rate derivatives market by product type. As expected,[34] most of the contracts are swaps, c.86% of total trades.[35] The remainder includes options (5.2%), forward rate agreements (4.3%), forwards (0.3%) and various other contract types (3.8%). It is interesting to note that, when we look at the breakdown in terms of notional, swaps account for a lower share (76.6%), as opposed to forward rate agreements that account for a significantly higher share (14.3%). This is consistent with the BIS global aggregate, where swaps account for c.74% of total notional outstanding.[36]

Figure 9: Interest rate derivatives - breakdown by product type.



Source: ECB calculations, based on DDRL EMIR confidential data.

[34] See Abad et al. (2016).

[35] The percentages refer to the last available observation, i.e. end of March 2017.

[36] See BIS (2016).

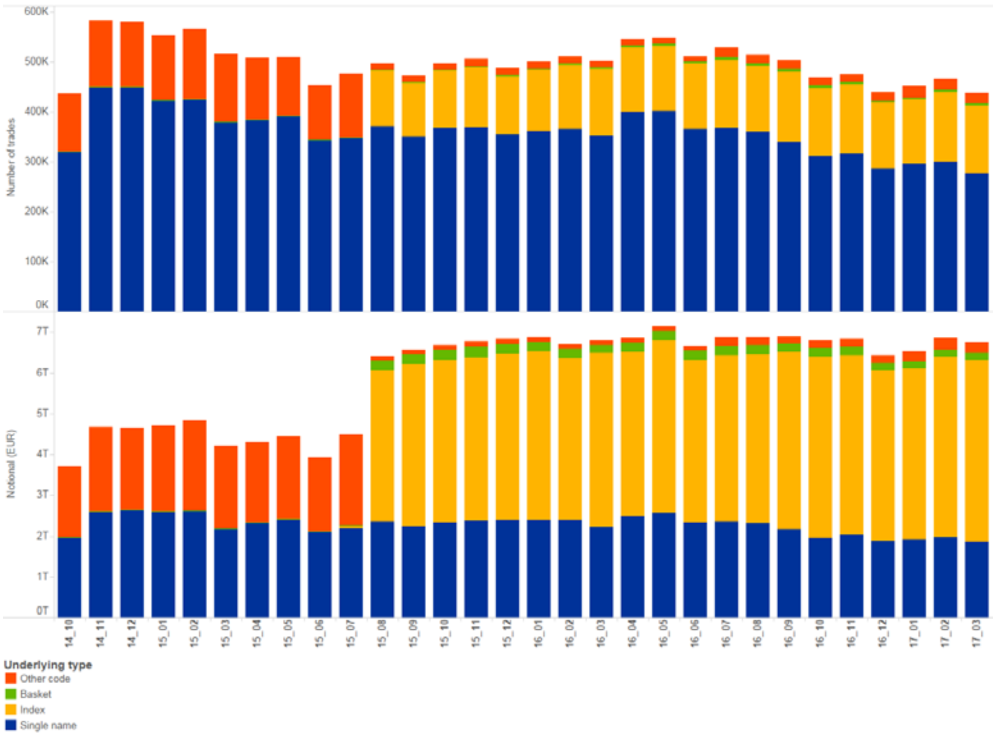
3.2 Credit derivatives

Moving to the credit derivatives market, our data confirm that swaps account roughly for 95-98% share both in terms of notional and number of trades over the time series.[37] The market for credit derivatives is worth c. EUR 7 trillion in terms of notional value and is on a contraction path, consistently with the global trend highlighted by BIS (2016) and partially justified by the contraction of the intra-dealer market segment.

Figure 10 shows the breakdown of contracts by type of underlying. The underlying can be an index, a basket, or a single-name security, such as a bond issue of a G16 dealer.[38] Interestingly, contracts written on indexes account for more than 60% of total notional outstanding, but only for c. 20% of total number of trades. This result suggests that in the euro area, index products account for a larger share of credit instruments as compared to the global aggregate published by BIS, where index products account for c.41% of total CDS notional outstanding.[39]

Figure 10 also shows a significant jump in the time series, indicating a sudden increase in total outstanding notional between July and August 2016. The reconciliation of those developments with market events or with technical issues linked to reporting practices go beyond the scope of this paper and warrant further investigation.

Figure 10: Credit derivatives - breakdown of by underlying type.



Source: ECB calculations, based on DDRL EMIR confidential data.

37 See Abad et al. (2016) and Ali et al. (2016)

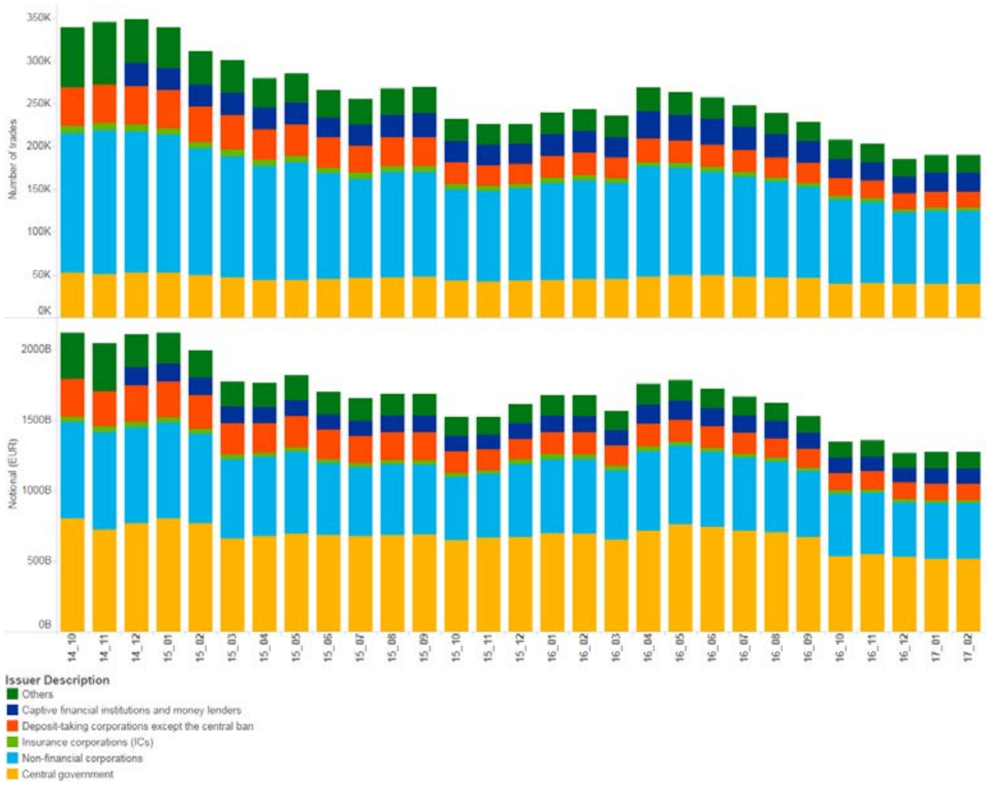
38 The group of the sixteen largest derivatives dealers (G16) includes Bank of America, Barclays, BNP Paribas, Citigroup, Crédit Agricole, Credit Suisse, Deutsche Bank, Goldman Sachs, HSBC, JPMorgan Chase, Morgan Stanley, Nomura, Royal Bank of Scotland, Société Générale, UBS, and Wells Fargo.

39 The comparison between EMIR and BIS semi-annual survey data on credit derivatives is subject to a number of caveats: BIS only covers CDS – while EMIR covers the whole credit derivatives product range, of which swaps represent more than 90% - and distinguish between multi-name and index based instruments – while EMIR only provides for a general “Index” flag. See footnote 22.

While current reporting standards do not allow tracking detailed information about underlying indexes and baskets, the integration of EMIR reporting with other databases allows gathering useful insights on the nature of single-name underlying securities' issuers. The ECB Centralised Securities Database (CSDB)[40] provides detailed information on securities, including with regards to the issuer ESA 2010 sector classification code.[41] Therefore, by merging our dataset with the CSDB, we obtain the breakdown outlined in Figure 11.

Non-financial corporations, sovereign entities and banks account for the largest part of total underlying securities to euro area CDS. Other significant sectors in the market include captive financial institutions, money lenders and other financial intermediaries, which represent c.25% of the market both in terms of notional and number of trades.

Figure 11: Credit derivatives - breakdown of single-name CDS by sector of the underlying security issuer.



Source: ECB calculations, based on DDRL EMIR confidential data.

3.3 Currency derivatives

Figure 12 shows the breakdown of outstanding contracts (and the related notional value) by currency pair. For clarity, we group pairs of "mirroring" currency pairs (e.g. EUR/USD and USD/EUR) and we assign pairs including a major currency (i.e. EUR, USD, JPY, GBP) and a non-major currency to the residual "Other" category.

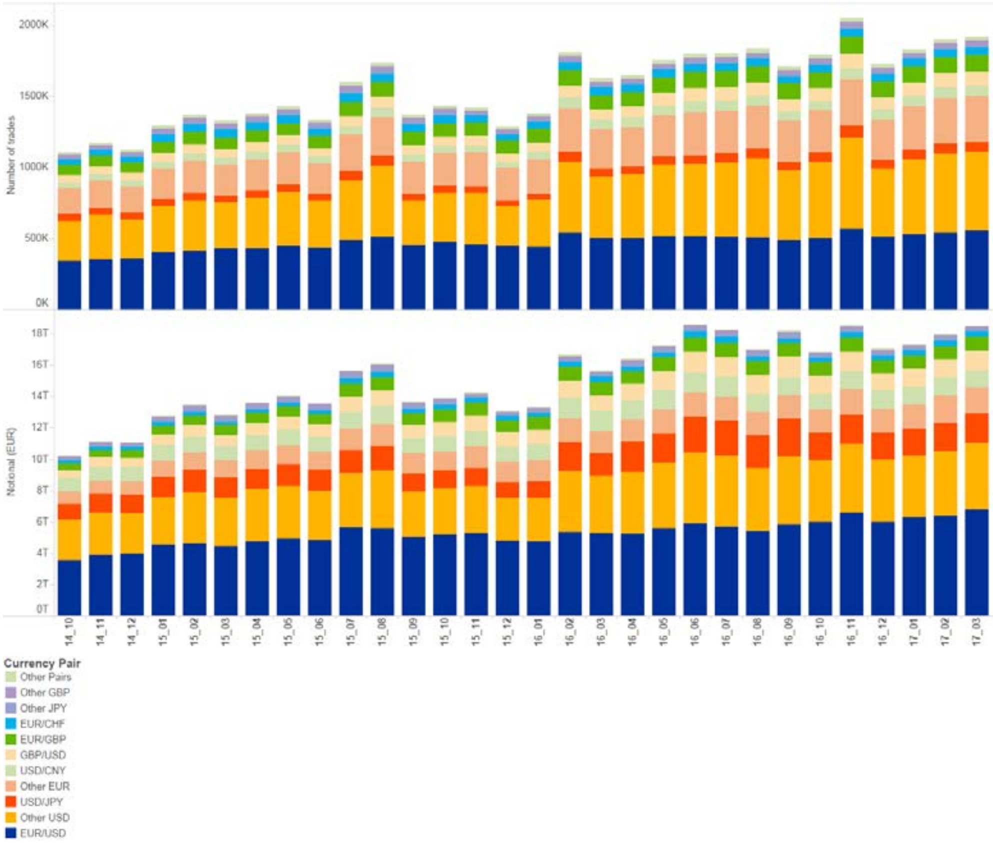
Overall, the euro area currency OTC derivatives market was worth c. EUR 20 trillion at the end of March 2017, and showed a slightly expanding trend.

[40] For a description of the structure and content of the CSDB, see ECB (2010).

[41] See http://ec.europa.eu/eurostat/web/esa-2010

Expectedly, EUR/USD contracts account for the largest share of euro area OTC derivatives, followed by other USD pairs. Contracts written on USD/JPY, GBP/USD, USD/CNY were the other most frequently traded ones.

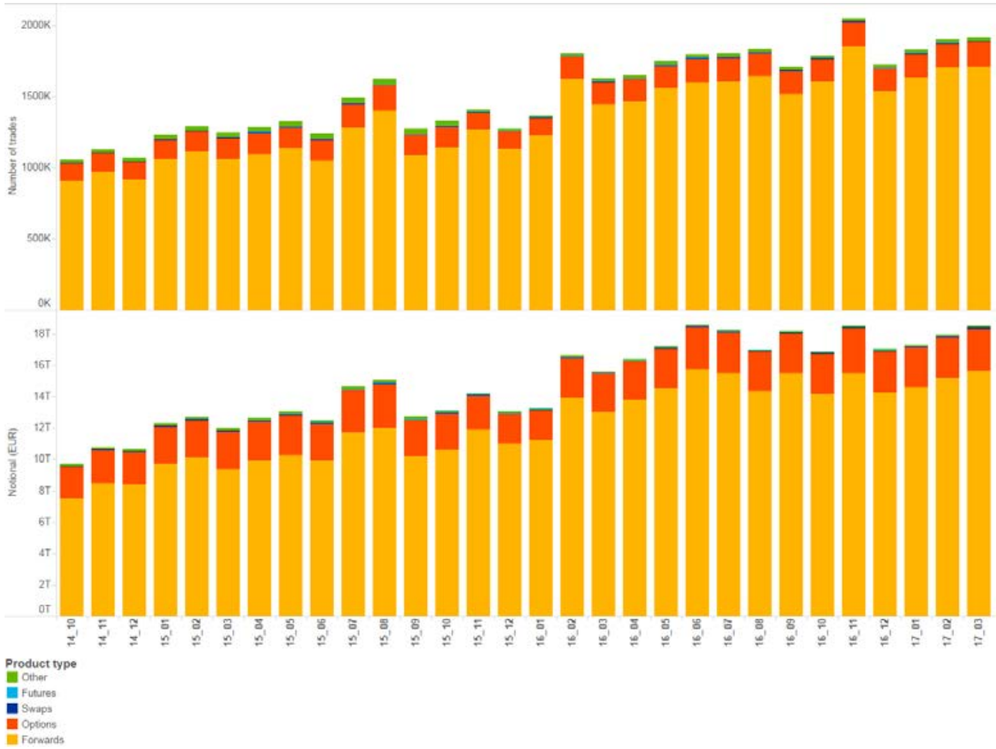
Figure 12: Currency derivatives - breakdown by currency pair.



Source: ECB calculations, based on DDRL EMIR confidential data.

With regards to the product breakdown, we find that majority of contracts are forwards (89% of total trades), with the remaining 11% being mostly options and various other contract types (see Figure 13).

Figure 13: Currency derivatives - breakdown by product type.



Source: ECB calculations, based on DDRL EMIR confidential data .

4. Clearing analysis

One of the pillars of the Pittsburgh reform agenda was the introduction of mandatory clearing for OTC derivatives. In the EU, EMIR established an obligation to clear certain contracts with adequate liquidity, standardisation and information availability.[42] Table 10 shows the timeline for the implementation of the clearing obligation.

Timeline for the implementation of the EMIR clearing obligation

Table 10

Category[43]	IRS in G4 currencies[44]	Index CDS[45]	IRS and FRAs in NOK, PLN, SEK[46]
Clearing obligation starting dates			
Cat. 1	21/06/2016	09/02/2017	09/02/2017
Cat. 2	21/12/2016	09/08/2017	09/07/2017
Cat. 3	21/06/2017	09/02/2018	09/02/2018
Cat. 4	21/12/2018	09/05/2019	09/07/2019
Frontloading dates			
Cat. 1	21/02/2016	09/10/2016	09/10/2016
Cat. 2	21/05/2016	09/10/2016	09/10/2016

Source: readapted from ECB (2016).

At the time of writing, the obligation to clear interest rate swaps in all major currencies as well as index CDS is already in force for the biggest dealers. In order to compute the share of cleared trades, we divide the total number of outstanding cleared trades by the total number of outstanding trades for each period. We do the same for the value of cleared trades' notional.

Figure 14 shows the evolution of clearing rates in the euro area interest rate OTC derivatives market. At the end of February 2017, 46.4% of all outstanding trades – accounting for more than 60% of the total notional outstanding – were cleared. A consistently increasing trend, starting at the end of 2015 – when Regulation (EU) 2205/2015 entered into force – is evident both in the volume and value of cleared contracts.[47] However, it is interesting to notice that more than 20% of trades were already cleared in 2014, well before the entry into force of the clearing obligation; this suggests that the clearing practice was already common in the market and justifies the non-exponential increase in clearing rates following the entry into force of the clearing obligation.

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42 See Article 5(2) of Regulation (EU) 648/2012.

43 Category 1 includes clearing members; category 2 includes other financial counterparties and alternative investment funds above the group-level threshold of non-cleared derivative positions (EUR 8 billion); category 3 includes other financial counterparties and alternative investment funds below the EUR 8 billion threshold; category 4 includes other non-financial counterparties.

44 Regulation (EU) 2205/2015.

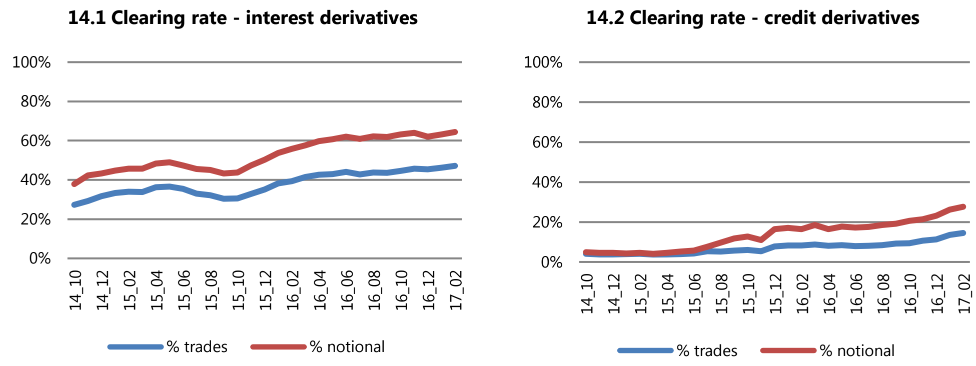
45 Regulation (EU) 592/2016.

46 Regulation (EU) 1178/2016.

47 The jump in the share of trades cleared by CCPs from October to November 2014 does not seem related to any institutional or market change. A possible explanation lays in the implementation of the level 1 validation rules, in force since October 24th 2014. Updated information on ESMA validation rules is available at: https://www.esma.europa.eu/press-news/esma-news/esma-updates-emir-qa-and-validation-rules

Expectedly, G16 dealers and banks account for the largest share of cleared trades, reflecting the overall participation in the interest rate derivatives market. On the other hand, other financial counterparties (including investment funds) account for a smaller but increasing share of cleared trades (c. 1.4%).

Figure 14: evolution of clearing rates in OTC interest rate and credit derivatives markets

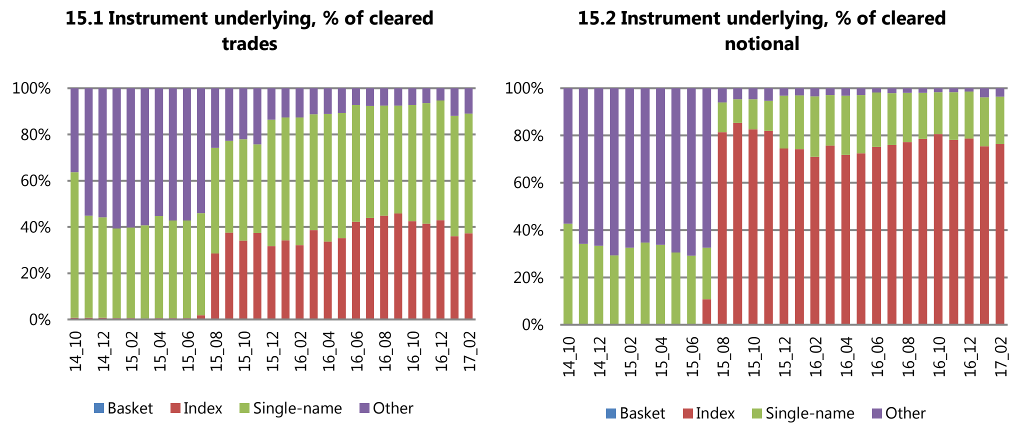


Source: ECB calculation based on DDRL EMIR confidential data.

Moving to credit derivatives, we observe that no or very low clearing activity took place until mid-2015. Afterwards, however, an increasing number of contracts has been cleared, up to 20% of total trades (and c.40% of total notional outstanding as of end March 2017). The lower values vis-à-vis interest rate derivatives are explained by the timeline and to the scope of the clearing obligation, which does not cover single-name CDS and entered into force only in February 2017.

Nevertheless, as shown in Figure 15, counterparties are also clearing a significant amount of single-name credit derivative contracts, even though they are not covered by a clearing obligation. Their relative importance, however, is smaller than index products, especially in terms of notional value.[48]

Figure 15: breakdown of cleared credit derivative trades by type of underlying.



Source: ECB calculation based on DDRL EMIR confidential data.

48 The jump in the time series between July and August 2015 was highlighted in Section 3 and seems related to changes in the reporting practices or TR validation rules rather than to market events.

5. Preliminary insights from a network analysis

Network analysis is now considered a standard tool to measure interconnectedness and assess contagion risks in inter-banking markets; however, due to the limited availability of data, it is only recently that researchers have extended their work to the derivatives market, including through the confidential EMIR data. In the last few years, an increasing number of studies has been published: Kenny et al. (2015) used Bank of Ireland data to investigate the CDS network, focusing on the activity of the shadow banking system. In the UK, Ali et al. (2016) explored the structure of the CDS market and Cielinska et al. (2017) carried out an event study to capture the effects of the Swiss Franc depegging on the FX derivatives network. Finally, Abad et al. (2016) conducted a broad investigation on the topology of the interest rate swaps (IRS), credit default swaps (CDS) and currency forwards in the EU.

Building on these contributions, we sketch the evolution of euro area OTC derivatives' market structure over time. This is particularly interesting in a context of significant regulatory activity and institutional changes: as highlighted in Section 1, between 2012 and 2017 the EU derivatives markets underwent far reaching reforms whose effect on market microstructure has not yet been fully investigated.

In order to achieve a smaller and homogeneous dataset, we focus on the filtered data obtained following the methodology outlined in Section 2 and including IRS on EURIBOR with a 6 month tenor, single-name CDS, and EUR-USD forwards. Our analysis spans between the relatively short period from January 2016 to March 2017; in fact, the data quality concerns highlighted in Section 1 and Section 2 suggest concentrating on recent reports.

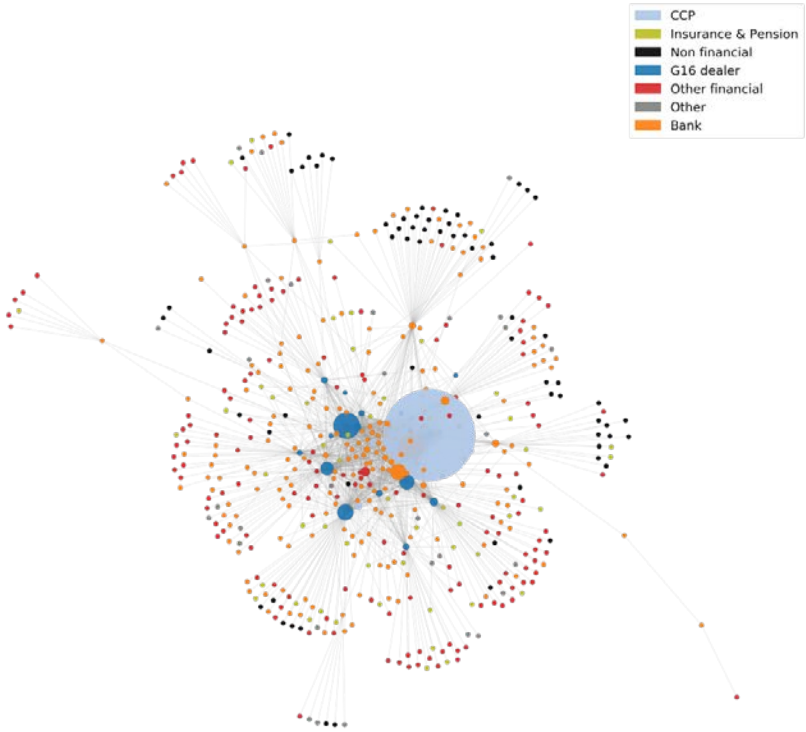
For each trade state we construct a network whose nodes represent the active counterparties to transactions and whose links capture the outstanding positions between each counterparty pair. Links are in turn weighted by the gross notional outstanding. While EMIR reports include a field dedicated to flagging the buyer/seller nature of the reporting counterparty, our analysis has identified a number of inconsistencies – most probably linked to different interpretation of the existing technical standards. Against this background, we build an undirected network.

5.1 A static view of selected derivatives submarkets

Before moving to the analysis of the market dynamics over time, we analyse the structure of the three networks statically, at the end of March 2017.

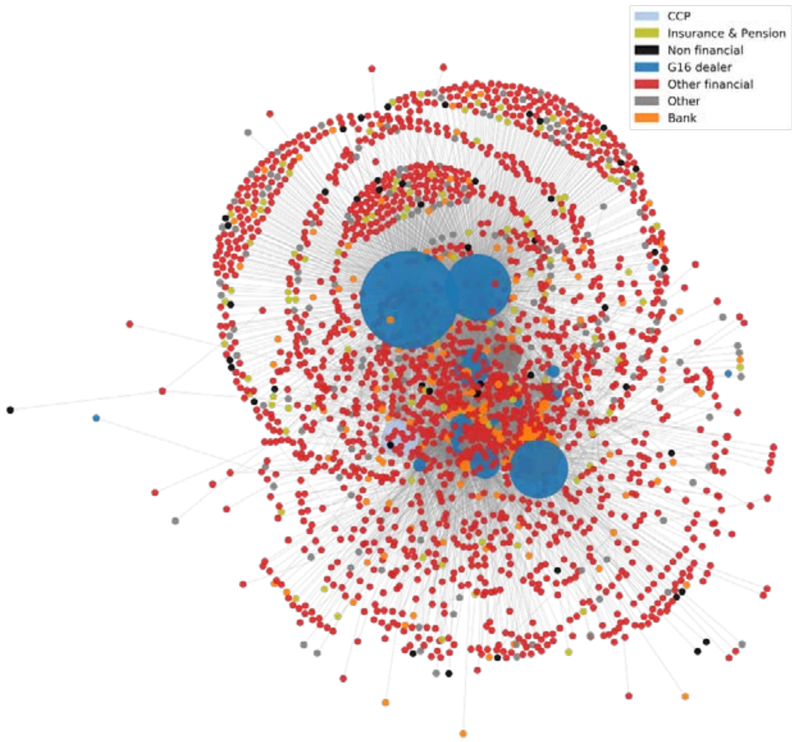
The network represented in Figure 16 shows the EURIBOR 6M interest rate swaps market. The high clearing rates highlighted in Section 4 increase the systemic importance of CCPs: in fact, the largest node outlined in the figure is a CCP. Figure 16 also shows the intermediary role played by banks and G16 dealers; this also implies that peripheral nodes (mostly non-banks and non-financial counterparties) get access to the core of the network via larger banks or G16 dealers that often clear trades on behalf of their clients.

Figure 16: Network of gross notional links between counterparties in euro area EURIBOR 6M interest rate swaps market (March 2017).



Source: ECB calculation based on DDRL EMIR confidential data.

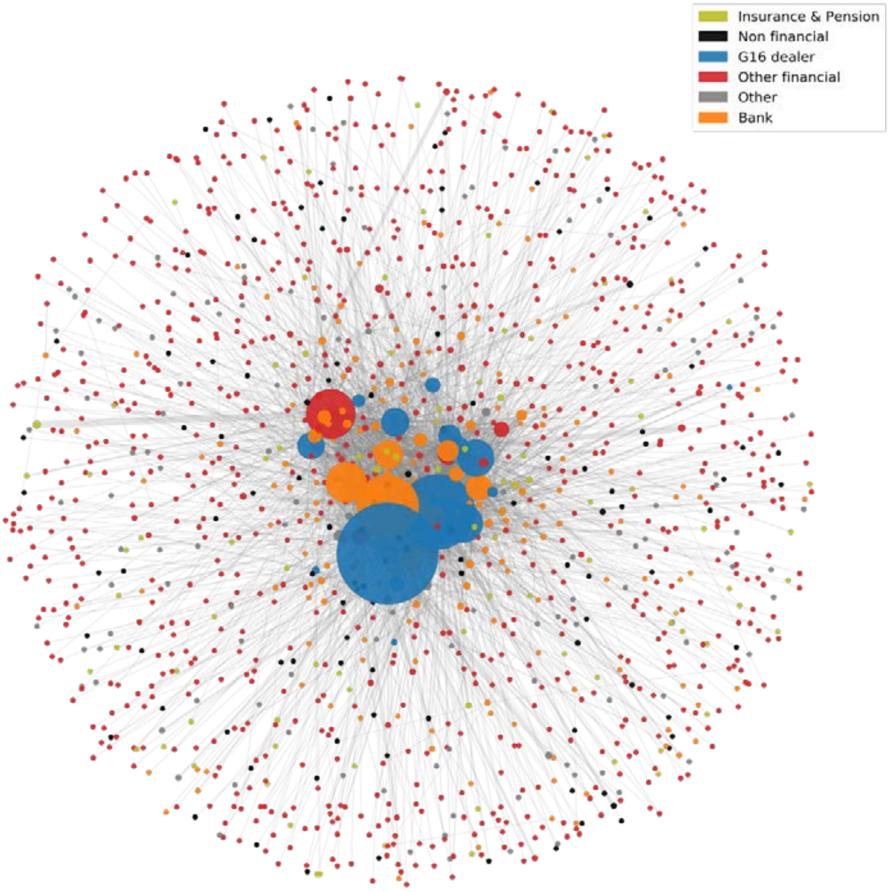
Figure 17: Network of gross notional links between counterparties in euro area single-name CDS market (March 2017).



Source: ECB calculation based on DDRL EMIR confidential data.

As outlined by Figure 17, the structure of the single-name CDS market is different from the one of EURIBOR IRS: first, the lower clearing rates outlined in Section 4 imply a lower relative importance of CCPs; G16 dealers and banks, on the other hand, seem to have a crucial intermediation role, which increases their exposure and, subsequently, the size of their nodes. Finally, we also note that the CDS network appears denser than the IRS, meaning that each node trades with more counterparties and is therefore more linked to the rest of the nodes.

Figure 18: Network of gross notional links between counterparties in euro area EUR/USD FX forwards (March 2017).



Source: ECB calculation based on DDRL EMIR confidential data.

The EUR/USD FX forwards market structure reflects on the one hand the lack of clearing obligation – in fact, no CCP is visible in the core of the network – and, on the other hand, the relatively higher presence in the market of non-financial counterparties (the black nodes in Figure 18). It is also interesting to note how peripheral nodes connect to the core of the network through the intermediation of small banks and other financial counterparties, which are in turn connected to large banks and G16 dealers at the core of the network. Opposite to the CDS network, the one represented in Figure 18 is sparser and closer to the EURIBOR IRS in terms of density.[49]

[49] See also paragraph 5.2 below.

5.2 Evolution in network structure by asset class

While static market visualization gives useful indications, the value added of granular data such as EMIR's also lies in their ability to capture changes in market structure over time. In order to leverage this opportunity, we compute a number of commonly used measures, whose definition and meaning is summarised in Table 11.

List of network measures and their definition

Table 11

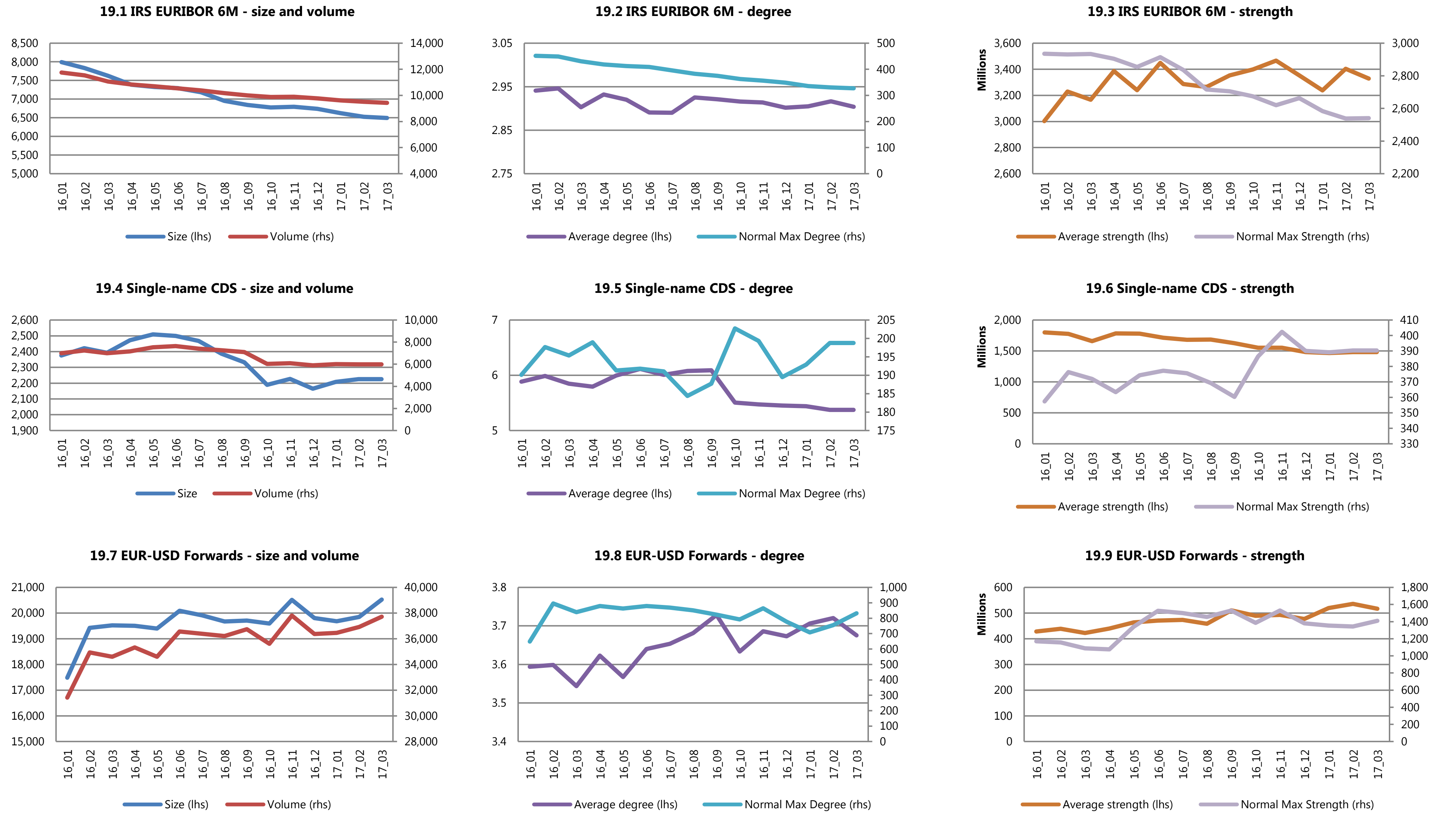
Measure	Definition
Network size	The number of nodes (i.e. counterparties) in the network.
Network volume	The number of links (i.e. outstanding trades) between nodes in the network.
Network degree (average and maximum)	The number of links connected to a node, i.e. the number of counterparty each node trades with.[50]
Network strength (average and maximum)	The sum of weights of all links connected to a node, i.e. the aggregate outstanding notional value of all trades a counterparty is involved in.[50]
Network density	The fraction of present connections to possible connections. In an undirected network it is equal to: $\frac{2(\text{Network Volume})}{\text{Network Size} \times (\text{Network Size}-1)}$.

Source: Adapted from Iori et al. (2008)

As a result, we obtain a time series composed by thirteen monthly observations for each measure and for each asset class. Before commenting on the outcome of the analysis, a number of caveats need to be highlighted: first, the ECB access rights limit the representativeness of the network, as they fail to capture other non-euro area countries that are major players in the EU derivatives markets; second, and perhaps most importantly, the relatively low frequency of the observations does not allow to capture "real-time" movements in the markets linked to specific events. In fact, as our time series is composed of end-of-month snapshots, it is prone to a number of biases and random effects that decrease their representativeness. On the other hand, our methodology highlights the general trend in market structure, and reflects to a certain extent regulatory and institutional changes in the EU OTC derivatives regulatory framework.

[50] In order to facilitate comparability across asset classes, we normalize the maximum degree and divide it by the average degree.

Figure 19: Evolution of selected measures for a subset of interest rate, credit and currency derivatives networks.



Source: ECB calculation based on DDRL EMIR confidential data.

Figure 19.1 shows that the number of counterparties to EURIBOR 6M IRS and the number of connections among them has decreased over time, going from about 8,000 to 6,500 counterparties and from about 12,000 to 9,500 links (c. 20%) respectively. As this trend, however, does not correspond to any decrease in outstanding notional,[51] it points towards an increase in density – a proxy of interconnectedness – and in market concentration. In fact, we find that the network density increases by c. 20% over the period, although the market remains very sparse in absolute terms: as indicated by Figure 19.2, the average network degree is lower than 3, meaning that on average each counterparty trades with only 3 other counterparties. On the other hand, the average strength of the network increased by c. 10% over time, suggesting that existing nodes become "heavier" in terms of notional. This result might be linked to the implementation of the clearing obligation although, perhaps due to the high clearing rate in the IRS market already before of the entry into force of EMIR clearing obligations, we don't see any radical shift at the frontloading and clearing obligation dates.[52] Figures 20.1 and 20.2 show the systemic importance of CCPs, that have the highest strength among active counterparties, although – in line with the practices in the clearing market, where clearing is delegated by smaller counterparties to bigger banks or G16 dealers that are usually clearing members to a CCP – a lower but increasing number of links as compared to G16 dealers. The decrease in the average degree of G16 dealers is an interesting trend, which deserves further analysis.

Moving to the single-name CDS dataset, we see a smaller network, both in terms of size and in terms of volume compared to the EURIBOR 6M interest rate swaps network. In terms of dynamics, we observe that starting from June 2016 and until October 2016 the network shrunk in terms of number of counterparties by 11% and, even more, in terms of number of links (-16%). This is consistent with the gradual increase in clearing rates for single-name CDS highlighted in Figure 15.1 and with the general decrease in the average network degree (in October 2016, each counterparty traded on average with 5 other counterparties, down from 6 in September 2016).[53] The increase in the clearing activity also emerges from Figures 20.3 and 20.4: the average degree and strength of CCPs have been increasing, especially after the entry into force of the clearing obligation for index CDS in February 2017.[54] The network density measure also confirms the finding outlined in Figure 17: the CDS network is the densest among the three asset classes we analyse (c. 0.25% over the entire period). Furthermore, we observe that the average strength decreases over time, i.e. the average outstanding position of each node becomes lower in terms of notional value.

Finally, the network for EUR-USD forwards appears to be the largest among the three analysed, both in terms of volume and size. This reflects the fact that, while the interest rate swaps and CDS market are dominated by big financial entities, there are many other financial and non-financial institutions that need to manage exchange rate risk.[55] The upward – although somewhat volatile – trend in the network size and volume shows that the number of unique counterparties and links increases over time (about 20%). Furthermore, the network density remains stable over the period analysed, as also reflected by the evolution of the average degree; in particular, as compared to the two other asset classes, we observe that the EUR-USD forward network density is comparable to the one of the EURIBOR 6M interest rate swaps market (c. 0.04%) and significantly lower than the single-name CDS network. As evident from the high values of degree and strength outlined in Figures 20.5 and 20.6, G16 dealers and banks - as already anticipated in Figure 18 - function as central nodes of the network.

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51 See Figure 7 in Section 3 above.

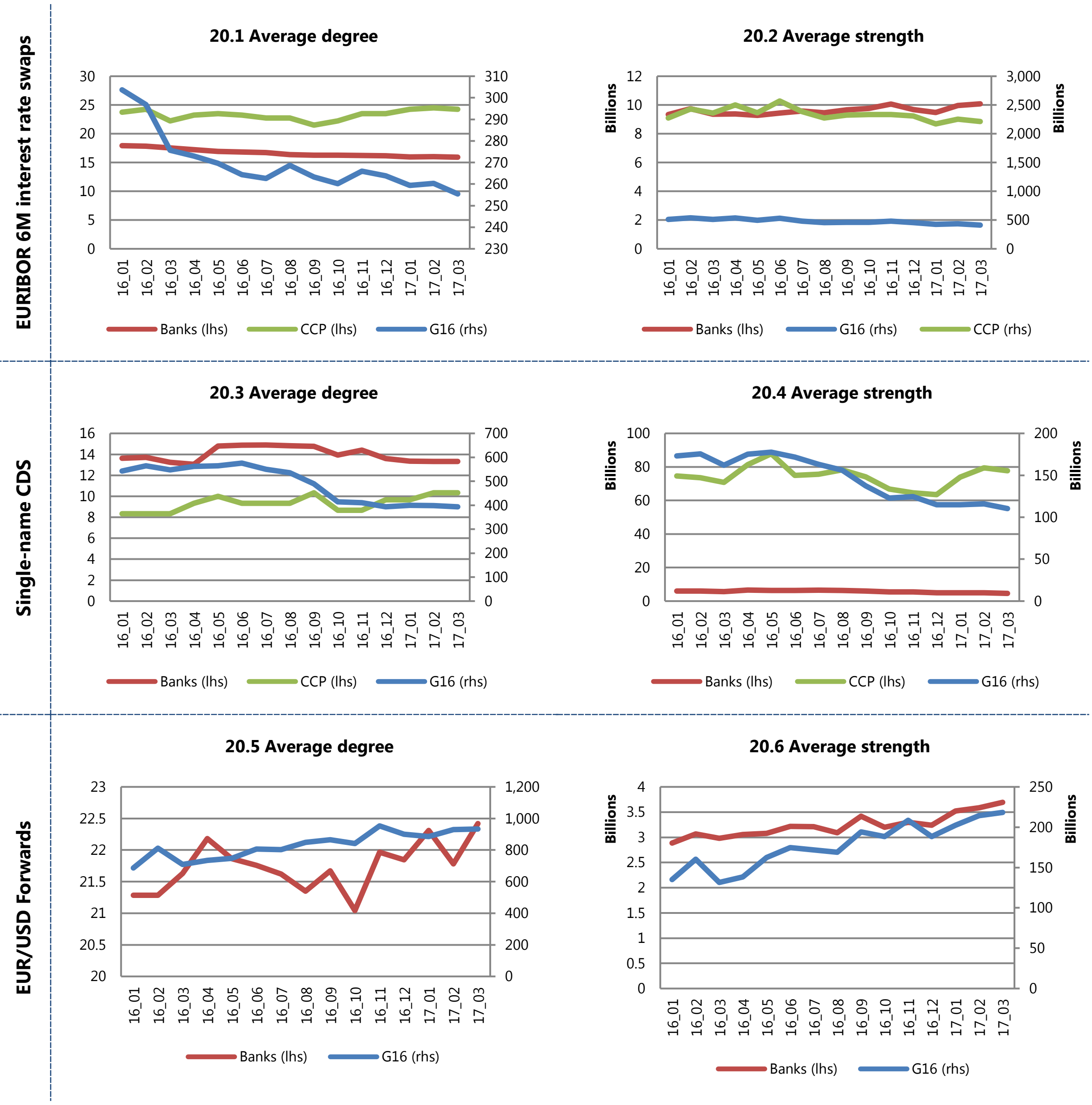
52 See Section 4.

53 The entry into force of the frontloading provision established by Regulation (EU) 592/2016 for the clearing of index-CDS was in October 2016. While no direct causality can be established – our dataset excludes the contracts flagged as "Index" in EMIR – the decrease in the average degree coupled with the increase in the maximum degree suggests that some form of concentration has impacted the core – i.e. the most active part - of the network.

54 As a reminder, the clearing obligation only applies to index CDS. However, some form of spill-over effect on other types of instruments may occur.

55 See Figure 18 above. This result is consistent with the one of Abad et al. (2016).

Figure 20: Average degree and average strength by counterparty type.



Source: ECB calculation based on DDRL EMIR confidential data.

Conclusions

The objective of this paper was twofold: first, we aimed at taking stock on EMIR data, almost three year after the entry into force of the reporting obligation in the EU; second, we tried to map and follow the developments in the euro area OTC derivatives markets with the purpose of concretely assessing the potential and challenges of EMIR data.

With regards to our first objective, we found that EMIR reporting framework, which needs to capture a complex and wide set of products with diverse characteristics and to rely on multiple private entities – the TRs – for data collection and validation, can be effective only if combined with clear, detailed and enforceable reporting rules. While the current situation shows significant margins for improvement, the entry into force of Regulation (EU) 104/2017 and of Regulation (EU) 105/2017 on 1 November 2017 is expected to bring some important progress.

The abovementioned data quality concerns affected our ability to identify trends and events affecting EMIR OTC derivatives markets, especially for the least recent periods. At the same time, existing data allow to capture the characteristics of the markets and the general trends following institutional changes such as the introduction of the clearing obligation. The use of network analysis techniques also provides useful insights on the features of the market and highlights the differences between sub-markets.

EMIR data are a uniquely source of information for macro-prudential policy makers: both the intrinsic characteristics of the derivatives market and the reporting policy choices and implementation history, however, pose a series of important challenges. In the coming years, only a wider use of the dataset, more investments in IT infrastructure and resources as well as more frequent opportunities for the research community to exchange views and share experience on the challenges met and the solutions found in the use of EMIR data will help create the necessary knowledge and conditions for them to unleash their full potential.

References

Abad, J. et al. (2016). Shedding light on the dark markets. First insights from the new EU-wide OTC derivatives dataset. *ESRB Occasional Paper Series*, N. 11/September 2016.

Ali, R. et al. (2016). Systemic risk in derivatives markets: a pilot study using CDS data. *Bank of England Financial Stability paper* No 38.

BIS (2016). Statistical release - OTC derivatives statistics at end-June 2016. Available online at: http://www.bis.org/publ/otc_hy1611.pdf.

Cielinska, O. et al. (2017). Gauging market dynamics using trade repository data: the case of the Swiss franc de-pegging. *Bank of England Financial Stability paper* No 41.

ECB (2010). The "Centralised Securities Database" in brief. Available online at: https://www.ecb.europa.eu/pub/pdf/other/centralisedsecuritiesdatabase201002en.pdf.

ECB (2016). Looking back at OTC derivative reforms - objectives, progress and gaps, 20 December 2016, Economic Bulletin Issue 8, 2016.

FSB (2017). OTC Derivatives Market Reforms: Eleventh Progress Report on Implementation, available online at http://www.fsb.org/wp-content/uploads/OTC-Derivatives-Market-Reforms-Eleventh-Progress-Report.pdf.

Kenny, O., et al. (2015). Network analysis using EMIR credit default swap data: Micro-level evidence from Irish domiciled special purpose vehicles (SPVs). Central Bank of Ireland Quarterly Bulletin, Q3.

Iori, G., et al. (2008). A network analysis of the Italian overnight money market. *Journal of Eocnomic Dynamics and Control*, 32(1), 259-278.

Nohrstedt, D., & Weible, C. M. (2010). The logic of policy change after crisis: Proximity and subsystem interaction. *Risk, Hazards & Crisis in Public Policy*, 1(2), 1-32.

Osiewicz, M., Fache Rousová, L. and Kulmala K.-M. (2015). Reporting of derivatives transactions in Europe - Exploring the potential of EMIR micro data against the challenges of aggregation across six trade repositories. IFC workshop on "Combining micro and macro statistical data for financial stability analysis. Experiences, opportunities and challenges" Warsaw, Poland, 14-15 December 2015

Irving Fisher Committee on
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BANK FOR INTERNATIONAL SETTLEMENTS

IFC-National Bank of Belgium Workshop on "*Data needs and Statistics compilation for macroprudential analysis*"

Brussels, Belgium, 18-19 May 2017

Euro-area derivatives markets: structure, dynamics and challenges[1]

Mario Ascolese, Annalisa Molino, Grzegorz Skrzypczynski, Julius Cerniauskas and Sébastien Pérez-Duarte,
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

Euro area derivatives markets: structure, dynamics and challenges.

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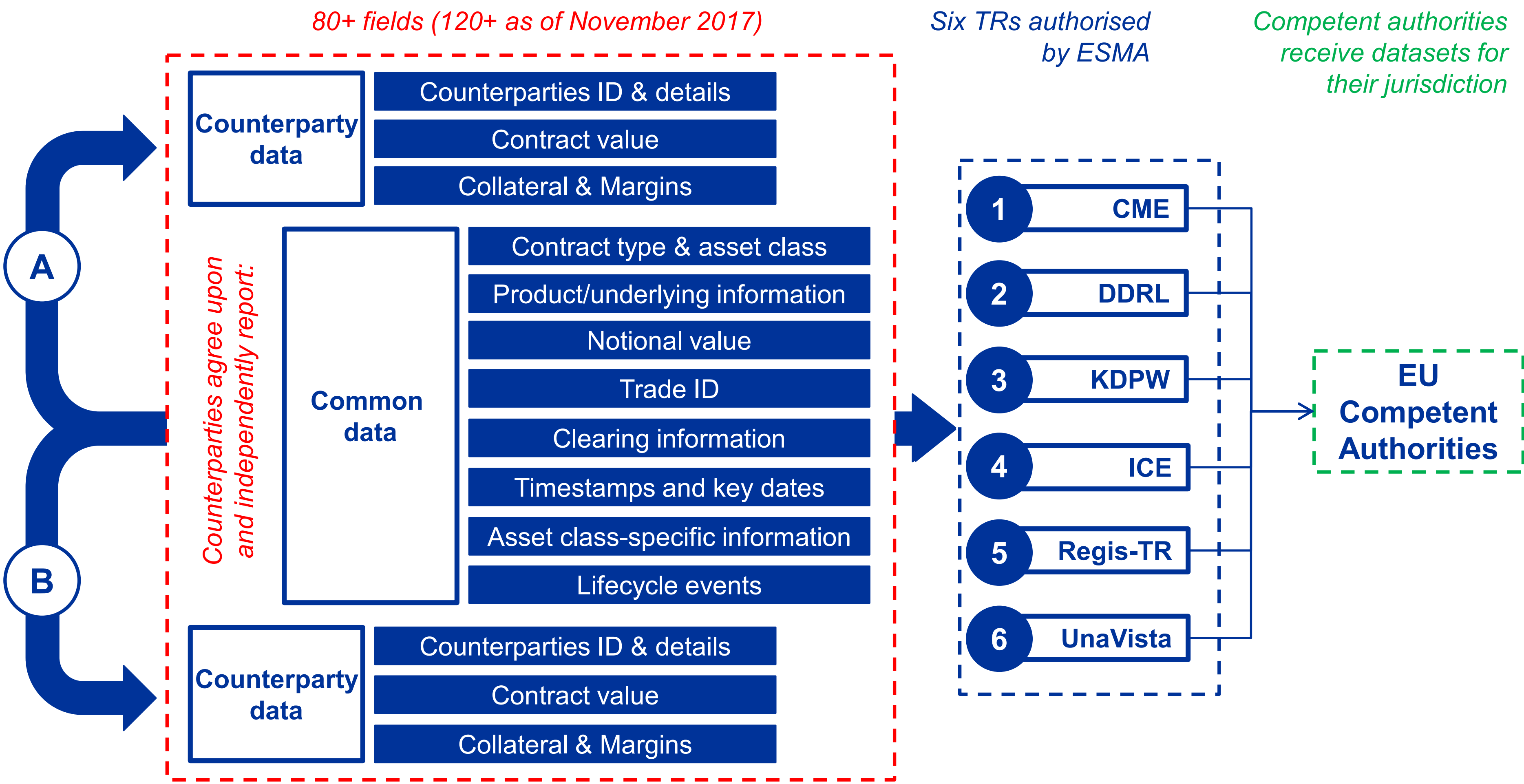
IFC-NBB Workshop

Data needs and statistics compilation for macroprudential analysis

19 May 2017, Brussels

Overview

EMIR confidential data collection process



Challenges and way forward

CHALLENGES		WAY FORWARD
Data quality & aggregation	Unidentifiable products and trades	UPI & UTI guidance
	Unidentifiable counterparties and underlying	Mandatory use of LEIs/ISINs
	Missing and outlier values	Stricter validation and enforcement
	Inconsistent reporting of rates, contract value, currencies, benchmarks…	Clearer technical standards
Data volume and accessibility	Data volume and data access infrastructure	Uniform TR technical specifications and big data infrastructure (efficiency from interinstitutional coordination)

Dataset and cleaning process

Dataset

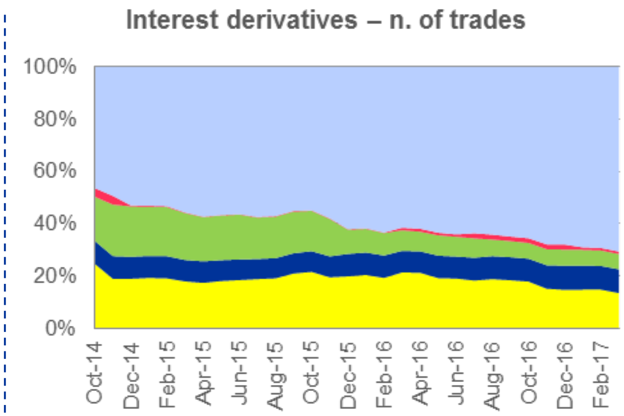
- TR: DDRL trade-state reports (euro area)
- Period: Oct 2014 to Mar 2017
- Asset classes: interest rate, credit, currency derivatives
- De-duplication based on trade ID and common data

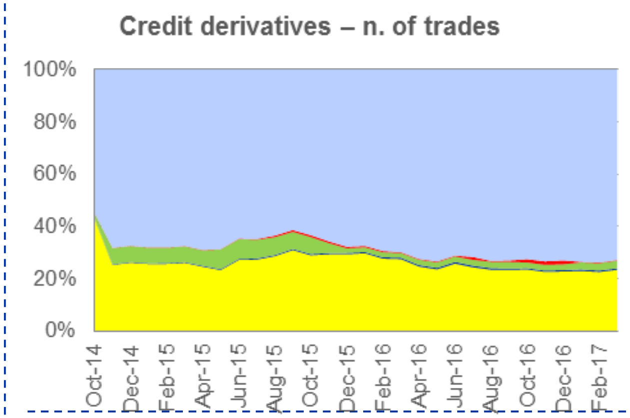
Cleaning procedure

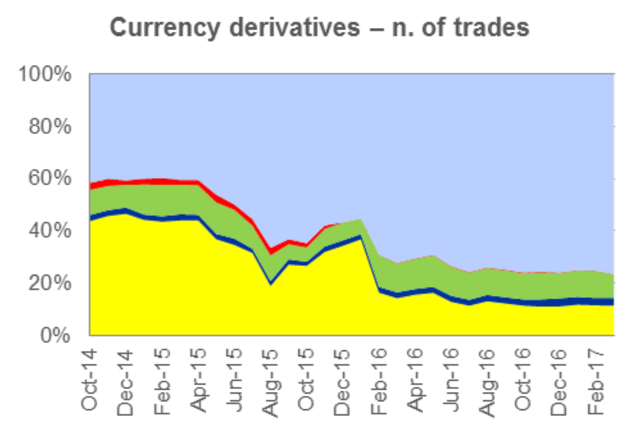
- Sequentially drop observations with:
  1. Missing or unrealistic contract value (yellow)
  2. Missing or unrealistic notional value (dark blue)
  3. Unidentifiable counterparties (green)
  4. Wrong timestamps (red)
  5. As a result, we obtain a clean dataset (light blue)
- Subsequently filter out:
  - Missing or irretrievable benchmarks (interest rate)
  - Missing or irretrievable underlying issuer (credit)
  - Missing or irretrievable currency pairs (currency)

Results

- Positive trend in data quality, but "survival" rate still 60%
- UPI/UTI/LEI/ISIN crucial for better data quality
- Need for stricter validation by TRs



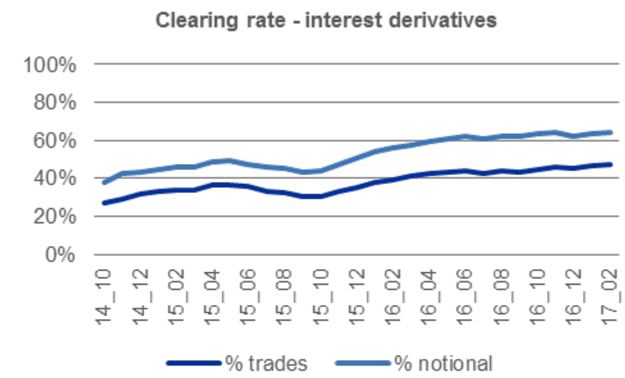




The euro area OTC interest rate derivatives market

Main characteristics

- Largest asset class, with a **total notional outstanding of over €100 trillion** (March 2017), c.25% of global BIS aggregate;
- Slightly decreasing in size since 2016;
- **Top product** types are swaps (86%), options (5%) and forward rate agreements (4%);
- **Top benchmarks** are EURIBOR (25%), USD LIBOR (11%) and JPY LIBOR (4%);
- **High and increasing clearing rates** (c.45% of trades and 60% of notional outstanding).



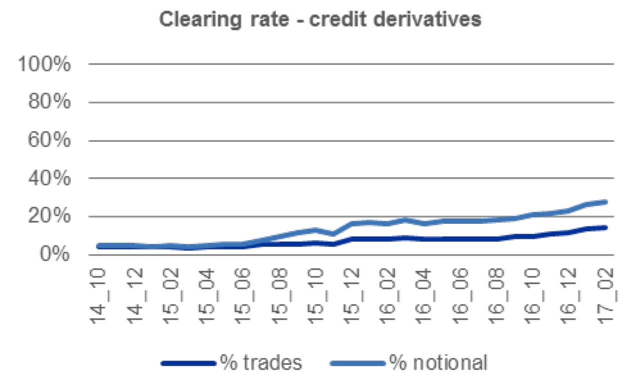
Sub-market (EURIBOR 6M IRS) network visualisation

- **CCPs at the core** of the network;
- Significant **intermediation role of G16 dealers and banks** (delegation of clearing);
- **Sparse network** with many small participants.

The euro area OTC credit derivatives market

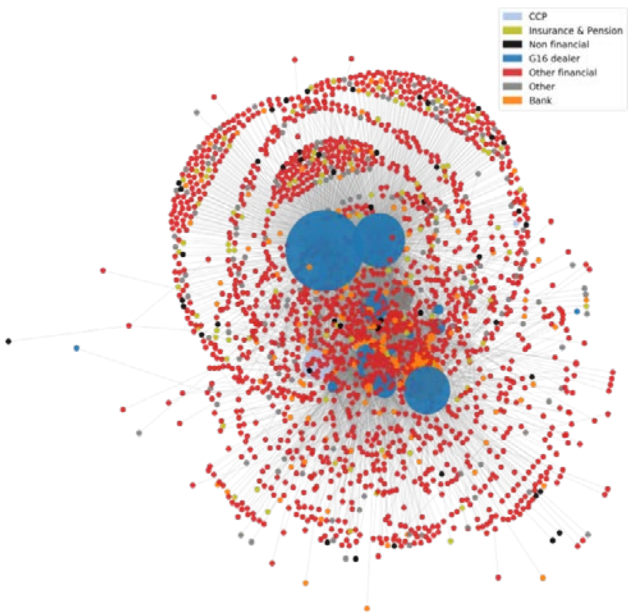
Main characteristics

- Smaller market, with a **total notional outstanding of c. €7 trillion** (March 2017), half of global BIS aggregate (caveat: BIS only considers CDS);
- Slightly decreasing in size since 2016;
- **Top product** type is swaps (95%);
- Increasing importance of **Index products** (20% of total trades but 60% of total notional);
- Sovereign (40%), non-financials (30%) and banks (10%) **top underlying securities issuers' sectors**;
- **Increasing clearing rates** (c.20% of trades and 40% of notional outstanding), both for index and single-name products.



Sub-market (single-name CDS) network visualisation

- **G16 dealers and banks at the core**;
- **Higher density** (each node trades with more other nodes);
- Lower impact of clearing obligation.



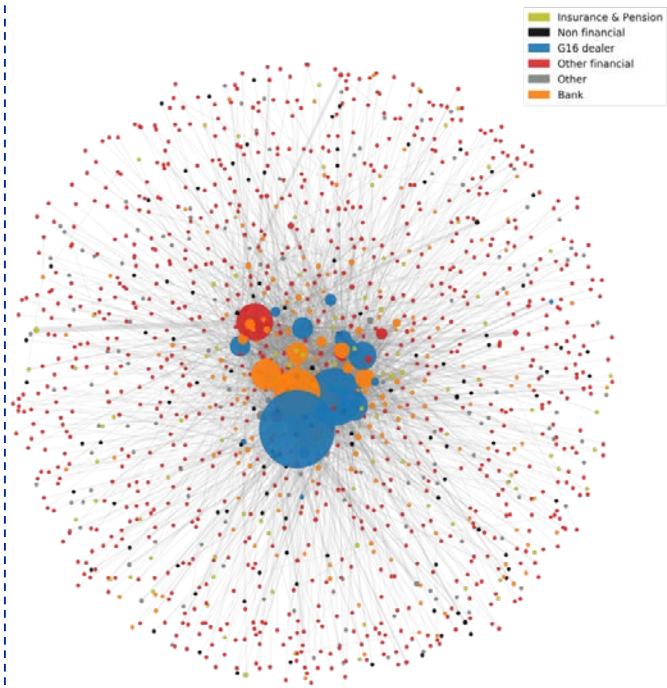
The euro area OTC currency derivatives market

Main characteristics

- Market in expansion, with a **total notional outstanding of c. €20 trillion** (March 2017), c.25% of global BIS aggregate;
- **Top product types** are forwards (80%) and options (15%);
- **Top currency pairs** are EUR/USD (37%) and USD/JPY (10%);
- Slightly higher number of contracts but lower total notional outstanding compared to interest derivatives points to a more dynamic market, with short-term contracts to cover specific currency risks;

Sub-market (EUR/USD forwards) network visualisation

- More **diverse structure**: G16 dealers, banks and other financial institution at the core;
- **Higher participation of non-financial counterparties**;
- Sparse network.



A dynamic view over the sub-markets' structure (1)

- We build an **undirected network** of the three sub-markets considered above (EURIBOR 6M IRS, single-name CDS and EUR/USD forwards) and compute the following measures **between January 2016 and March 2017**:

Measure	Definition	Meaning
Size	The number of nodes in the network.	How many counterparties?
Volume	The number of links between nodes in the network.	How many outstanding trades among counterparties?
Degree	The number of links connected to a node.	How many other counterparties does each counterparty trade with?
Strength	The sum of weights of all links connected to a node.	What is the aggregate outstanding notional of all trades each counterparty is involved in?
Density	The fraction of present connections to possible connections.	How interconnected are counterparties among themselves?

A dynamic view over the sub-markets' structure (2)

	1 EURIBOR 6M IRS	2 Single-name CDS	3 EUR/USD forwards
Size	High but decreasing	Lower than IRS and slightly decreasing	Very high and increasing
Volume	High but decreasing	Lower than IRS and slightly decreasing	Very high and increasing
Average degree	Low and stable	Higher and slightly decreasing; CCPs increasing	Low and stable
Average strength	Increasing, driven by CCPs; high values for G16 too	Slightly decreasing, with the exception of CCPs	Very low and slightly increasing
Density	Low and slightly increasing	Higher than IRS and stable	Low and stable

1. **Slight increase in density and strength** (especially for CCPs) resulting from the clearing obligation; **G16 remain the core** of the network.
2. **Denser network**, with **CCPs acquiring increasing importance** (although clearing obligation only applies to Index products).
3. **Sparse and expanding network**, with the largest number of participants and the highest volume; **G16 and banks playing an increasingly important role**.

Conclusions

- EMIR data are a **powerful tool to monitor OTC derivative markets dynamics**, but still subject to a number of caveats.
- EMIR **data quality challenges** is a result of:
  1. Intrinsic complexity of OTC derivatives markets and products (*we can't do anything about it*);
  2. Incompleteness of regulatory standards and insufficient reporting standardisation (*we can do a lot*).
- **A lot has been done** and the conclusion of the work of UPI/UTI, as well as the entry into force of the new ITS/RTS will bring **further improvements**.
- **Investment in resources** and infrastructure, **better coordination among authorities** as well as more **opportunities for exchange of views** and experience among users will increase the knowledge in the area and **favour a broader use of the data**.

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The use of derivatives trade repository data: possibilities and challenges[1]

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[1] This paper 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.

The use of derivatives trade repository data: possibilities and challenges

Iman van Lelyveld[1]

Abstract

The EMIR derivatives data collected through trade repositories is coming to fruition. Given the scale of the reporting exercise and the complexity of the subject matter it has taken some time to develop but now the data is used in earnest in more and more institutions. It is potentially useful for both micro and macro prudential supervision as well as for producing statistics. In this paper, I first sketch these potential uses and then sketch how we are currently approaching the EMIR project at De Nederlandsche Bank.

Keywords: EMIR, derivatives reporting, trade repositories

Introduction

The 2008-2009 crisis made it abundantly clear that we did not have an accurate picture of risk concentrations in the global financial system. Reporting of exposures was mainly aggregated, on a consolidated basis, and confined within borders. This is now changing rapidly for many markets due to new reporting, although gaps remain (e.g. shadow banking). In many cases the new reporting allows for analysis based on individual transactions between two counterparties known by name. Often the frequency is such that analyses could potentially be done in real time.

A prime example of newly collected data is the reporting on derivatives – once one of the most opaque financial markets in the world which is in the process of becoming much more transparent. In 2009, G20 leaders committed to a requirement that all OTC derivative contracts be reported to trade repositories.[2] In the EU, this G20 commitment is implemented in the European Markets Infrastructure Regulation (EMIR).[3] Since 2014, counterparties resident in the EU (including CCPs) have been required to report the details of new and outstanding derivatives transactions to trade repositories. Whereas EMIR grants the ESRB and ESMA access to the full EU-wide dataset, Dutch competent authorities have access to those transactions where at least one of the counterparties is a Dutch resident or where the underlying is Dutch.[4]

[1] Views expressed are those of the author and do not necessarily reflect official positions of De Nederlandsche Bank. I would like to thank colleagues at DNB for their comments and Sanne Schimmel for her work on the network section. All remaining errors are mine.

[2] See http://www.g20.utoronto.ca/2009/2009communique0925.html. It is part of 20 recommendations aiming to improve financial stability analysis (cf. Heath and Goksu (2013)). In the Netherlands these are at the moment CME, DTCC, Ice Trade Vault, Regis-TR, and UnaVista

[3] See Art. 9 of EMIR (http://eur-lex.europa.eu/legalcontent/EN/TXT/?uri=CELEX:32012R0648).

[4] See Art. 81(3) of EMIR (ibid).

This paper aims to cover two topics. First, we want to describe the potential uses the EMIR data can have at de Nederlandsche Bank (DNB). Secondly, we aim to describe our current two-track approach towards opening up the data source. We will briefly describe both aims below, starting with the data's use at DNB. The EMIR trade repository (TR) data provides granular information on a daily frequency that can potentially inform many parts of a central bank with supervisory responsibilities such as DNB. The use of the data can broadly be classified in 1) checking the compliance with legal requirements following from EMIR, 2) microprudential supervisory questions, 3) macroprudential issues and 4) statistical uses. For the first, ascertaining legal requirements, the data could provide information on the timeliness of confirmations, revaluation and margining. The second area, microprudential questions, could for instance analyse the risk of an individual institution's position. Given the scope of reporting, these institutions can be banks, pension funds, insurance firms or other (financial) firms of interest. The third use is in answering macroprudential questions. Here one could look at where risks flow in the system. Finally, the data could be used for producing national accounts or balance of payments statistics. The data could be used either to check the existing reporting or even to replace the current reporting altogether. We will describe our progress in this area and give examples of the analysis produced.

The second aim of the paper is to describe our current two-track approach to unlocking the data. On the one hand, we are taking a rigorous approach where we have first defined the Logical Data Model (LDM) for the 'Activities' report. It is currently being adapted for the 'Trade State' reports including the upcoming ESMA changes. Given the quality of submissions, a strict application of the LDM results in a very small data set. Using business rules, a data set of sufficient quality can nevertheless be constructed. To understand where quality could be improved most, we have built an application in SAS Visual Analytics and are working closely with the Dutch Authority for Financial Markets (AFM) to improve the data quality feedback loop with reporters.[5]

In parallel, we are also taking a more pragmatic approach where we process the files from just a single TR and asset class (i.e. DTCC Credit CDS) from December 1*st* 2015 onwards.[6] In cleaning, we apply 'business rules' such as making the spelling of country names compliant with ISO standard names. Strict application of the LDM would lead to dropping some otherwise compliant observations. We are also enriching the data with information from Legal Entity Identifier (LEI) registers, the Centralised Securities Data Base (CSDB), the Securities Holding Statistics (SHS), Bloomberg, and Datastream. This pragmatic approach allows us to already get acquainted with the data, suggest plausible business rules and provide relevant and timely analysis speaking to supervisory and policy questions.

Given the aims of the paper, the set-up is straightforward. I will first provide an overview of the existing work. Then we will discuss the potential uses of trade repository data followed by a section on the caveats. This brings us to the second part of the paper where I give a brief overview of how the EMIR project is progressing at DNB. Finally, I conclude.

5 In another effort to improve the feedback loop we organised a seminar at the end of 2015 entitled "TR data: Sharing is Caring" and invited all parties involved in the reporting (trading firms, TRs, regulators and supervisors).

6 Stata is the main package used although part of the process is handled in R, Python and Gephi.

Overview of existing work

Analysing the trade repository data has been slow to take off but now shows a steady stream of papers being published. The stock of papers I am currently aware of includes the following. An early paper was published by Clerc et al. (2014) who look at the network structure of the European derivatives market. The ESRB has been very supportive of work in this area, coordinating efforts between National Competent Authorities (NCAs) and inviting academics to work on the data. This has resulted in several papers that look at the market as a whole (Peltonen et al. (2014), Abad et al. (2016)). In addition, there are a number of topical papers on for example the Greek crisis, the transfer of risk, compression, and the structure of the interest rate swap market (See Hal aj et al.(2016), D'Errico et al. (2016), D'Errico and Roukny (2017), and Fiedor et al. (2017), respectively). Some NCAs have been very active as well, in particular the Bank of England. This had led to contributions focussing on for example the structure of the market, counterparty credit risk and the de-pegging of the Swiss Franc (Ali et al. (2016), Benos et al. (2013), Benos et al. (2016), Morrison et al. (2016), and Cielinska et al. (2017)). The Deutsche Bundesbank is quite active in this field as well (Gehde-Trapp et al. (2015), Gu¨ndu¨z et al. (2016), and Gündüz (2016)). Another noteworthy paper is Kenny et al. (2016). In this analysis the use of derivatives by Irish SPVs is examined.

Since the Dodd-Frank act in the US mandates a very similar reporting framework, several recent publications make use of trade repository data as well. For example, Cetina et al. (2016) and Paddrik et al. (2016) use CDS data to look at counterparty concentration and systemic risks, respectively. Iercosan and Jiron (2017) look at the value of trading relationships.

Since the trade repository data include the names of the counterparties, it consequently has the drawback that access is restricted for academic researchers. Some researchers have therefore turned to the information in DTCC's Trade Information Warehouse. This has for instance resulted in an excellent job market paper by Siriwardane (2015). Finally, there is a wealth of data in the ESMA reporting on EMIR progress (ESMA (2015a), ESMA (2015b)).

Potential use of the trade repository data

The trade repository data can be used in many areas relevant for supervisors, regulators and central banks. We will discuss applications in the area of micro prudential, macro prudential and statistics in turn.

Using one reporting framework to answer different data needs is part of a wider trend. Traditionally, authorities reacted to information demands by designing forms with a precise structure and definitions. These definitions were fit-for-purpose – because they for instance matched a particular regulatory or accounting framework – but were often very inflexible and had little regard for other data needs. Data from different reports are thus difficult to reconcile. Also, if a slightly different question arises, costly new reporting is required. By collecting data on a much more granular level, it is potentially possible to aggregate the data in multiple ways and thus flexibly answer several data questions with just one report. The flexibility comes with a cost: the compiler of the data needs to have a much deeper understanding of the aggregation process and the resources to compile the data as well. Furthermore, there needs to be a discussion on standardisation of financial records keeping and on where the optimal collection point of the data is. It is clear, however, that in the long run we will be relying on more granular data that is collected closer to the source.

Micro prudential

From a micro-prudential regulation perspective, the TR data provide a wealth of information on a frequent basis. For those parts of the supervised firm that operate in the European Area, all transactions - including intragroup - need to be reported.

Derivative contracts are often non-linear and hence the value of a position can fluctuate drastically. To asses a firm's position thus requires frequent updates on the value of the exposures.

To accurately assess the net risk, more information is needed. For one, to mitigate the impact of a possible default, counterparties exchange margin aiming to reduce the exposure as much as possible. Often the required margin is computed based on the net value of a portfolio of positions (netting set). A proper assessment of real exposures thus requires information on what has been legally agreed to as netting sets. The TR reporting does include the type of information to come to a comprehensive assessment although further work is needed in matching the TR positions with those reported in prudential reporting. Moreover, many derivative positions are used to hedge other risks such as credit or interest rate risk on loans. The derivative portfolio should thus be assessed jointly with other positions. For example, to assess interest rate risk we could start with linking the bond portfolio information reported in the ESCB Securities Holdings Statistics with the TR data.

Macro prudential

One of the key motivations for the G20 to push for more comprehensive reporting on derivatives was that due to the global and over-the-counter nature of this market, no single authority had a proper understanding of the structure of the market. This made it difficult to assess the macro risk. A macro risk is for instance the risk of an individual institution being too systemic. The insurer AIG is a case in point. Alternatively, it can also emerge because a group of firms act in a very similar way. Such herding can lead to unpredictable overreactions. In both cases we need a better understanding of the structure of the market.

An empirical argument for why the structure of the market matters is provided by Morrison et al. (2016). The authors argue that market participants price the counterparty risk. That is, firms hit by a negative shock can charge less for protection sold. Intriguingly, participants charge a risk premium for a risk they cannot readily observe. This means that shocks to the creditworthiness of key players will affect the price of risk, charged to financials but also to the real economy.

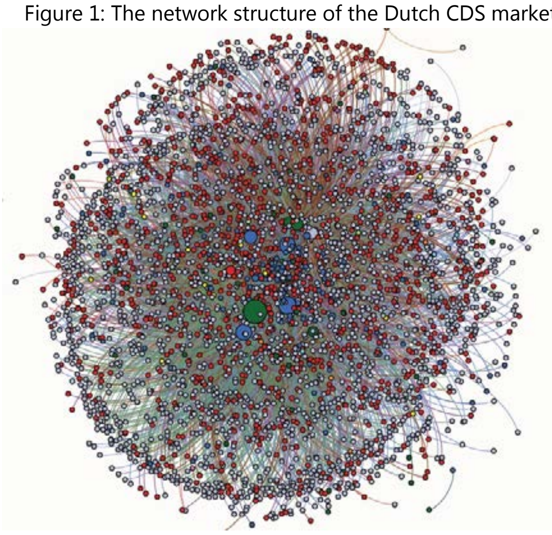
Another example is given by D'Errico et al. (2016). This paper traces out how risk is sold into the market, intermediated by big dealer banks and then absorbed by other market players. This is exactly how textbooks see the role of derivatives: risk is being redistributed to those willing to bear it. With the current reporting set we can now see who the parties are that are providing credit risk insurance to the market. If these parties have sufficient buffers, then this will not pose any a risk to the system.

However, if buffers are too low or providers are politically connected making a bailout more likely, this might not be a stable situation.

Finally, Paddrik et al. (2016) provide a macro perspective on the distribution of stress through margin calls. In their paper, the authors apply the US prudential stress test scenario (CCAR) to the value of the derivative portfolio in the system. They then analyse how margin requirements would be redistributed. Interestingly they find that those firms most exposed are not necessarily the core firms.

Using the Dutch credit derivative data, we have examined the structure of the Dutch market as well. Figure 1 plots the relations amongst all counterparties in the data. This network has a core-periphery structure with several large banks in the core similar to the interbank market (cf. in 't Veld and van Lelyveld (2014)). Interestingly there is also a Other Financial Intermediary quite important in the in core. The structure is relatively stable over time.

Figure 1: The network structure of the Dutch CDS market



Statistics

There is a growing recognition that collecting micro data can improve and complement traditional ways of constructing (macro) statistics (Tissot, 2016). A key challenge is the aggregation from micro to macro. Financial transaction reporting has generally been set up for a different purpose and hence has definitions that might be different from those used in statistics. Also, since the data is at the level of individual entities (or even natural persons), data sharing can be very sensitive and is usually protected by quite restrictive rules. Notwithstanding these issues, trade repository information can be potentially useful in cross-checking or even replacing existing reporting exercises. This holds for both statistics on financials flows ("Flow of Funds") as well as for positions ("National Accounts"). For both the stock and flow terms, the micro data has to be consistent not just on the national level but also internationally. For both we thus need a broad coverage and the location of the ultimate owner which the TR data provide. However, the TR data were set up to monitor trading relations and hence do not have the ultimate owner information embedded. Using group information the legal entity level reporting (i.e., LEI) can be aggregated to various definition of what constitutes a group (See the box).

Other statistical reporting, for example on the activities of less or nonregulated parts of the financial system can also benefit from TR information. For example, special purpose vehicles in Ireland are keen users of derivatives. Kenny et al. (2016) use TR data for an analysis of this sector and identify SPVs who are net sellers of CDS contracts with linkages to regulated, non-domestic monetary financial institutions (MFIs). Overall, the authors note that their analysis "points to the importance of access to good quality micro-level regulatory data when monitoring financial stability risks".

The importance of consolidation

A major challenge in the use of data that is reported on the individual legal entity is its relationship with the data of other related firms. A firm might for instance own (part of) another firm or conversely be owned. Such ownership relations might be reflected or not (i.e. consolidated versus solo). Although the Legal Entity Identifier (LEI) should uniquely identify the firm, it currently does not record the ultimate owner structure although this is envisaged in the future.[a] The relationship data will allow for combining groups of firms according to particular views. This could be 1) an accounting view, 2) a prudential regulatory view, 3) a counterparty credit risk (CCR) view or 4) the resolution authority view. The first two views are the firm as it is defined by the accountant or the regulator. The third, the CCR view is the view taken by the counterparty of the group. The difference with the accounting view is that the counterparty might for instance judge that a securitisation vehicle will come back on the balance sheet and hence the effective consolidation perimeter would be different. Finally, the resolution authority might carve out some parts of the firm that are within its jurisdiction. It would therefore delineate the firm differently. With a well-maintained dynamic database of granular ownership data, users can generate their own group definition whenever needed. The same reporting can then be used to generate different views.

[a] The GLEIF is currently finalising, in consultation with LEI Issuers, the technical specifications for recording relationship data, which will start being implemented in early 2017. It is expected that all LEI Issuers will have developed the capacity to record relationships with direct and ultimate parents as defined in the report (cf LEI ROC (2016)).

Caveats

TR reports are relatively new and have yet to be used to their full potential. As with any new reporting framework there are flaws in reporting that need to be addressed. Since the start of reporting, ESMA has undertaken various steps to improve the data collection, also as part of ESMAs data quality action plan. In particular, ESMA is involved in on-going TR supervision, provides regular updates of Questions and Answers (Q&As), and now enforces validation rules implemented by TRs (Level 1 and Level 2 validations). All of this has contributed to gradual improvements in data quality.

Some of the shortcomings will be addressed by the Regulatory Technical Standard (RTS) coming into force on November 1^{st} 2017.[7] For instance, in reporting an index derivative, the composition of the index currently does not have to be disclosed. For bespoke baskets this might be defensible but if the index is a widely used benchmark (e.g., the S&P 500), it would seem quite informative if reporters indicate the relevant underlying benchmark. Another example is that it is currently not possible to link individual components of a complex derivative. End-users thus see several transactions, without knowing that they are a part of one (complex) derivative. The new reporting regime introduces the field "Complex trade component ID" which can be used to identify all the observations that should be evaluated jointly.

Tackling the EMIR repository data at DNB

The second aim of the paper is to describe our current two-track approach to unlocking the data: one the one hand a rigorous approach, handling EMIR as a regular statistical resource, and on the other a more pragmatic exploratory approach. EMIR fits into a more general development at DNB which aims to make our supervision and policy work more data-driven. It also fits in the trend – discussed above in Section 3.3 – of moving away from the single form and single purpose reporting to comprehensive granular reporting to be used for multiple objectives.

At the same time, on-boarding the EMIR data is a daunting task with little in terms of low hanging fruit at first. Three aspects of the data are particularly problematic: 1) the lack of a natural owner, 2) the size of the data, and 3) the complexity of the subject matter.

First, there is no natural owner for TR-data. The data does not cover a particular sector, nor does it neatly follow the prudential / conduct-of-business split and hence there is not one business area that is clearly best placed to take ownership. And at DNB – as will be common in many institutions – a data sets needs an ultimate owner who is willing to organise budget and wants to overcome hurdles. To address this issue, we have set up a group of owners from across the bank. This group now jointly decides on things such as access rights and Business Intelligence (BI) tooling.

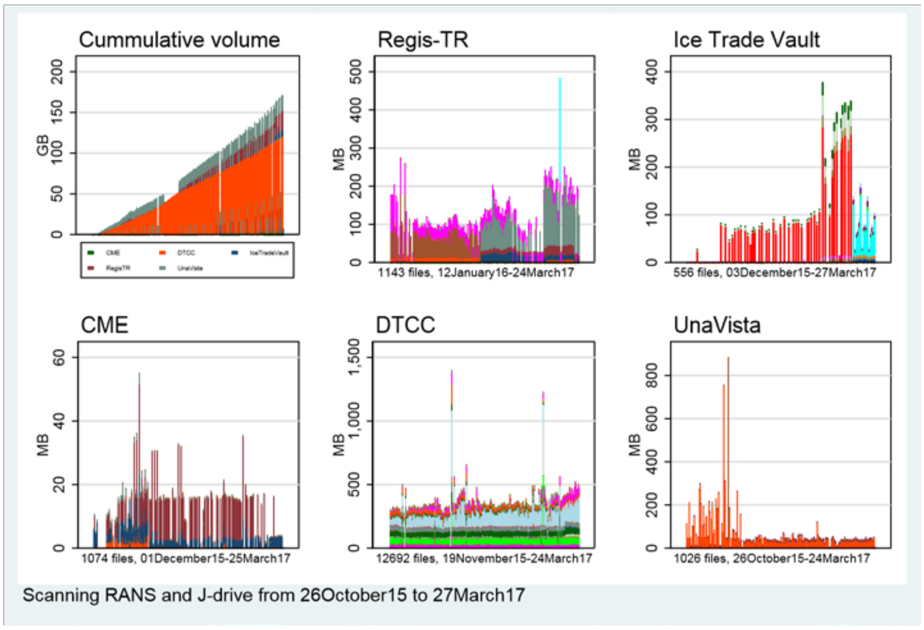
Second, the size of data coming in is daunting. Figure 2 shows the number and volume of zipped files currently available. In the top-left panel we see that total volume currently stands at 160 GB, growing at roughly 900 MB a day. With a compression factor of about 80% this translates into 800 GB in raw csv files. Since the data quality is at places rather poor it is difficult to reduce the volume through clever database management. The other panels in Figure 2 show the files by trade repository where each of the colours indicates a different type of files (based on the naming convention used). Clearly repositories use different names, change the names occasionally, provide just a few or many files and sometimes misreport (leading to spikes in reporting volume).

Finally, complexity. Derivatives are not easy to value. The current value is determined by a myriad of factors such as the volatility of the underlying, the length of the contract, the credit worthiness of the protection seller, margins exchanged and

[7] See https://www.esma.europa.eu/convergence/guidelines-and-technical-standards for a full description of the changes in the RTS.

so on and so forth. Nevertheless the EMIR reporting framework can potentially provide many of the building blocks to come to a proper evaluation. For instance, we should be able to come to gross notional positions for all participants. Assuming we can always net on the same underlying, we can also come to net positions. Going one step further we could even take an educated guess at real net positions. Where things become more complicated is for instance in reported mark to market values. Counterparties do not necessarily have to agree on these. However, the values should be in the same ballpark. Big discrepancies can indicate a failure of risk management of at least one of the counterparties.

Figure 2: The volume of files

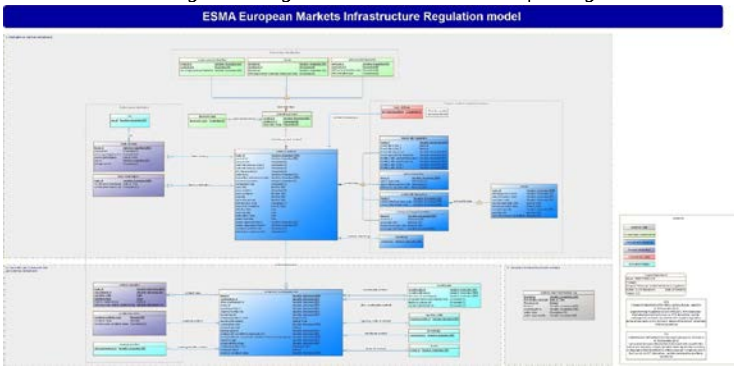


The high road

The first of our two parallel tracks is taking a rigorous approach where we first define a Logical Data Model (LDM) for the 'Activities' report. Such a model, shown in Figure 3, describes in detail the aspects of each data point submitted and can be used to assess the quality of the submissions. Currently we are drawing up the data model for the 'Trade State' reports. In addition, we will be adapting the model to account for the upcoming ESMA changes. Given the quality of submission, a strict application of the LDM does not result in anything useful.

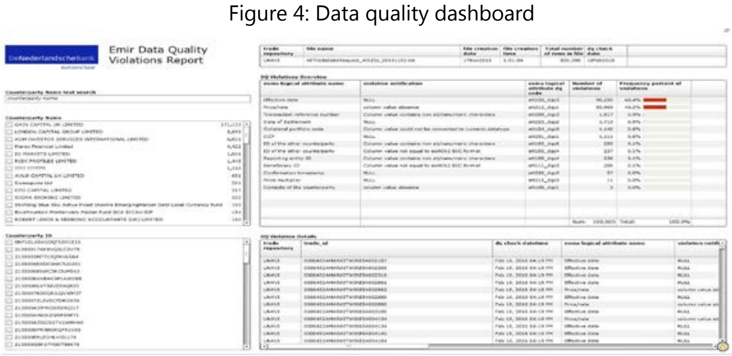
To understand where the quality could be improved most, we have built an application in SAS Visual Analytics (screenshot in Figure 4). In this application it is possible to see the number of errors the data generates. It is also possible to drill down into the quality for a particular reporter or underlying ISIN. We are working closely together with the Dutch Authority for Financial Markets (AFM) to improve the data quality feedback loop with reporters.

Figure 3: Logical Data Model for TR reporting



Available on request: emir_analysis@dnb.nl

Figure 4: Data quality dashboard



EMIR Analysis group

In parallel, we are also taking a more pragmatic approach where we process the files from just a single TR and asset class (i.e. DTCC Credit CDS) from December 1*st* 2015 onwards.[8] Given our very limited resources, we decided to focus on this single slice but write our code flexibly so that it should in principle be able to handle other asset classes and TRs.

In cleaning we apply 'business rules' such as making the spelling of country names compliant with ISO standard names. Daily currency rates sourced from the ECB are used to denominate all amounts in euro. We are also enriching the data with information from LEI registers, the Centralised Securities Data Base (CSDB), the Securities Holding Statistics (SHS), Bloomberg, and Datastream. This pragmatic approach allows us to already get acquainted with the data, suggest plausible business rules and provide relevant and timely analysis speaking to supervisory and policy questions.

We apply a complete set of data quality checks to DTCC credit trade state reports between December 1*st* 2015 and all of 2016. For each of the steps (documented below the figure), Figure 5 shows the distribution of remaining observations after the

8 Stata is the main package used although part of the process is handled in R, Python, Ox and Gephi. We would be very happy to share our Stata code with competent authorities to promote cooperation in terms of coding.

applying the particular check. This figure is useful in detecting clear reporting errors such as for instance reporting an entire reporting date twice in one file (now fixed).

We are now in the process of examining our compiled data to put together an overview of the Dutch market. Such a first, exploratory exercise allows us to set the stage for more focussed papers such as discussed in Section 2.

Figure 5: The cumulative effect of data quality checks

1) invalid cpa LEI 2) invalid cpb LEI 3) the notional amount should not be missing or negative 4) the reference entity should not be missing 5) non-ISIN should be removed, but keep Index CDS 6) the maturity date should be larger than the effective date 7) the maturity date should be larger than the execution date 8) termination date should not be prior to fileDate (we only want active contracts) 9) double reports are dropped 10) triplicates are dropped 11) inconsistent notionals are dropped 12) inconsistent counterparty ID 13) inconsistent counterparty side 14) inconsistent maturities 15) inconsistent reference entities 16) inconsistent intragroup flags 17) mtmEur/notiEur AND notiEur should not be disproportional. 18) mtmEur winsorized at the top 1% and notiEur winsorized at the top 1%.

Conclusions

Derivatives markets across the globe are slowly becoming more transparent. The EMIR data that is being collected through the TRs is helping to "shed light on dark markets" (Sánchez et al. (2015)). The data becoming available has led to a fast developing research area which I briefly summarised.

The EMIR data are highly granular, have a broad scope and are collected daily. This fits into a more general trend of reporting with detail yet flexibly which arguably could replace some traditional reports (collected in a rigid format for just one particular purpose). Granular and flexible reporting has multiple uses and we discussed the possibilities for micro and macro prudential supervision as well as for statistical collection. We also discussed the caveats that come with a relatively new reporting framework.

In the second part of the paper, I described how DNB approaches the EMIR data. We take a two-pronged approach where we run a statistical and an exploratory track in parallel. The former aims to on-board the data as a fully fledged statistical resource. This is a rigorous process with the emphasis on traceability, reproducibility, and dependability. Obviously this is a resource intensive and thus – given budget restrictions – a slow process that in itself does not provide any insights into the trends and risks in the market. Therefore we also take a more pragmatic approach where we start with a limited scope, explore the data and then fix problems along the way. Naturally this process is coded and thus no less rigorous. But, for instance, reproducing the analysis for another TR requires a deeper understanding of the code and manual updating of auxiliary data such as for example exchange rates. The clear advantage is that it provides insights much faster. Moreover, the blemishes in the data identified along the way are helpful in the first statistical track.

In the coming year we aim to on-board both the "Flow" and the "Trade State" reports. The former will be used to assess the data quality while the latter is more useful in risk analysis. Hopefully we can make progress in understanding how to match them up. With both types of reports on our statistical platform, access, performance and thus ultimately the analysis will be much improved.

References

Abad J, Aldasoro I, Aymanns C, D'Errico M, Rousová LF, Hoffmann P, Langfield S, Neychev M, Roukny T. Shedding light on dark markets: First insights from the new EU-wide OTC derivatives dataset. ESRB Occasional Paper 2016;11.

Ali R, Vause N, Zikes F. Systemic risk in derivatives markets: a pilot study using CDS data. Bank of England Financial Stability Paper 2016;38.

Benos E, Richard Payne , Michalis Vasios . Centralising trading in the interest rate swap markets: The impact of Dodd-Frank. Bank of England Staff Working Paper 2016;580.

Benos E, Wetherilt A, Zikes F. The structure and dynamics of the UK credit default swap market. Financial Stability Paper 2013;25.

Cetina J, Rajan S, Paddrik M. Stressed to the Core : Counterparty Concentrations and Systemic Losses in CDS Markets. OFR Working Paper 2016;.

Cielinska O, Joseph A, Shreyas U, Tanner J, Vasios M. Gauging market dynamics using trade repository data: The case of the Swiss franc de-pegging. Bank of England Financial Stability Paper 2017;41.

Clerc L, Gabrieli S, Kern S, Omari YE. Monitoring the European CDS Market through networks: Implications for contagion risks. ESMA Working Paper 2014;1.

Committee LEIO. Collecting data on direct and ultimate parents of legal entities in the Global LEI System Phase 1. 2016. URL: http://www.leiroc.org/publications/gls/lou_20161003-1.pdf.

D'Errico M, Battiston S, Peltonen T, Scheicher M. How does risk flow in the Credit Default Swap market?, 2016.

D'Errico M, Roukny T. Compressing over-the-counter markets. Mimeo 2017;.

ESMA . EMIR Review Report no . 1: Review on the use of OTC derivatives by non-financial counterparties 2015a;(1).

ESMA . EMIR Review Report no . 4: ESMA input as part of the Commission consultation on the EMIR Review 2015b;(4).

Fiedor P, Lapschies S, Orszaghova L. Networks of counterparties in the centrally cleared EU-wide interest rate derivatives market 2017;.

Gehde-Trapp M, Gündüz Y, Nasev J. The liquidity premium in CDS transaction prices: Do frictions matter? Journal of Banking and Finance 2015;61:184– 205.

Gündüz Y. Mitigating Counterparty Risk. Working Paper 2016;.

Gündüz Y, Ongena S, Tümer-Alkan G, Yu Y. CDS and Credit : Testing the Small Bang Theory of the Financial Universe with Micro Data. Working Paper 2016;.

Halaj G, Peltonen TA, Scheicher M. How Did the Greek Credit Event Impact the Credit Default Swap Market ? Journal of Financial Stability 2016.

Heath R, Goksu E. Why are the G-20 Data Gaps Initiative and the SDDS Plus Relevant for Financial Stability Analysis? IMF Working Paper 2013;WP/13/6.

Iercosan D, Jiron A. The Value Of Trading Relationships and Networks in the CDS Market. Working Paper 2017;.

Kenny O, Killeen N, Moloney K. Network analysis using EMIR credit default swap data: Micro-level evidence from Irish domiciled special purpose vehicles (SPVs). Working Paper 2016;:1–20.

Morrison A, Vasios M, Wilson M, Zikes F. Identifying Contagion in a Banking Network. Working Paper 2016;.

Paddrik M, Rajan S, Peyton Young H. Contagion in the CDS Market. OFR working paper 2016;.

Peltonen T, Scheicher M, Vuillemey G. The network structure of the CDS market and its determinants. Journal of Financial Stability 2014;13:118– 33.

Sánchez JA, Hoffmann P, Langfield S., Mining for gold : Unearthing macro-prudential treasures in the new EU-wide transactions-level derivatives ('EMIR') data. Mimeo 2015;(August).

Siriwardane EN. Concentrated Capital Losses and the Pricing of Corporate Credit Risk. Job Market Paper 2015.

Tissot B. Development of financial sectoral accounts. Irving Fisher Committee on Central Bank Statistics Working Papers 2016;15.

in 't Veld D, van Lelyveld I. Finding the Core: Network Structure in Interbank Markets. Journal of Banking & Finance 2014;49:27–40.

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The European central counterparty (CCP) ecosystem[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.

The European central counterparty (CCP) ecosystem

Angela Armakolla and Benedetta Bianchi

Abstract

This paper provides a description of the EU centrally cleared markets. Based on data available under the Public Quantitative Disclosure framework (PQD) and further public data sources, we document aspects of central clearing counterparty (CCP) operations, such as member bases, asset classes cleared, transaction amounts, default waterfall resources, and the liquidity of the resources contained in the default waterfall. We also explore liquidity management of pre-funded default resources and CCP reinvestment strategies for participants' cash. Based on the analysis of the issues encountered when using PQD data, we propose a set of policy measures aimed at improving the reliability of the PQD data and possible usage for systemic risk assessment.

Keywords: CCP, Public Quantitative Disclosures, default waterfall, liquidity management, liquidity risk

Contents

1. Introduction

One of the main characteristics of the credit crisis was the opaqueness of the bilateral over-the-counter (OTC) derivatives markets and the inability of regulators and market participants to assess the extent of exposures, leading to a loss of confidence in the financial markets. The build-up of exposures amongst financial traders has placed the Financial Market Infrastructures (FMIs) reform on top of the agenda for policy makers, as it became clear that FMIs are key to the resilience of the markets served and play a critical role in fostering financial stability.

An important change in the international framework for FMIs was the publication of the 'Principles for Financial Market Infrastructures' (PFMI) by the Committee on Payment and Settlement Systems (CPSS) and the Technical Committee of the International Organization of Securities Commissions (IOSCO). This set of international standards for good practices in FMIs extend, harmonise, and strengthen the previous standards, covering a range of FMI operations, including, among other things, credit and liquidity management, default management, general business and operational risk management, with a focus on transparency (CPSS-IOSCO, 2012).

This paper is concerned with Central Clearing Counterparties (CCPs), also called clearing houses, the FMIs that facilitate post-trade settlement and clearing of financial transactions, including OTC derivatives. The centrally cleared market has grown in size since the global financial crisis. At the global level, the percentage of notional amounts outstanding of interest rate and credit derivatives which are centrally cleared has increased from approximately 27% to over 52% between 2009 and 2014 (Domanski et al., 2015). Regulatory reforms imposing mandatory clearing of certain types of interest rate and credit derivatives are likely to contribute to the continuation of this trend in the future (Rahman, 2015). In the European Union, certain categories of interest rate derivatives and Credit Default Swaps (CDS) are already subject to the clearing obligation, whereas the implementation of other categories is due to take place gradually until 2019.[1]

Against this background, the goal of this paper is to construct a dataset to study the European CCP ecosystem using publicly available information. The contribution of the paper consists in documenting aspects of CCP operations, including the number of traders served by each CCP (clearing members), the asset classes cleared and the amounts of transactions, the default resources raised by the CCPs to protect themselves from counterparty credit risk, and the liquid resources maintained to settle payment obligations.

On the policy side, we provide an assessment of the extent to which the public disclosures required of CCPs by international standard-setting bodies an assessment of the risks posed by CCPs, for the clearing members and the financial system at large. We propose a number of policy actions aimed at improving the reliability of the data disclosed and their helpfulness for systemic risk assessment.

The paper is organised as follows. In the next Section we motivate our analysis. In Section 3, we describe the dataset. In Section 4, we present stylised facts on the markets served by European CCPs and the resources held for credit risk management.

[1] The dates from which the clearing obligations take effect, and the categories of assets to which they apply are detailed in the Regulatory Technical Standards supplementing the European Market Infrastructure Regulation (Regulation (EU) No. 648/2012).

Liquid resources are the focus of section 5. We conclude with a set of policy recommendations, including possible actions to improve the usefulness of the public data.

2. Motivation

In this Section, we provide a conceptual framework to guide the analysis. While our dataset covers several aspects of CCP operations, we focus on the following concepts. First, we review general characteristics of the member base: number of members by CCP, proportion of domestic and foreign members, and memberships in multiple CCPs. Second, we provide an overview of markets served, and whether and when CCPs segregate default funds, by asset class or ET/OTC. The size of market segments by transaction volume and the amount of resources available for default is also studied. Third, we investigate liquidity strategies of CCPs. By their very nature, CCPs hold considerable amounts of resources posted by members and need to readily avail of liquid resources in the event a member defaults. We investigate liquidity management of CCPs, including the reinvestment of cash received from participants.

A clear view of member bases, in terms of size and degree of interconnectedness of participants, is crucial to understanding possible channels of contagion. CCPs replace a network of bilateral exposures with a new set of interconnections. Whereas risk management systems of CCPs are designed to insulate clearing members from other members' default, contagion may occur when a default event depletes the default fund, or in the case of default of the CCP (Wendt, 2015). Furthermore, the interconnectedness of member bases of different CCPs bears contagion risks. Under extreme market conditions, the default of a trader holding clearing memberships in several CCPs may transmit liquidity pressures to otherwise healthy clearing members or other market participants outside the CCP, for example by triggering the replenishment of the default fund(s) of several CCPs where another member is also active (Domanski et al., 2015; Roe, 2013).

Accordingly, the literature has studied the structure of member bases of CCPs from several points of view. Armakolla and Laurent (2017) focus on credit quality of CCP users. The paper provides an estimate of the deterioration in the creditworthiness of surviving clearing members after two average clearing members default. In the context of CCP interconnectedness through multiple memberships, the European Securities and Markets Authority (ESMA) considers the issue of common members in its first EU-wide stress test (ESMA, 2016). On interconnections between market participants, Braithwaite (2015) highlights issues related to recent changes in the structure of member bases, focusing on the relationship between direct clearing members and their clients, which in this context are traders who use the CCP through a direct clearing member. Also, the geographical distribution of clearing members has received attention, in terms of the average share of domestic and foreign clearing participants, or the distribution of initial margin requirements by location of clearing members (Domanski et al., 2015; Rahman, 2015).

In addition to the number of clearing members, the size of CCPs by notional amounts determines netting efficiency and single point of failure risk. Duffie and Zhu (2011) show that, under some conditions, the highest degree of netting is obtained when a single, global CCP clears all asset classes. However, Pirrong (2014) and Gregory (2014) point out that netting redistributes risk, not necessarily reducing it.

Netting benefits are reaped mostly by the members with the largest portfolios, and in case of default, netting redistributes losses at the expense of non-member creditors. Moreover, the benefits of multilateral netting from a higher concentration of the cleared market have to be weighed against the increased single point of failure risk associated with large CCPs (Cont and Kokholm, 2014).

The netting benefits of a CCP depend on its default management strategy, of pooling or segregating the asset classes cleared into a single or multiple default funds. Pooling many asset classes within one default fund has advantages and disadvantages. On the positive side are diversification of risk and margin efficiency. In the futures market, Gemmill (1994) shows that the benefits from diversification can be large; the size of benefits depends on the correlation between products cleared, which can be difficult to predict in case of market disruptions. On the negative side, mutualisation of losses across asset classes results in a subsidy of riskier asset classes, which could lead to moral hazard issues and increased risk-taking by clearing members (Gregory, 2014).

Moreover, the size of a CCP may determine its substitutability. If a CCP is in resolution, or in any other situation where members can no longer clear at a CCP, the transfer of transactions to another CCP can be challenging and lead to legal disputes. Although the European Market Infrastructure Regulation (EMIR) provides certain requirements for CCP recovery frameworks the EU, there are still differences between EU member states in insolvency laws and tax regimes (see for example Braithwaite and Murphy (2016)). Moreover, the initial clearing agreement would have to be amended (Duffie, 2014). In the case of a large CCP, substitutability issues may lead to a systemic event.

In addition to legal issues, transferring all positions from a large CCP may give rise to technical difficulties. If only that CCP is in the market for a specific product, it may take time for new entrants to acquire product-specific know-how, set up the necessary internal structures, and implement risk management strategies. Should more than one CCP be in the market, clearing members can obtain membership at another CCP. On the one side, differences in membership criteria and possibly higher costs may prevent some clearing members from continuing to centrally clear that product. On the other side, the addition of new clearing members necessitates documentation and due diligence work by the CCPs taking over the market share. If the size of the exiting CCP is large, the remaining ones may be put under significant resource constraints, and clearing members may temporarily lose access to central clearing for certain products.

The last aspect investigated in this study is liquidity management. The matched book of a CCP means that if a member defaults, liquid resources are needed to meet the obligations towards the other leg of the contract (Gregory, 2014; Hughes and Manning, 2015). When liquidating the initial margin of the defaulted member, CCPs face liquidation risk. For this reason, CCPs apply haircuts to non-cash collateral posted by members, to account for possible adverse price movements at the time of liquidation. However, CCPs also re-invest cash collateral, and retain exposure to credit and liquidity risk from such investments (CPSS-IOSCO, 2004).[2] The risk that reinvestment poses is similar to margin wrong-way risk: if the price of the asset used as collateral is positively correlated with the creditworthiness of the member posting

2 The only resource available to CCPs to cover losses stemming from investment (non-default losses) is own capital (Rehlon and Nixon, 2013).

it, the value of initial margin tends to decrease when the member defaults. Similarly, reinvestment wrong-way risk occurs if the price of the securities purchased by the CCP tends to drop when they need to be liquidated, that is when the member whose cash has been invested defaults.

A fall in price of the reinvested instrument may be due to credit or liquidity risk, for example if the CCP buys corporate bonds of the clearing member from which it received cash collateral. When the clearing member defaults, the bond price will reflect the decrease in creditworthiness; if bonds are illiquid, liquidation will further decrease the price. To avoid this, EMIR requires CCPs to invest participants' cash in assets which remain liquid even in extreme market conditions.

Margin wrong-way risk also occurs, if the risk premium - applied to instruments held as collateral - increases under stressed market conditions. The European sovereign debt crisis showed that government bond prices are more sensitive to weak fundamentals, including domestic financial sector health, when uncertainty in global financial markets is high (Bianchi, 2016). In Section 5, we will show that CCPs invest non-negligible amounts in sovereign bonds, domestic bonds in particular. If risk premia were to spike again when the financial sector is in stress, CCPs may incur losses. Whereas the Banking Union and the European Stability Mechanism were developed to limit the negative feedback between banks and sovereigns, their effectiveness under stress has not yet been tested.

3. Data

The main source of our data is the Public Quantitative Disclosure (PQD) framework for CCPs. The PQD is the result of the application of Principle 23 of the 'Principles for Financial Market Infrastructures'.[3] In accordance with the PQD framework, CCPs are encouraged to publish a set of standardised data intended to enable stakeholders to compare risk control strategies, understand the risks associated with the CCP, assess the systemic importance of the CCP and its impact on systemic risk, and understand the risks involved in becoming a member (CPMI-IOSCO, 2015).

To our knowledge, this is the first paper to have assembled and analysed the information in the PQDs for European CCPs. One of our contributions is highlighting a number of issues encountered while studying the PQD data and suggesting possible improvements to enhance CCP transparency and extend the scope of analyses which can be done using this source of data.

The PQD data is provided quarterly and contains information on several aspects of CCP operations. The variables are grouped according to the principles set out in the PFMI: Credit risk (Principle 4), Collateral (Principle 5), Margin (Principle 6), Liquidity risk (Principle 7), Exchange of value settlement systems (Principle 12), Default rules and procedures (Principle 13), Segregation and portability (Principle 14), General business risk (Principle 15), Custody and investment risks (Principle 16), Operational risk (Principle 17), Access and participation requirements (Principle 18), Tiered

[3] Principle 23 of the PFMI states that '*an FMI should have clear and comprehensive rules and procedures and should provide sufficient information to enable participants to have an accurate understanding of the risks, fees, and other material costs they incur by participating in the financial market infrastructure. All relevant rules and key procedures should be publicly disclosed*' (CPSS-IOSCO (2012), p. 121).

participation arrangements (Principle 19), FMI links (Principle 20), and Disclosure of rules, key procedures, and market data (Principle 23). In this paper, we analyse a subset of the disclosure data and present a high-level picture of the actors in the clearing landscape, including size and aspects of their risk management strategies. In the Appendix, a summary of the variables used and the modifications made to the original disclosures, implemented to correct mistakes and ensure consistency, is provided.

The disclosure data is provided by CCPs at three levels: CCP level, when the data refers to the whole CCP; default fund level, when the data refers to products covered by a segregated default fund; and clearing service level when there are clearing services that are not delimited by a segregated default fund (for instance, when there is more than one clearing service covered by a default fund). If a CCP uses an integrated default fund covering all products cleared, CCP and default fund levels coincide. If a default fund covers all products cleared in a clearing service, default fund and clearing service levels coincide.[4]

Table 1 lists the CCPs included in the sample and the respective country of domicile. Three additional European CCPs have published PQD data following a template different to the one used by CCPs in Table 1 and were excluded. Future work aims at filling the gap. PQD data is available since 1st January 2016, and has been disclosed with a three-month lag. At the time of writing (September 2016), information for three quarters is available, ending on 30th September 2015, 31st December 2015, and 31st March 2016.

In addition, we extend the dataset with publicly available information on clearing members and contracts cleared. The member lists were retrieved from CCPs' websites and matched with information on domestic or foreign residency of the members. We also gathered the list of products cleared in each CCP, when relevant by segregated default fund.

4. The European CCP ecosystem

In this Section, we show stylised facts from our dataset, including size of member bases and degree of interconnectedness through common memberships, size of CCPs by volume of transactions, and size and composition of default resources. Table 1 defines the abbreviations used for the names of the CCPs in our sample.

4 There is a slight difference between the provisions set out by CPMI-IOSCO (2015) and the scheme CCPs follow in the excel templates used for reporting, in terms of names for the reported level. The template has been developed in a collaboration between associations of CCPs (the European Association of CCP Clearing Houses (EACH) and the Global Association of Central Counterparties (CCP12)) to ensure consistency and standardisation of reporting. The difference has caused some confusion regarding the level reported, thus we have homogenised the naming of the statistical units' level using the definition noted above: CCP level, default fund level, and clearing service level. Information available on the websites of CCPs has been used to identify the correct level reported for each CCP, when the classification of levels did not comply with this definition.

CCP member bases and interconnectedness

The PQD data provide aggregated information on clearing members at the default fund level, limited to the number of members by type of membership held, type of institution (bank, central bank, CCP, etc.), and residency (foreign or domestic). We use the member lists provided by CCPs on their websites to give a more detailed view of the member bases and the degree of interconnectedness at the CCP level.

Table 2 shows the total number of clearing members, the proportion of domestic and foreign participants, and the average number of clearing memberships per individual participant. Nasdaq OMX has the largest participation with 247 clearing members, followed by Eurex Clearing with 192 and LCH.Clearnet LTD with 153 members. ICE Clear NL serves three members, which are financial institutions with large trading activity, mostly conducted on behalf of their clients. The CCPs with the largest proportions of domestic members are KDPW, BME Clearing, and CC&G.

The shares of domestic and foreign participants in Table 2 do not provide a complete picture of the international relevance of CCPs as they do not capture interoperability agreements.[5] For instance, the international relevance of CC&G according to Table 2 may be underestimated by not accounting for the interoperability agreement with LCH.Clearnet SA. CC&G and LCH.Clearnet SA have an interoperability agreement enabling members from both CCPs to enter into repo transactions with each other directly, without being a clearing member at the other CCP. Moreover, the residency of clearing members' clients is not represented in the Table. In the case of ICE Clear NL, the residence of clearing members carries little information on the residence of the ultimate counterparties of the trades cleared. This can be seen from the proportion of initial margin posted by the clients of ICE Clear NL, which is 93.6% of total initial margin. Whereas two of the three clearing members are domestic, the same proportion may not apply to their clients.

In addition to the size of the member base, it is instructive to consider the number of CCPs in which a single member participates. This is important to understand the potential for contemporaneous stress in multiple CCPs, driven by the default of an interconnected member. Consistent with the definition of interconnectedness applied by ESMA (2016), in Table 2 we show, for each CCP, the average number of memberships.[6]

ICE Clear NL has the highest degree of interconnectedness per clearing participant. One of the clearing members of ICE Clear NL has 11 clearing memberships in the 12 CCPs we consider, which is the largest number of multiple memberships per member in our sample. This is a financial institution specialised in client clearing services. By being a member in several CCPs, it offers a wide set of clearing opportunities. In contrast, the members of KDPW, in average, clear only at KDPW. Given the high proportion of domestic members in this CCP, its degree of interconnectedness with the rest of the European system is likely to be small.

Overall, our sample comprises 726 clearing members. Of these, 564 entities clear at only one CCP, representing about 78% of the overall number of clearing members.

5 Interoperability arrangements are links between CCPs whereby members of each CCP can clear trades with members of the other CCP without becoming a member of the other CCP.

6 The average does not consider group level affiliation of individual clearing members. If this were to be considered, the average number of memberships would be higher.

This is in line with the findings of ESMA (2016) EU-wide stress test, reporting that 85% of the more than 900 members of the 17 CCPs considered clear at only one CCP. ESMA (2016) also reports that 11 individual clearing participants clear at 10 or more CCPs, whereas in our sample we identify one.

Interconnectedness in the CCP ecosystem is of primary concern (Wendt, 2015; Yellen, 2013), as risk is concentrated in the clearing structures and the default of highly interconnected G-SIB members may pose a threat to CCP resilience. To fully understand the structure and consequences of interconnectedness in the CCP ecosystem, the exposure each individual participant has at each CCP should be considered together with its activities in the bilateral markets.

Products cleared and default fund segregation

Tables 4 to 9 list, for each default fund, the asset classes covered, the types of contract, and the underlying assets. Being at the default fund level, the Tables convey information on the degree of mutualisation across asset classes. We grouped the default funds together on the basis of similarities in the composition of asset classes cleared. A residual group contains default funds covering a wider range of asset classes.

Five CCPs in our sample have a single default fund covering all products cleared. EuroCCP and ICE Clear NL clear equity, derivative and cash products, LME Clear clears commodity derivatives traded in the London Metal Exchange, and CCP.A and Eurex Clearing clear a mix of asset classes, including equity and bond derivatives, interest rate derivatives, and other securities. The extent of mutualisation within these CCPs varies, owing to differing degrees of heterogeneity in the type of transactions cleared and to different loss allocation rules.

Given a mixed default fund, loss allocation rules can mitigate mutualisation across asset classes. Generally, pooling different asset classes in the same default fund means that the mutualisation of losses occurs regardless of the markets in which the defaulting clearing member is active. In the case of single default fund, clearing members trading in less risky markets are exposed to losses caused by riskier clearing members. To avoid this, Eurex Clearing clusters the trades cleared according to the risk characteristics of the underlying products (Liquidation Groups). Each Liquidation Group is assigned to a segment of the default fund. Losses arising from trades in each Liquidation Group are distributed first among the participants active in the relevant Liquidation Group (Eurex Clearing, 2014).

The remaining eight CCPs in our sample limit mutualisation within segregated segments, defined by the asset class cleared. Four CCPs established default funds specific to fixed income products (Table 4). Of these, BME Clearing has a segment exclusively for repurchase agreements (repo), whereas CC&G, LCH.Clearnet SA and LCH.Clearnet LTD cover both cash bonds and repos within the same default fund. LCH.Clearnet SA also has a separate default fund for tri-party repos (€GC Plus).

In the equities market, four CCPs have a segregated default fund, which in several cases also covers certain types of bond transactions.[7] The origin of the underlying stock relates to the residency of the CCP in two cases: BME clears mostly ET Spanish

[7] LCH.Clearnet SA also covers ET commodity derivatives in this default fund.

equity derivatives and futures on government bonds; CC&G clears cash equities and ET equity derivatives in the Italian market. Other CCPs have more geographically sparse operations: LCH.Clearnet SA covers stock issued in several European countries, including ET equities and bonds, and transactions traded in a multilateral trading facility.[8] LCH.Clearnet LTD covers bonds and equity products issued in several countries (Table 5).

As shown in Table 6, six default funds cover the energy and commodity markets. Futures and options, often traded in regulated markets, are the financial product typically cleared in this segment.

Only two CCPs have a segregated segment for interest rate derivatives (Table 7). BME Clearing started a new segment in November 2015 covering the interest rate derivatives for which the EU clearing obligation entered into force in June 2016.[9] LCH.Clearnet LTD holds two segments in this market, segregating ET from OTC interest rate derivatives.

In Table 8, only two CCPs offer segregated default funds for CDS: ICE Clear EU and LCH.Clearnet SA. The clearing obligation for this type of products is not in place at the time of writing (September 2016), but will take effect gradually for different categories of CDS between February 2017 and May 2019.

Size of Segments and Waterfalls

Having described the products covered in each segment, we now look at CCP size and waterfall size in each segment (Figures 1 to 6). Size is measured by average daily transactions cleared, in nominal (or principal) amounts. All contracts covered by a default fund are summed up, regardless of the product type. As segments often contain a mix of different products, this is a rough measure of CCP activity. Yet, with this caveat in mind and considering the description of the products covered by the default funds in our sample, this measure allows comparing the activities of CCPs in a market segment.

The juxtaposition of notional amounts and waterfall in Figures 1 to 6 is not meant to provide an assessment of risk management practices of CCPs. In fact, the transactions cleared may increase without increasing exposures. Conversely, the same amount of transactions for the same product may be associated with different levels of exposure, depending on the time to maturity of the contracts and the frequency of trades. For instance, a two-day contract is less risky than a two-year contract with the same notional amount; a two-year contract traded out after two days is less risky than an identical contract kept until maturity. The figures are intended to show the size of the markets served by CCPs in each segment and the corresponding default resources.

The connected scatter plots in Figures 1 to 6 show average daily volumes of OTC products and ET derivatives at the default fund level (right-hand-side scale). The stacked bars show the amount and composition of the default waterfall resources:

8 Multilateral trading facilities are non-exchange trading venues operated by financial firms in order to facilitate retail trades.

9 Other types of interest rate derivatives will be subject to mandatory clearing in the future; the clearing obligation for last category will take effect in 2019.

total initial margin required, own CCP capital, and default fund, recorded at the end of the quarter (left-hand-side scale).

The PQD data on initial margin and default fund contributions reflect exposures at different points in time. Initial margin is calculated at least daily, so it tracks exposures relatively well, while the default fund is sized monthly (or at even lower frequencies). Rather than assessing whether these resources are appropriate, we use them as a measure of exposure. By comparing default waterfall resources and CCP size, it is then possible to relate the evolution of the cleared market with the evolution of exposures.

For LCH.Clearnet SA and CC&G, average daily transactions cleared in the fixed income segment increased between the third quarter of 2015 and the first quarter of 2016, and so did exposures (Figure 1). For LCH.Clearnet LTD and BME Clearing, the data shows a decrease in both transactions and exposures in the same period. Cash bond and repo transactions cleared via LCH.Clearnet LTD's 'Fixed Income' service dropped at the same rate, by around 12% between the third and the fourth quarter of 2015, and increased by around 6.7% in the following quarter. More recent monthly data published by LCH.Clearnet LTD shows that the drop in repo transactions has been more than recovered by June 2016.[10] On the contrary, in the case of BME Clearing, the timing of the PQD framework somewhat hides the plunge in cleared repo transactions that occurred after June 2015, with average daily transactions falling by nearly 30% monthly in July 2015 and 50% year-on-year in June 2016.[11]

The composition of the waterfall resources for fixed income products is related to the type of transactions. CCPs clearing traditional repurchase agreements only, such as BME Clearing, or in large proportions, such as LCH.Clearnet SA ('Bonds and Repos'), have a low percentage of default fund in the total waterfall compared to segments where the share of cash bonds cleared is higher.

Figure 2 charts the evolution of volumes and exposures for default funds covering mostly equity transactions, cash and derivatives. Only CC&G, ICE Clear NL, and EuroCCP report notional amounts in this segment. For four CCPs, exposures decreased in the period considered. For LCH.Clearnet LTD's 'Equities' and EuroCCP, exposures increased between the third quarter of 2015 and the first quarter of 2016, although in both cases a significant decrease was observed in the preceding quarter. The temporary drop in waterfall resources is due to a decrease, and a subsequent increase, in initial margin. Whereas for LCH.Clearnet LTD's 'Equities' the initial relative size of default fund is restored in the last quarter, for EuroCCP the default fund increases more than proportionally to 25% of the waterfall resources. In the most recent quarter, the weight of the default fund in total waterfall ranges between 3% for BME Clearing's 'Financial derivatives' and 39% at ICE Clear NL. Segments with a larger proportion of equities cleared have a larger proportion of the default fund.

In the Energy and Commodities segment, depicted in Figure 3, transaction volumes reported by Nasdaq OMX, CC&G, and LME Clear have decreased in the observed period. Default waterfalls have shrunk in all segments with the exception of Nasdaq OMX' 'Commodities' and BME Clearing's 'Power' segments. BME Clearing nearly doubled its waterfall resources in this segment, in stark contrast to the decrease by 80% in default waterfall resources observed for LCH.Clearnet LTD.

10 See http://www.lch.com/asset-classes/repoclear/volumes.

11 See http://www.bmeclearing.es/ing/aspx/MeffREPO/EstadisticasDiarias.aspx.

Excluding CC&G, the composition of the waterfall in this segment is relatively homogeneous: the default fund represents between 4% and 12% of the total. For CC&G, the default fund constitutes more than half of the default waterfall resources in all quarters.

Five CCPs in our sample offer clearing services for interest rate derivatives: LCH.Clearnet LTD, BME Clearing, KDPW, Nasdaq OMX, and Eurex Clearing. The latter three CCPs do not segregate a specific default fund for this product. LCH.Clearnet LTD has two segregated default funds, for ET and OTC derivatives, respectively. BME Clearing is a new entrant, having started a new default fund in November 2015. The segment started to be used effectively in the first quarter of 2016. Monthly notional volumes increased from 20 million euro in January to 1,623 million euro in March.[12] In Figure 4, the process of implementation of the waterfall for the new segment is visible. As the size of a default fund depends on exposures, when members do not yet have open positions, the calibration of a new default fund depends on estimated clearing activity.

LCH.Clearnet LTD's 'OTC interest rates' transactions increased in the three quarters (Figure 4). The sample period does not include the start of the clearing obligation. Consequently, the complete adjustment of the market will be visible from the PQD when data when the third quarter of 2016 will be available.

Only ICE Clear Europe and LCH.Clearnet SA are active in the cleared OTC CDS market (Figure 5). Volumes increased between the first and the last quarter in the sample for ICE Clear Europe while default waterfall size decreased slightly. In contrast, volumes decreased for LCH.Clearnet SA while the waterfall increased dramatically. Notional amounts for LCH.Clearnet SA's 'OTC CDS' service increased four-fold in the first quarter of the sample, dropping ten-fold in the following quarter. Without knowledge of the characteristics of the specific contracts, it is difficult to determine the descriptive ability of these numbers. The percentage of default fund in total waterfall oscillates between 12% and 14% for ICE Clear Europe, and between 31% and 38% for LCH.Clearnet SA.

In Figure 6, we show all segments that do not have a comparable product mix to other CCPs in the sample, along with segments (or CCPs) covering many asset classes in the same default fund.[13] Eurex Clearing stands out as the largest segment in terms of waterfall amounts in this group, as well as compared to any other segment. The total waterfall of Eurex Clearing is on a decreasing path, from 50 billion euro in the third quarter 2015 to just above 40 billion euro in the first quarter of 2016. ICE Clear Europe's 'Futures and Options' segment has the second largest waterfall. The product mix cleared via ICE Clear Europe's 'Futures and Options' is more homogeneous than that of Eurex Clearing. Nasdaq OMX' 'Seafood' is the third largest segment in the group as per waterfall amounts, clearing derivatives on salmon.

[12] Statistics on monthly notional volumes are available at http://www.bmeclearing.es/ing/aspx/MeffREPO/EstadisticasMensuales.aspx.

[13] CCP.A starts reporting PQD in the first quarter of 2016.

5. Liquidity and liquidation risk

In this Section, we investigate the liquidity management of the default waterfall resources held by CCPs to withstand member defaults. We first consider the amount of liquid resources CCPs hold relative to the total resources at their disposal. Then, we explore the liquidity management of reinvested participant cash and the composition of initial margin and default funds.

Qualifying liquid resources

According to EMIR, CCPs have to hold enough qualifying liquid resources (QLR) to withstand the default of any two clearing members, at the CCP level. Whereas the segregation of default funds is implemented for solvency reasons, to isolate members clearing one asset class from members clearing in a different asset class, there is no similar rationale to segregate liquidity at the default fund level. It is therefore appropriate to consider the amount of liquid resources CCPs hold relative to the total resources at their disposal, across all default funds.

Table 3 reports the total amount of QLR held in any currency, total amount of default resources across all segments, and the ratio between the two. A ratio greater than 1 means that the amount of qualifying liquid resources is greater than the pre-funded default resources.[14] While looking at QLR relative to the overall default resources is informative as to the potential availability of default resources in case of a default, the actual liquidity needs will depend on the size of the exposure vis-à-vis the members in default. All else being equal, a CCP where exposure is concentrated in a small number of members will need more liquid resources than a CCP where exposures are dispersed across the members. To address this issue, in Table 3 we also show the percentage of initial margin posted by the largest 5 clearing members.[15]

The ratio of QLR over default resources tends to be higher in CCPs with more concentrated exposures; the correlation is 0.5. For example, the QLR ratio of Eurex Clearing is amongst the lowest, but the largest 5 members account for only 39% of total initial margin. The QLR ratio of EuroCCP is higher, and so is the concentration of initial margin. This is to be expected: were concentration of exposures is high, a larger portion of default resources have to be liquidated when large members default.

To complete the picture, the table also reports total QLR and total default resources. When a default event depletes the available QLR, the CCP will need to raise additional liquid resources. The size of the CCP's exposure then determines the additional liquidity needs. Whereas the ability of CCPs to raise funds in stressed market conditions depends on the resilience of liquidity providers and the CCP's access to central bank liquidity, the level of emergency liquidity needs is a function of exposures.

[14] The liquid resources could also be used by the CCP to pay variation margins when a member delays on its obligation. The default resources include both those provided by clearing members (initial margin and default fund contributions) and by the CCP itself (Skin-in-the-game).

[15] The PQDs contain data on concentration in the largest 5 and largest 10 clearing members.

Two CCPs with similar QLR and concentration ratios are Nasdaq OMX and LCH.Clearnet LTD. If the default of the five largest clearing members depletes the QLRs of both CCPs, then assuming the same percentage of exposure remains uncovered, the liquidity crisis of LCH.Clearnet LTD will be more severe. This is because the exposure of LCH.Clearnet LTD is 17 times the exposure of Nasdaq OMX.

The discussion so far assumes that QLR are homogeneously liquid resources. However, not all types of qualifying liquid resources share the same degree of liquidity. For instance, central bank deposits are the only instrument to be virtually 100 per cent reliable in stressed market conditions. Commercial bank deposits, committed lines of credit and '*highly marketable collateral held in custody and investments that are readily available and convertible into cash with prearranged and highly reliable funding arrangements even in extreme but plausible market conditions*' (European Union, 2012), on the other hand, are liquid insofar as the liquidity provider is able to fulfil its obligations when the resources are needed.[16]

Figure 7 shows the composition of QLR. Eight CCPs hold central bank deposits; three of which in amounts larger than half the total waterfall resources. Overall, there is high reliance on commercial bank secured deposits, which include reverse repo. Also important is the reliance on highly marketable collateral and secured committed lines of credit and, to a smaller extent, unsecured committed lines of credit. Unsecured deposits at commercial banks and other QLRs are less common liquidity instruments.

In summary, in this section we exposed the information on the liquid resources of CCPs which is available from the PQDs. This is a valuable source of information which allowed us to give a bird-eye view of the liquid resources of CCPs. In the next section, we zoom in the disclosures in order to assess whether it is possible to use the information provided to draw conclusions on liquidity risk.

Reinvestment of participant cash

To cover margin or default fund requirements, participants can provide eligible securities or cash to the CCP, in accordance with collateral rules specific to each CCP. Typically, CCPs require members to post a percentage of collateral in cash and restrict the proportions of specific securities in the collateral pool. CCPs are allowed to reinvest this cash in highly liquid resources. According to EMIR Article § 47, a '*CCP shall invest its financial resources only in cash or in highly liquid financial instruments with minimal market and credit risk. A CCP's investments shall be capable of being liquidated rapidly with minimal adverse price effect*' (European Union (2012), p. 39). This Section describes how CCPs manage the cash received from participants.

Figure 8 shows that five CCPs deposit the majority or all of participants' cash in central banks. Five other CCPs deposit the majority or all cash in other financial institutions. The remaining two CCPs have a mixed reinvestment policy, whereby a significant proportion of the cash is invested in securities. Focusing on the first quarter of 2016, CC&G invested 66% of participants' cash in securities. Of this, 48% were invested in Italian government bonds (5.4 billion euro), 40% in foreign government

[16] Liquidity providers of CCPs are often clearing members; since initial margin and default resources are needed when clearing members are under stress, it is possible that the liquidity providers are not able to meet their obligations towards the CCP when needed.

bonds (4.5 billion euro), and 12% in agency or municipal bonds (1.3 billion euro). Nasdaq OMX reinvested a third of participants' cash in government bonds (the equivalent of 1 billion euro), a third in central bank deposits, and the remaining third in commercial bank deposits and other securities. Other CCPs with non-negligible investments in government bonds are LCH.Clearnet LTD, ICE Clear Europe, LCH.Clearnet SA, LME Clear, and KDPW.

While for securities received by CCPs directly from clearing members, haircuts are applied to account for liquidation risk, securities bought by a CCP with members' cash do not have a haircut applied to them, even though they are often the same securities. However, CCPs have 'prearranged and highly reliable funding arrangements' to liquidate collateral even in extreme but plausible market conditions. We now turn to comparing the amount of reinvested securities with the amount of highly reliable funding arrangements that are available to convert securities into cash even in extreme but plausible market conditions.

Figure 9 shows securities holdings of CCPs. The first two bars illustrate securities held as initial margin and default fund, respectively. This includes both securities posted by clearing members (post haircut) and securities purchased by the CCP with members' cash posted as initial margin and default fund, respectively.[17] The third bar is participants' reinvested cash, for which the PQD does not provide the allocation along the waterfall. The fourth bar is '*highly marketable collateral held in custody and investments that are readily available and convertible into cash with prearranged and highly reliable funding arrangements even in extreme but plausible market conditions*' (European Union, 2012).

According to PQD standards, the third bar should be *at most* equal to the sum of the first two bars, since securities held as initial margin or default fund include reinvested cash. This is not the case for CC&G; this CCP may not be following PQD standards closely. Cross-checking PQD data with information from the collateral rules of CC&G, we concluded that initial margin composition is reported by CC&G as it is posted by members, rather than held by CC&G. For the other CCPs, figures are consistent with the other information available and in what follows we will assume they follow PQD standards precisely.

Comparing the third and fourth bars in Figure 9 allows us to determine whether the highly reliable funding arrangements are sufficient to liquidate the securities in which the CCP reinvested members' cash.[18] This is not the case for CC&G and KDPW: if these CCPs need to liquidate all the securities bought with members' cash, they may face the risk of selling at market price.

Furthermore, the member bases of CC&G and KDPW are mostly domestic, and both invest significant amounts of the cash received in securities issued by the domestic public sector. This means that there may be a positive correlation between the price of collateral and the default probabilities of clearing members, if for example there is a public guarantee on bank deposits. Therefore, if these CCPs have to sell domestic government bonds at market price when a domestic member defaults, they will be exposed to margin wrong-way risk. Future data requirements, for instance on

17 Bond holdings are based on concepts 4.3 and 6.2 of the PQD, which require CCPs to report the composition of prefunded default resources and initial margin held, as opposed to posted.

18 While it is not possible to ascertain whether the contracts to which the QLR item refers apply to the securities reinvested in by the CCP, it is still true that, if the fourth bar is lower than the third, there are not enough prearranged and highly reliable contracts to cover all reinvested cash.

the arrangements in place with the liquidity providers, could help shed light on the magnitude of such risk.

To sum up, the PQDs provide useful data to understand liquidity management of CCPs. However, we believe this is not sufficient to appropriately assess the adequacy of liquidity strategies.

Composition of initial margin and defaults funds

In order to complete the picture describing liquidity management, Figures 10 and 11 show the composition of initial margin and default fund held. As is often the case with the PQD, some CCPs do not respect requirements fully and report at a lower level of detail, which makes comparison difficult.[19]

The way in which CCPs can hold initial margin and default fund resources is regulated in EMIR and EMIR related technical standards. Every CCP sets rules on the specific assets and currencies that clearing members can post as collateral. CCPs also impose restrictions on the composition of posted collateral, such as concentration limits, rules on the proportion of cash, exclusion of own assets, and the like. CCPs also decide the haircut to apply to each specific asset. For a comparison of collateral eligibility frameworks across asset classes, see European Central Bank (2013) and European Central Bank (2014).

Among the different ways a CCP can invest resources, central bank cash deposits are the safest way to deposit waterfall resources and represent the most liquid portion. Investing the waterfall resources in high-quality securities fosters diversification and may generate a modest return on investment without significant risks (Gregory, 2014). Depositing cash with a commercial bank can be concluded via secured and unsecured deposits.

As shown in Figure 10, most CCPs in our sample hold a large proportion of initial margin as a mix of central bank deposits, commercial banks deposits, and sovereign bonds. Holdings of initial margin in riskier assets, such as corporate bonds, represents a lower, although in some cases non-negligible, portion.

Figure 11 shows that the resources in the default fund are held in more liquid assets than initial margin. This is due to the stressed market conditions under which the default fund is typically tapped.

6. Conclusion

After the global financial crisis, central clearing has been placed at the heart of the new financial regulatory framework. The introduction of mandatory clearing has reinforced the recent trend followed by market participants to clear financial trades through CCPs. At the same time, risk management strategies of CCPs have been strengthened by the application of the PFMI.

[19] The composition of initial margin should be reported for each currency in which the margin is posted. The composition of default resources should be reported at the default fund level.

An important aspect of the PMFI is the importance assigned to transparency: *'transparency helps ensure that relevant information is provided to an FMI's participants, authorities, and the public to inform sound decision making and foster confidence'* (see CPSS-IOSCO (2012), p.121). The public quantitative disclosures (PQD) for central counterparties are the application of this principle to CCPs; the disclosures should enable all interested parties to compare risk controls and to have a clear, full and accurate understanding of the risks associated with CCPs, to assess CCPs systemic relevance and the impact on systemic risk (CPMI-IOSCO, 2015).

The contribution of this paper is twofold. First, we assemble a dataset which comprises the public quantitative disclosures as well as other publicly available information. Whereas the disclosures are meant to follow standards that ensure comparability, the data is provided in different formats, which made compiling the dataset non-trivial. Moreover, the raw data was not always comparable; we used further publicly available information to fill the gaps and ensure consistency.

Second, we provide stylised facts on the European CCP ecosystem. European CCPs are heterogeneous in terms of number of clearing members, type of assets cleared and size of markets served. Moreover, CCPs have differing risk management strategies. This is reflected in the size and structure of the default resources and the size and structure of the liquid resources. In our analysis, we encountered a number of issues which reduce the usefulness of the data from a risk assessment perspective.

Our analysis shows that the PQD data can be used to monitor the evolution of the CCP landscape across various aspects, including risk management strategies - a very important step towards full understanding of the central clearing environment. However, data quality is not consistent across CCPs, and data are not provided at the high frequency needed to construct indicators of systemic risk. These would also need to account for differences in margining models and stress test methodologies, which are only marginally covered. In the remainder of this section, we provide a number of suggestions which could help improve the usefulness of PQD data.

The PQD framework is voluntarily followed by CCPs. There is no legal requirement for CCPs in the EU to provide this data. Therefore, there are CCPs not reporting, or publishing data in different formats to the template agreed on by the majority of EU CCPs. Regulatory authorities may wish to make the provision of PQD data mandatory and fully standardised for all CCPs.

Besides the absence of a legal requirement to publish PQD data, and possibly as a consequence of the lack of legal binding, no process of validation is in place to ensure that the figures reported are correct, in terms of interpretation of the requirements and truthfulness of the reporting. Competent authorities mandated with CCP oversight could perform data quality checks and require CCPs to correct possible mistakes.

The PQD data is currently provided at quarterly frequency and with a three-month lag. In order for analyses on systemic risk to be possible, and to create early warning indicators for CCP distress, the provision of PQD data on a monthly basis could be considered. A one-month lag in reporting may be sufficient to increase the signalling properties of indicators based on PQD.

To conclude, the public quantitative disclosures for CCP are a welcome first step towards a clear, full and accurate description of the operations of CCPs. Further work is needed to enable stakeholders to fully understand the risks they pose.

Tables

Overview of CCPs in the sample

Table 1

Group	CCP	Abbreviation	CCP domicile
BME Group	BME Clearing	BME Clearing	Spain
London Stock Exchange Group	Cassa di Compensazione e Garanzia SpA	CC&G	Italy
	CCP Austria Abwicklungsstelle für Börsengeschäfte GmbH	CCP.A	Austria
Deutsche Börse Group	Eurex Clearing AG	Eurex Clearing	Germany
	European Central Counterparty NV	EuroCCP	Netherlands
Intercontinental Exchange INC	ICE Clear Europe LTD ICE Clear Netherlands BV	ICE Clear Europe ICE Clear NL	United Kingdom Netherlands
	KDPW CCP	KDPW	Poland
LCH.Clearnet Group LTD	LCH.Clearnet LTD LCH.Clearnet SA	LCH.Clearnet LTD LCH.Clearnet SA	United Kingdom France
London Metal Exchange	LME Clear LTD	LME Clear	United Kingdom
Nasdaq INC	Nasdaq OMX Clearing AB	Nasdaq OMX	Sweden

Note: Data refer to July 2016.

Total number of clearing members and proportions of domestic and foreign participants

Table 2

CCP	Number of members (in percent)	Domestic CMs (in percent)	Foreign CMs (in percent)	Average number of clearing memberships
BME Clearing	71	76.06	23.94	3
CC&G	84	75.00	25.00	3
CCP.A	51	50.98	49.02	3
Eurex Clearing	192	32.81	67.19	3
EuroCCP	46	4.35	95.65	4
ICE Clear Europe	77	37.66	62.34	4
ICE Clear NL	3	66.67	33.33	7
KDPW	43	97.67	2.33	1
LCH.Clearnet LTD	153	30.65	69.93	3
LCH.Clearnet SA	102	18.63	81.37	4
LME Clear	44	75.00	25.00	4
Nasdaq OMX	247	27.13	72.87	2

Note: Data refer to July 2016.

QLR, Default Resources, and concentration of IM — Table 3

CCP	QLR (€ mn)	QLR/DR	IM5/IM
BME Clearing	3,550	0.96	0.56
CC&G	13,600	1.03	0.61
CCP.A	75.3	1.67	0.55
Eurex Clearing	24,700	0.60	0.39
EuroCCP	1,520	1.60	0.73
ICE Clear Europe	33,800	0.76	0.46
KDPW	378	0.96	0.56
LCH.Clearnet LTD	53,600	0.59	0.60
LCH.Clearnet SA	31,000	1.17	0.70
LME Clear	7,580	1.04	0.39
Nasdaq OMX	4,100	0.77	0.55

Note: Data from Public Quantitative Disclosures at the first quarter of 2016. QLR is Qualified liquid resources; DR is default resources; IM5/IM is the portion of initial margin posted by the largest 5 clearing members. The latter is a simple average of concentrations at the default fund level. Concentrations are taken at the peak over the quarter.

Products per fixed income default funds — Table 4

CCP	Segregated default fund	Products covered	Contract type	Underlying
LCH.Clearnet SA	€GC Plus	Fixed income	Triparty Repo	ECB Collateral baskets
LCH.Clearnet SA	Fixed income	Fixed income	Cash trades and repo	Government bonds
CC&G	Bond	ETD Bonds and repo	Bonds and repo	Government bonds & corporate bonds
LCH.Clearnet LTD	Fixed Income	Fixed income products	Cash bond and repo trades	Government bonds, German Jumbo bonds, Agency, supranational, regional, government guaranteed bonds, liquid bonds baskets
BME Clearing	Fixed Income Securities	Repo	ETD and OTC	Government bonds

Note: Data refer to September 2016.

Products covered by equity default funds				Table 5
CCP	Segregated default fund	Products covered	Contract type	Underlying
BME Clearing	Financial derivatives	Listed derivatives	Futures & Options	Stock index, 10-yr government bonds, & single stock dividend, single stock index, American and European style stock index
LCH.Clearnet SA	Cash and derivatives	Equity cash and derivatives (also bonds and commodities)	Government and corporate bonds, Single company equities, Cash equities, Equities, ETFs, ETCs, REITs, Securities, Stocks, Warrants, Certificates, Funds, UCITS trackers and structured funds, ET commodity derivatives	NA
CC&G	Equity	Equity products and Equity derivatives	Shares, warrants, convertible bonds, closed-end funds, ET funds, exchange traded commodities, Futures, Options	 Index, single stock Index, single stock
LCH.Clearnet LTD	Equities	Equity products	Single company equities, Cash equities, ETFs, ETCs, REITs, ccCFDs	Equity, index, securities
EuroCCP	EuroCCP NV	ETD and OTC cash equity	NA	NA
ICE Clear NL	Futures and options	European equity derivatives	Futures, Options	Index American-style stock, European-style index

Note: Data refer to September 2016.

Products covered by energy and commodity default funds

Table 6

CCP	Segregated default fund	Products covered	Contract type	Underlying
BME Clearing	Power derivatives	OTC electricity derivatives	Futures	Electricity
			Swaps	Electricity
LCH.Clearnet LTD	Commodities	Derivatives	Block Futures	Fertilizer
			Forward Freight Agreements	Dry time charter, dry voyage, dry trip
			Forward Freight Agreement options	Dry time charter basket routes
			Iron Ore contract	TSI index
			Iron Ore option	European-style, TSI Iron Ore contract
			Steel contracts	Hot Rolled Coil, Northern Europe
				Hot Rolled Coil, Southern Europe Turkish Import Scrap
Nasdaq OMX	Commodities	Derivatives	Futures	Power, gas, renewables, freight, fuel oil, ferrous products
			Options	Power, gas, freight, ferrous products
			Electricity Price Area Differentials	Power
			Electricity Certificate futures	Electricity
			EU Allowance futures	Carbon
			EU Allowance options	Carbon
CC&G	IDEX	Energy derivatives	Futures	Energy
LME Clear	CCP level	Commodities	Futures	Metal, index, steel
			Options	Metal
			Traded average price options	Future
			Monthly average futures	Metal

Note: Data refer to September 2016.

Products covered by interest rate default funds

Table 7

CCP	Segregated default fund	Products covered	Contract type	Underlying
BME Clearing	IRS	Interest rate swaps	Swaps OIS FRA	EURIBOR EONIA EURIBOR
LCH.Clearnet LTD	Listed Interest Rates	Listed interest rate derivatives	Futures	EURIBOR, short Sterling, long Gilt, German government bond
LCH.Clearnet LTD	OTC Interest Rates	OTC interest rate products	IRS space	BBR-BBSW, BBR-FRA, BA-CDOR, LIBOR, PRIBOR, CIBOR, EURIBOR, BUBOR, HIBOR, NIBOR, WIBOR, STIBOR, SOR, JIBAR
			Forward rate agreement	LIBOR, PRIBOR, CIBOR, EURIBOR, BUBOR, NIBOR, WIBORS, TIBOR
			OIS	AONIA, CORRA, TOIS, EONIA, TONA, FEDFUNDS
			Variable Notional Swaps	BBR-BBSW, BA-CDOR, EURIBOR, LIBOR, LIBOR-BBA, LIBOR-SONIA, LIBOR-USD
			Basis overnight	LIBOR-FedFunds, LIBOR-H15, LIBOR-BBA
			Inflation ZCIIS	HICPxT, CPIxT, RPI, CPI

Note: Data refer to September 2016.

Products covered by OTC CDS default fund

Table 8

CCP	Segregated default fund	Products covered	Contract type	Underlying
ICE Clear Europe	CDS	European CDS	Swaps	Index, Corporate single names, Sovereign single names
LCH.Clearnet SA	OTC CDS	Credit default swaps	Swaps	Index, single names

Note: Data refer to September 2016.

Products per mixed default funds				Table 9
CCP	Segregated default fund	Products covered	Contract type	Underlying
ICE Clear Europe	Futures and options	Energy, agricultural, interest rates, equity derivatives	Futures	Oil, natural gas, power, coal, Emissions, cocoa, coffee, sugar, Wheat, index, dividend index, Stock index, government bonds
			Options	Oil, natural gas, emissions, cocoa, coffee
			Index	Oil, natural gas, emissions, cocoa, Coffee, sugar, wheat, index, stock, Government bonds, bond future
LCH.Clearnet LTD	OTC FX pairs	OTC non-deliverable FX transactions	Forwards	Currency pairs
Nasdaq OMX	Financial Markets	ET and OTC equity derivatives	Futures	Single stock, index
			Options	Single stock, index, fixed income
			Forwards	Single stock
		OTC rates	IRS	STIBOR, CIBOR, EURIBOR, NIBOR
			OIS	STIBOR
			FRA	FRA & STIBOR, CIBOR, EURIBOR, NIBOR
		Fixed income derivatives	Futures	Government and mortgage bonds, rates
			Options	Government and mortgage bonds, rates
		Repo products	Repos	Bonds
Nasdaq OMX	Seafood	Salmon derivatives	Futures	Nasdaq Salmon Index

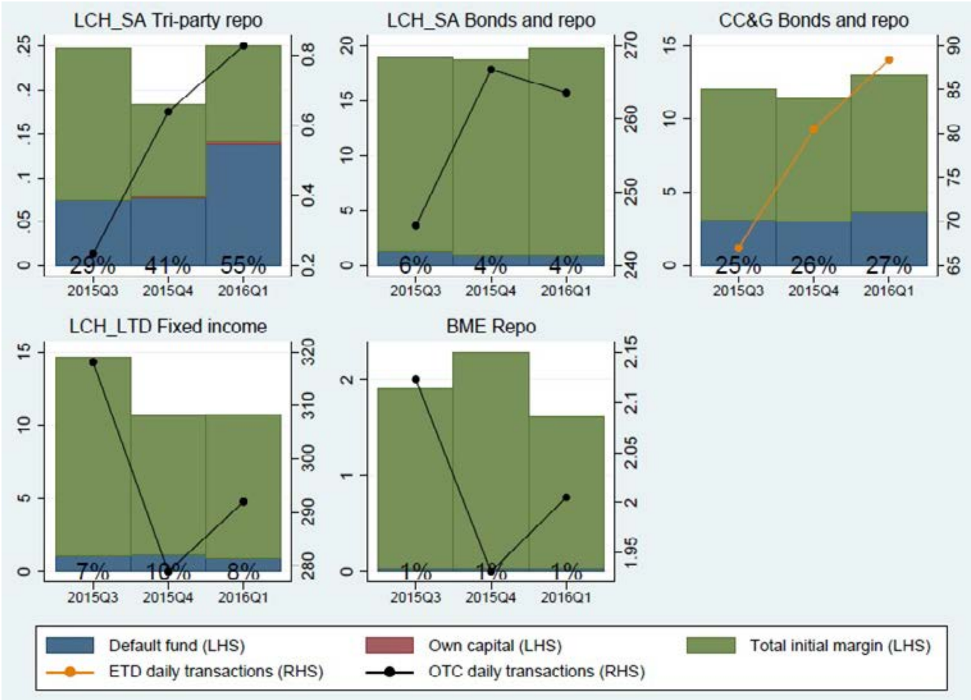
Eurex Clearing	Integrated default fund	All products cleared	All contracts cleared	NA
CCP.A	Integrated default fund	Equity market	Stocks	NA
		Bond market	Government bonds, federal treasury certificates, Treasury notes, interest rate and government strips, Corporate and banking bonds, convertible bonds	
		Structured products	Certificates, exchange traded funds, warrants	
		Other securities	Profit-sharing rights, UCITS shares, stocks	
CC&G	AGREX	Agricultural Derivatives	Futures	Durum Wheat

Note: Data refer to September 2016.

Figures

Fixed income segment

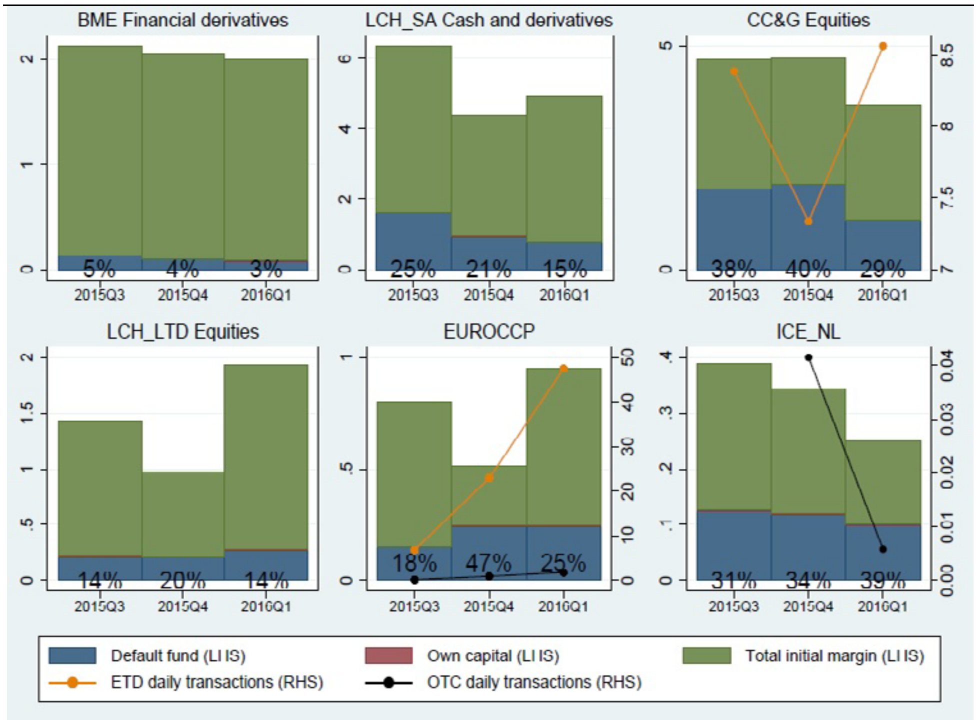
Average daily volumes and waterfall Figure 1



Note: Transaction volumes are notional (or principal) amounts, right-hand side scale (RHS), billion euro. Initial margin, default fund and own capital are also in billion euro, left-hand side scale. Percentages are share of the default fund in total waterfall. CC&G does not provide split by ET and OTC transactions.

Equity segment

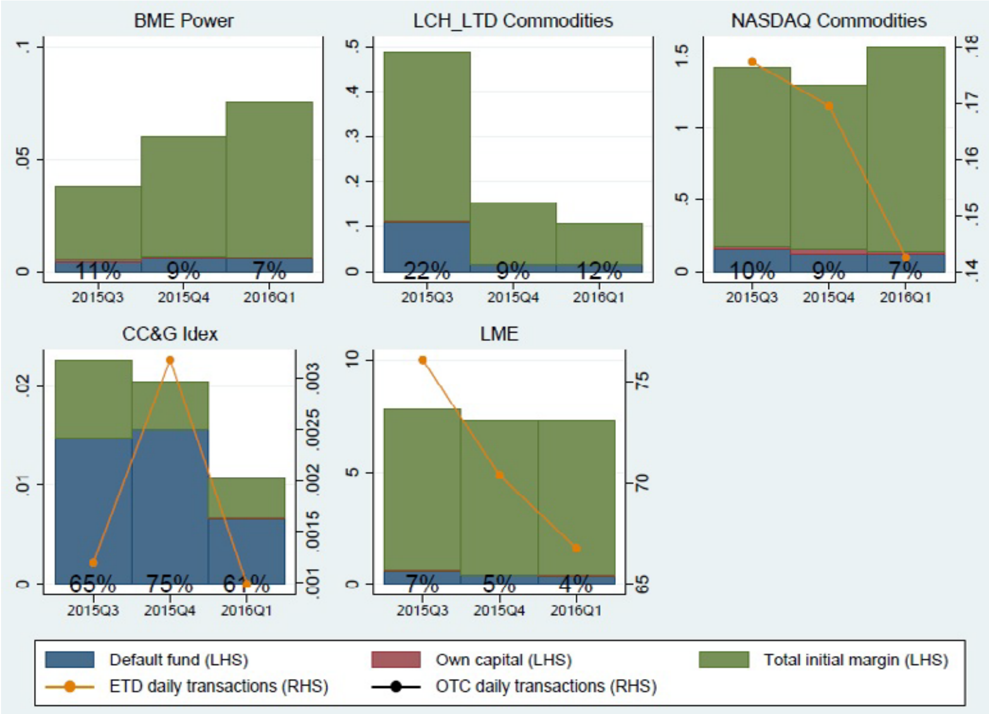
Average daily volumes and waterfall | Figure 2



Note: Transaction volumes are notional (or principal) amounts, right-hand side scale (RHS), billion euro. Initial margin, default fund and own capital are also in billion euro, left-hand side scale. Percentages are share of the default fund in total waterfall. CC&G does not provide split by ET and OTC transactions. BME Clearing, LCH.Clearnet SA, and LCH.Clearnet LTD also clear non-equity products in this segment. See Table 5.

Energy and commodity segment

Average daily volumes and waterfall — Figure 3

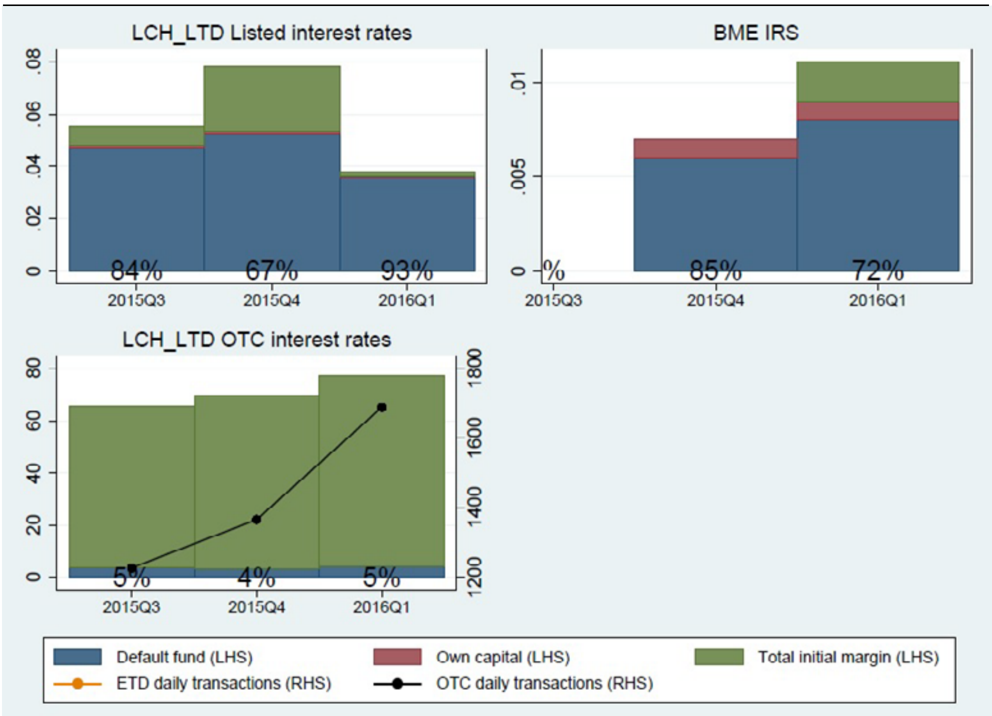


Note: Transaction volumes are notional (or principal) amounts, right-hand side scale (RHS), billion euro. Initial margin, default fund and own capital are also in billion euro, left-hand side scale. Percentages are share of the default fund in total waterfall. CC&G does not provide split by ET and OTC transactions.

Interest rate derivatives segment

Average daily volumes and waterfall

Figure 4

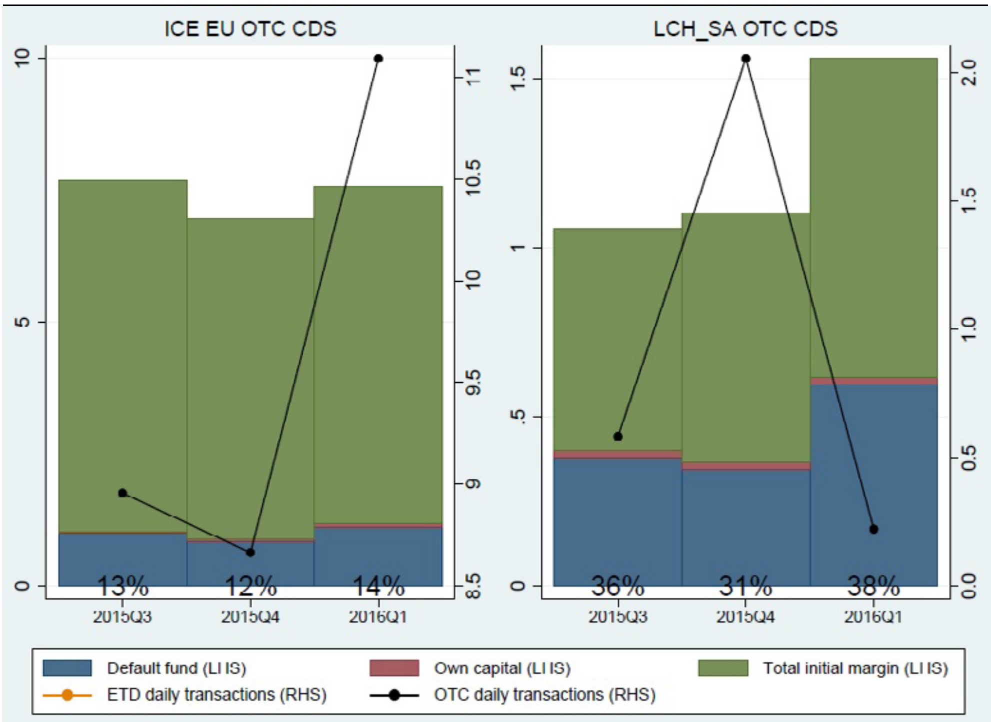


Note: Transaction volumes are notional (or principal) amounts, right-hand side scale (RHS), billion euro. Initial margin, default fund and own capital are also in billion euro, left-hand side scale. Percentages are share of the default fund in total waterfall.

OTC CDS segment

Average daily volumes and waterfall

Figure 5

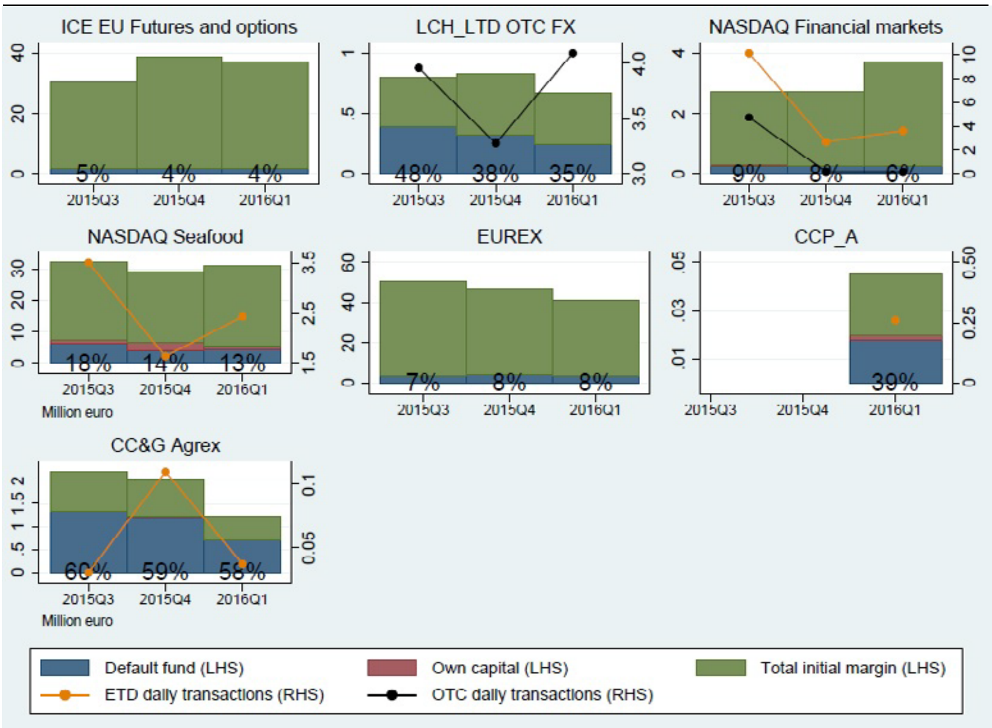


Note: Transaction volumes are notional (or principal) amounts, right-hand side scale (RHS), billion euro. Initial margin, default fund and own capital are also in billion euro, left-hand side scale. Percentages are share of the default fund in total waterfall.

Mixed segment

Average daily volumes and waterfall

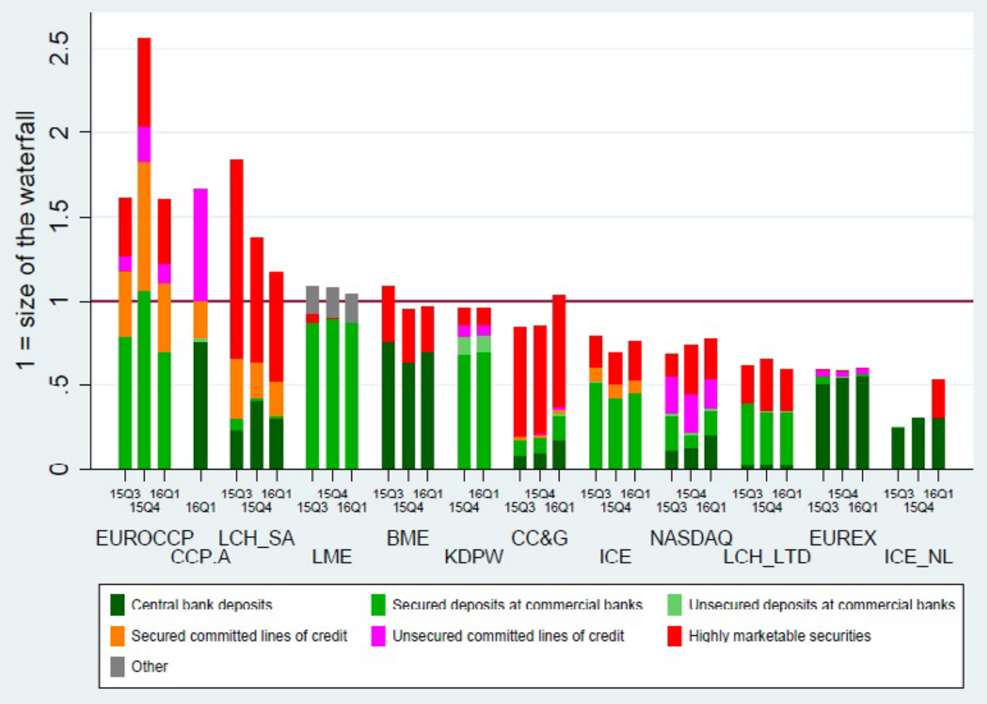
Figure 6



Note: Transaction volumes are notional (or principal) amounts, right-hand side scale (RHS), billion euro. Initial margin, default fund and own capital are also in billion euro, left-hand side scale. Percentages are share of the default fund in total waterfall. For a description of the products cleared, see Table 9.

Ratio of QLR to total waterfall at CCP level

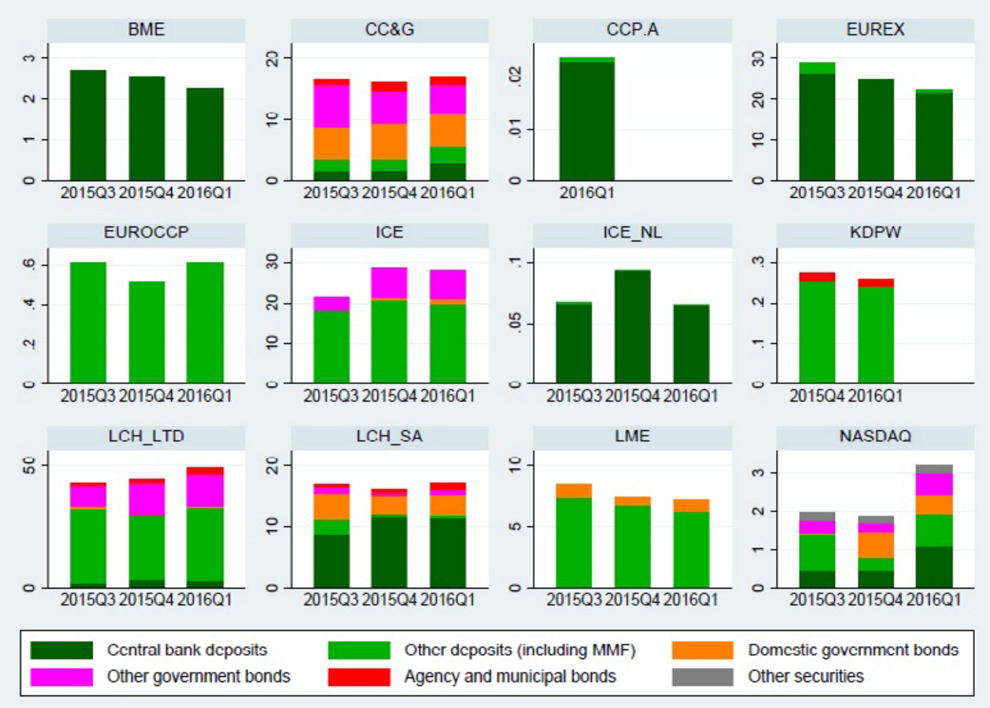
Figure 7



Note: ICE is ICE Clear Europe. ICE_NL is ICE Clear NL. LCH_LTD is LCH.Clearnet LTD. LCH_SA is LCH.Clearnet SA. Two CCPs deposits cash at foreign central banks: EuroCCP (less than 0.8% of QLR) and LCH.Clearnet LTD (less than 0.001% of QLR).

Reinvestment of participant cash

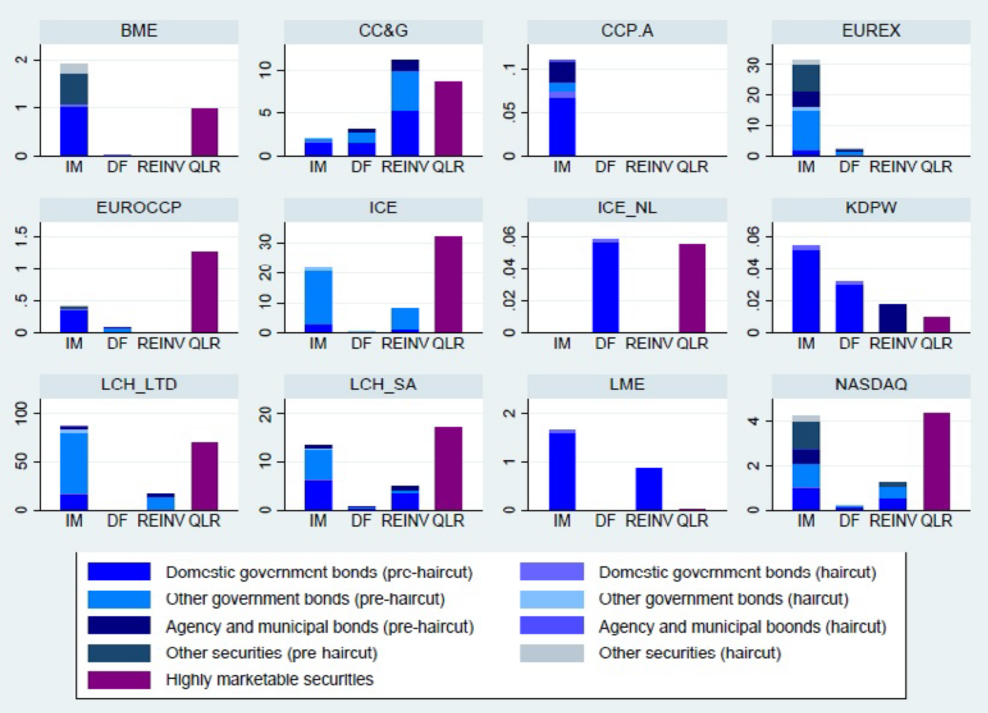
Figure 8



Note: Values in billion euro.

Focus on securities held

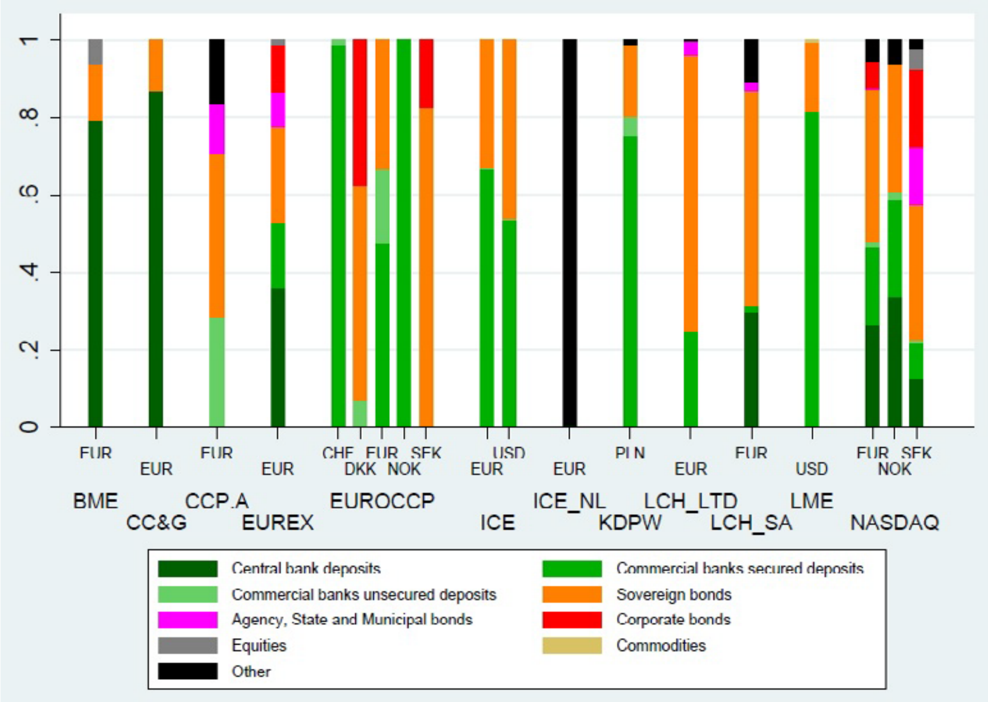
Figure 9



Note: Values in billion euro.

Composition of initial margin

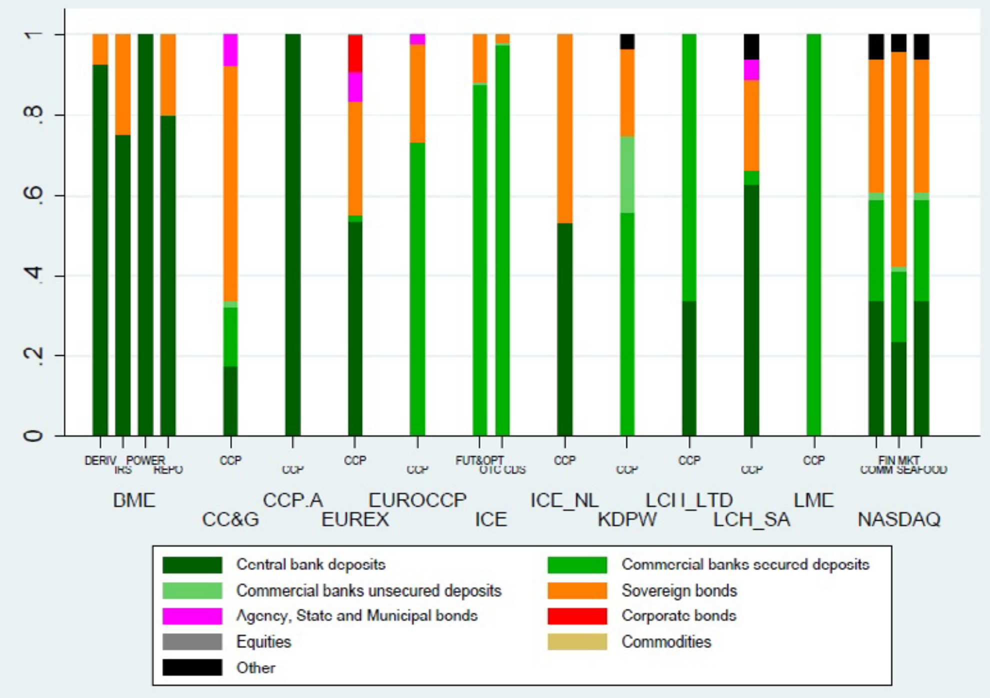
Figure 10



Note: ICE is ICE Clear Europe. ICE_NL is ICE Clear NL. LCH_ LTD is LCH.Clearnet LTD. LCH_ SA is LCH.Clearnet SA.

Composition of default funds

Figure 11



Note: ICE is ICE Clear Europe. ICE_NL is ICE Clear NL. LCH_ LTD is LCH.Clearnet LTD. LCH_ SA is LCH.Clearnet SA.

Overview of PQD variables used per Figure

This section is to provide an overview of the PQD variables used in the paper and the modifications that were necessary to make the data, partly provided in differing currencies or measuring units, comparable and to enable data aggregation.

PQD variables used

In Table 10, an overview of the different variables extracted from the PQD data files provided by each CCP is provided. The figures were converted to euro using either end-of-period (quarter end) or period-average exchange rates (quarterly) depending on the PQD 'snapshot type'.

Overview of PQD variables used — Table 10

Figure	Measure	PQD reference variable(s)	Variable description	Data unit
Figure 1 to Figure 6	Default waterfall size and structure	4.1.1	Prefunded CCP capital (SIG)	EUR,GBP,HUF,JPY, NOK,PLN,SEK,USD
		4.1.2	Prefunded CCP capital alongside default fund	EUR,GBP,HUF,JPY, NOK,PLN,SEK,USD
		4.1.3	Prefunded CCP capital after default fund	EUR,GBP,HUF,JPY, NOK,PLN,SEK,USD
		4.1.4	Required prefunded participants' default fund contributions	EUR,GBP,HUF,JPY, NOK,PLN,SEK,USD
		6.1.1	Total initial margin required split by house, client gross, client net and total (if not segregated)	CHF,DKK,EUR,GBP, NOK,PLN,SEK,USD

Figure 7	Ratio of qualifying liquid resources to total waterfall resources	7.1.2	Cash deposited at a central bank of issue of the currency concerned	CHF,DKK,EUR,GBP, NOK,PLN,SEK,USD
		7.1.3	Cash deposited at other central banks	CHF,DKK,EUR,GBP, NOK,PLN,SEK,USD
		7.1.4	Secured cash deposited at commercial banks (including reverse repo)	CHF,DKK,EUR,GBP, NOK,PLN,SEK,USD
		7.1.5	Unsecured cash deposited at commercial banks	CHF,DKK,EUR,GBP, NOK,PLN,SEK,USD
		7.1.6	Secured committed lines of credit including foreign exchange swaps and committed repos	CHF,DKK,EUR,GBP, NOK,PLN,SEK,USD
		7.1.7	Unsecured committed lines of credit Unsecured committed lines of credit	CHF,DKK,EUR,GBPN OK,PLN,SEK,US
		7.1.8	Highly marketable collateral held in custody and investments that are readily available and convertible into cash with prearranged and highly reliable funding arrangements even in extreme but plausible market conditions	CHF,DKK,EUR,GBP, NOK,PLN,SEK,USD
		7.1.9	Other	CHF,DKK,EUR,GBP, NOK,PLN,SEK,USD

Figure 8	Reinvestment of participant cash	16.1.1	Total cash (but not securities) received from participants as IM	DKK,EUR,GBP,NOK, PLN,SEK,USD
		16.1.2	Total cash (but not securities) received from participants as default fund contribution	EUR,GBP,NOK,PLN, SEK,USD
		16.2.1	Percentage of total participant cash held as cash deposits	Percentage
		16.2.2	Percentage of total participant cash held as cash deposits at central banks of issue of the currency deposited	Percentage
		16.2.3	Percentage of total participant cash held as cash deposits at other central banks	Percentage
		16.2.4	Percentage of total participant cash held as cash deposits at commercial banks	Percentage
		16.2.5	Percentage of total participant cash held as cash deposits at commercial banks	Percentage
		16.2.6	Percentage of total participant cash held as cash deposits in money market funds	Percentage
		16.2.7	Percentage of total participant cash held as cash deposits in other forms	Percentage
		16.2.10	Percentage of total participant cash invested in securities; Domestic sovereign government bonds	Percentage
		16.2.11	Percentage of total participant cash invested in securities; Other sovereign government bonds	Percentage

		16.2.12	Percentage of total participant cash invested in securities; Agency bonds	Percentage
		16.2.13	Percentage of total participant cash invested in securities; State or municipal bonds	Percentage
		16.2.14	Percentage of total participant cash invested in securities; State or municipal bonds	Percentage
Figure 9	Focus on securities held	4.3.5	Non-Cash Sovereign Government Bonds-Domestic	EUR,NOK,PLN,SEK, USD
		4.3.6	Non-Cash Sovereign Government Bonds-Other	EUR,NOK,PLN,SEK, USD
		4.3.7	Non-Cash Agency Bonds	EUR,NOK,PLN,SEK, USD
		4.3.8	Non-Cash State/municipal bonds	EUR,NOK,PLN,SEK, USD
		4.3.9	Non-Cash Corporate bonds	EUR,NOK,PLN,SEK, USD
		4.3.10	Non-Cash Equities	EUR,NOK,PLN,SEK, USD
		6.2.5	Non-Cash Sovereign Government Bonds-Domestic	CHF,DKK,EUR,NOK, PLN,SEK,USD
		6.2.6	Non-Cash Sovereign Government Bonds-Other	CHF,DKK,EUR,NOK, PLN,SEK,USD
		6.2.7	Non-Cash Agency Bonds	CHF,DKK,EUR,NOK, PLN,SEK,USD
		6.2.8	Non-Cash State/municipal bonds	CHF,DKK,EUR,NOK, PLN,SEK,USD
		6.2.9	Non-Cash Corporate bonds	CHF,DKK,EUR,NOK, PLN,SEK,USD
		6.2.10	Non-Cash Equities	CHF,DKK,EUR,NOK, PLN,SEK,USD

Figure 10	Composition of initial margin	6.2.1	Cash deposited at a central bank of issue of the currency concerned	CHF,DKK,EUR,NOK, PLN,SEK,USD
		6.2.2	Cash deposited at other central banks	CHF,DKK,EUR,NOK, PLN,SEK,USD
		6.2.3	Secured cash deposited at commercial banks	CHF,DKK,EUR,NOK, PLN,SEK,USD
		6.2.4	Unsecured cash deposited at commercial banks	CHF,DKK,EUR,NOK, PLN,SEK,USD
		6.2.11	Non-Cash Commodities-Gold	CHF,DKK,EUR,NOK, PLN,SEK,USD
		6.2.12	Non-Cash Commodities-Other	CHF,DKK,EUR,NOK, PLN,SEK,USD
		6.2.13	Non-Cash-Mutual Funds OR UCITs	CHF,DKK,EUR,NOK, PLN,SEK,USD
		6.2.14	Non-Cash-Other	CHF,DKK,EUR,NOK, PLN,SEK,USD
		6.2.15	Total initial margin held	CHF,DKK,EUR,NOK, PLN,SEK,USD
Figure 11	Composition of default funds	4.3.1	Cash deposited at a central bank of issue of the currency concerned	EUR,NOK,PLN,SEK, USD
		4.3.2	Cash deposited at other central banks	EUR,NOK,PLN,SEK, USD
		4.3.3	Secured cash deposited at commercial banks	EUR,NOK,PLN,SEK, USD
		4.3.4	Unsecured cash deposited at commercial banks	EUR,NOK,PLN,SEK, USD
		4.3.11	Non-Cash Commodities-Gold	EUR,NOK,PLN,SEK, USD
		4.3.12	Non-Cash Commodities-Other	EUR,NOK,PLN,SEK, USD
		4.3.13	Non-Cash Commodities-Mutual Funds and UCITs	EUR,NOK,PLN,SEK, USD
		4.3.14	Non-Cash Commodities-Other	EUR,NOK,PLN,SEK, USD
		4.3.15	In total	EUR,NOK,PLN,SEK, USD

Note 1: PQD variables 4.1.1 – 4.1.4 and 6.1.1 are split by clearing service if default funds are segregated by clearing service. For PQD variables 7.1.2 – 7.1.8, size and composition of qualifying liquid resources are for each clearing service. For PQD variables 16.1.1 and 16.1.2 total cash is reported regardless of the form in which it is held, deposited or invested, split by whether it was received as initial margin or default fund contribution. For PQD variables 16.2.1 and 16.2.2 cash deposits including through reverse repo. For PQD variable 16.2.4, the figure refers to secured cash deposits, including through reverse repo. For PQD variable 16.2.5, the figure refers to unsecured cash deposits. The PQD variables used for Figures 9 to 11 include pre- and post-haircut. PQD variables 4.3.1 – 4.3.15 are held for each clearing service, in total and split by. PQD variables 6.2.1 – 6.2.15 are for each clearing service, total initial margin held, split by house and client.

Note 2: The PQD variables are reported at quarter end.

Note 3: The PQD variables used for Figures 1 to 6 are also used for Figure 7.

Note 4: The PQD variables 16.1.1 – 16.1.2, 16.2.10 - 16.2.14, and 7.1.8 are also used for Figure 9.

Note 5: The PQD variables 6.2.5 – 6.2.10 are also used for Figure 10.

Note 6: The PQD variables 4.3.5 – 4.3.10 are also used for Figure 11.

Explanatory notes on Figures

Figures containing PQD reference variables relating to CCP capital (4.1.2 and 4.1.3) The PQD reference variables 4.1.2 and 4.1.3 refer to the own capital of the CCP to be used alongside and after non-defaulting clearing members' contributions to the default fund (PQD reference variable 4.1.4), respectively. For regulatory reasons, they are not allocated to each default fund, thus the reporting in the PQD data is at the CCP level. To be used in the measures proposed in this paper, these CCP capital resources are allocated to each default fund in proportion to the amounts of the CCP's SIG for the respective default fund.

Figure 8 The QLR concept (denominator), covering PQD reference variables 7.1, refers to how financial resources are held by the CCP. The pre-funded waterfall amounts (that are part of the denominator) are required amounts (default fund (4.1.4) and initial margin (6.1.1)). This approach was chosen as to compare the liquid resources to the resources available to the CCP, excluding any over-collateralisation.

Figure 9 For the IM, we use total IM held in securities, covering PQD reference variables 6.2.. 'Domestic government bonds' and 'Other government bonds' refer to PQD reference variables 6.2.5 and 6.2.6, respectively. The proportion named 'Agency and Municipal bonds' is the sum of PQD reference variables 6.2.7 and 6.2.8. 'Other securities' covers corporate bonds (PQD reference variable 6.2.9) and equities (PQD reference variable 6.2.10). Similarly, for DF we use concept 4.3 or 'Value of pre-funded default resources (excluding initial and retained variation margin)', split into the same buckets as PQD reference variables 6.2.5 to 6.2.10. All figures are converted to euro at end-of period exchange rates before being summed up in order to get total IM and DF resources held in securities in any currency.

Total cash received as IM or DF reinvested in securities is obtained using concept 16.1: 'Total cash (but not securities) received from participants, regardless of the form in which it is held, deposited or invested, received as' initial margin (PQD reference variable 16.1.1) and default fund (PQD reference variable 16.1.2) and PQD reference variables 16.2.10 to 16.2.14, on 'Percentage of total participants cash invested in securities', split by domestic and foreign sovereign, agency, municipal and other securities. The QLR PQD reference variable is 7.1.8, 'Highly marketable collateral held in custody and investments that are readily available and convertible into cash with prearranged and highly reliable funding arrangements even in extreme but plausible market conditions'.

The Figure aims at showing how CCPs hold the securities within default resources and in turn the extent to which the securities held have been invested into by the CCP using cash posted by clearing members or they have been posted by members directly. Concepts 4.3 and 6.2 refer to how the CCP is holding IM and DF, rather than how members have posted resources. Therefore, according to the PQD standards, the sum of PQD reference variables 4.3.5 to 4.3.10 and 6.2.5 to 6.2.10 (sum of the first and second sets of stacked bars) should be at most equal to the third set of stacked bars. Equality holds when the CCP receives all IM and DF contributions in cash, and the securities held as IM or DF are only those into which the CCP has reinvested participant cash. Conversely, when the reinvestment bar is zero, all securities in IM and DF are those posted by members. The difference between the sum of the first two bars and the third bar in the chart is the collateral posted in securities by participants.

However, in the Figure, the reinvestment bar is greater than the sum of DF and IM bars for CC&G.

References

Armakolla, A. and J.-P. Laurent (2017). CCP resilience and clearing membership. Working Paper.

Bianchi, B. (2016). Sovereign risk premia and the international balance sheet: Lessons from the European crisis. Open Economies Review 27 (3), 471-493.

Braithwaite, J. (2015). Legal perspectives on client clearing. London School of Economics and Political Science Law, Society and Economy Working Papers 14/2015.

Braithwaite, J. and D. Murphy (2016). Got to be certain: the legal framework for CCP default management processes. Bank of England Financial Stability Paper (37).

Committee on Payment and Settlement Systems - International Organization of Securities Commissions (2004). Recommendations for central counterparties. Bank for International Settlements.

Committee on Payment and Settlement Systems - International Organization of Securities Commissions (2012). Principles for financial market infrastructures. Bank for International Settlements.

Committee on Payments and Market Infrastructures - International Organization of Securities Commissions (2015). Public quantitative disclosure standards for central counterparties. Bank for International Settlements.

Cont, R. and T. Kokholm (2014). Central clearing of OTC derivatives: bilateral vs. multilateral netting. Statistics and Risk Modeling 31 (1), 3-22.

Domanski, D., L. Gambacorta, and C. Picillo (2015, December). Central clearing: trends and current issues. Bank for International Settlements Quarterly Review.

Duffie, D. (2014). Resolution of failing central counterparties. Working paper. Graduate School of Business. Stanford University.

Duffie, D. and H. Zhu (2011). Does a central clearing counterparty reduce counterparty risk?Review of Asset Pricing Studies 1, 74-95.

Eurex Clearing (2014). Eurex Clearing Prisma portfolio-based risk management.

European Central Bank (2013). Collateral eligibility requirements. A comparative study across specific frameworks.

European Central Bank (2014, July). Collateral eligibility and availability. Follow-up to the report on 'collateral eligibility requirements. A comparative study across specific frameworks. Dated July 2013.

European Securities and Markets Authority (2016). Report. EU-wide CCP stress test 2016.

European Union (2012). Regulation (EU) No 648/2012 of the European Parliament and of the Council of 4 July 2012 on OTC derivatives, central counterparties and trade repositories.

Gemmill, G. (1994). Margins and the safety of clearing houses. Journal of Banking & Finance 18 (5), 979-996.

Gregory, J. (2014). Central counterparties: mandatory central clearing and initial margin requirements for OTC derivatives. John Wiley & Sons.

Hughes, D. and M. Manning (2015, December). CCPs and banks: different risks, different regulations. Reserve Bank of Australia Quarterly Bulletin.

Pirrong, C. (2014). A bill of goods: CCPs and systemic risk. Journal of Financial Market Infrastructures 2 (4), 55-85.

Rahman, A. (2015). Over-the-counter (OTC) derivatives, central clearing and financial stability. Bank of England Quarterly Bulletin 55 (3), 283-295.

Rehlon, A. and D. Nixon (2013). Central counterparties: what are they, why do they matter and how does the Bank supervise them? Bank of England Financial Quarterly Bulletin 53 (2), 147-56.

Roe, M. J. (2013). Clearinghouse overconfidence. California Law Review 101 (6).

Wendt, F. (2015). Central counterparties: addressing their too important to fail nature. International Monetary Fund Working Paper (15/21).

Yellen, J. L. (2013). Interconnectedness and systemic risk: Lessons from the financial crisis and policy implications. Speech at the American Economic Association/American Finance Association Joint Luncheon. San Diego. California.

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The European central counterparty (CCP) ecosystem[1]

Angela Armakolla, Université Paris 1 Panthéon-Sorbonne and LabEx ReFi,
and Benedetta Bianchi, Trinity College Dublin

[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 European CCP ecosystem

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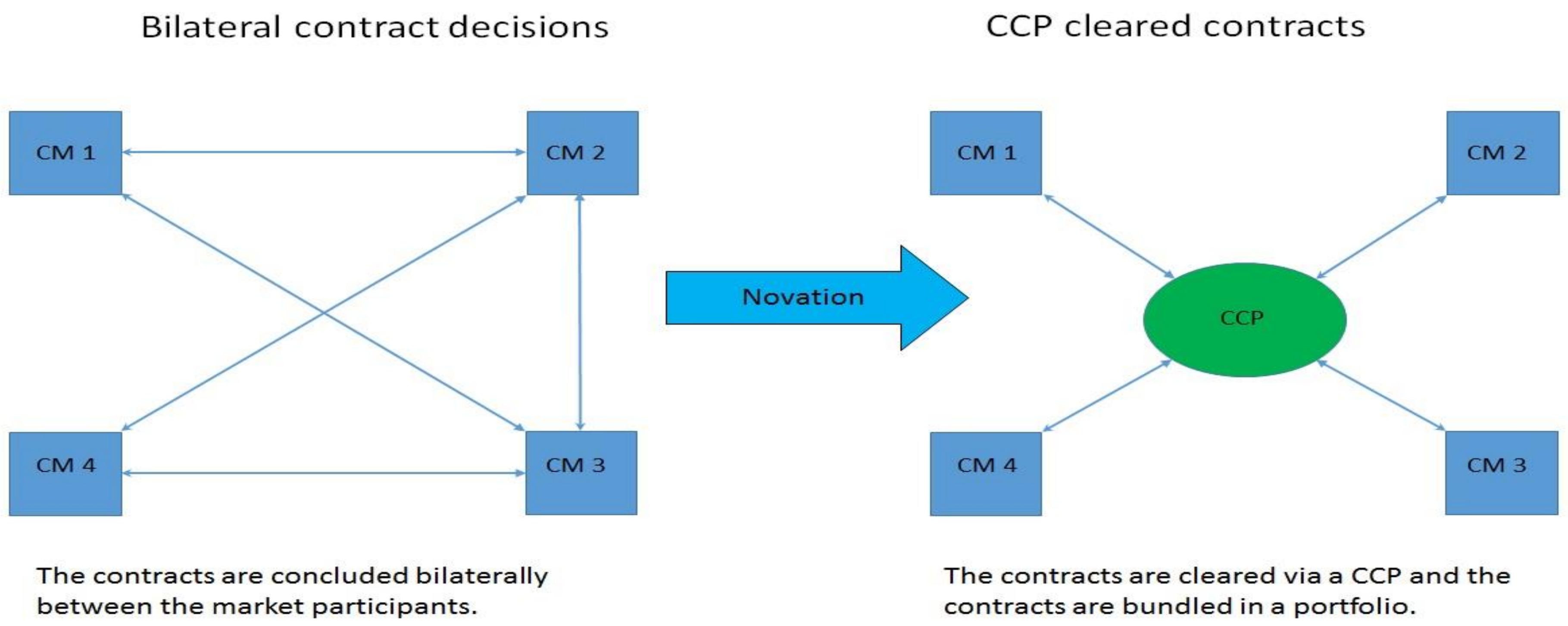
Outline

1. Central clearing: a short introduction
    a) Central clearing counterparties in a nutshell
    b) The default waterfall
    c) Benefits and risks of central clearing
2. The data set: regulatory framework and data availability
    a) The public disclosure framework for CCPs
    b) CCPs included in our data set
    c) Standardisation and data quality issues of the Public Quantitative Disclosures (PQD)
3. The European CCP ecosystem
    a) Size of CCPs in terms of waterfall resources at the default fund level
    b) Liquidity monitoring of default resources
    c) Interconnectedness
4. Conclusion

Central clearing counterparties in a nutshell



Source: Armakola (2016)

A central clearing counterparty (CCP)

- Interposes itself between the initial parties (novation)
- Collects initial margin (IM) from Clearing Members (CMs)
- Mutualises losses in excess of defaulted CM's IM + DF contribution

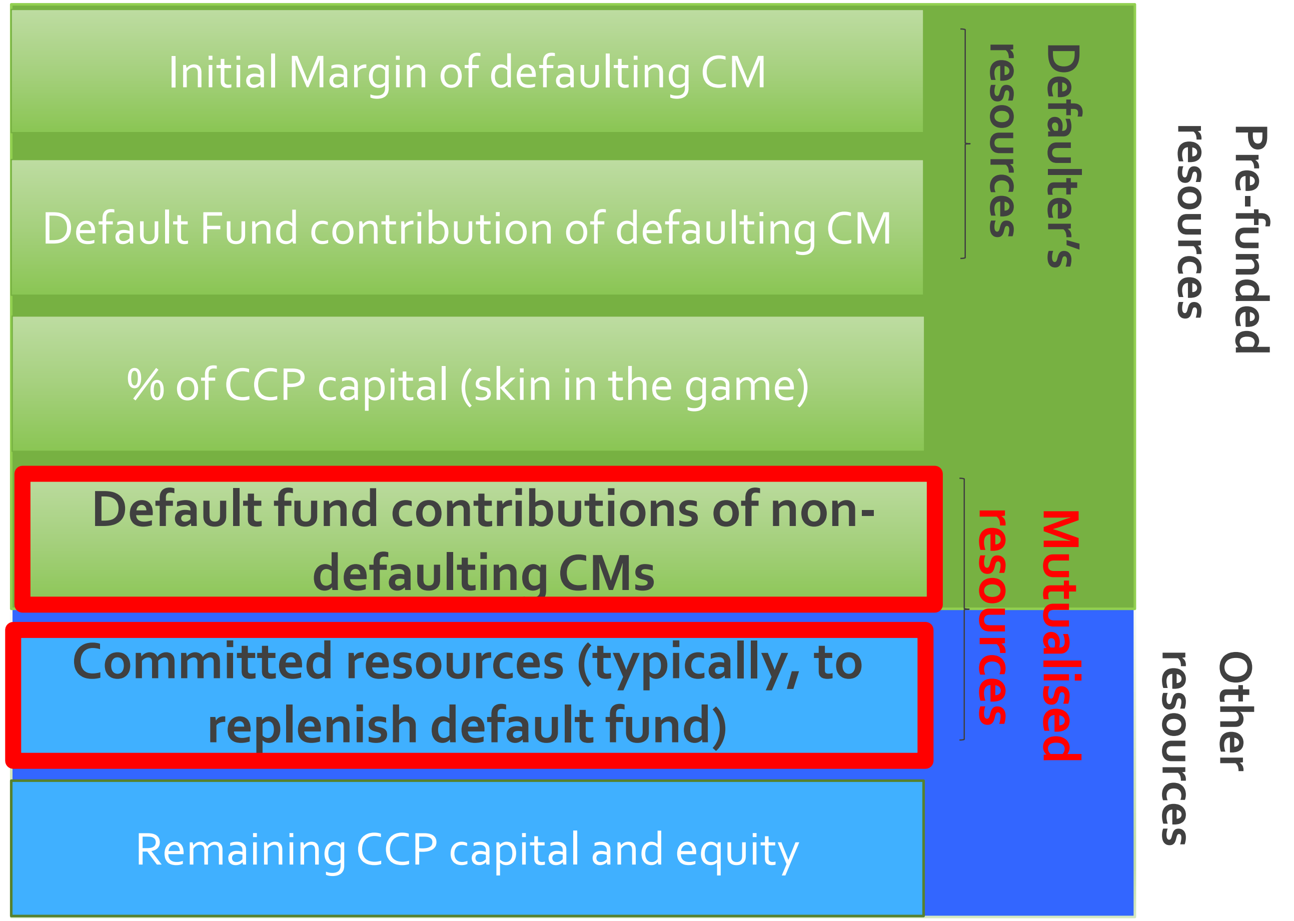
Default waterfall: how CCPs protect themselves from default risk

Initial margin: collateral to cover 'ordinary' losses

Default fund: mutualised resources to cover losses arising in extreme but plausible market conditions

Prefunded vs **Committed default resources**

Many CCPs 'segregate' default funds, ie have several default funds, each covering a different set of products.
Mutualisation limited to traders of similar products.



Source: Armakola and Laurent (2016)

Benefits and risks of central clearing

Benefits

- **Increased transparency of OTC markets** (G20 2009)
- **Reduction of counterparty credit risk among dealers and minimisation of systemic risk associated with cascading counterparty failures** (IMF, 2010)
- **Increased netting efficiency** (Duffie and Zhu (2011)
- **CCPs functioned smoothly after Lehman default despite abnormally volatile markets** (Cecchetti et al., 2009)

Risks

- **Risk concentration in clearing structure** (OFR, 2015; Cont and Kokholm, 2014)
- **Increase in interconnectedness between CCPs and market participants** (Wendt, 2015; Yellen, 2013)
- **Increased systemic risk** (Domanski et al, 2015)
  - Propagation of (exogenous) shocks through domino effects
  - Endogenous shocks: forced deleveraging, fire sales, runs
- **Amplification of market stress via contingent liquidity demands to CMs** (Armakolla and Laurent, 2016; Wendt, 2015)

The European CCP ecosystem – data set

- **Increased use of CCPs, but public data on CCPs is scarce.**
- **Dataset based on disclosures required by CPMI-IOSCO**
  - Principles for financial market infrastructures (2012)
  - Public quantitative disclosure standards for central counterparties (2015)
- **The standards shall allow all interested parties**
  - To compare CCP risk controls
  - To have a clear and accurate understanding of the risks associated with a CCP
  - To assess a CCP's systemic importance and its impact on systemic risk
  - To assess the risks associated with different levels of participation in a CCP
- **Other public information: member lists, end-of- year reports, ….**
- **This paper: overview of CCP landscape and focus on liquidity of default resources.**

Public Quantitative Disclosures (PQD) availability in Europe

AUTHORISED CCPs				
No	Name of the CCP	Database inclusion		
		2015 Q3	2015 Q4	2016 Q1
1	Nasdaq OMX Clearing AB	IN	IN	IN
2	European Central Counterparty N.V.	IN	IN	IN
3	KDPW_CCP	NA	IN	IN
4	Eurex Clearing AG	IN	IN	IN
5	Cassa di Compensazione e Garanzia S.p.A. (CC&G)	IN	IN	IN
6	LCH.Clearnet SA	IN	IN	IN
7	European Commodity Clearing	NA	NA	NA
8	LCH.Clearnet Ltd	IN	IN	IN
9	Keler INP	NA	NA	NA
10	CME Clearing Europe Ltd	FI	FI	FI
11	CCP.A	NA	NA	IN
12	LME Clear Ltd	IN	IN	IN
13	BME Clearing	IN	IN	IN
14	OMIClear - C.C., S.A.	FI	FI	FI
15	ICE Clear Netherlands B.V.	IN	IN	IN
16	Athex Clear	NA	NA	NA
NON-AUTHORISED AND RECOGNISED CCPs				
17	ICE Clear Europe	IN	IN	IN
18	SIX x-clear Ltd.	FI	FI	FI

IN	Included
FI	Format Issue
NA	Not Available

Overview of segments

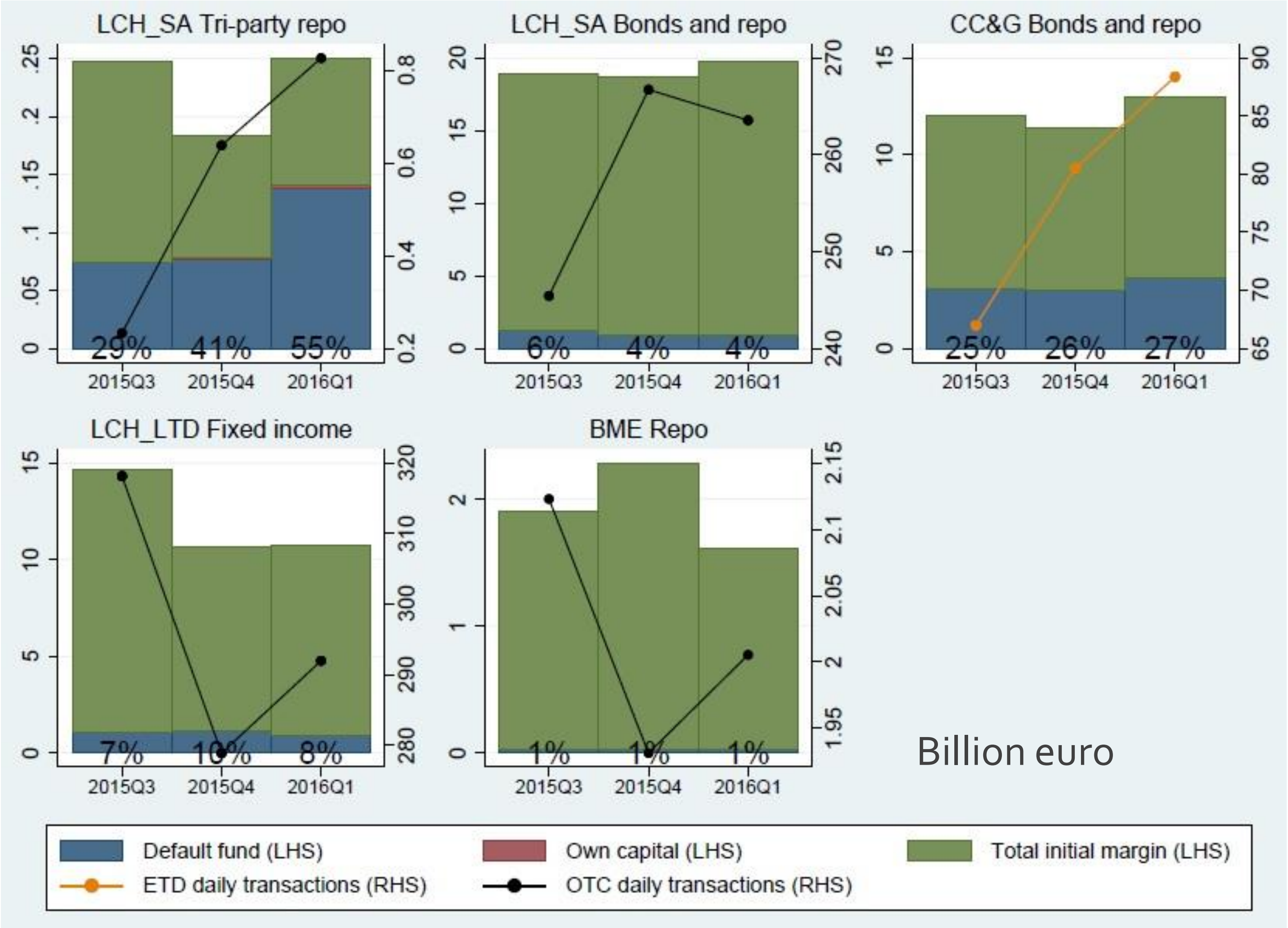
- **12 CCPs in the sample**
- **7 CCPs have segregated default funds**
- **32 default funds in the sample**
- **We group them by asset class cleared**
  - Fixed income
  - Equity
  - Commodities
  - Interest rate derivatives
  - CDS
  - Mixed
- **We show, for 28 default funds (KDPW excluded):**
  - Volumes of transactions (daily average, notional or principal amounts)
  - Amounts in the waterfall

The data set: standardisation and data quality issues

- Reporting of PQD not mandatory
  - Not all CCPs publish the data
  - Not all reporting CCPs use the same format (e.g. SIX x-clear Ltd reports in PDF and does not follow variable naming of PQD standards)
  - Reporting not always complete: some variables missing
- Reporting of PQD not subject to quality check
  - Interpretation of concepts might differ
  - There might be mistakes
- PQD has the potential to be a valuable means to improve transparency of CCP operations. Quality checks by overseeing authorities would improve reliability of analyses using this source.

Size of segments and respective waterfall: fixed income market

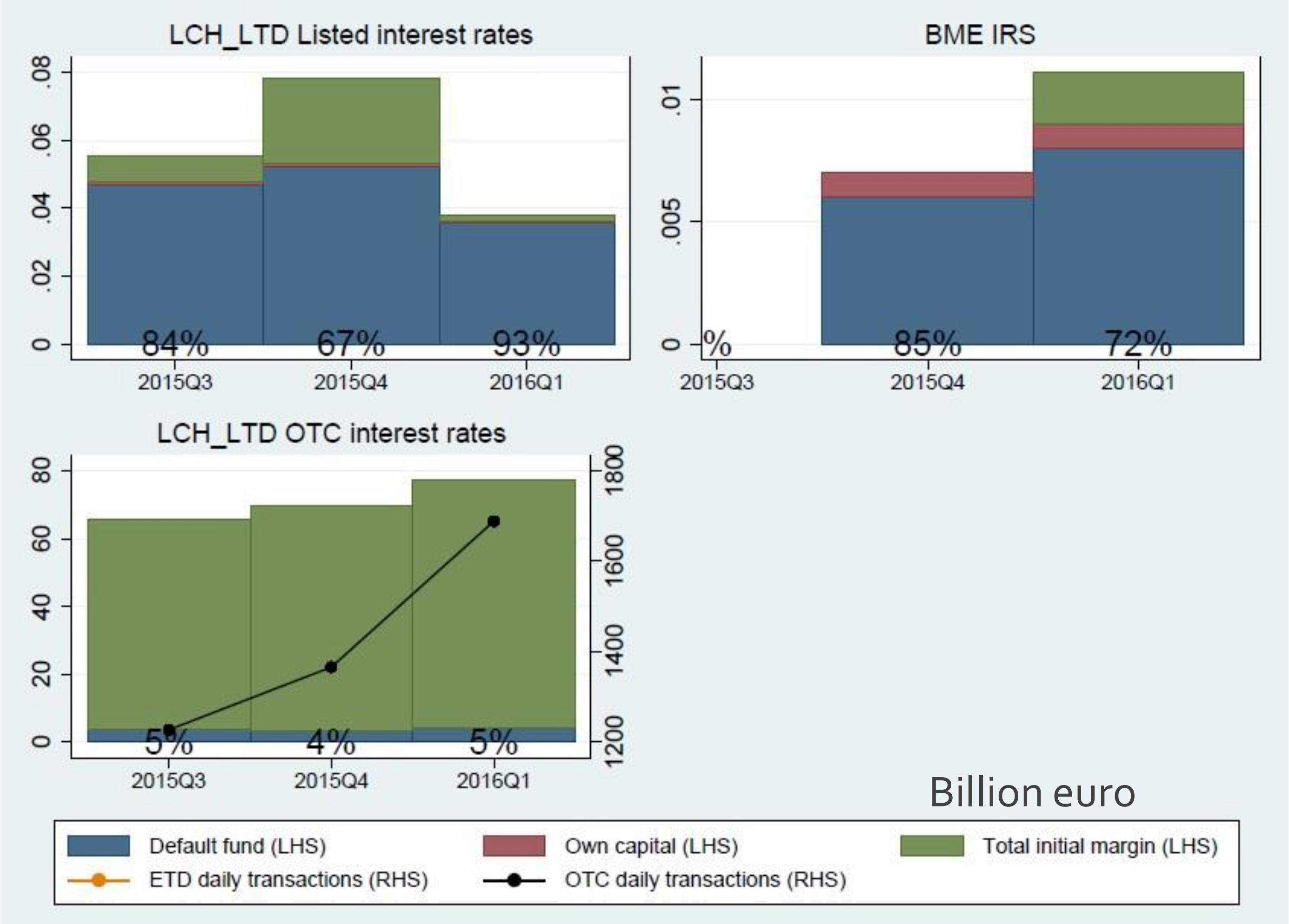
- Relation between notional value of transactions and waterfall not straightforward: exposures do not necessarily increase with transactions
- Waterfall reported at end of the quarter, transactions are daily average
- Most CCPs pool cash and repo in the same waterfall
- LCH SA and CC&G: increase in both transactions and waterfall
- LCH LTD and BME: decrease in both transactions and waterfall
- Percentage of default fund in waterfall decreases in the proportion of repo cleared



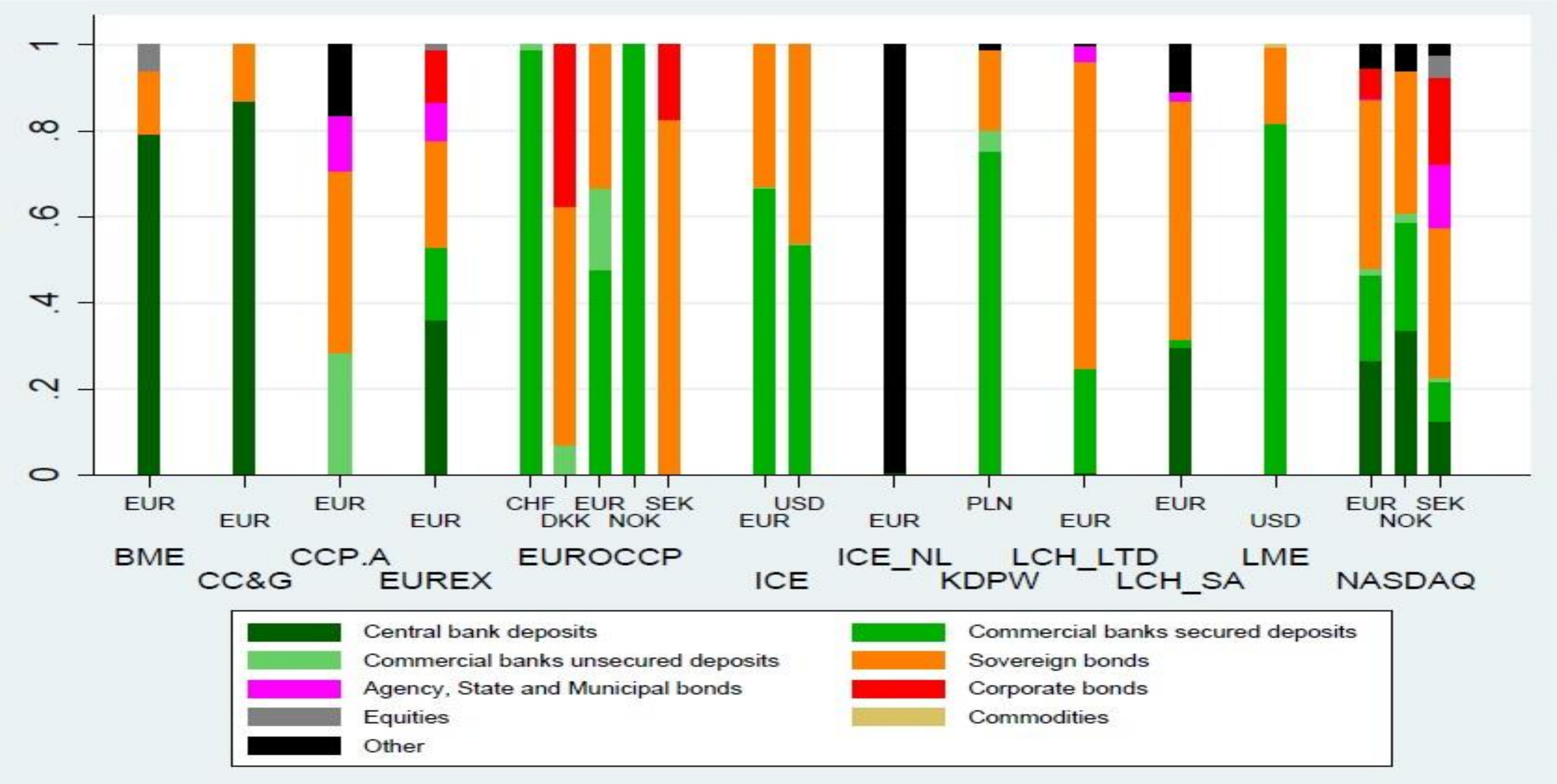
For CC&G, transactions also include OTC products.

Size of segments and respective waterfall: interest rate derivatives (IRD)

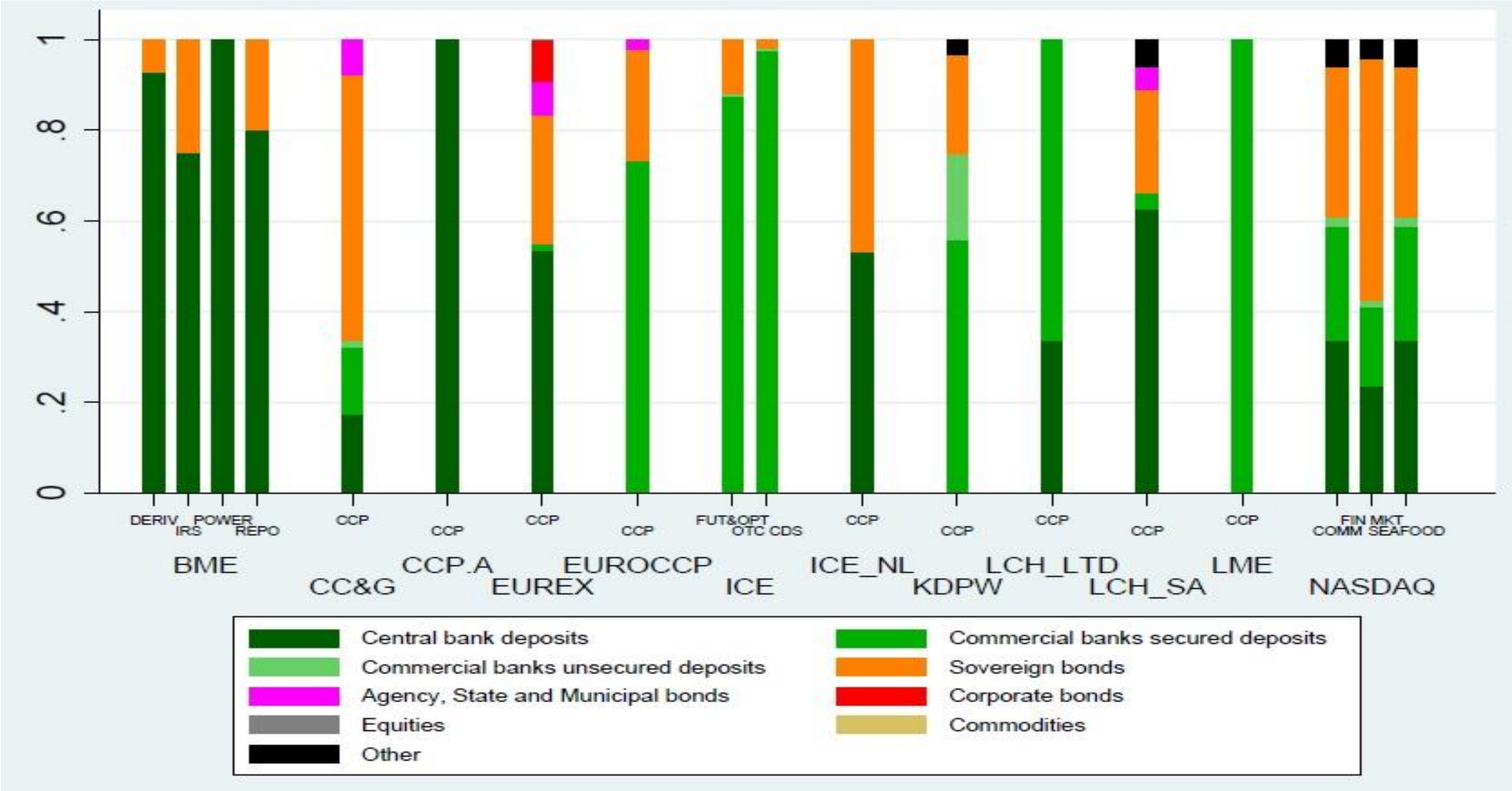
- Chart shows CCP with a segregated default fund for IRD
- In November 2015, BME started a new segment covering all IRD subject to mandatory clearing
- Increase to be expected in 2016 Q2 and Q3
- The only CCP reporting transactions figures (LCH LTD) records a 38% increase in OTC IRD in two quarters



How ‘liquid’ is the initial margin held?



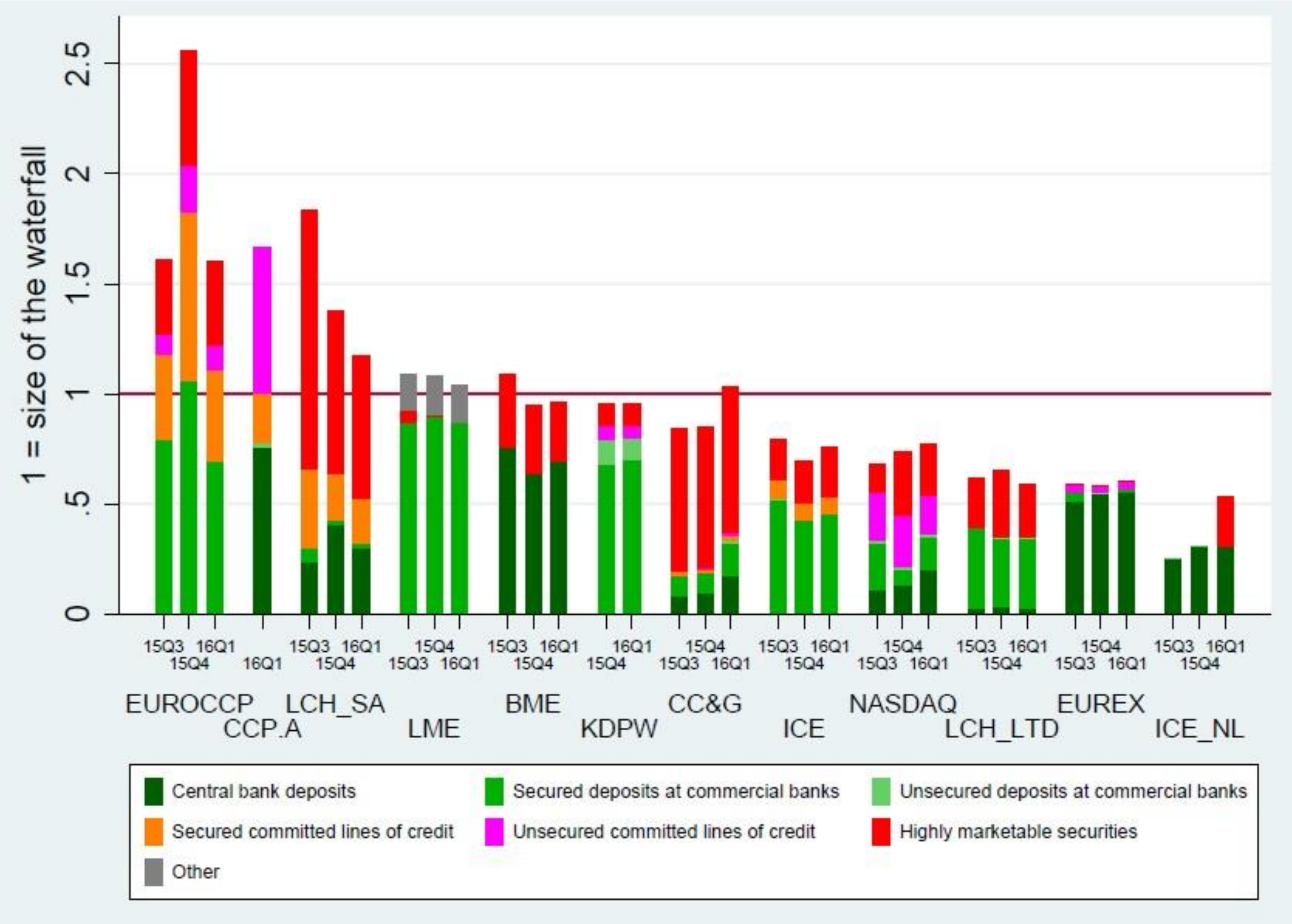
How ‘liquid’ are the default resources held?



Qualifying liquid resources (QLR) relative to total waterfall (TW)

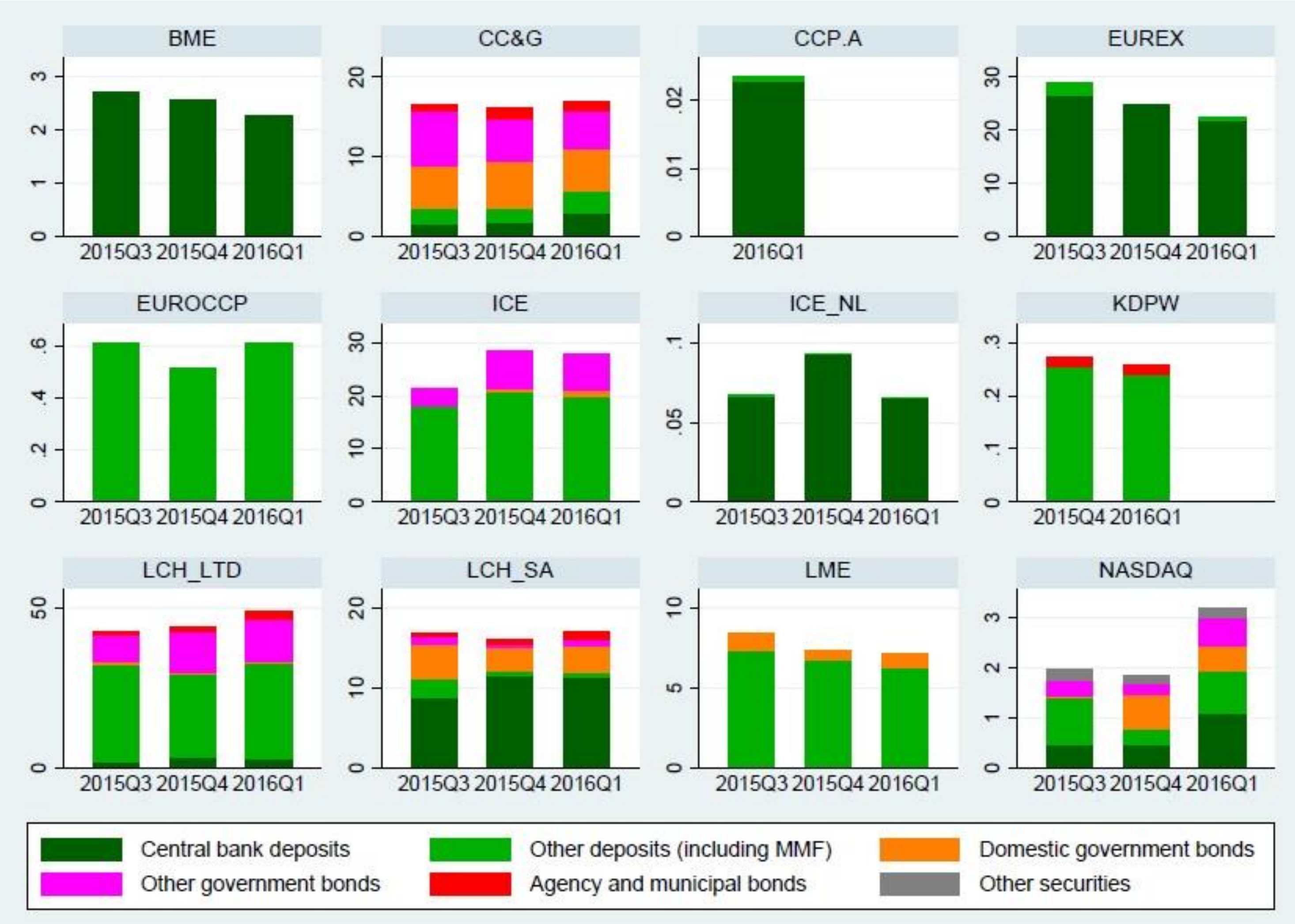
- TW=sum of all waterfalls in a CCP
- QLR/TW=1: if all clearing members default at the same time, the CCP has enough liquidity to readily make use of all of the default resources at their disposal
- If total QLR are liquid, liquidity risk in European CCPs is low

  All CCPs except ICE NL have the equivalent of half their total default resources in QLR
- However, not all types of QLR share the same degree of liquidity
- Strong reliance on:
  - secured deposits at commercial banks (including reverse repo)
  - *'Highly marketable collateral held in custody and investments that are readily available and convertible into cash with pre-arranged and highly reliable funding arrangements even in extreme but plausible market conditions'*



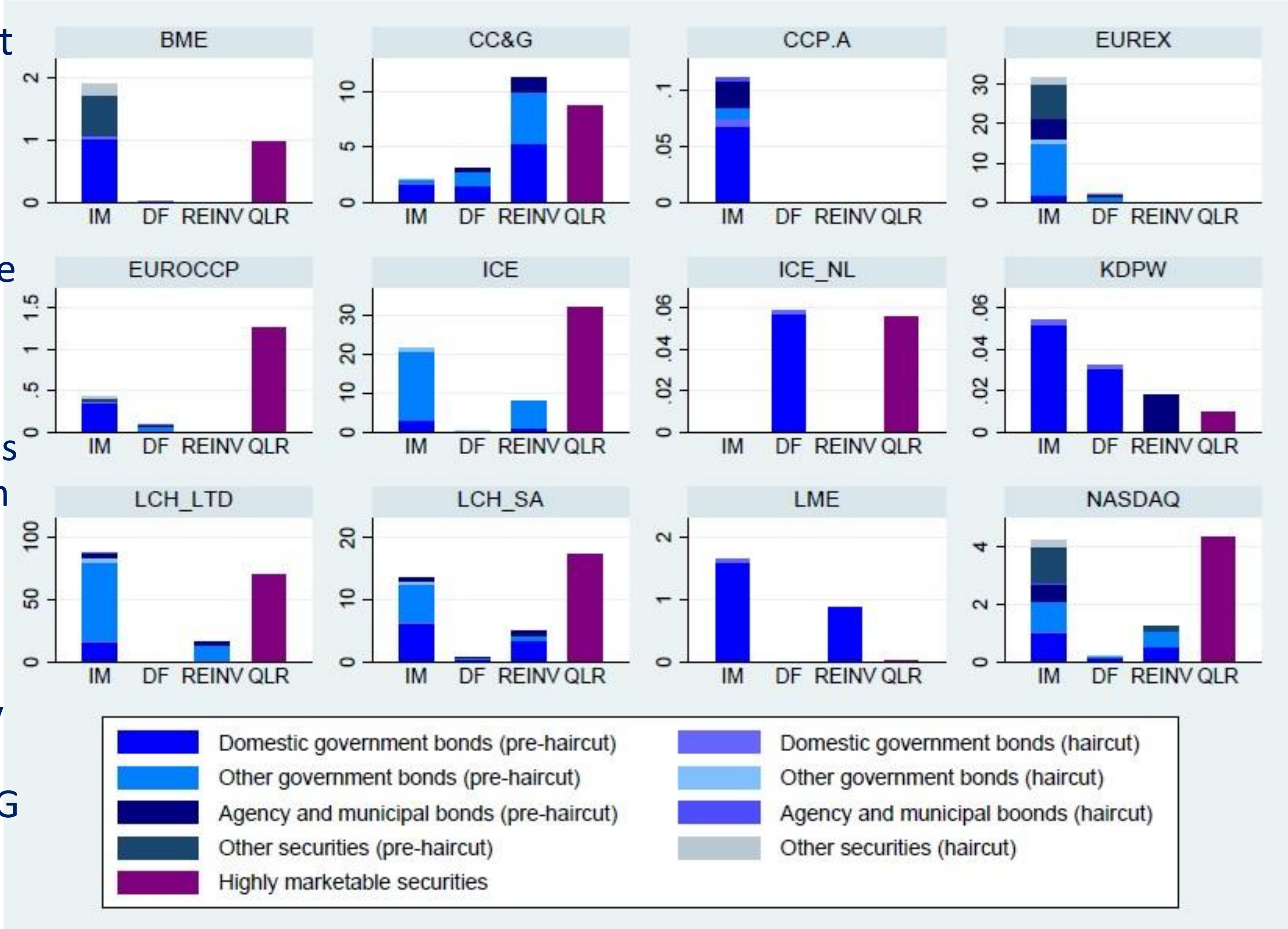
Reinvestment of participants cash

- Cash received from CMs (as IM or DF contribution) can be reinvested by CCPs in ‘highly liquid financial instruments with minimal market and credit risk’
- In 2016 Q1, CC&G reinvested 66% of cash received from its participants, 48% of which (5.4 billion) in Italian government bonds
- Also ICE, KDPW, LCH LTD, LCH SA, LME and Nasdaq have non-negligible reinvestment in sovereign bonds
- If no haircut is applied, CCPs could incur losses if government bonds prices are low when CMs default on the CCP



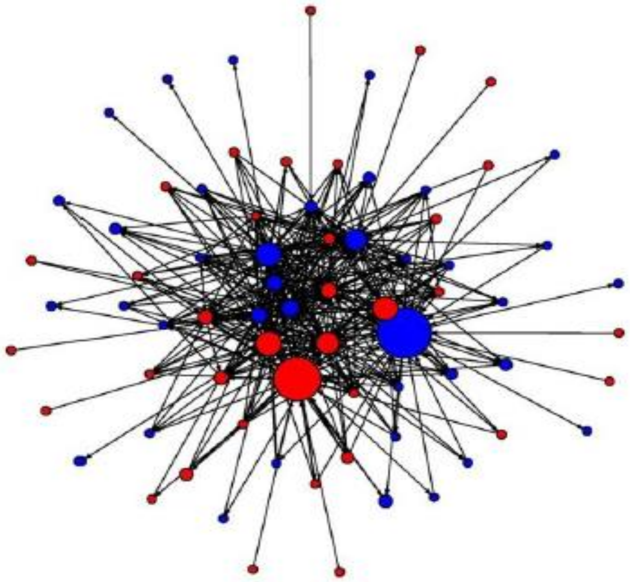
Bond holdings, reinvestment, and highly marketable collateral.

- Do CCPs have enough ‘highly reliable arrangements’ to convert reinvestment back into cash?
- If KDPW and CC&G have to convert back into cash securities bought with cash received from participants, they may face the risk of price changes.
- Additionally, the reliability of ‘pre-arranged funding arrangements’ depends on the ability of liquidity providers (often CMs) to meet their obligation
- Need of standardisation and data quality check most evident here: IM and DF should be reported as held, though CC&G seems to be reporting IM posted



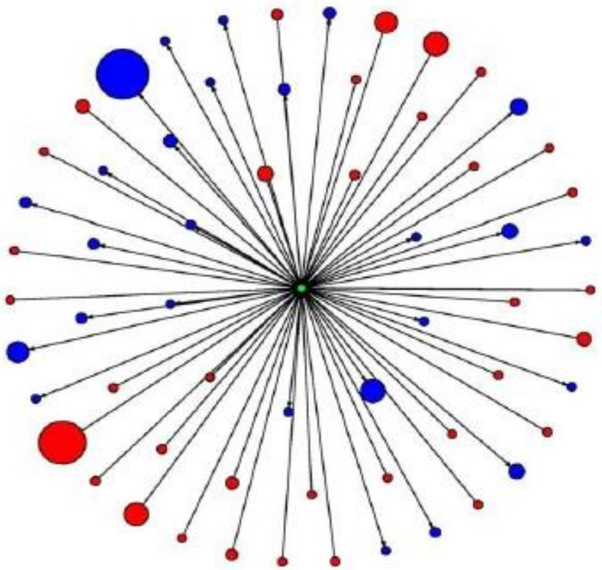
CCPs and systemic risk: interconnectedness

- “Mandatory clearing will turn CCPs into systemic nodes in the financial system, with unknown, but possibly far-reaching, consequences.” (ESRB, 2013)



From fully bilateral

to centrally cleared networks of trading exposure



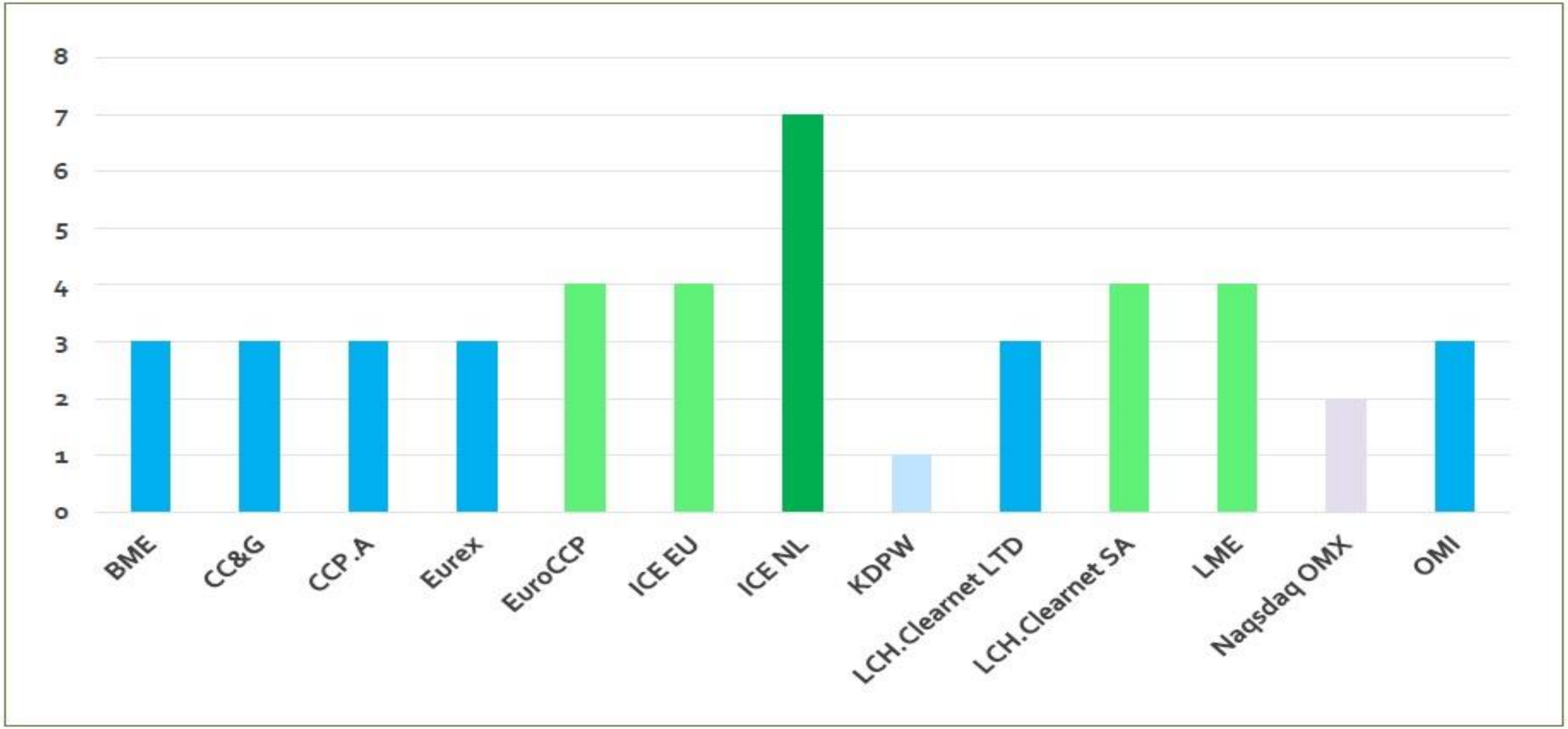
- CCPs and systemic risk (Domanski et al., 2015)
  - Propagation of (exogenous) shocks through domino effects
  - Endogenous shocks: forced deleveraging, fire sales, runs….

Source: Yellen (2013)

17

Interconnectedness: What is the degree of interconnectedness?

Average degree of interconnectedness per individual clearing member



Conclusion

- **PQD issues:**
  - Legal requirement for reporting of PQD would ensure compliance by all European CCPs
  - National competent authorities could perform quality checks
  - Higher frequency of reporting would allow systemic risk monitoring
- **The European CCP ecosystem**
  - Central clearing is growing. Structural changes in the market occurring
  - Total QLR are large: they cover more than 50% of total default resources in all CCPs
  - More than half the CCPs in our sample reinvest non-negligible amounts of cash received from participants in government bonds or agency and municipal bonds. This could be a problem if creditworthiness of CMs and price of bonds reinvested in are positively correlated (margin wrong-way risk), and if CCPs do not have enough arrangements qualifying as QLR to sell securities purchased
  - Two CCPs have larger reinvestment than ‘highly marketable collateral’ (a QLR item), which exposes them to (a re-investment version of) margin wrong-way risk
  - European CCPs are highly interconnected with their ecosystem: members, settlement banks,..

References

Armakolla, A. and Laurent, J.P. (2016). CCP resilience and clearing membership. Presentation.

Arnsdorf, M. (2012). Quantification of central counterparty risk. Journal of Risk Management in Financial Institutions 5 (3), 273-287.

Cecchetti, S, J Gyntelberg and M Hollanders (2009).Central counterparties for over-the-counter derivatives. *BIS Quarterly Review*, September, 45-58.

Cont, R. and T. Kokholm (2014). Central clearing of OTC derivatives: bilateral vs. multilateral netting. Statistics and Risk Modeling 31 (1), 3-22.

CPMI-IOSCO (2015). Public quantitative disclosure standards for central counterparties. BIS.
CPSS-IOSCO (2012). Principles for financial market infrastructures. BIS.

Domanski, D., Gambacorta, L.and Picillo, C.. (2015). Central clearing: trends and current issues. BIS.

Duffie, D. and H. Zhu (2011). Does a central clearing counterparty reduce counterparty risk? Review of Asset Pricing Studies 1, 74-95.

References

G20 (2009). G20 Leaders Statement: The Pittsburgh Summit.

IMF (2010). Making over-the-counter derivatives safer: the role of central counterparties. Global Financial Stability Report, April, 91–117.

Office of Financial Research (2015). Financial stability report.

Pirrong, C. (2011). The Economics of Central Clearing: Theory and Practice. ISDA Discussion Papers Series (1).

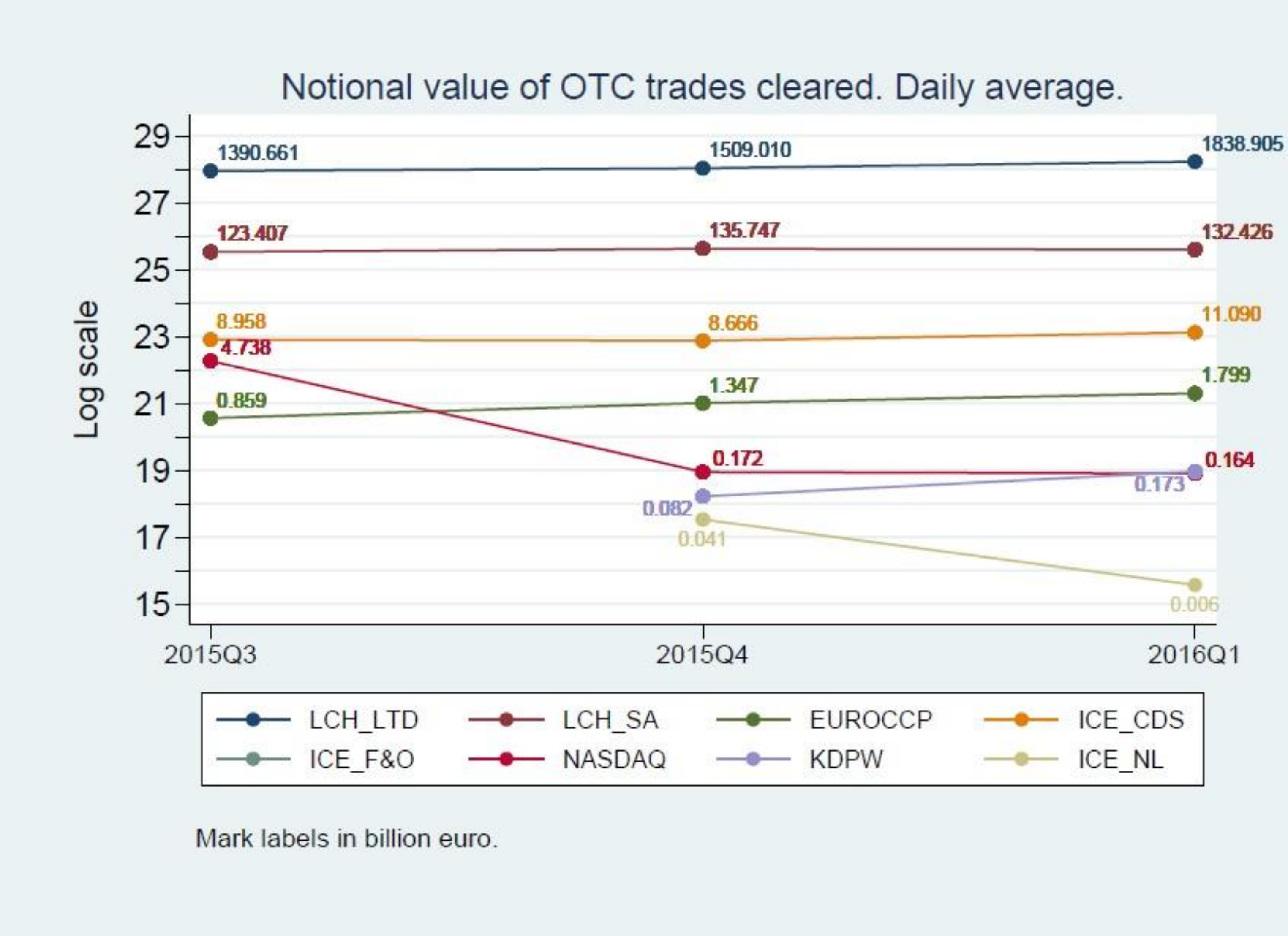
Wendt, F. (2015). Central counterparties: adressing their too important to fail nature. IMF Working Paper (15/21).

Yellen, J. L. (2013). Interconnectedness and systemic risk: Lessons from the financial crisis and policy implications. Speech at the American Economic Association/American Finance Association Joint Luncheon.

Annex

Size of CCPs by cleared transactions: OTC products

- Different orders of magnitude across CCPs
- CCPs are growing in size (Nasdaq stops reporting repo and overnight index swaps from 2015Q4; ICE NL peculiar: only 3 CMs)
- Mandatory clearing: more growth to be expected
- Brexit: substitutability of LCH LTD

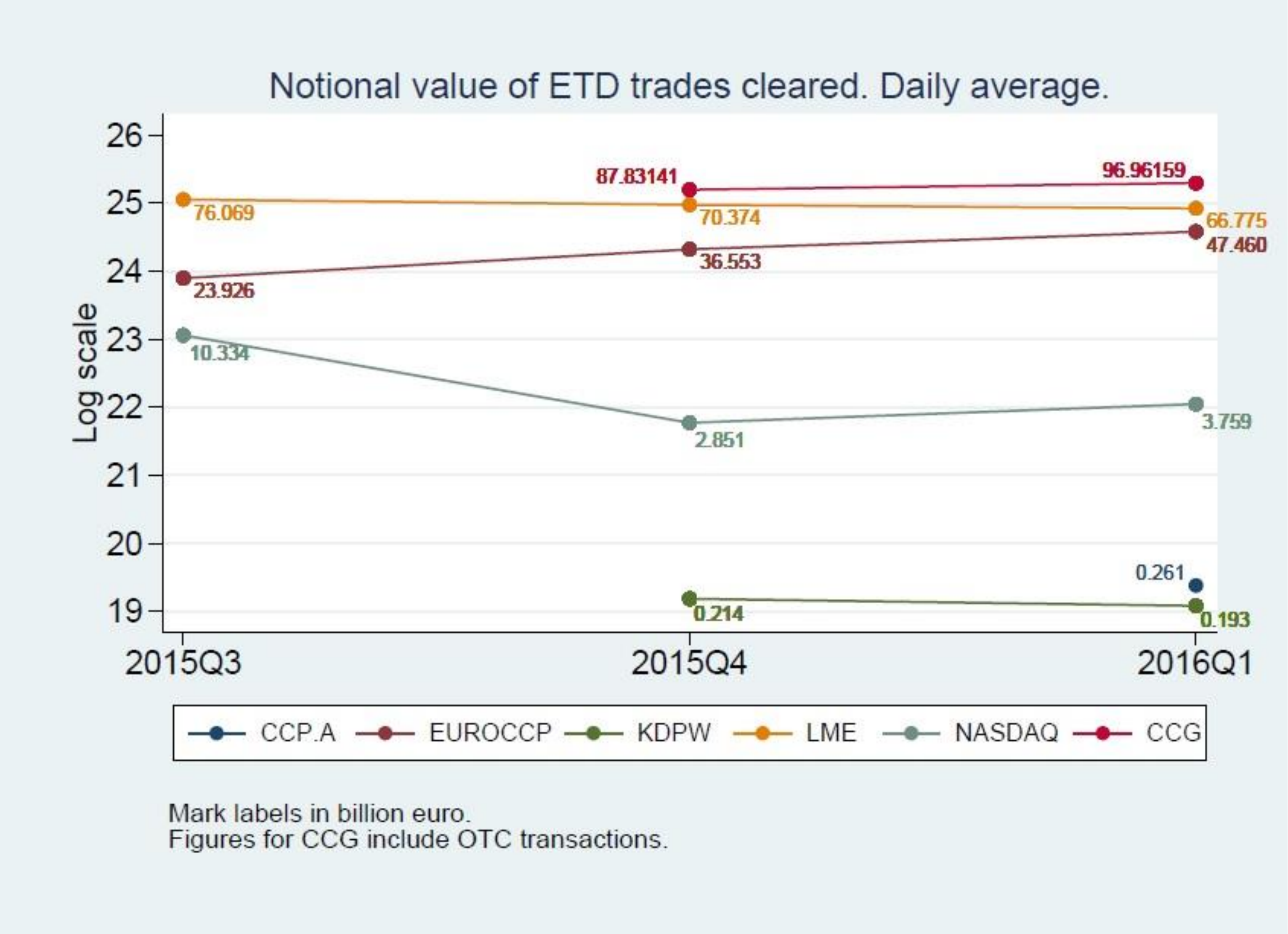


Size of CCPs by cleared transactions: ET derivatives

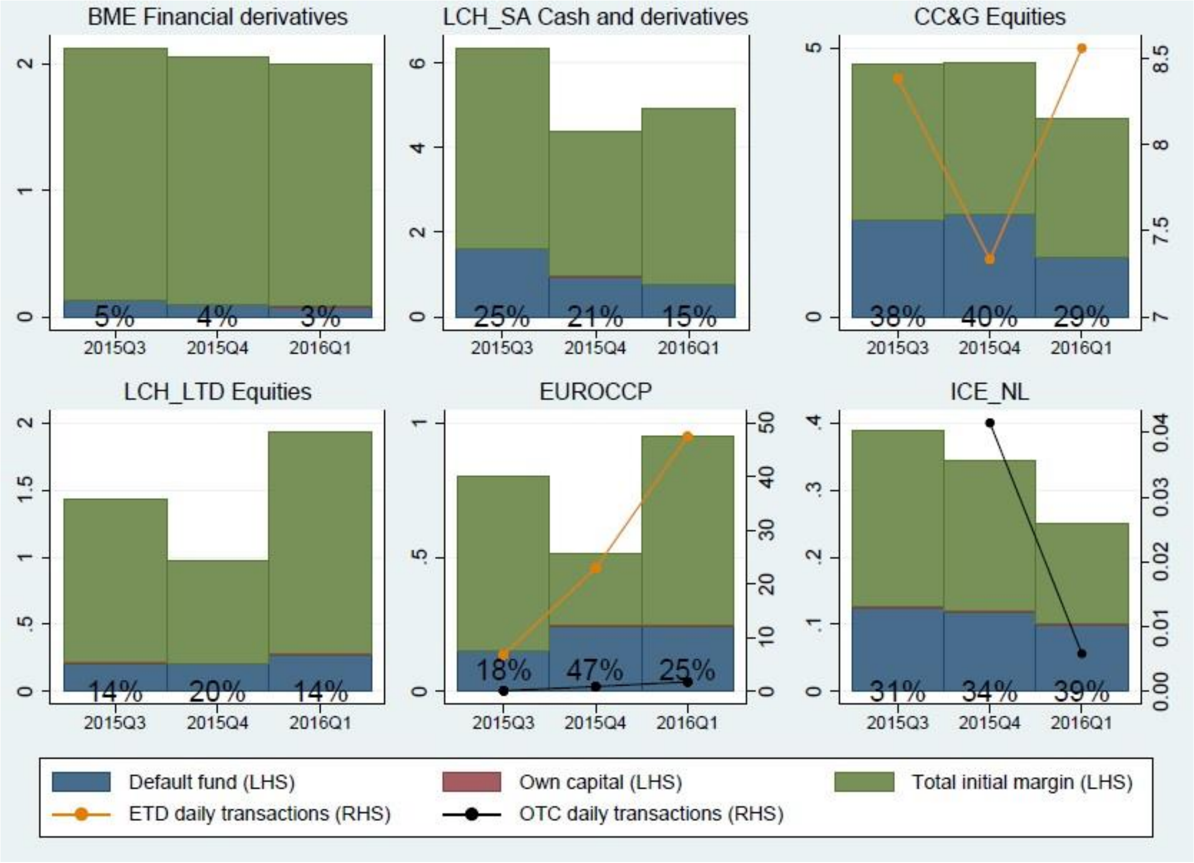
- Many CCPs missing: Eurex, BME, LCH LTD and LCH SA do not publish these data

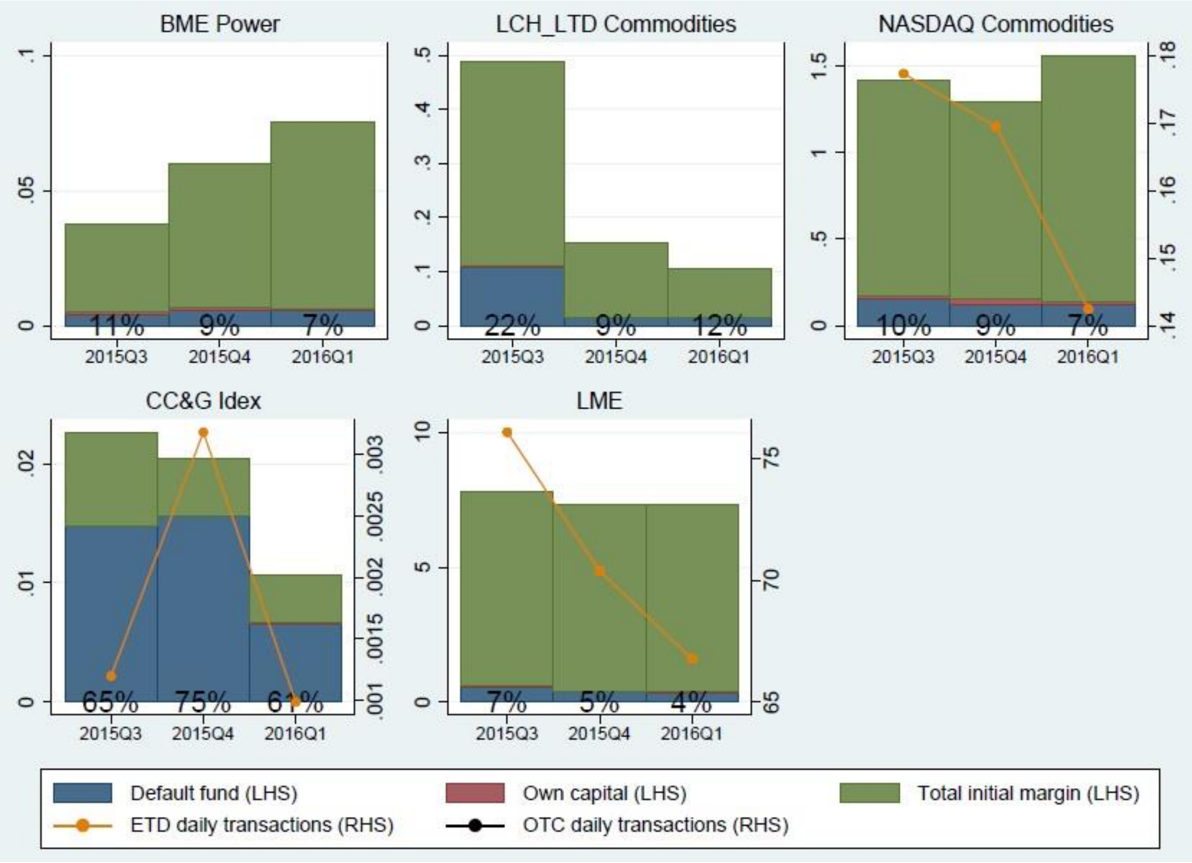
- Less pronounced difference in size across CCPs than for OTC (although largest CCPs are missing)

- Less evident increase in central clearing

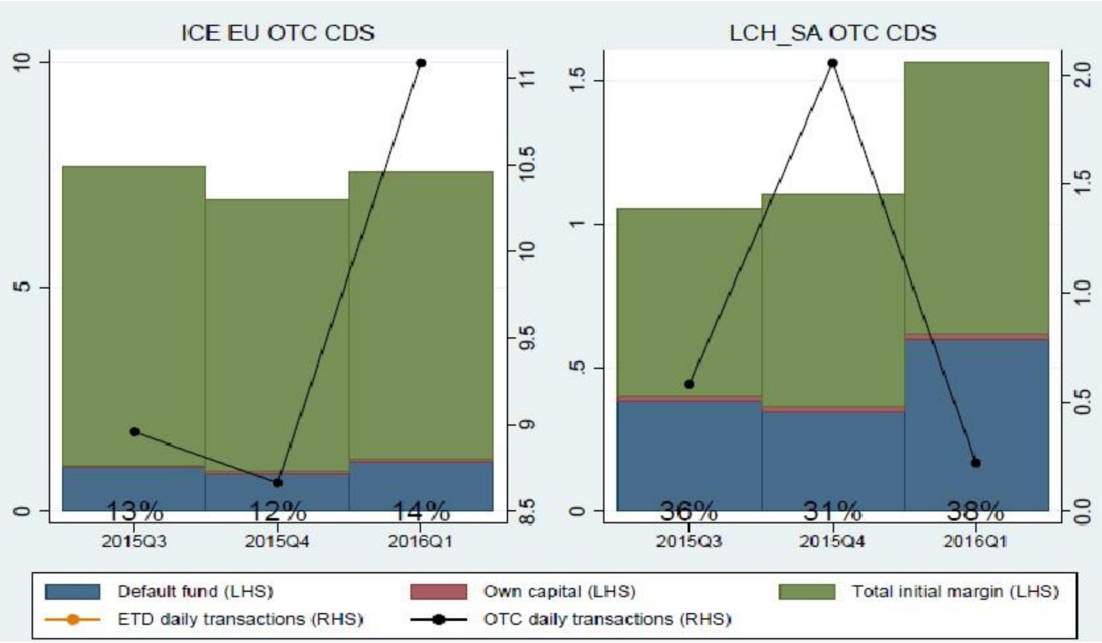


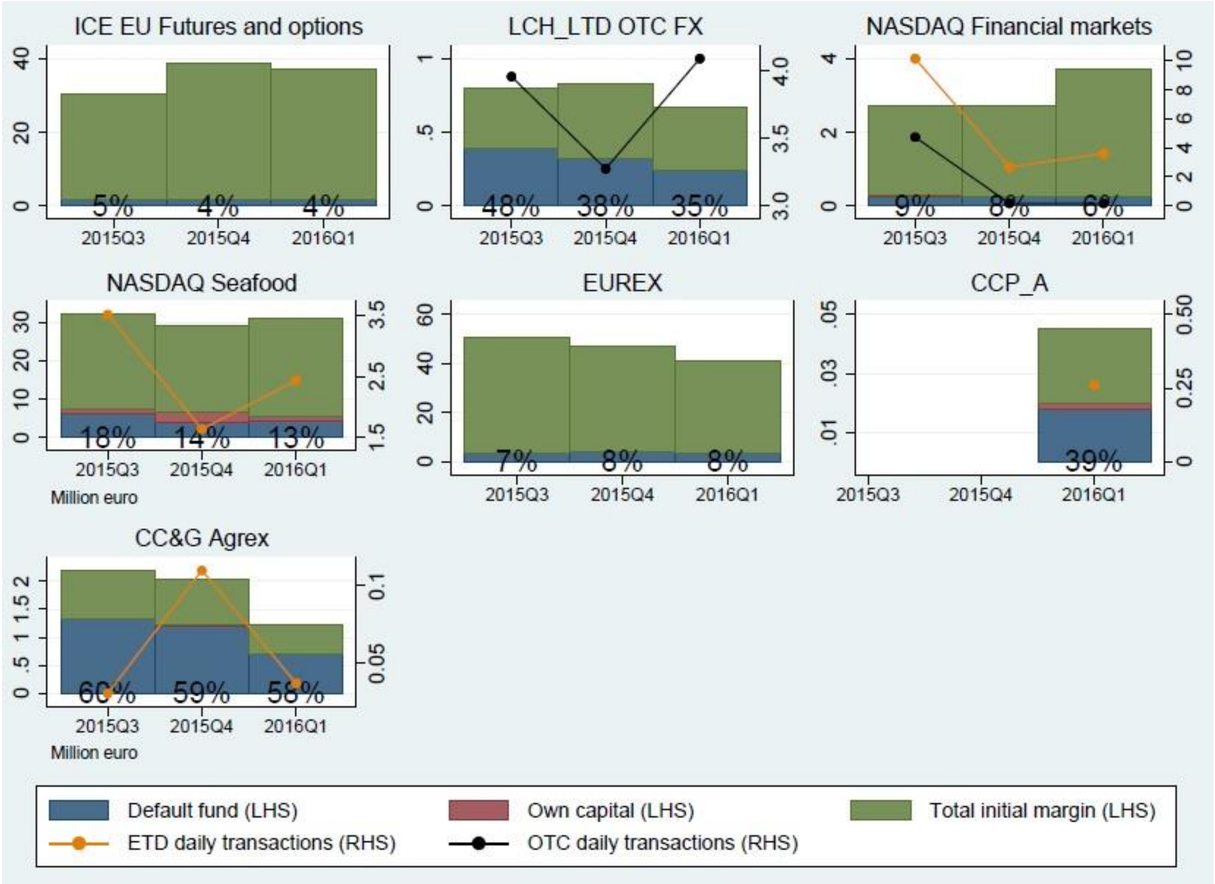
Size of segments and respective waterfall: Equity (LHS) and Energy (RHS)





Size of segments and respective waterfall: CDS (LHS), Mixed products (RHS)





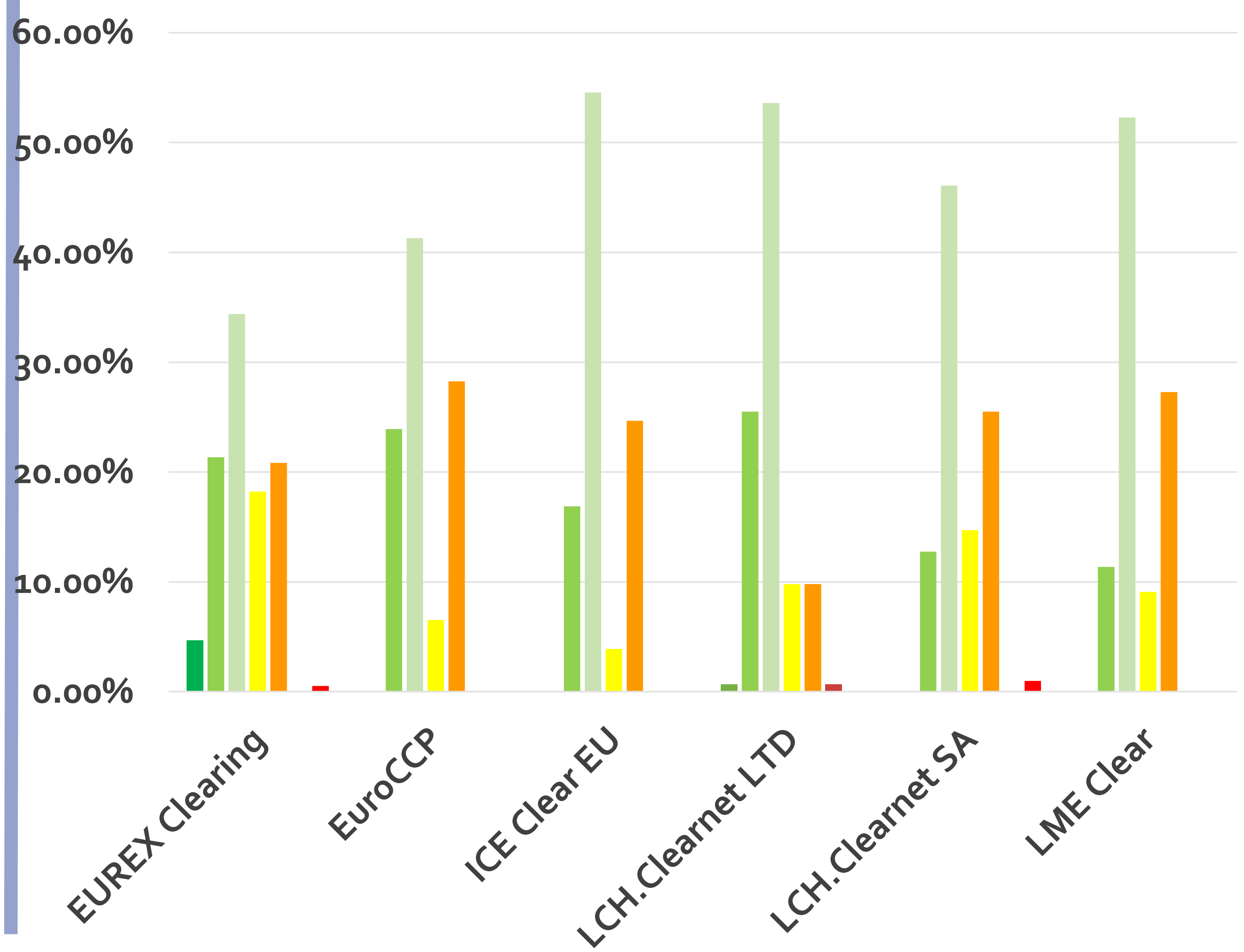
DMP liquidity: Can members sustain a CCP in a crisis?

- **Credit ratings of clearing members as a proxy of financial strength**

CCP	Number of members	Members without credit rating (in %)
BME	71	28.17 %
CC&G	84	34.52 %
CCP.A	51	39.26 %
Eurex	192	18.75 %
EuroCCP	46	23.91 %
ICE Clear EU	77	23.88 %
ICE Clear NL	3	0 %
KDPW	43	30.23 %
LCH.Clearnet LTD	153	6.54 %
LCH.Clearnet SA	102	17.65 %
LME	44	25 %
Nasdaq OMX	247	65.59 %
OMI Clear	13	23.07 %

Standard & Poor's Rating Traffic lights
AAA
AA
A
BBB
BB
B
CCC

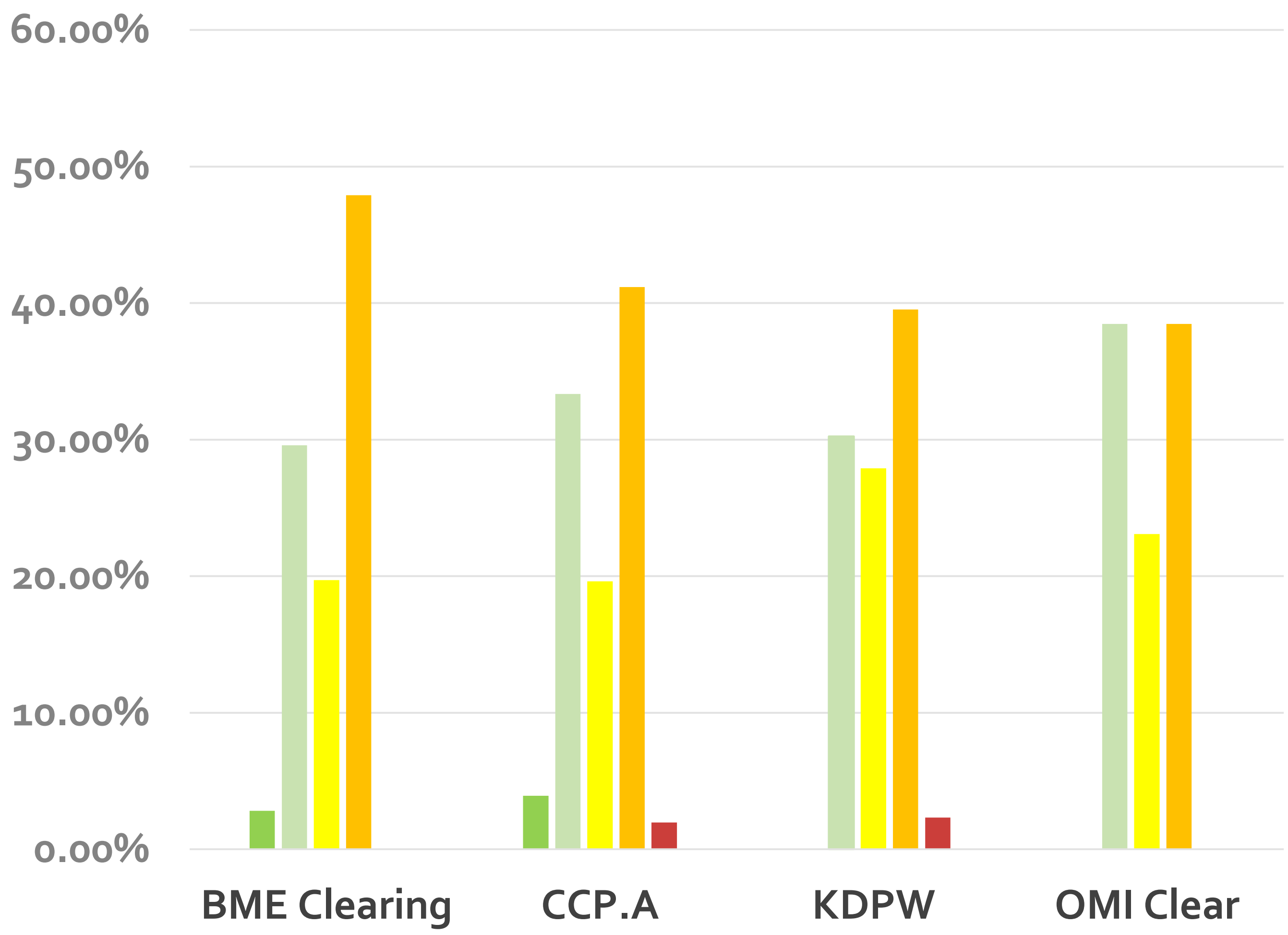
Cluster 1 – default probability distribution under normal scenario



S&P Rating Category	DRW (in %)	PD (in %)
AAA	0.05	0.01
AA	2	0.05
A	3	0.09
BBB	6	0.23
BB	15	1.16
B	30	5.44
CCC	50	14.21

- Average default probablity: 0.09 %
- >70% CMs above investment grade
- Member bases are heterogenous

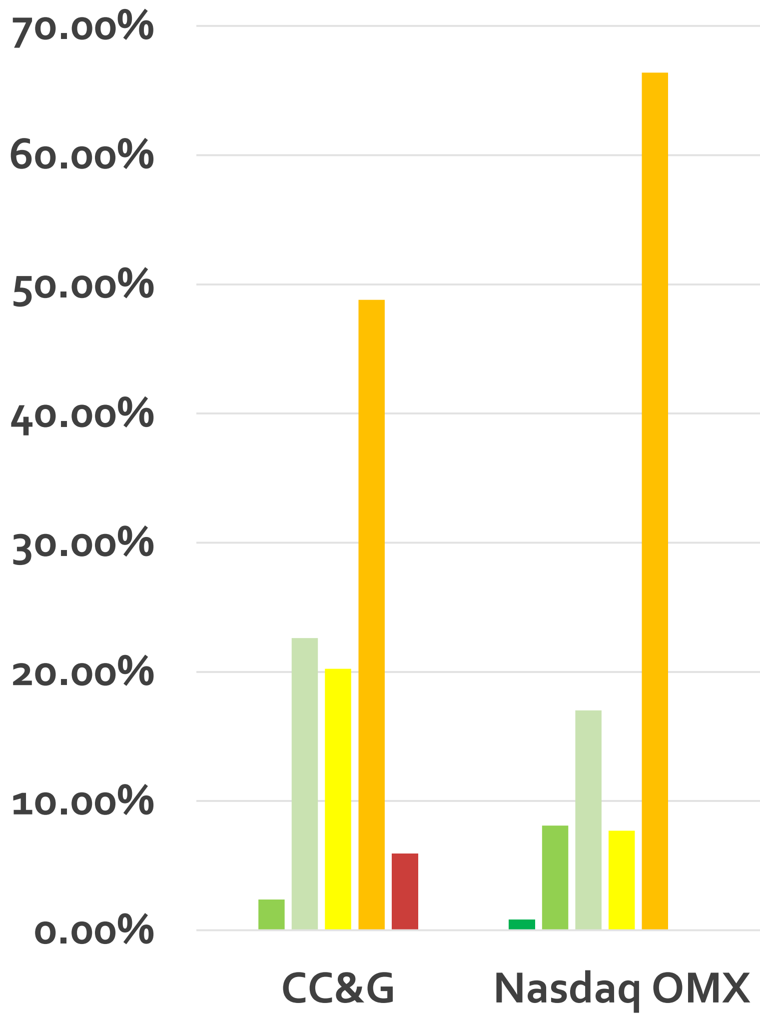
Cluster 2 – default probability distribution under normal scenario



S&P Rating Category	DRW (in %)	PD (in %)
AAA	0.05	0.01
AA	2	0.05
A	3	0.09
BBB	6	0.23
BB	15	1.16
B	30	5.44
CCC	50	14.21

- Average default probablity: 0.23 %
- >40% CMs below investment grade
- Member bases very heterogenous

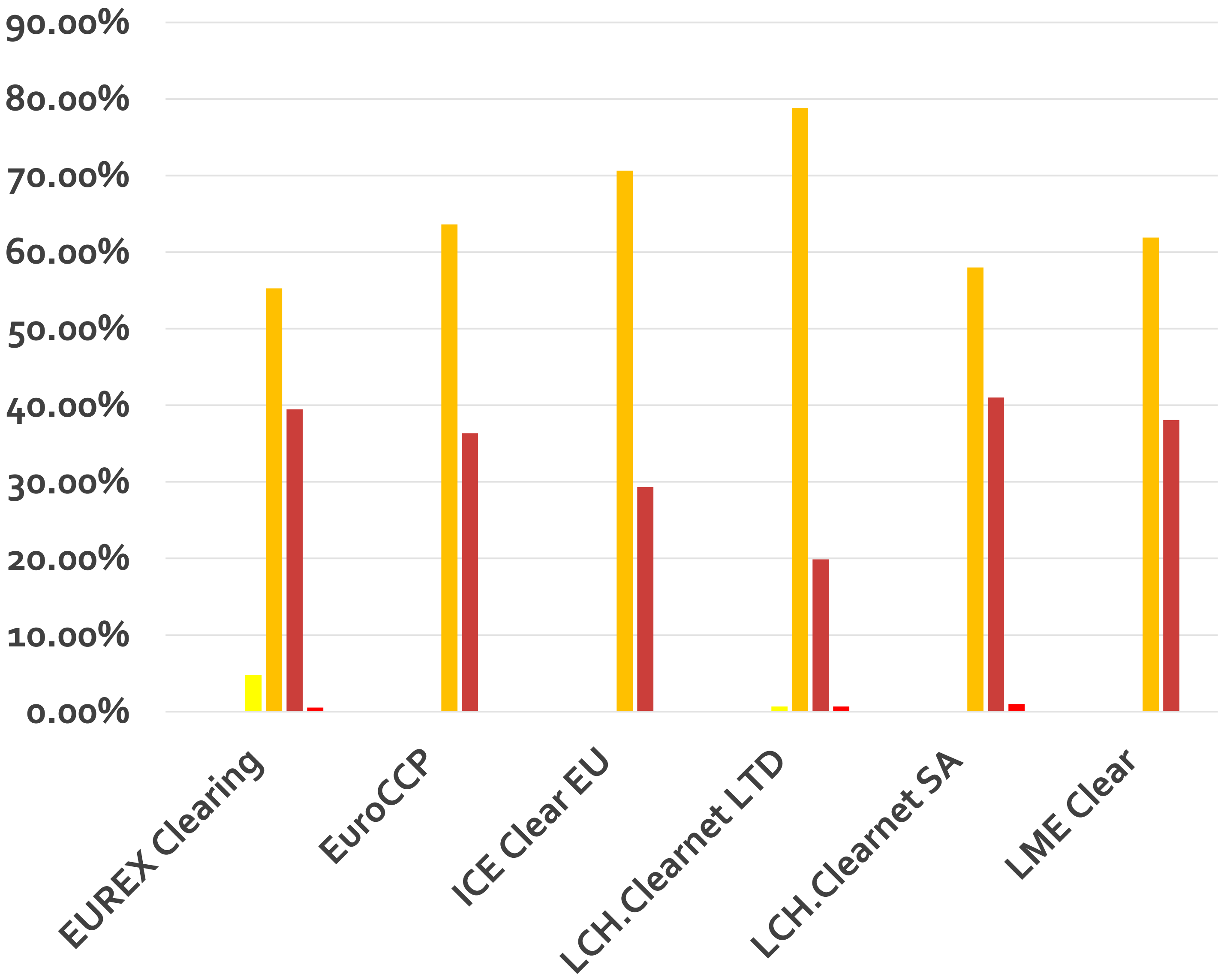
Cluster 3 – default probability distribution under normal scenario



S&P Rating Category	DRW (in %)	PD (in %)
AAA	0.05	0.01
AA	2	0.05
A	3	0.09
BBB	6	0.23
BB	15	1.16
B	30	5.44
CCC	50	14.21

- Average default probablity: 1.16 %
- CC&G has 6% of CMs with a credit rating of 'B' or lower
  - 75% domestic CMs
  - ~60% Italian banks

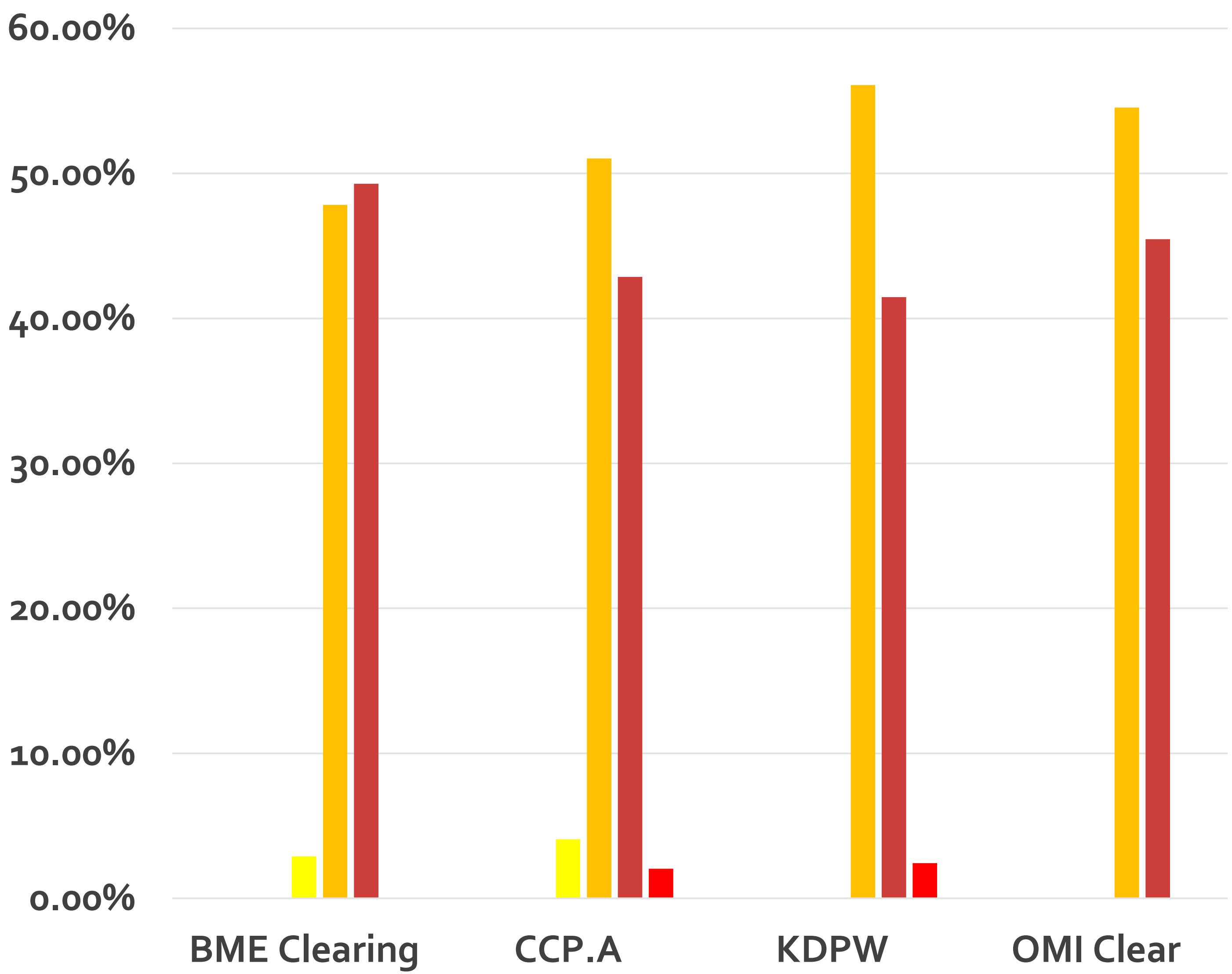
Cluster 1 – default probability distribution under stressed scenario



DP under cover 2 approach

CM PD conditional on the default of two average CMs (in %)	
PD of average CMs	0.09 %
0.01 %	0.45
0.05 %	1.83
0.09 %	2.97
0.23 %	5.84
1.16 %	12.28
5.44 %	25.94
14.21 %	43.78

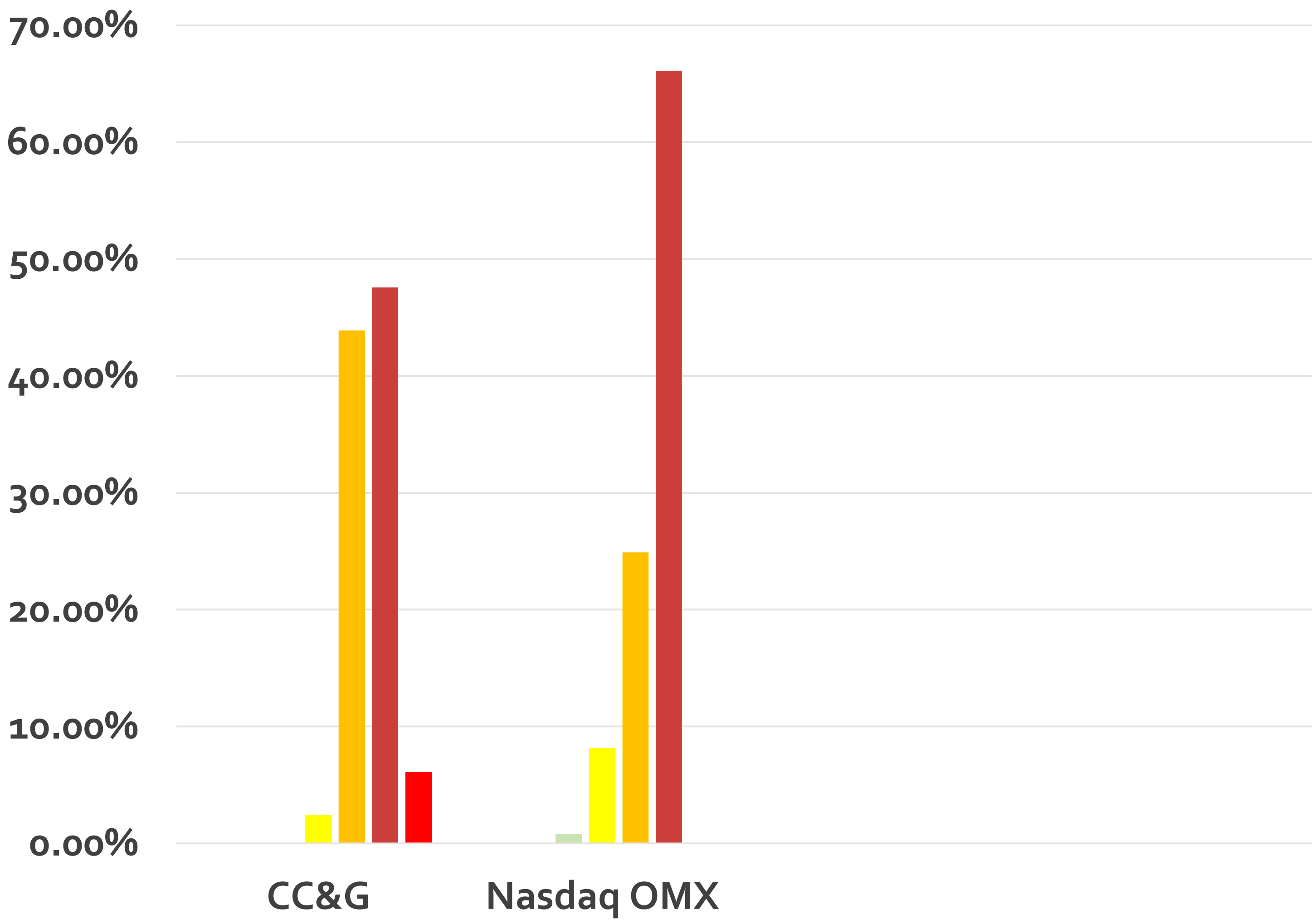
Cluster 2 – default probability distribution under stressed scenario



DP under cover 2 approach

CM PD conditional on the default of two average CMs (in %)	
PD of average CMs / CM PD	0.23 %
0.01 %	0.42
0.05 %	1.51
0.09 %	2.23
0.23 %	4.23
1.16 %	11.00
5.44 %	22.87
14.21 %	41.35

Cluster 3 – default probability distribution under stressed scenario



DP under cover 2 approach

CM PD conditional on the default of two average CMs (in %)	
CM PD \ PD of average CMs	1.16 %
0.01 %	0.21
0.05 %	0.75
0.09 %	1.19
0.23 %	2.42
1.16 %	7.12
5.44 %	17.79
14.21 %	34.30

Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

IFC-National Bank of Belgium Workshop on "*Data needs and Statistics compilation for macroprudential analysis*"

Brussels, Belgium, 18-19 May 2017

Use of credit registers to monitor financial stability risks: A cross-country application to sectoral risk[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.

Use of credit registers to monitor financial stability risks: A cross-country application to sectoral risk

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Abstract

This paper discusses the use of credit register data for financial stability purposes, illustrating possible applications of these data to the monitoring of sectoral risks, with focus on risks related to construction and other commercial real estate activities in a cross country framework.

The paper first reviews how central credit register (CCR) data can be used for financial stability purposes and illustrates the advantages of granular data to detect vulnerabilities. While existing national central credit register (CCR) data are used in several EU Member States, possibilities for cross country analysis are currently limited due to the heterogeneity of national credit registers. The introduction of the AnaCredit Regulation adopted in May 2016 for the collection of harmonised loan-by-loan data fosters the comparability across countries and thus also increase the relevance of credit register data.

The paper presents a euro area initiative which aims at illustrating the potential of AnaCredit for macroprudential analysis by bridging data gaps on the euro area level. The project puts forward a set of coherent indicators for the monitoring of commercial real estate (CRE) risk, derived from the national CCR of a number of euro area countries. While the focus of the project is on the risk posed by the CRE sector, many of the constructed indicators are not sector-specific and can be easily used to monitor other systemic sectors.

The paper will also highlight the challenges associated with comparing and analysing indicators calculated based on national credit registers and will outline strategies how a maximum of cross country consistency can be achieved despite heterogeneous data sources.

Keywords: Macroprudential, statistics

JEL classification: C82, E60

*Note: This paper should not be reported as representing the views of the European Central Bank (ECB) or the National Bank of Belgium (NBB). The views expressed are those of the authors and do not necessarily reflect those of the ECB or the NBB. The authors are grateful to the members of the Advisory Group on AnaCredit (Manuel Lingo, Stéphane Clesse, David Kierok, Thomas Ferrière, Roberto Felici, Mirko Moscatelli, Skirmantė Matkenaite, Jozef Kalman) for their useful contribution without which this project would not have been possible.

Contents

1. Introduction and motivation

This paper discusses the use of credit register data for financial stability purposes, illustrating possible applications of these data to the monitoring of sectoral risks, in particular risk related to construction and other commercial real estate activities.

Given the severe data gaps in the area of commercial real estate activities, the use of national credit register data can provide a valuable contribution to shed more light on this particular sector and activities. The global financial crisis has highlighted the importance of real estate markets for financial stability and the relatively pronounced cyclicality (Ellis and Naughtin (2010), Olszewski (2013), ESRB (2015)) of commercial real estate.

The project puts forward a set of coherent indicators for the monitoring of risk related to construction and commercial real estate activities, derived from the national CCR of a number of euro area countries. While the focus of the project is on the risk posed by the commercial real estate sector, many of the constructed indicators are not sector-specific, and can be easily used to monitor other sectors of potential systemic importance.

The remaining part of the paper is structured the following way. Section 2 reviews how central credit register (CCR) data can be used for financial stability purposes. Section 3 presents how national credit registers differ and also outlines how the introduction of AnaCredit will improve cross-country comparability. Section 4 recalls the importance of CRE monitoring for financial stability, highlighting the severe data gaps in the area of commercial real estates, and motivates why looking at credit register data can contribute to monitoring risks from this sector. Particular attention is dedicated to the challenges associated with the definition of Commercial Real Estate in the context of credit register data. Section 5 presents a list of indicators that can be calculated using credit register data and highlights the challenges associated with comparing and analysing indicators across countries. Strategies to achieve a maximum cross country consistency despite heterogeneous data sources are outlined. Section 6 presents the preliminary results of a euro area initiative which aims at illustrating the potential of AnaCredit for macroprudential analysis by bridging data gaps on the euro area level. Section 7 concludes and outlines further work.

2. The use of credit register data for financial stability

Credit register data represents a particularly valuable source of information for financial stability analysis due to the granularity of the data. Micro level credit and credit risk data provides useful insights not only at aggregated level, but also allow analysis of distributions and help identifying tail risks. This is particularly relevant for macroprudential analysis as averages and aggregated values are often not sufficient to detect vulnerabilities and risks.

Several examples of analytical projects based on the use of credit register data are present in the recent literature. A number of authors focus on credit risk analysis, such as large exposure concentration or sector concentration (see e.g. Konečný et al (2015), Holub et al (2015)). Thanks to their granularity, CCR data are particularly suitable also for network and interconnectedness analysis. The data can also be used to assess the effectiveness of macroprudential measures.[1] The impact of LTV and DSTI measures was for example studied by the Banque de France (Dietsch and Welter-Nicol, (2014)), while Basten and Koch (2015) and Uluc and Wieladeck (2015) focus respectively on the effects of capital requirements and CCyB on mortgage lending.

Girault and Hwang (2010) stress that credit register data present an important factor to enhance supervision and regulation of the financial system. The information can be used to monitor credit risks undertaken by individual institutions, the banking sector as a whole, or segments of it. Credit register data allows supervisors to look at a broad picture of the concentration of risk exposures by sector, geographic distribution, type of borrower or type of credit (see Dent, 2014). Moreover, CCRs can help supervisors to identify parts of the loan portfolio which might require a more in-depth review and can thus play a role as input in supervisory planning decisions. IFC (2012) also supports the role CCR can play in monitoring risk on and off-site, for example by helping to detect differences in the ratings assigned to borrowers by different banks (World Bank, 2011). In general, CCR data can serve as key input to model PDs or LGDs (Artigas (2004)), which are key risk indicators, and also support the development of early warning systems, stress tests and other monitoring tools or methods (Centre for European Policy Studies — European Credit Research Institute (2013)). Dent (2014) highlights the importance of CCR data in the area of real estate risk monitoring by central banks and banking supervisors. Analysis of the credit conditions is vital for monitoring credit risk and applying the correct macroprudential tools. CRR data allows identifying trends in lending, gaining a better understanding of underwriting standards and borrower creditworthiness and can thus contribute from a macroprudential perspective in achieving a higher stability for the entire financial system.

For these types of analysis, information about the distribution of risk indicators within the credit portfolio is crucial, which can only be extracted from granular data.

Due to the granularity of CCR, it is not only possible to extract information about the distribution of risks within the loan portfolio of banks, but also to look at further break downs in terms of either sectors, counterparts or borrower characteristics. A tribute to the importance of CCRs for macroprudential monitoring can also be found in Konečný et al (2015). They present some of the indicators extracted by CCR data and used for credit risk monitoring in Czech National Bank, such as a default rate indicator, a credit standards indicator, the ratio of NPLs to total loans, indicators for differences in client risk classification across banks, as well as for credit risk vintage analysis.

A survey conducted among several NCBs within the work of the Advisory Group on AnaCredit has highlighted the importance of credit registers for financial stability and macroprudential analysis in national central banks and provided interesting insights of the current use of these data by financial stability departments in the euro area. Some examples of projects carried out include: (i) credit risk analysis (e.g. monitoring of concentration risk, assessment of banks exposures, assessment of creditworthiness of debtors), (ii) network analysis and analysis of contagion risk, to

[1] See e.g. the Closing Conference of the BIS CCA CGDFS Working Group "The impact of macroprudential policies: an empirical analysis using credit registry data", June 2016.

help the assessment of banks’ systemic importance, (iii) stress tests and impact assessment exercises and (iv) assessment of the impact and effectiveness of macroprudential measures.

3. National credit registers and the introduction of AnaCredit

While existing national central credit register data are used in several EU Member States for financial stability analysis and are very useful to analyse risks at country level, possibilities for cross country analysis are currently limited due to the heterogeneity of national credit registers.

Currently, 15 Member States have a CCR (see Table 1). Characteristics of national CCRs can vary significantly along different dimensions. First, the reporting threshold can range from EUR 0 in countries such as Belgium to EUR 1 million in Germany, inducing huge differences in the type of lending recorded in the database. Furthermore, the length of time series is highly diverse; some national CCRs date back to the nineties, and in some cases the data collection started even before (Spain, 1984), while other countries, e.g. Lithuania, only recently developed one (2011). Although credit register data are generally collected from resident lenders on an unconsolidated basis, there can be differences in the reporting scope of national CCRs, e.g. for what concerns the type of borrowers (in some cases non-resident borrowers are excluded from the perimeter) and the type instruments. Finally, the type of information collected within the different CCRs is neither complete nor comparable, as the range of available attributes considerably differs across country, and it is based on non-harmonised definitions.

Table 1: Overview of thresholds in national CCRs in the EU

	AT	BE	CZ	DE	ES	FR	IE	IT	LV	LT	MT	PT	RO	SI	SK
Threshold	350,000	0	0	1,000,000	6,000	25,000	500	30,000	0	290	5,000	50	4,440	0	0

The need for a euro area level granular analytical database on credit and credit risk data based on a common set of definitions has become more and more urgent in the aftermath of the financial crisis, and as a consequence the idea of AnaCredit was put forward. The introduction of the AnaCredit Regulation[2] adopted in May 2016 for the collection of harmonised loan-by-loan data fosters the comparability across countries and thus also increases the relevance of credit register data.

AnaCredit is a loan-by-loan database containing information on credit to companies and other legal entities granted by credit institutions and their foreign branches on a monthly basis. The information collected consists of 88 different attributes based on harmonised concepts and definitions and covers various aspects of the credit exposure. The dataset is organised in several tables based on three

[2] Regulation (EU) 2016/867 of the ECB of 18 May 2016 on the collection of granular credit and credit risk data (ECB/2016/13), OJ L 144, 1.6.2016, p. 44.

main elements: instruments, counterparties and protection received. The reporting threshold is EUR 25 000[3].

The introduction of AnaCredit will enhance data availability and harmonisation of information, allowing more in-depth and accurate analysis. However, AnaCredit will only be available as from end-2018, and no time series dimension will be available for data users. In order to already illustrate the potential of AnaCredit and to complement the existing risk assessment indicators available from other data sources without delay, this paper presents a project to construct (time series) indicators for sectoral risk monitoring based on existing national CCRs, focusing on risk in the CRE sector.

4. Sectoral risk monitoring, data gaps in CRE and CRE sector definitions

Monitoring risks stemming from CRE markets and understanding how they can affect the financial system is crucial for financial stability. The recent global financial crisis has shown that CRE markets are prone to strong boom and bust cycles (Olszewski (2013)). In comparison with residential real estate, cumulated prices changes in CRE between the boom and bust were around twice as high, as analysis in Ellis and Naughtin (2010) shows and also contributed to the significant losses of banks in the financial crisis. Disorderly price adjustments in the CRE markets can significantly affect financial stability since loans for CRE account for a significant part of the total mortgage lending: banks in most euro area countries are significantly exposed to CRE via their loan portfolio (see ECB (2008) and Hiebert and Wredenborg (2012)). Furthermore, commercial property markets tend to be more cyclical and volatile than residential property, due to closer linkages with general economic developments and to the lower elasticity of supply (see ECB (2008) and ESRB (2015)).[4] Cyclicality is further exacerbated by opaqueness of CRE markets, as the lack of reliable information and data sources hampers the possibility of efficiently pricing CRE properties. Overall, the CRE market therefore presents a relatively risky market for banks (see Nyberg (2005)).

It is also observed that CRE loans present higher default rates compared to RRE loans, increasing the riskiness of this sector.[5] This is partly due to the highly capital intensive nature and the strong reliance on external financing, which has characterised the market for many years.[6] This higher riskiness is especially relevant considering that exposures to CRE markets are more concentrated than exposures to RRE, given the lower number of borrowers which though hold a higher share of banks exposures (Olszewski (2013)).

The importance of CRE sector for financial stability is also reflected a study undertaken by the ESRB in 2015, which identified the CRE sector as potentially

[3] Israël et al. (2017).

[4] See for example Benford and Burrows (2013), ECB (2008), Ellis and Naughtin (2010) and ESRB (2015).

[5] ESRB (2015).

[6] ECB (2008), Gyourko (2009).

systemic, along with 3 other economic sectors: consumer durables (mainly automotive industry), materials and fabrication (mainly steel and chemical industries), and utilities (mainly gas and electricity).

Given the importance of the sector, it is crucial from a financial stability perspective to monitor risks and vulnerabilities stemming from these exposures held by the financial sector. However, such an analysis is currently hampered by the general scarcity of CRE data. Therefore, collection data and closing data gaps is an important and necessary step towards a better monitoring of risks (Olszewski (2013)). Until credit gaps are closed in a more encompassing way, credit register data can be a valuable source of information for the monitoring of risks in the CRE markets.

The closing of data gaps in the area of Commercial Real Estate is complicated by the fact that there is no harmonised definition of CRE. The recent work in an ESRB Expert Group on commercial real estate has confirmed that there is, as yet, no consensus on a precise definition of what should fall under "exposure to CRE". The ESRB report however suggested the following working definition for commercial property: "buildings, including occupied land, which are held for the express purpose of generating an income. While the expert group broadly agrees that CRE should include multi-family residential dwellings, there is some debate as to whether buy-to-let housing and property under development should also be included." (ESRB (2015)).

For the purposes of the project, CRE exposures are defined very broadly as all the bank loans — mainly to corporations — falling under the NACE economic branches "Construction" (NACE code 41) and "Real estate activities" (NACE code 68). This definition was chosen, as credit registers only allow distinguishing between different NACE codes and therefore a NACE-code based definition of the sector is the only feasible option.

One can certainly dispute this definition, as it probably includes more (and potentially at the same time also less) exposures than what is needed to efficiently assess all risks associated with commercial real estate, as it is defined by the ESRB. On one hand, the definition of CRE used in this project can be considered as broader than the ESRB definition, as the analysis focuses on all loans to corporations active in NACE branches 41 and 68, regardless of whether these loans serve to produce or hold income-producing real estate. On the other hand, the definition of CRE on the basis of the NACE codes is narrower than the ESRB definition, as the exposure of banks to CRE should preferably also take into account the loans made to non-CRE companies but collateralised with their CRE assets (e.g. office buildings, retail commerce buildings). The proposed definition of CRE is relatively broad, but nonetheless not entirely comprehensive as regards banks' exposure to potential risks related to commercial real estate assets that are defined — as a working definition — in the abovementioned ESRB report as "buildings, including occupied land, which are held for the expressed purpose of generating an income". These differences notwithstanding, the proposed definition of CRE based on NACE codes presents good proxy for monitoring of risks associated with CRE. The next section details the indicators for CRE monitoring that were developed.

5. Cross-country sectoral risk monitoring based on national credit register data

The following section presents the indicators which are calculated based on national credit register data. It is important to keep in mind that the indicators in isolation do not present a complete monitoring framework, as they are designed to be complementary to other, existing information, coming from other public or private data sources (see also section 4). The indicators will provide added-value on the national level given the overall scarcity of CRE data, and will also help to assess developments from a cross-country perspective.

5.1 Set of indicators

Sectoral risk concentration

The following indicators partly reproduce those developed in the ESRB report on Sectoral Risk (2015) and focus on risk concentration. Other credit risk or exposure indicators presented in the remaining part of this section can also be calculated for a subsample of banks with high exposure concentration scoring.

Table 2: Sectoral risk concentration indicators

Indicator description	Description	Details and formula
Sector granularity	HHI of firms' borrowing within a sector, to see how concentrated borrowing is within a sector	$HHI_k^{firms} = \sum_{i=1}^{N} s_i^2$ With s_i being the share of lending to firm *i* over total lending to that sector i.e. $s_i = E_i / \sum_{i=1}^{n}(E_i)$ for each firm *i*=1..*N* in sector *k*
Risk of funding concentration	HHI of banks' shares of total exposures towards a sector, to see how dependent a given sector is on a certain number of banks. The lower the HHI index, the more diversified that sector is in terms of its funding sources	$HHI_k^{banks} = \sum_{j=1}^{J} s_j^2$ With $s_j = E_j / \sum_{i=1}^{J}(E_j)$ for each bank *j*=1..*J* lending to sector *k*

Credit risk indicators

The following indicators examine credit risk by monitoring the evolution of PDs and NPLs. Moreover, they help to assess how well credit is protected and collateralised, which would provide insight into the losses banks may face in the event of defaults.

There are a number of other descriptive statistics that can provide further insight into sectoral risk. As mentioned in the ESRB Report on Sectoral Risk (2015), for each sector one could look at the average and the standard deviation of the PD. Another possibility is also to look at the quartiles of PDs within sectors, and complement this with the share of sectoral exposure coming from the worst quartile of the PD distribution. These descriptive statistics could be calculated for both the stock and flow of lending.

Table 3: Exposure indicators

Indicator description	Details and formula
Total exposure to sector as % of Tier1 capital (or other capital measure) per bank, *potential additional version: quartiles of this indicators*	$\lambda_{k,j} = \frac{\sum_1^H E_h}{T1_j}$ Loop over all exposures of bank j to sector k, divided by Tier1 capital of bank j
% of total exposures with collateral, by sector *potential additional version: quartiles of bank level indicators*	$\mu_k^1 = \frac{\sum_1^H E_h \delta_h}{\sum_1^H E_h}$ Loop over all exposures to sector k, with $\delta_h = 1$ if exposure E_h has dedicated collateral
Total pledged collateral as a % of total collateralised exposures, by sector for all banks in one country, *potential additional version: quartiles of bank level indicators*	$\mu_k^2 = \frac{\sum_1^H C_h}{\sum_1^H E_h \delta_h}$ Loop over all exposures E_h.to sector k, where C_h is the collateral value assigned to E_h with $\delta_h = 1$ if exposure E_h has dedicated collateral

Table 4: Credit risk indicators

Indicator description	Details and formula
% of total exposures with positive non-performing amount (exposure weighted)	$\omega_k^1 = \frac{\sum_1^H E_h \delta_h}{\sum_1^H E_h}$ with $\delta_h = 1$ if exposure E_h has positive non-performing amount
% of total exposures to vulnerable debtors (% of total exposures to debtors with any positive non-performing amount); Calculation for each bank, then illustration of the distribution in each country (anonymised)	$\omega_{k,j}^2 = \frac{\sum_1^N E_i \delta_i}{\sum_1^N E_i}$ Loop over all *N* debtors of a bank *j*, where E_i is the total borrowing of debtor *i*, and $\delta_i = 1$ if debtor i has any positive non-performing amount
% of new lending towards a certain sector going to borrowers already registered as non-performing	$\omega_{k,j}^3 = \frac{\sum_1^N NewLending_i \delta_i}{\sum_1^N NewLending_i}$ Loop over all *N* debtors of a bank *j*, where $NewLending_i$ is the amount of new lending to borrower *i*, and $\delta_i = 1$ if debtor i has any positive non-performing amount
Value of collateral pledged to non-performing exposures as a % of total non-performing exposures	$\omega_k^3 = \frac{\sum_1^H C_h \delta_h}{\sum_1^H E_h \delta_h}$ Loop over all collateral C_h for exposures *H* with

	$\delta_h = 1$ if exposure is non-performing.
Change in exposure-weighted PD, by sector *Alternative: Graphically, PD in period t on the x axis and PD in period t-1 on the y axis to illustrate the development of PDs in the sector*	$\Delta\overline{PD}_k = \sum PD_{it}.s_{it} - \sum PD_{i,t-1}.s_{i,t-1}$ Where s_i is defined as above, and we are comparing periods *t* and *t-1*
Change in the % of exposures with non-performing status	$\Delta NPL_{k,t} = \frac{\sum_1^H E_{h,t}\,\delta_h}{\sum_1^H E_{h,t}} - \frac{\sum_1^H E_{h,t-1}\,\delta_h}{\sum_1^H E_{h,t-1}}$ with $\delta_h = 1$ if exposure E_h is non-performing

Maturity developments and debt roll over indicators

The indicators below can help to judge whether there are a large number of firms who will want to rollover their debt, and how the maturity profile of their exposures has changed over time.

Table 5: Maturity profiles indicators

Indicator description	Description	Details and formula
Maturity Profile of Exposures	Distribution of maturity of exposures	Distinguishing between 3 maturity buckets ([<1Y], [1Y, 5Y], [>5Y])
Debt rollover demand *potential additional version: quartiles of this indicators on bank level*	% of exposures with maturity less than one year, by sector	$\eta_k = \frac{\sum_1^H E_h\,\delta_i}{\sum_1^H E_h}$ with $\delta_h = 1$ if exposure *h* has a maturity of less than one year and $\delta_h = 0$ otherwise
Maturity of new loans *potential additional version: quartiles of this indicators on bank level*	The weighted average maturity of loans issued, by sector	$m_{k,j} = \sum_1^H s_h M_h$ Where *H* is the total number of loans issued to sector *k* within a given period, $s_h = \frac{E_h}{\sum E_h}$, and M_h is the original maturity of loan *h*
Average loan volume *potential additional version: quartiles of this indicators on bank level*	The average volume of loans issued, by sector	$v_k = \frac{\sum_1^H E_h}{H}$ Where *H* is the total number of loans issued to sector *k*, and E_h is the volume of loan *h*

Lending standards

Monitoring lending standards through indicators such as LTV at the origination of new loans or interest rate margins is very important from a financial stability perspective. However, calculating these indicators is not feasible for most of the countries. Moreover, information on the general level of interest rates as well as on interest rate margins can only be found in other data sources (e.g. iMIR) at bank level.

Common exposures/multiple lending

These indicators examine how many borrowers have multiple banking relationships. If a borrower has many banking relationships, this can contribute to a higher degree of interconnectedness. However, multiple lending can also have stabilising effects on the market. To have a clearer picture of how significant this issue is, the proposed list could be potentially complemented by a measure that reflects the number of relationships, e.g. the number of lending relationships in case of a multiple lending relationship.

Table 6: Indicators for common exposures and multiple lending (Single vs. multiple borrower relationship).

Indicator description	Details and formula
% of total exposure going to borrowers with multiple banking relationships, by sector	$\alpha_k^1 = \frac{\sum_i^N \mathrm{E_i} \delta_i}{\sum_i^N \mathrm{E_i}}$ Where $\delta_i = 1$ if firm i borrows from more than one bank and is equal to 0 otherwise
% of firms with multiple banking relationships, by sector	$\alpha_k^2 = \frac{\sum_i^N \delta_i}{\mathrm{N}}$ Where $\delta_i = 1$ if firm i borrows from more than one bank and is equal to 0 otherwise, and *N* is the total number of firms in sector *k*

Cross-border risk

The indicators in Table 7 help to assess whether a sector is particularly reliant on funding from abroad; such funding could be less stable in the event of turbulent market conditions. Moreover, the degree to which domestic banks lend to foreign entities and whether this foreign lending is exposed to currency risk could be monitored. These exposures could be more risky not only due to potential exchange rate risk, but also due to the issue of asymmetric information which could be more relevant for these exposures. Data availability for these indicators across countries is rather low. In general, it is only possible to monitor borrowing from foreign branches or subsidiaries.

Table 7: Cross-border risk indicators

Indicator description	Description	Details and formula
Lender Origination	% of total exposures that are being lent from foreign	$\beta_k = \frac{\sum_{j=1}^J \mathrm{E_j} \delta_j}{\sum_1^J \mathrm{E_j}}$

	entities, by sector	E_j is the money lent to sector k by bank j. With $\delta_j = 1$ if j is a foreign bank and is equal to 0 otherwise.
Currency Risk	% of credit issued domestically but denominated in foreign currency, by sector	$\gamma_{k,c} = \frac{\sum_1^H \widetilde{E}_h^c}{\sum_1^H E_h}$ With $\widetilde{E}_h^c$ being denominated in foreign currency *c*

5.2 Challenges and robustness checks

As mentioned above, national credit registers are not harmonised and therefore the list of attributes, but also the definitions of attributes as well as the threshold of transactions included in CCR can vary significantly across countries. These differences need to be taken into account when choosing the sample of underlying data to be included for the calculation of the indicators. A careful review of the selection choices is therefore needed for each indicator to ensure a maximum level of comparability.

The lack of a commonly agreed EU definition of CRE and the subsequent heterogeneity of underlying data can be another challenge in terms of cross-country comparability of indicators. It may be useful to consider exposures towards construction and real estate firms (NACE codes F41 and L68) as a starting point. Moreover, quality checks are envisaged to identify possible problems in the data or to avoid the inclusion of companies that could distort results. A percentile analysis can be useful in this respect. Moreover, to further test the quality of the indicators, cross-checks with other data sources such as FINREP were performed. Nevertheless, given the different characteristics of the national CRE markets, caution and expert judgement will always be needed to interpret results.

Scope of the analysis

As discussed above, the reporting scope of different national CCRs is not comparable in many cases. To overcome this issue and with the aim of having the most comparable sample across countries, the following perimeter of the analysis was defined.

Regarding **lenders**, only resident credit institutions, including branches and subsidiaries of foreign institutions are considered. Loans from special purpose vehicles (SPVs) can be included for those countries (e.g. Italy) that deem it advisable. Data are on an unconsolidated level.

Only the following types of **borrowers** are included in the analysis: resident individuals, resident institutions, resident NFCs and resident general government or other public entities. For sake of comparability, non-resident borrowers are excluded from the scope of the analysis.

For what concerns the type of **instruments**, only cash credit (including defaulted loans) is considered.

Regarding the **threshold**, no harmonisation is imposed. Considering the high threshold in some countries (e.g. Germany), a common threshold would imply a considerable loss of information. The same reasoning applies to the **length of time series**. To strike a good balance between harmonisation and amount of information, 2004 Q1 was chosen as starting point for the time series.

Attributes definition and cross-country comparison

Given the high heterogeneity in concepts and attributes definition across national CCRs, a thorough review of existing definition and cross-country comparison was carried out among the attributes involved in the calculation of indicators. Decision on which attribute or definition to choose was made with the aim of ensuring highest cross-country comparability.

Availability of each attribute at national level is shown in Table 8.

Table 8: Availability of each attribute at national level

Attribute	Description	AT	BE	DE	ES	FR	IT	SK
Threshold		350,000	0	1,000,000	6,000	25,000	30,000	0
Currency	EUR/non-EUR distinction	✗	✓	✗	✓	✓	✓	✓
NACE codes	Any type of NACE coding	✓	✓	✓	✓	✓	✓	✓
Borrower ID/Lender ID	Any type of coding	✓	✓	✓	✓	✓	✓	✓
Exposure Value	Book value, gross carrying amount	✓	✓	✓	✓	✓	✓	✓
Residual Maturity/Original Maturity	3 buckets: [<1Y], [>1Y to <5Y], [>5Y]*	✗	✓	✗	✓	✗	✓	✓
Collateral Value	Total amount of all collaterals/protections which is recorded	✓	✓	✓	✓	✗	✓	✓
Type of Protection	Create new dummy variable for "Protection Availability"**	✓	✓	✓	✓	✗	✓	✓
NP Status	As two dummy variables, one at obligor level and one at loan level if available.	✗	✓	✗	✓	✗	✓	✓
NP amount	Amount if available (as a sum of past-due over 90 days + unlikely to pay + bad loans)	✗	✓	✓	✓	✗	✓	✓
PDs	Use PDs available in national CR	✓	✓	✓	✓	✓	✓	✓

** For Italy only 2 buckets: [<1Y], [>1Y]. A different dummy will be used to distinguish from the three buckets variable.*
*** Can be also calculated through collateral value*
**** To define NP status, use all subcategories if different sub-categories are available (past-due over 90 days + unlikely to pay + bad loans)*

Some basic attributes (green highlighted in Table 8) are either relatively harmonised (e.g. NACE code) or the fact that they rely on different approaches in the national CCRs does not matter in the context of this project (e.g. borrower/lender ID). Regarding the exposure value to be considered, it was agreed to use the book value (gross carrying amount), which is available in all CCRs.

For other attributes (yellow highlighted in Table 8), some adjustments were needed. Regarding original and residual maturity, it was decided to only collect information divided in three buckets (<1Y; >1Y to <5Y; >5Y), to allow the highest possible country coverage. Protection and collateral value are treated as the same variable and include the total amount of all collaterals and protections recorded. Whenever such amount is greater than EUR 0, it is considered that a protection is available.

Credit risk attributes represent the most critical in terms of heterogeneity of definitions across CCRs. For the scope of our analysis, the non-performing amount is defined as the sum of loans past-due over 90 days, unlikely to pay loans and bad loans. The probability of default (PD) is used whenever possible. This can be supervisory PD (as in Austria and Belgium), ICAS PD (Italy), or it can be derived from complementary data sources (Slovakia). In some countries the PD is not available, and some similar concepts are used instead. In France, Banque de France's internal credit rating is used, while in Spain the default rate can be a proxy for this attribute.

A particular attention has to be paid when analysing indicators for which the underlying attributes present relevant differences across countries.

Robustness check: a comparison with FINREP data

Exposures to commercial real estate related sectors such as construction and real estate activities are available also in FINREP data. To strength the basis of our analysis, a comparison between exposures amount in the national CCRs and in FINREP was carried out. First, the differences in scope between these two data sources are recalled.

<u>FINREP data (*consolidated basis*)</u>: these supervisory data show the banks' exposures to various economic sectors (FINREP Table F.06.00), including their geographical breakdown (F.20.07). The CRE exposures from this data source correspond to banks' on-balance sheet exposures. In this connection, it is important to flag that what is understood as the construction sector in FINREP is somewhat broader than the scope of CRE defined above. In FINREP, the construction sector does not only encompass the NACE economic branch 41 "Construction of buildings" but also 42 "Civil engineering" and 43 "Specialised construction activities". For the other sector ("Real estate activities"), the FINREP concept coincides with the NACE branch 68.

<u>National Corporate Credit Register data (*unconsolidated basis*)</u>: This data source normally provides detailed (generally borrower-by-borrower and more rarely – e.g. Spain – credit by credit) information on bank exposures to companies of the NACE branches 41 and 68, which are mainly vis-à-vis domestic counterparties. In addition to the "used" amounts (which correspond to the amounts shown in the balance sheet), credit registers sometimes also provides "authorised" amounts, which include the contingent/off-balance sheet exposures (credit lines). The table below summarises the main differences in the scope between both data sources:

Table 10: Comparison between FINREP and CCR scopes

	FINREP	National CCR[7]
Reporting entities	All consolidating banks	All credit institutions (incl. branches of foreign banks)
Reporting basis	Consolidated	Unconsolidated
Nature of information	Aggregated at the level of the economic sector	Borrower-by-borrower (Spain: credit-by-credit)
	Amount of non-performing loan and coverage ratio	Some credit risk data (extremely patchy and heterogeneous across countries)

[7] The table refers to Belgian CCR. However, CCR in the other euro area countries share similar features.

When comparing CCR and FINREP data, other differences has to be taken into account. First, very often CCR data are subject to a reporting threshold, which in some cases can be very high (e.g. Germany). No reporting threshold is foreseen in the case of FINREP data. Furthermore, the sector classification system between the two data sources generally differs, as the internal NACE code attributed by a bank to the borrower may differ from the NACE code used in the CCR. The NACE code and institutional sector of domestic companies in the CCR are assigned by the NCBs. One entity could be classified differently (different NACE code or institutional sector) in FINREP (banks' classification) and in the CCR (NCBs' classification). Finally FINREP data include all borrowers independently from the state of residence, while in some CCRs (e.g. Italy) no NACE code is available for non-resident borrowers.

All these differences notwithstanding, a simple comparison of total exposure value in some national CCRs and FINREP data show that values are fairly comparable. Major differences are registered in Germany and to a lesser extent in Austria. This is mainly due to the fact that the number of banks included in the FINREP sample is much smaller than in the CCR.

Chart 1: Exposures to all NACE sectors

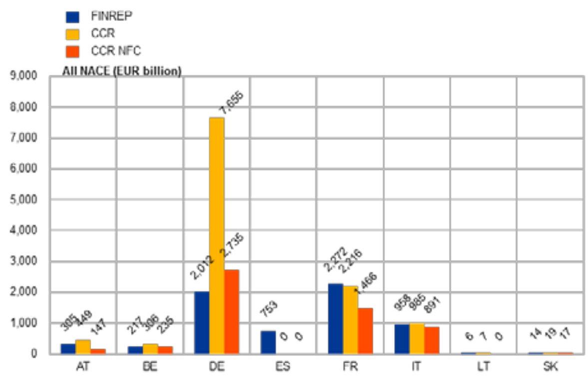
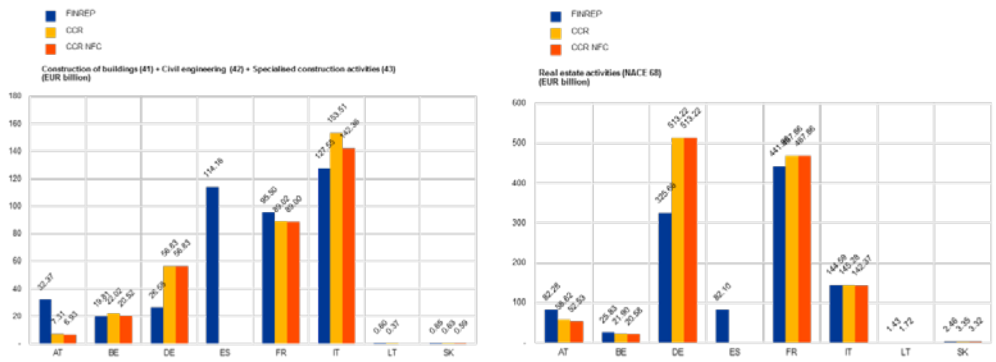


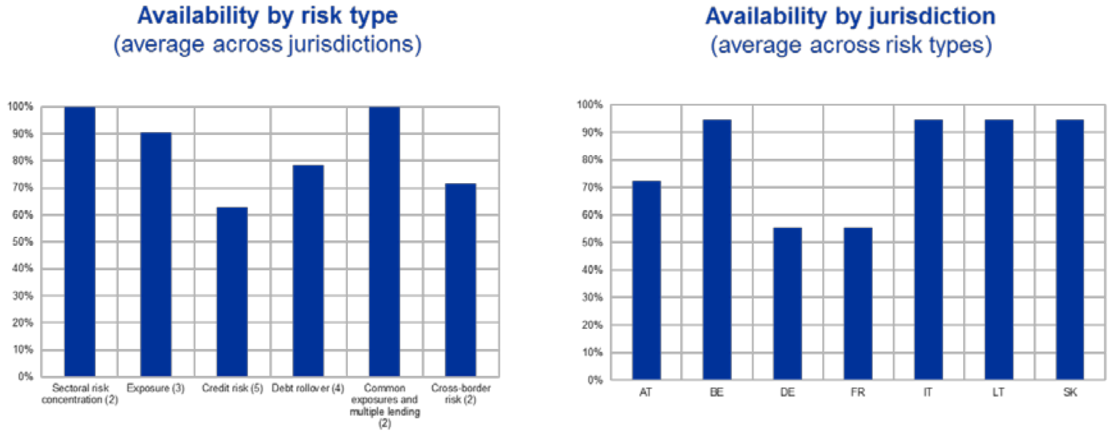
Chart 2: Exposures to Construction sector (left) and real estate activities (right)



6. Overview of results

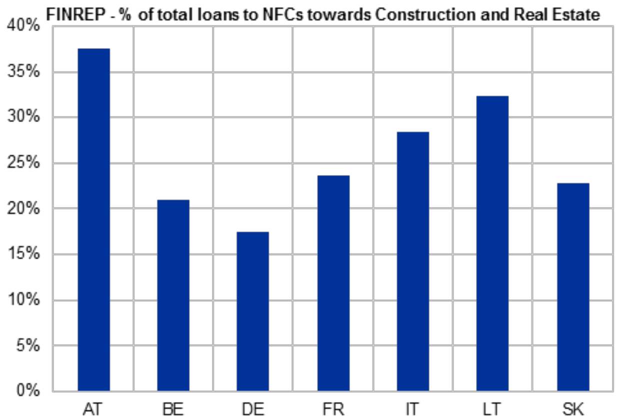
This section presents the main findings of the analysis. Not all indicators can be calculated for all countries, due to availability of attributes or data quality. Chart 3 provides an overview of the general availability of indicators across countries.

Chart 3: Availability of calculated indicator



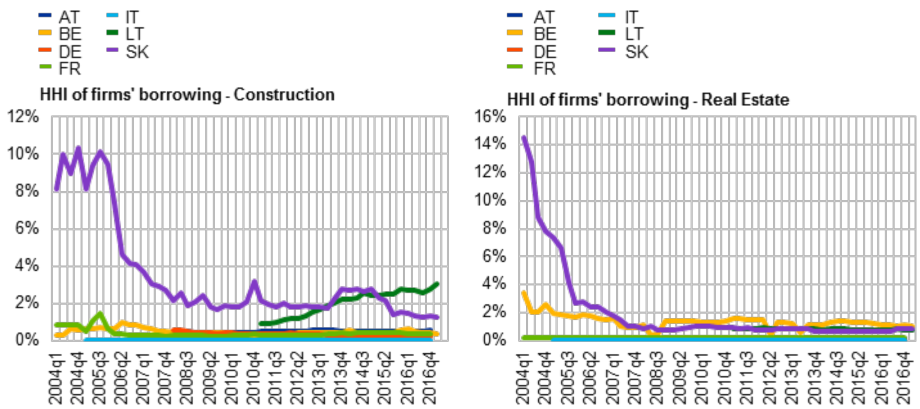
The analysis shows that banks are highly exposed to both construction and real estate sectors in all countries participating to the project, with exposures to these sectors accounting from 35% of total exposures in Austria to around 17% in Germany in 2016Q2 (Chart 4). However, a qualitative analysis of the largest CRE exposures in some jurisdictions has revealed that the nature of these exposures is very heterogeneous. This finding needs to be taken into account when performing a risk assessment of this sector.

Chart 4: Share of exposures to construction and real estate activities over total exposures to NFCs.



As an example of results obtained, calculated indicators show that the concentration of firms borrowing is generally low for all countries in both constructions and real estate activities sectors. The industry is generally highly competitive (HHI < 0.01) or unconcentrated (HHI < 0.15), meaning that no single borrower or a small group of borrowers attracts a high share of lending. The analysis shows that the trend in concentration has remained fairly stable, although some differences exist across countries. Slovakia presents a sharp decrease in borrowing concentration of both sectors from 2004 (more than 10%) to 2007 (less than 1%). An increasing trend in the construction sector is observed in Lithuania since 2012, indicating a decreasing competition in this sector. Some minor fluctuations are observed in the case of France, but these can be attributed to a possible outlier (the exposure of a single bank to one borrower) and may also reflect an accounting problem. This low concentration however only implies diversification benefits for lenders, if the sector is not characterised by strong co-movements.

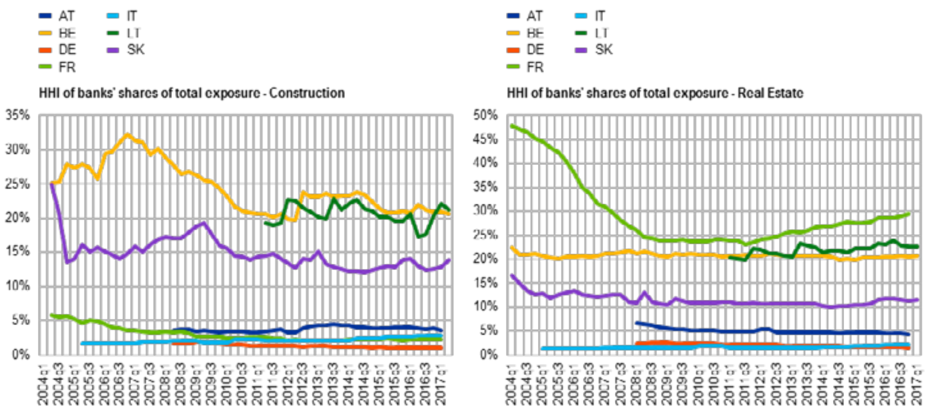
Chart 5: Borrowing concentration.



Source: national CCRs.

More cross-country variation is observed in funding concentration. Unsurprisingly, smaller countries characterised by a more concentrated banking system present a moderate funding concentration (ranging from around 15% in Slovakia to more than 20% in Belgium and Lithuania). Conversely, funding concentration is extremely low in Austria, Germany and Italy. France represents an exception, as notwithstanding the large number of banks, lending concentration to companies involved in real estate activities was over 45% in 2004 and stands currently at around 30%. However, this is due to the weight of the public bank financing the social housing. When excluding it, the HHI is flat at around 3%.

Chart 6**:** Lending concentration.



Source: national CCRs.

Other findings are as follows. The results based on the ratio of non-performing exposures (NPEs) to total exposures indicate that the CRE sector, and especially its construction component, is highly cyclical and volatile. According to previous studies, this is explained by the closer linkages with general economic developments and the lower elasticity of supply of commercial property compared to residential property (see ECB (2008) and ESRB (2015)). In addition, the NPE ratio appears to be higher and more volatile in the construction sector than in the real estate activities sector, which could suggest a higher riskiness and pro-cyclicality of the former sector compared to the latter. The high heterogeneity observed across countries, both in terms of levels and trends, is probably partly due to different cyclical situations but it should also interpreted with care given that the definition of nonperforming exposures has only been recently (2014) harmonized in the EU and that some jurisdictions part of the project relied on proxies to calculate this indicator. Nevertheless, the relatively large fluctuations of the NPL ratios over time and the existence of high peaks, in particular for the construction sector, can be interpreted as a sign of the general riskiness of the sector in economic downturns.

Exposures to construction and real estate activities are generally highly collateralised, although these levels should be interpreted with caution given the somewhat heterogeneous definition of the collateral variable across countries. The evolution over time nevertheless suggests that the financial crisis has led to a significant increase in collateral requirements, which is expected to improve the resilience of the banking sector towards a shock, as long as the applied valuation measures are reliable and consistent over time.

In terms of maturity profile, the share of long-term exposures to firms active in the construction and real estate activities sector is higher and seems to have even increased in the recent past, potentially due to firms taking advantage of the low interest rate environment. The maturity of exposures to construction firms is shorter in all countries, probably due to the more short term project length in this sector, where financing is normally only needed until the constructed building is sold. In the presence of a drop in demand for buildings, this short-term funding can present a vulnerability of the sector.

7. Outlook and conclusions

The granularity of credit register data provides an excellent basis for analysing risk and vulnerabilities in the banking sector, as information about the distribution of key risk indicators can be obtained. Apart from the distribution of risks within banks and the banking sector as a whole, credit register data in particular allows to identify links between banks, either via similar exposures or via direct or multiple lending relationships.

While on the national level, countries with a credit register are already able to exploit this rich set of information, cross-country comparisons are currently hampered by the different definitions and coverage of national credit registers. The AnaCredit project, starting in September 2018 with the first data collection, will overcome this situation by introducing a euro area wide, harmonised credit register. Still, the time series dimension of the AnaCredit database will only gradually develop over time, as past data will not be available. Until harmonised time series are available in AnaCredit, efforts can be undertaken to create indicators for financial stability monitoring based on credit registers in a cross-country framework.

This paper presented a project to build indicators to monitor risks stemming from the sectors construction and real estate related exposure (NACE codes 41 and 68) for several countries. The recent global financial crisis has shown that CRE markets are prone to strong boom and bust cycles and should therefore be monitored from a macroprudential perspective. However, analysis of CRE markets is currently hampered by significant data gaps. The project presented in this paper puts forward a set of coherent indicators, derived from the national CCR of a number of euro area countries and aims at bridging some of the data gaps which hinder analysis of commercial real estate exposures and associated risks in banks' balance sheets. The indicators capture different aspects of risk, like a) concentration measures, b) exposures and credit risk indicators, c) maturity profile, d) common exposures and multiple lending and e) cross-border exposures. Thanks to the granularity of credit register data, it is possible to calculate indicators on bank level, and therefore to capture the distribution of certain risk dimensions in the banking sector. Moreover, depending on the specificities of the national banking sector, different breakdowns of the indicators could be constructed for further analysis. The paper gives a preview on results of the project for selected indicators for one country as illustration. However, work is still ongoing and in particular the time series dimension of indicators will provide additional insights.

Given the different definitions and thresholds in the national credit registers, efforts were undertaken to ensure a sufficient level of comparability across countries. Nevertheless, the interpretation of results requires expert judgement and background information about national characteristics and specialities of the national credit register. Moreover, when combining indicators calculated based on credit register data for specific NACE codes, and data about CRE market developments from other data sources, potential deviations in terms of definitions and sectoral coverage need to be kept in mind.

While the focus of the project is on the risk posed by the commercial real estate sector, many of the constructed indicators are not sector-specific, and can be easily used to monitor other systemic sectors.

References

Artigas, C., 2004. A review of credit registers and their use for Basel II, Financial Stability Institute, available at http://www.bis.org/fsi/awp2004.pdf.

Basten, C., and Koch, C., 2015. Higher Bank Capital Requirements and Mortgage Pricing: Evidence from the Countercyclical Capital Buffer (CCB), BIS Working Papers No 511.

Benford, J. and Burrows, O., 2013. Commercial property and financial stability. Bank of England Quarterly Bulletin 2013 Q1.

Centre for European Policy Studies - European Credit Research Institute, 2013. Towards better use of credit reporting in Europe, Task Force Report, available at www.ceps.be/book/towards-better-use-credit-reporting-europe.

Dent, K., 2014. Should the Availability of UK Credit Data Be Improved?, Bank of England Discussion Paper, May 2014.

Dietsch, M. and Welter-Nicol, C., 2014. Do LTV and DSTI caps make banks more resilient?, Débats économiques et financiers N°13, Banque de France ACPR.

ECB, 2008. Commercial property market – financial stability, recent developments and EU banks' exposures, December 2008.

Ellis, L., and Naughtin,C., 2010. Commercial Property and Financial Stability – An International Perspective, Reserve Bank of Australia Bulletin, June Quarter 2010.

ESRB, 2015. Report on commercial real estate and financial stability in the EU December 2015.

Girault, M and Hwang, J., 2010. Public credit registries as a tool for bank regulation and supervision, World Bank Policy Research Working Paper No 5489.

Gyourko, J., 2009. Understanding Commercial Real Estate: How Different from Housing Is It?, NBER Working Paper 14708.

Hiebert, P., and Wredenborg, S., 2012. Commercial property analysis: an ECB perspective. Presentation at the Joint BIS – ECB – Eurostat – IMF – OECD international conference on Commercial property price indicators, held at the European Central Bank, Frankfurt am Main

Holub, L., Nyklíček, M. and Sedlář, P., 2015. Credit portfolio sector concentration and its capital requirements, Czech National Bank / Financial Stability Report 2014/2015.

International Finance Corporation, 2012. Credit reporting knowledge guide, available at http://www.ifc.org/mwg-internal/de5fs23hu73ds/progress?id=HmD1mjQIjCPrYYm0sHUpXxqCHqWd8npVvs7HWVab4Vg

Israël, J-M, Damia, V., Bonci, R. and Watfe, G., 2017. A magnifying glass for analysing credit in the euro area, ECB Occasional Paper Series No 187.

Konečný, T., Plašil, M., Rusnák, M., and Řežábek, P., 2015. Use of the Czech Central Credit Register for Financial Stability Purposes, Czech National Bank Financial Stability Report 2014/2015

Nyberg L., 2005. House Price Developments and Monetary Policy, Speech at Evli Bank, Stockholm, 19 December 2005, Bank of Sweden.

Olszewski,K., 2013. The Commercial Real Estate Market, Central Bank Monitoring and Macroprudential Policy, Review of Economic Analysis, Rimini Centre for Economic Analysis, vol. 5(2), pages 213-250.

Regulation (EU) 2016/867 of the ECB of 18 May 2016 on the collection of granular credit and credit risk data (ECB/2016/13), OJ L 144, 1.6.2016, p. 44.

Uluc, A., and Wieladek, T., 2015. Capital requirements, risk shifting and the mortgage market, Bank of England working papers 572, Bank of England.

World Bank, 2011. General principles for credit reporting, available at http://documents.worldbank.org/curated/en/662161468147557554/pdf/701930ESW0P1180ting0pub010028011web.pdf.

IFC-National Bank of Belgium Workshop on "*Data needs and Statistics compilation for macroprudential analysis*"

Brussels, Belgium, 18-19 May 2017

Use of credit registers to monitor financial stability risk: An application to commercial real estate[1]

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and

Gaia Barbic, Anne Koban and Charalampos Kouratzoglou, 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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Brussels, 19 May 2017

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Overview

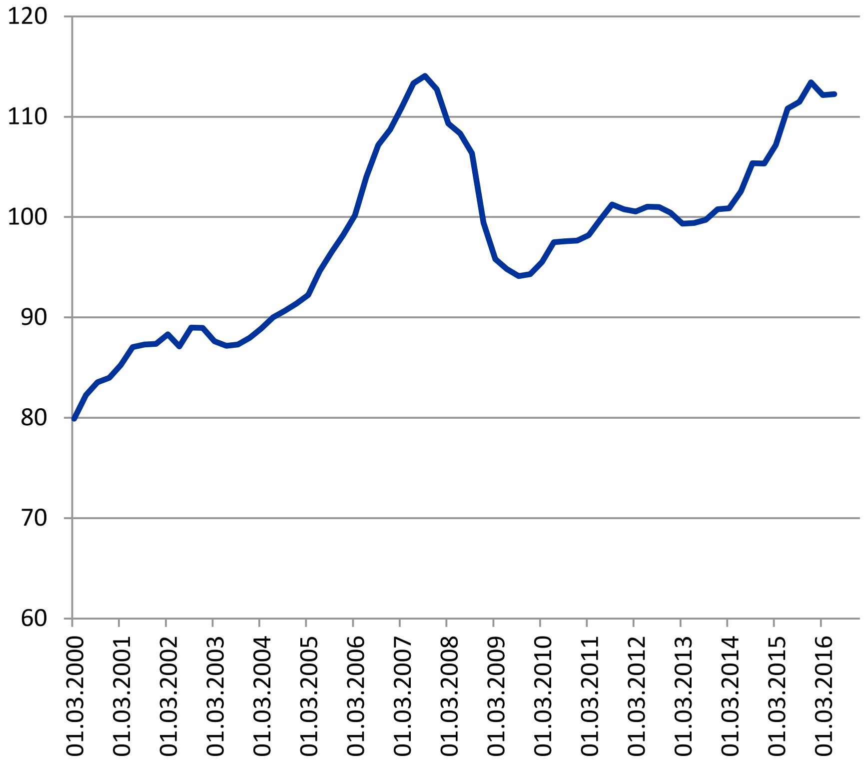
What is the CRE sector?

- **Many definitions** of the CRE sector exist.

- **ESRB:** “Buildings, including occupied land, which are held for the express purpose of generating an income” (2015 Report on commercial real estate and financial stability in the EU).

Why focusing on the CRE sector? (1/2)

EU CRE Property Price Index
(all types, 2011 = 100)

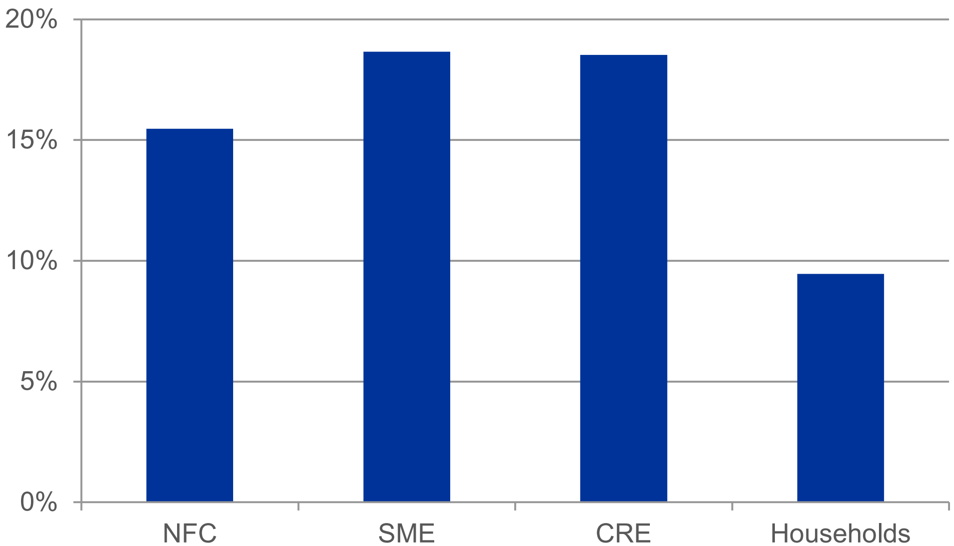


Sources: ECB and Experimental ECB estimates based on MSCI

- EU CRE prices have recently **reached their pre-crisis level.**
- Disorderly price adjustments in the CRE markets could affect **financial stability** because:
  - Loans for CRE account for a **significant part** of the **total mortgage lending** in some euro area countries;
  - Commercial property markets tend to be **more volatile** and **more reactive** to business cycles than residential property.

Why focusing on the CRE sector? (2/2)

Non-performing loan ratios by sector, Q4 2016
(average across euro area countries)



Source: ECB stocktake reports of national supervisory practices and legal frameworks related to NPLs

- CRE loans show almost the **highest NPL ratio** in the euro area.
- Large amounts of NPLs affect **financial stability**:
  - For **banks in "going concern"**, they lower profitability and constrain the ability to provide new financing to the economy;
  - For **banks in "gone concern"**, they can hamper efficient resolution.

Which data is missing?

- Although the regulatory reporting framework (e.g. Finrep/Corep) has improved and ECB/ESRB initiatives have been taken to enhance the monitoring of national CRE markets, **data gaps remain**.

- For instance, the available commercial real estate figures from private vendors only cover *prime* commercial real estate sector and reflect a combination of market evidence (where available) and a survey of expert opinion, **rather than transaction (volume) or valuation (price) information**.

- In addition, there is not much information available on the **credit granted by banks and associated exposures and risks**. In our paper, we focus on the **latter dimension**.

Credit registers can shed light on credit, exposures and risks because they contain:

- **Many variables** thereby allowing to look at several risk types.

- **Granular (i.e. borrower or loan) level information**, which is important given that financial stability risk assessment is interested in the tails (not so much in averages).

⇒ Key question: make use of national credit registers or wait for AnaCredit?

- **AnaCredit** (see also presentation in this session):
  - No data available before end-2018
  - No time-series available before a couple of years

Advisory Group on AnaCredit (AGA)

- Group set-up under the ECB's FSC. Current membership: **AT**, **BE**, **DE**, **ES**, **FR**, **IT**, **SK**, **LT** and the **ECB**.

- In order to already **illustrate** the potential of AnaCredit and to **complement** the existing risk assessment indicators available **without delay**, the AGA has constructed **financial stability indicators for CRE based on existing national credit registers**.

- This approach could also be extended later to **other sectors** e.g. those identified as being **systemic** in the 2015 ESRB report on sectoral risk.

- AGA's indicators of sectoral risk are useful not only from an **ESRB/ECB perspective**, but also from a **national perspective**, as countries do not yet calculate these or similar indicators.

3. Work of AGA

Challenges

- Finding **harmonised risk indicators** across countries was **not obvious** due to different set-up and definitions of national credit registers.
- **CRE definition** needed to be operationalized.

Implications

- **Careful choice** of underlying data and definitions of indicators was made to ensure sufficient comparability.
- **CRE definition**: “Bank loans – mainly to corporations – falling under the NACE economic branches **Construction** (41) and **Real estate activities** (68)”.

Caveat

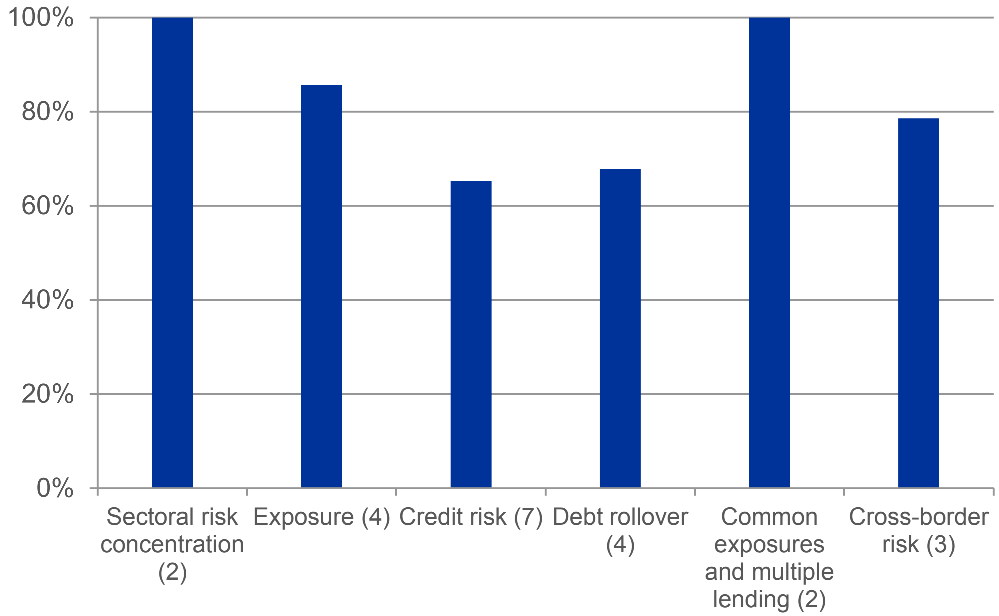
- Indicators can **only** provide **additional input** among other hard and soft evidence.
- Emphasis should not only be on **cross-country comparisons** but also on **time-series evolution** for the same country.

22 indicators organized by risk types (see Annex)

Sectoral risk concentration(2)	• Sector granularity • Risk of funding concentration
Exposures (4)	• Total exposures (with or without collateral) • Total pledged collateral as a % of total collateralised exposures
Credit risk (7)	• Vulnerable exposures and exposures towards vulnerable debtors (firms) • PDs and NPLs • Collateral and protection amounts
Debt rollover (4)	• Debt rollover ability and demand • Maturity of new loans and average loan volume
Common exposures and mult. lending (2)	• % of exposures to firms with multiple banking relationships • % of firms with multiple banking relationships
Cross-border risk (3)	• Lender origination • Borrower origination • Currency risk

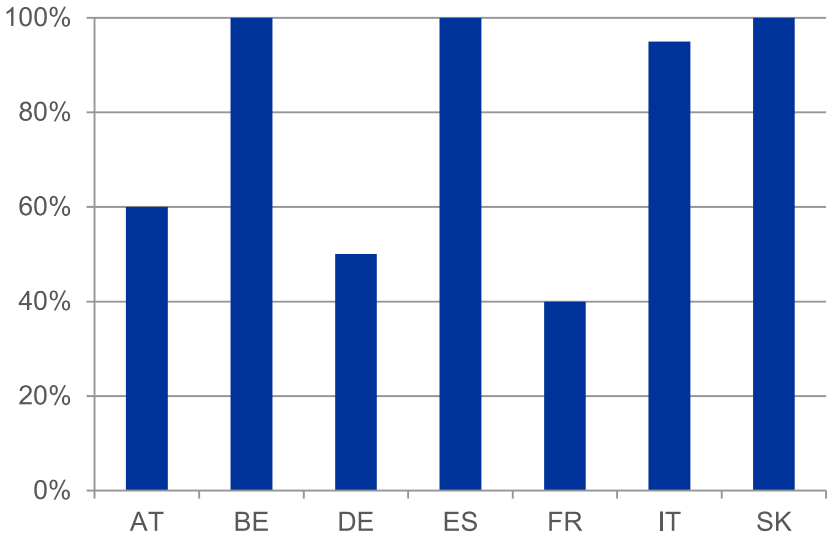
Availability of risk indicators (Q4 2016) - Preliminary assessment

Availability by risk type
(average across jurisdictions)



Source: Advisory Group on AnaCredit

Availability by jurisdiction
(average across risk types)



Source: Advisory Group on AnaCredit

Caveat

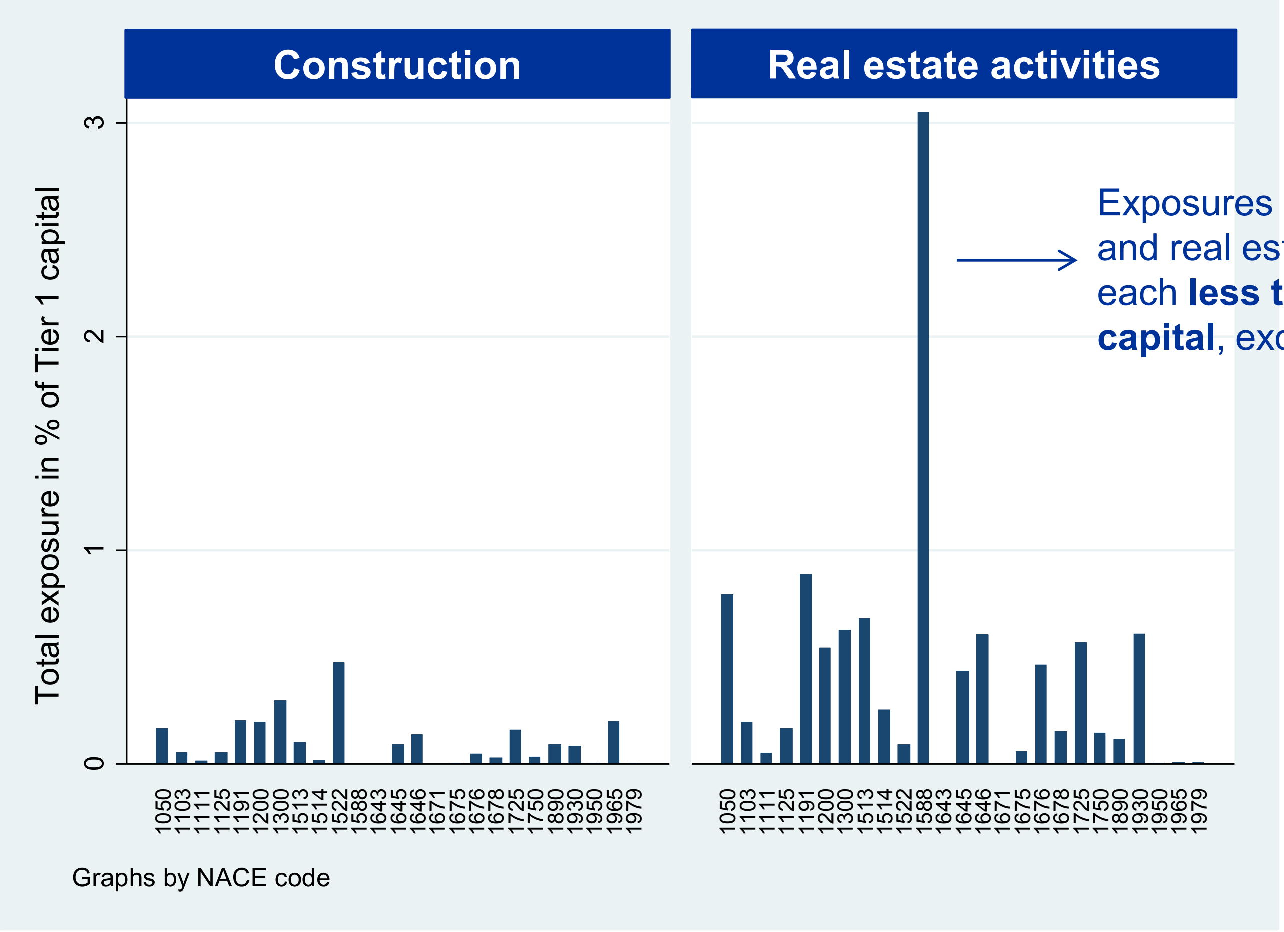
The following slides **illustrate** some very preliminary results of AGA's work for:

- **2 indicators** (instead of 22)
- **1 jurisdiction** (instead of 7)
- **1 quarter** (instead of a 10-year history, when available)

Indicators can be calculated at the **jurisdiction** or at the **bank level**. In the case of the latter, **only aggregated statistics** will be shared within the AGA.

Example of concentration indicator (Q4 2016)

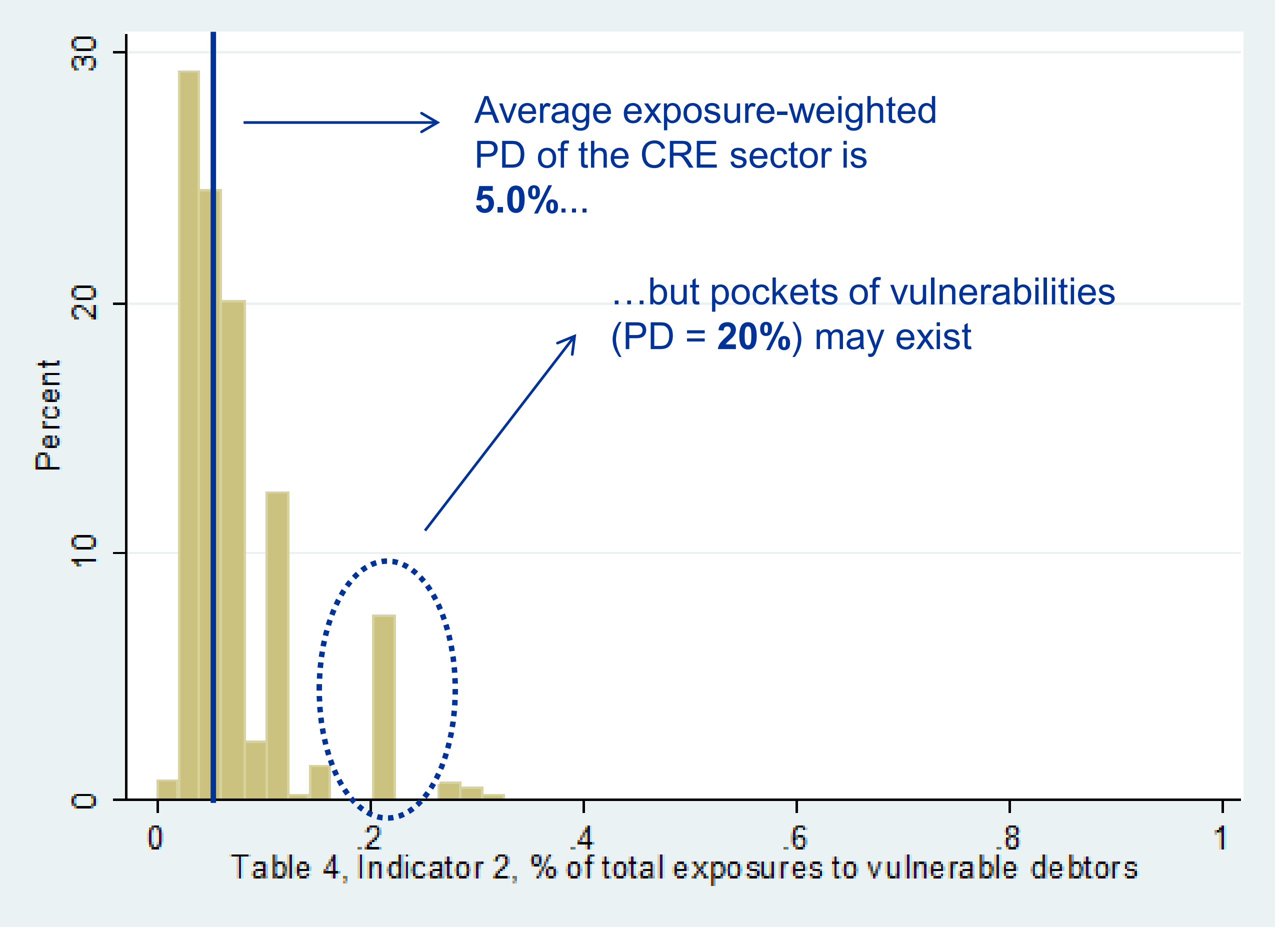
Distribution of banks (X-axis) according to the size of their CRE exposures scaled their by Tier 1 capital (Y-axis, %):



Exposures towards construction and real estate activities represent each **less than 1% of Tier 1 capital**, except for one bank

Example of credit risk indicator (Q4 2016)

Distribution of CRE exposures (Y-axis, in %) according to their probability of default (X-axis, in %):



Outlook

- **June 2017:** first results for all jurisdictions.
- **Summer 2017:** review of first results.
- **Fall 2017:** final results to be integrated into monitoring frameworks and approach to be possibly extended to other sectors.

ANNEX

Sectoral risk concentration indicators (2)

Indicator description	Description	Details and formula
Sector granularity	HHI of firms' borrowing within a sector, to see how concentrated borrowing is within a sector	$HHI_k^{firms} = \sum_{i=1}^{N} {s_i}^2$ With s_i being the share of lending to firm *i* over total lending to that sector i.e. $s_i = E_i / \sum_{i=1}^{n}(E_i)$ for each firm *i*=1..*N* in sector *k*
Risk of funding concentration	HHI of banks' shares of total exposures towards a sector, to see how dependent a given sector is on a certain number of banks. The lower the HHI index, the more diversified that sector is in terms of its funding sources	$HHI_k^{banks} = \sum_{j=1}^{J} s_j^2$ With $s_j = E_j / \sum_{i=1}^{J}(E_j)$ for each bank *j*=1..*J* lending to sector *k*

Exposure indicators (4)

Indicator description	Details and formula
Total exposure to sector as % of Tier1 capital (or other capital measure) per bank, *potential additional version: quartiles of this indicators*	$\lambda_{k,j} = \frac{\sum_1^H E_h}{T1_j}$ Loop over all exposures of bank j to sector k, divided by Tier1 capital of bank j
% of total exposures with collateral, by sector *potential additional version: quartiles of bank level indicators*	$\mu_k^1 = \frac{\sum_1^H E_h \delta_h}{\sum_1^H E_h}$ Loop over all exposures to sector k, with $\delta_h = 1$ if exposure E_h has dedicated collateral
Total pledged collateral as a % of total collateralised exposures, by sector for all banks in one country, *potential additional version: quartiles of bank level indicators*	$\mu_k^2 = \frac{\sum_1^H C_h}{\sum_1^H E_h \delta_h}$ Loop over all exposures E_h.to sector k, where C_h is the collateral value assigned to E_h with $\delta_h = 1$ if exposure E_h has dedicated collateral

Credit risk indicators (7) – Part 1

Indicator description	Details and formula
% of total exposures with positive non-performing amount (exposure weighted)	$\omega_k^1 = \frac{\sum_1^H E_h \delta_h}{\sum_1^H E_h}$ with $\delta_h = 1$ if exposure E_h has positive non-performing amount
% of total exposures to vulnerable debtors (% of total exposures to debtors with any positive non-performing amount); Calculation for each bank, then illustration of the distribution in each country (anonymised)	$\omega_{k,j}^2 = \frac{\sum_1^N E_i \delta_i}{\sum_1^N E_i}$ Loop over all *N* debtors of a bank *j*, where E_i is the total borrowing of debtor *i*, and $\delta_i = 1$ if debtor *i* has any positive non-performing amount

Credit risk indicators (7) – Part 2

Indicator description	Details and formula
% of new lending towards a certain sector going to borrowers already registered as non-performing	$$\omega_{k,j}^{3} = \frac{\sum_1^N NewLending_i\, \delta_i}{\sum_1^N NewLending_i}$$ Loop over all *N* debtors of a bank *j*, where $NewLending_i$ is the amount of new lending to borrower *i*, and $\delta_i = 1$ if debtor *i* has any positive non-performing amount
Value of collateral pledged to non-performing exposures as a % of total non-performing exposures	$$\omega_k^3 = \frac{\sum_1^H C_h\ \delta_h}{\sum_1^H E_h\, \delta_h}$$ Loop over all collateral C_h for exposures *H* with $\delta_h = 1$ if exposure is non-performing.
Change in exposure-weighted PD, by sector *Alternative: Graphically, PD in period t on the x axis and PD in period t-1 on the y axis to illustrate the development of PDs in the sector*	$$\Delta\overline{PD}_k = \sum PD_{it} \cdot s_{it} - \sum PD_{i,t-1} \cdot s_{i,t-1}$$ Where s_i is defined as above, and we are comparing periods *t* and *t-1*
Change in the % of exposures with non-performing status	$$\Delta NPL_{k,t} = \frac{\sum_1^H E_{h,t}\, \delta_h}{\sum_1^H E_{h,t}} - \frac{\sum_1^H E_{h,t-1}\, \delta_h}{\sum_1^H E_{h,t-1}}$$ with $\delta_h = 1$ if exposure E_h is non-performing

Debt rollover indicators (4)

Indicator description	Description	Details and formula
Maturity Profile of Exposures	Distribution of maturity of exposures	Distinguishing between 3 maturity buckets ([<1Y], [1Y, 5Y], [>5Y])
Debt rollover demand *potential additional version: quartiles of this indicators on bank level*	% of exposures with maturity less than one year, by sector	$\eta_k = \frac{\sum_1^H E_h \delta_i}{\sum_1^H E_h}$ with $\delta_h = 1$ if exposure *h* has a maturity of less than one year and $\delta_h = 0$ otherwise
Maturity of new loans *potential additional version: quartiles of this indicators on bank level*	The weighted average maturity of loans issued, by sector	$m_{k,j} = \sum_1^H s_h M_h$ Where *H* is the total number of loans issued to sector *k* within a given period, $s_h = \frac{E_h}{\sum E_h}$, and M_h is the original maturity of loan *h*
Average loan volume *potential additional version: quartiles of this indicators on bank level*	The average volume of loans issued, by sector	$v_k = \frac{\sum_1^H E_h}{H}$ Where *H* is the total number of loans issued to sector *k*, and E_h is the volume of loan *h*

Common exposures / multiple lending indicators (2)

Indicator description	Details and formula
% of total exposure going to borrowers with multiple banking relationships, by sector	$\alpha_k^1 = \frac{\sum_i^N E_i \delta_i}{\sum_i^N E_i}$ Where $\delta_i = 1$ if firm *i* borrows from more than one bank and is equal to 0 otherwise
% of firms with multiple banking relationships, by sector	$\alpha_k^2 = \frac{\sum_i^N \delta_i}{N}$ Where $\delta_i = 1$ if firm *i* borrows from more than one bank and is equal to 0 otherwise, and *N* is the total number of firms in sector *k*

Cross-border risk indicators (3)

Indicator description	Description	Details and formula
Lender Origination	% of total exposures that are being lent from foreign entities, by sector	$\beta_k = \frac{\sum_{j=1}^{J} E_j \delta_j}{\sum_1^J E_j}$ E_j is the money lent to sector k by bank j. With $\delta_j = 1$ if j is a foreign bank and is equal to 0 otherwise.
Currency Risk	% of credit issued domestically but denominated in foreign currency, by sector	$\gamma_{k,c} = \frac{\sum_1^H \tilde{E}_h^c}{\sum_1^H E_h}$ With $\tilde{E}_h^c$ being denominated in foreign currency *c*

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Brussels, Belgium, 18-19 May 2017

Use of AnaCredit granular data for macroprudential analysis[1]

Orestes Collazo Brananova and Gibran Watfe,
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.

Use of AnaCredit Granular Data for Macroprudential Analysis

Orestes Collazo, Gibran Watfe

Abstract

AnaCredit will provide a rich set of granular data on credit and credit risk for macroprudential analysis allowing the calibration and assessment of macroprudential instruments. Adapting financial indicators to changing conditions over time is facilitated by the extensive breadth of counterparty and credit data attributes collected in AnaCredit. Compared to the compilation of aggregate statistics, individual data (loan-by-loan and counterparty-by-counterparty) allows the analysis of the distribution of risk across the whole population.

This paper explores macroprudential instruments that can be defined using AnaCredit data, and how they can be used to drill down in the main sources of risk concentration. The paper concludes exploring the need to integrate AnaCredit with other datasets in order to fully exploit the granular data available.

Keywords: Analytical Credit Dataset, loan-by-loan data, credit risk, macroprudential analysis

JEL classification: C81, E44, E51, E58, G28

The views expressed are those of the authors and do not necessarily reflect those of the ECB.

Contents

1. Introduction

AnaCredit will provide a rich set of granular data on credit and credit risk for macroprudential analysis and various other purposes. Regulation ECB/2016/13 adopted in May 2016 is the legal basis for data collection starting in November 2018 with September 2018 as a first reference date. The breadth of the 88 AnaCredit data attributes in conjunction with its granularity and the fact that data is collected on an individual basis will allow for adapting financial indicators to changing conditions over time. The AnaCredit framework will support the calibration and assessment of macroprudential instruments and thus contribute to financial stability in line with the ESCB's task specified in Art. 127(5) TFEU.

Economic and financial indicators attempt to capture the behaviour of economic agents and describe complex economic phenomena using a small number of metrics. Defining indicators is usually a long process starting from real economic events that become important and which reveal a specific data gap. On this basis indicators are defined either specifically for a particular purpose or as a one-size-fits-all solution for several purposes. The former allows a detailed analysis on a specific issue but often does not cover the data needs for different analyses; while the latter may only be of limited interest for a larger number of analysts. The detailed granular data in AnaCredit will allow the definition of very specific indicators for a large number of different analyses.

The approach in the past, when no granular data were available, was to define indicators and calculate a single metric representing the aggregate behaviour of very heterogeneous agents. Describing the complex behaviour of agents by means of a small set of indicators led to a substantial loss of information. The dispersion of the indicator across the population was condensed into a simple or weighted average. In this process the complex relationships between agents were ignored. Moreover, the definition of the indicator was fixed ex ante and could thus hardly be adapted to changing circumstances.

Individual data by (borrowing or guaranteeing firms) and, in particular, granular data on credit can alleviate the information loss considerably by using a different approach: measuring economic phenomena at the level at which they occur. The AnaCredit data model was conceived from this perspective. AnaCredit is a granular database modelling credit intermediation on an individual instrument-by-instrument, counterparty-by-counterparty and protection-by-protection basis as well as the relationship among these three building blocks. Therefore, it offers three distinct advantages for defining financial indicators relative to the broad approach in the past.

Firstly, AnaCredit provides an unprecedented level of detail for analysing credit intermediation and defining related indicators for the euro area. The database contains 88 attributes that were defined based on the needs of a variety of business areas. This high level of detail in itself provides flexibility to define indicators, including the possibility for back-casting, as well as allowing calibration and estimation of models, e.g. in the context of stress testing. The dimensions and measures included in AnaCredit can be combined in multiple ways to measure economic phenomena at different levels. The attributes and values provide a starting point for improving existing indicators or defining new ones in a flexible manner. This approach, in particular, stands in contrast to the current methodology to establish indicators to track economic events that in the *past* have been found of relevance. While these stable indicators are undoubtedly useful, a more dynamic way to track current economic phenomena as they occur is needed.

Secondly, AnaCredit will allow users to both identify and construct networks between agents. This stems from the unique identification of counterparties in AnaCredit based on the reporting of unique and exclusive identifiers. This will help, among others, to analyse concentration of risk at different levels, e.g. according to banking and corporate groups, or according to sectors of economic activity.

Thirdly, given that AnaCredit facilitates the measurement of indicators at an individual level, analysis of credit can go beyond the averages. Within the scope of AnaCredit, the distribution of an indicator across the whole population can be identified. Hence, the user can focus on specific parts of the distribution. Most importantly, the tail(s) of the distribution reveal important insights about particularly risky counterparties or sectors for financial stability purposes.

Finally, AnaCredit will be complemented by a full register of financial, governmental and non-financial entities. Data on counterparts involved in transactions will be available in the Register of Institutions and Affiliates Database (RIAD) both at individual (legal) entity level and on group structures. This will also allow for identification, classification by size of firms, by industry activity, but also to consolidate exposures on the lending side and indebtedness on the borrowing side.

Aggregated data and derived indicators currently do not cover the new tasks and needs of financial stability. More granular information is needed to analyse credit intermediation and other parts of the economy to better inform decision-makers. AnaCredit is needed in order to fully understand the financial stability implications of credit intermediation. This paper describes how AnaCredit can contribute to macroprudential analysis.

The paper is structured as follows. The next section describes the main elements of the AnaCredit data model and points out important attributes for macroprudential analysis. Section three looks into the definition of financial stability indicators with AnaCredit data. It also includes a case study on real estate. Section four describes the use of AnaCredit data for exploring financial indicators from the top down and thus provides a different perspective. Possible future enhancements of AnaCredit are described in Section five on the basis of identified data gaps.

2. AnaCredit data model

The AnaCredit conceptual data model describes the broad structure of the AnaCredit database. As AnaCredit is an instrument-by-instrument database, the data model is structured on the basis of modelling credit. In a more detailed manner, the logical data model specifies each part of the structure of AnaCredit including all attributes contained therein. It also specifies all required primary and foreign keys which allow an identification of relationships between entities. Annex 1 provides a graphical representation of AnaCredit conceptual data model[1].

Main elements

The conceptual data model aims to replicate any financial intermediation on the basis of the three main distinct but interconnected arising in each credit transaction: instrument, counterparty and protection. The instrument entity is at the heart of AnaCredit. It contains the information about the individual credit, i.e. individual commitments with unique terms under a credit agreement such as product type, maturity date, interest rate, etc. Instruments arise under a contract. The AnaCredit model allows registering multiple instruments under a single contract to identify instruments which raise common risk for the counterparties involved in these instruments.

Whenever an instrument is secured by a protection, the latter is captured in the separate protection entity. The protection entity contains information about all protection items (i.e. valuable assets or rights) that are committed to the fulfilment of the terms of an instrument (i.e. that secure the payments under a credit transaction), as specified in the (credit) contract that gives rise to the instrument. All protection items in the protection entity contain an instrument identifier such that the protection item can be mapped to the instrument it secures. Detailed information about protection (e.g. value, valuation date and type) is potentially important for estimating recoveries in macroprudential stress test exercises.

All protections securing an instrument are registered in AnaCredit. Moreover, a single protection may secure multiple instruments; however, the protection is only uniquely identified locally, i.e. at the level of the credit institution reporting the information to AnaCredit. If the same protection is securing two loans held by the same credit institution, then the protection is uniquely identified. However, if the same protection, e.g. commercial real estate, is securing two loans held by different credit institutions, two different protections appear in AnaCredit. To overcome this limitation, AnaCredit includes the attribute 'third party priority claims against the protection' which registers the maximum amount of any existing higher ranked liens against the protection with respect to third parties. This allows a quantification of the share of the protection which is committed with third parties.

The counterparty entity contains information about counterparties related to the instrument entity and, if relevant, to the protection entity. The counterparty entity also contains information about certain counterparties affiliated with debtors and

[1] See AnaCredit reporting manual Part I – General Methodology for a detailed description of the AnaCredit conceptual model.

protection providers of an instrument in the instrument entity. In a similar way to the modelling of the instrument and protection entities, the modelling of the counterparty entity takes into account the fact that the same counterparty may relate to several instruments and protection items. For the purpose of AnaCredit, all counterparties which take any of the following roles should be reflected in the counterparty entity:

1. the creditor of the instrument;
2. the originator of the instrument, if the instrument is a securitisation transaction;
3. the servicer of the instrument;
4. the debtor of the instrument;
5. the protection provider that provides protection to the instrument (if any protection item is provided);
6. the head office undertaking of (any foreign branch or a special fund that is) a debtor of the instrument or a protection provider that provides protection to the instrument;
7. the immediate parent undertaking of any debtor of the instrument, or of any protection provider that provides protection to the instrument;
8. the ultimate parent undertaking of any debtor of the instrument, or of any protection provider that provides protection to the instrument.

The individual connections between the instrument and the counterparties participating in the instrument allow identifying all relevant risks that each counterparty is holding or raising. Concretely, both joint liabilities where multiple debtors are jointly liable for a credit, and instruments held by multiple creditors can be identified. In addition, AnaCredit allows connecting the multiple shares of a syndicated loan held by different credit institutions.

In contrast to the local identification of the protection, AnaCredit provides universal identification of counterparties. The individual identification of all counterparties participating in the instrument, regardless of their residency or type, provides a comprehensive view of the level of indebtedness and credit that each debtor and creditor hold.

On the basis of the conceptual data model, the logical data model of AnaCredit comprises six entity tables which in turn include one or more actual datasets.

1. the instrument entity table includes three datasets: instrument data, financial data, accounting data;
2. the protection entity table corresponds to protection received data;
3. the instrument-protection received entity table corresponds to instrument-protection received data;
4. the counterparty reference data entity table corresponds to counterparty reference data;
5. the counterparty risk/default entity table includes two datasets: counterparty risk data and counterparty default data; and

6. the counterparty-instrument entity table includes two datasets: counterparty-instrument data, joint liabilities data.

This structure enables the user to identify relationships among instruments, counterparties and protections. Of these connections, the relationships among counterparties may prove of significant relevance for macroprudential analysis as they allow identifying concentration of risk in areas of activity and possible contagion effects.

Attributes

AnaCredit contains 88 data attributes collected with a monthly or quarterly frequency depending on the dataset and, possibly, on derogations for certain small reporting agents. The large number of attributes enables the user to conduct extensive analyses with AnaCredit data. Next to macroprudential analysis, users from various business areas in the ECB and NCBs will make use of the data. From the perspective of macroprudential analysis multiple categories of attributes are of particular interest. Moreover, the use of standards and common definitions across countries in AnaCredit will enhance the comparability of results in the Euro Area.

A significant set of attributes inform about the financial aspects of a particular instrument. Examples include interest rate, outstanding nominal amount, off-balance sheet amount, transferred amount, default status, arrears and date of past due. The combination of outstanding nominal amount, transferred amount and the unique identification of counterparties in RIAD allow, for example, to track securitisation transactions in which the credit institution continues to service an instrument after the transfer.[2] The attributes default status, arrears and date of past due are important for the analysis of NPLs in particular given that these attributes are reported at a monthly frequency.

An important aspect for macroprudential analysis is that AnaCredit contains both backward-looking (loss measures) and forward-looking (risk measures) attributes. For example, attributes such as transferred amount, accumulated impairments and cumulative recoveries since default contain cumulative information from the past. In addition, the history of data provided in AnaCredit will enable the precise calculation of the payment history of debtors, e.g. debtor days past due and largest days past due within the last 3 months (across all instruments). Other attributes in AnaCredit are forward looking, enabling the user to estimate the future cash flows of an instrument (e.g. amortisation type) or the subjective probability of a negative credit event using the probability of default. This attribute can serve as an ex ante expected default rate and for the calculation of expected credit losses. While expected credit losses are based on the creditor probability of default, the probabilities of default provided for a single debtor by multiple credit institutions

[2] For a more detailed description of RIAD, see Neudorfer (2016) and Thijs & Corvoisier (2017).

may allow the calculation of a more objective measure of default which may then be used for industry-wise stress test purposes. In addition, related derived data may be defined to include various measures of industry probabilities of default allowing for sectoral risk analysis.

Counterparties are described in detail by way of reference data attributes that are collected under AnaCredit and stored in RIAD. Attributes inform among others about the name, the address, the legal form, institutional sector, economic activity as well as the size of a counterparty. Moreover, the counterparty risk/default table contains attributes on the probability of default and the default status. As described above the counterparties in AnaCredit take different roles and can thus be connected based on the instruments in which they have one or more of the roles.

In the context of analysing concentration of risk, for example, the analyst could make use of the identifiers relating counterparties with their parent companies and using outstanding nominal amounts in order to gauge the risk at group level. Alternatively, risk concentration based on location could be analysed with the help of address attributes, e.g. Address: country. Finally, the analyst could exploit the attribute on economic activity to identify risk concentrating in specific sectors of the economy.

Another example relevant for financial stability purposes is the analysis of exposure levels. Absolute exposure might be based, for instance, on the sum of outstanding nominal amount and off-balance sheet amount. It could potentially be widened by taking into account transferred amount, joint liability amount and carrying amount. In one specific use case, exposures to non-financial corporations of different size could be derived based on the attribute enterprise size. The aspect of risk might be introduced by including the attribute probability of default in the analysis.

Connections among counterparties

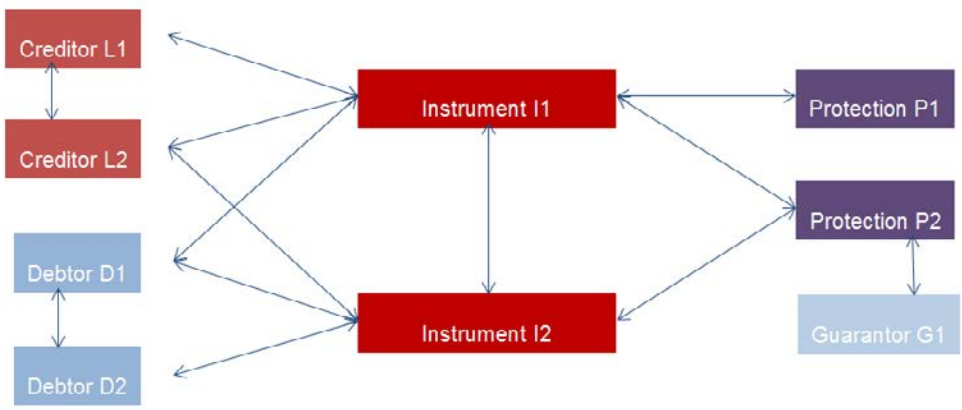


Figure 1: An illustration of n-to-m relationships between instruments, counterparties and protections that can be traced with AnaCredit data.

A central feature of AnaCredit is that it allows users to infer information from the relationships among counterparties. Connections can take different forms: connections that identify an entities' position within a group, connections from the perspectives of contagion and concentration as well as aggregation of lenders with similar characteristics (e.g. institutional replicas).

First of all, AnaCredit collects information on group structures which are enhanced via RIAD combining other sources of information. Specific identifiers for head offices, immediate parent and ultimate parent undertakings are reported. Hence the position of a particular counterparty within a group can be identified. This information may allow the users to prepare pseudo-consolidated data for a group on the basis of the individual data provided. This applies to both banking and corporate groups as reference data is collected for creditors and debtors. Moreover, as reference data will be updated on a monthly basis, mergers can be tracked in a timely manner.

Secondly, AnaCredit will be important for macroprudential analysis of contagion effects both ex ante and ex post. The coverage of the database enables the user to analyse positions within the MFI sector and thus allows for inference on possible contagion through interbank markets. Possible contagion effects from the financial to the real sector or vice versa can also be analysed with AnaCredit data. A caveat is that AnaCredit does not contain information about natural persons and will thus not allow for possible contagion effects stemming from and/or affecting household exposures. Importantly, contagion effects can not only be analysed on the basis of direct exposures (i.e. loans or securities), but also based on collateral exposures. AnaCredit will mainly inform about positions in the form of loans while the Securities Holdings Statistics Database (SHSDB) contains the relevant information about securities. Efforts are currently ongoing within the ESCB to facilitate an integration of the two databases.

Thirdly, and related to the aspect of group structures, AnaCredit will facilitate the analysis of risk concentration. For instance, the exposures of creditors within the same banking group can be aggregated to analyse the degree of concentration within the group. Similarly, the degree of dependence of debtors within the same corporate group on particular lenders can be analysed with AnaCredit data. In addition to that, the attribute on economic activity of a counterparty enables the user to identify sectoral concentration and dependencies of particular lenders or of a banking group.

Another type of analysis that is facilitated by being able to connect counterparties in AnaCredit is the construction of portfolio replicas. The portfolio of a group of small banks taken together might replicate the portfolio of big, possible systemically important, lenders. Alternatively, banks with similar business models might be grouped together. AnaCredit attributes help the user to identify concentration of exposures within sub-groups of lenders and thus to trace another form of macroprudential risk over time. Finally, the data attributes enable the user to analyse instruments with one or more lenders (e.g. syndicated loans) or with multiple debtors as well as to exploit the connections between multiple instruments connected to one or more protection items.

3. Definition of financial stability indicators

AnaCredit offers the possibility to construct a large amount of financial indicators for various purposes including macroprudential analysis. AnaCredit was developed as a multi-purpose dataset. The granularity of the data in AnaCredit enables the user to obtain information about individual instruments and individual counterparties. Financial stability indicators can therefore be constructed and tracked over time on instrument and counterparty level. Moreover, both the quantity and the variety of the attributes make it a useful tool to develop new indicators. The unique identification of counterparties as well as the use of harmonised concepts and definitions facilitates a connection of AnaCredit with other granular datasets such as the SHSDB.

Flexibility

A challenge often encountered in the past was that data needs became evident only after crisis events unfolded. This is frequently exacerbated by long time lags between formulating data requirements and the provision of reliable data, let alone histories sufficient for meaningful inference. To some extent, granular data will rectify this challenge as it can be aggregated and used in various contexts. Granular data can help to understand, for example, underlying forces at work during an imminent crisis in a particular sector which cannot be foreseen ex ante. Changing conditions can hence be addressed with current information without the need to establish new and lengthy reporting requirements. The monthly frequency and relatively tight time frames for reporting agents will make AnaCredit useful to understand unfolding events almost in real time compared to existing macro datasets on credit.

Distributions

Apart from tracking financial indicators over time, the individual information in AnaCredit allows the user to look at full distributions of financial indicators for nearly the whole population. For example, macroprudential analysis may use various aggregates of probabilities of default and their development over time as important measures for financial stability. Apart from that, probabilities of default assigned by all lenders of a particular debtor can be monitored. On a more aggregated basis the probabilities of default assigned by lenders to particular sectors might be checked.

More generally, distributions derived from AnaCredit data may be used to enrich aggregated macro datasets and thereby provide macroprudential policy with more precise information. Possible aspects that enrich the commonly used average figures are measures of central tendency, dispersion and concentrations. This will reveal a new sort of information previously hidden behind averages (see Figure 2). This allows analysts, for example, to focus on the tail of the distributions in order to identify particularly risky (groups of) counterparties. Finally, the information value of AnaCredit can best be harnessed when indicators are combined in order to obtain a more holistic view. A practical example for macroprudential analysis would be the combination of loan-to-value, NPL ratio and bank size. Another option would be to introduce correlations between indicators to increase the breadth of the analysis.

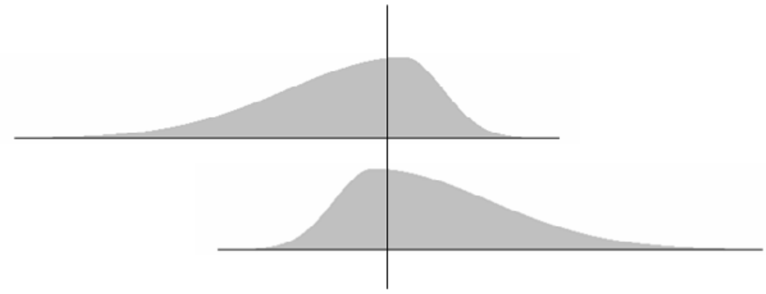


Figure 2. Illustration of two different distributions with the same mean.

Case study: real estate data gaps

In October 2016, the ESRB published a Recommendation on closing real estate data gaps (ESRB Recommendation)[3]. It lists various key indicators for monitoring developments in the residential and commercial segments of the real estate market. National macroprudential authorities and the European Supervisory Authorities (ESAs) are recommended to collect data for these indicators from existing data sources. The real estate data gaps identified in the Recommendation serve as a case study for the use of AnaCredit data.

The Recommendation explicitly refers to AnaCredit as a possible source for the proposed indicators. However, it points out that AnaCredit cannot be relied alone for meeting the information needs identified in the Recommendation due to some of its features:

- The definitions for residential real estate (RRE) and commercial real estate (CRE) differ;
- Natural persons are beyond the scope of AnaCredit;
- Some key indicators and market segments are not covered;
- AnaCredit focuses on Euro Area members;
- Loans from non-credit institutions are only covered if they are serviced by a credit institution;
- Small banks might be excluded by way of derogations.

3 Recommendation of the European Systemic Risk Board of 31 October 2016 on closing real estate data gaps (ESRB/2016/14) (European Systemic Risk Board, 2016)

Despite these caveats, our analysis will show that AnaCredit could be used to cover some of the indicators required in the Recommendation. Moreover, an extension of AnaCredit to cover loans granted to natural persons would significantly increase the coverage of the indicators proposed in the Recommendation.

A detailed analysis of the information in AnaCredit reveals that while the definition of CRE and RRE in the Recommendation and in AnaCredit differ, the use of additional information included in AnaCredit may reduce the gap between the two definitions.

In the context of AnaCredit CRE and RRE are not defined in isolation but used as part of two attributes, namely 'purpose' and 'type of protection'. The attribute 'purpose' classifies AnaCredit instruments according to their purpose. Two values are of relevance for the identification of CRE loans, namely 'residential real estate purchase' which applies to instruments financing residential property, and 'commercial real estate purchase' which applies to instruments financing real estate property other than residential property.

On the other hand, the attribute 'type of protection' allows the identification of the type of protection securing an instrument reported to AnaCredit. Three values are of relevance in this context:

a) Residential real estate collateral which is defined as residential property in accordance with Article 4(1)(75) of CRR;
b) Offices and commercial premises which is defined as real estate other than residential real estate that qualifies as "offices or other commercial premises" for the purposes of Article 126(1) of the CRR; and
c) Commercial real estate collateral which is defined as any real estate property other than residential real estate collateral and offices and commercial premises.

The distinction between offices and commercial premises and commercial real estate collateral is of no relevance for the identification of CRE loans as it is based on the relationship between the collateral and the creditworthiness of the debtor. Thus we will refer to the combination of both as commercial immovable property.

The values of these two attributes rely on the definition of residential property within the meaning of Article 4(1)(75) of the CRR. Residential property is defined as residence which is occupied by the owner or the lessee of the residence. Consequently, any real estate property that is not residential real estate is considered to be commercial immovable property. On the other hand, the ESRB Recommendation defines CRE as any income-producing real estate, either existing or under development, and excludes: (a) social housing; (b) property owned by end-users; and (c) buy-to-let housing. The relevance of this definition lies on its use to identify CRE loans, which are defined as loans aimed at acquiring a CRE property (or set of CRE properties) or secured by a CRE property (or set of CRE properties). The indicators suggested focus on this loan portfolio.

A direct approach to identify CRE loans in AnaCredit would be to focus on loans whose purpose is to finance commercial real estate or secured by commercial immovable property. As indicated in the ESRB Recommendation, the definitions used in both frameworks are not aligned, and the differences may be significant. However, this mapping can be further refined. The loans registered in AnaCredit are granted to legal entities[4]. As a result, the loans granted to legal entities for the purpose of financing residential real estate purchase or secured by residential property should satisfy the CRE loan definition as this real estate is expected to be income-producing real estate. Moreover, these loans do not include buy-to-let housing[5] as those are loans granted to natural persons.

It is important to note that this portfolio may include loans financing social housing or protected by this type of real estate. However, once more the portfolio can be refined to exclude these loans. Social housing is not defined in the ESRB Recommendation, however, it is commonly understood as real estate owned by the state or non-profit organisations which is rented to provide affordable housing. As a result, these loans can be identified as i) loans granted to the general government or to a non-profit institutions serving households (NPISH), or as ii) loans secured by residential real estate property provided by the general government or by a NPISH. These categories can be identified in AnaCredit by means of the institutional sector of the debtor and protection provider of the loans.

The portfolio of loans defined so far may still diverge from the CRE loans portfolio defined in the ESRB recommendation as it may include loans aimed at acquiring property owned by end-users which is not income-producing real estate or secured by such property, and which are excluded from the definition of CRE loans. The identification of such loans can only be approximate in AnaCredit, and a new property would be needed to identify this category. A proposed approach to identify these loans under the current AnaCredit specification would be to exclude loans granted to debtors in economic sectors of activity which are not expected to acquire income-producing commercial real estate and which are secured by commercial immovable property.

While a perfect matching of CRE loans defined in the ESRB Recommendation is not possible with the current definitions, a better approximation of CRE loans can be achieved by combining additional AnaCredit data. It remains to be assessed, once data is available, to which extent the proposed mapping would cover the CRE loan market defined in the ESRB Recommendation, also taking into account the differences in scope indicated before. Similarly, residential real estate loans will be covered in AnaCredit when and if the scope of borrowers is extended to natural persons, but currently does not provide information for this segment.

4 In case natural persons are included in a future stage, natural persons and legal entities will be distinguishable in AnaCredit on the basis of the attribute 'legal form' of the counterparty.

5 ‘Buy-to-let housing’ means any RRE directly owned by a private household primarily for letting to tenants.

The indicators defined in the ESRB Recommendation can be broken down into a set of variables needed for their calculation. We propose a mapping of AnaCredit attributes to calculate the variables used in the indicators proposed in the ESRB Recommendation:

- Current lending: this variable is accurately captured by the attribute 'outstanding nominal amount' at each reference date.

- Lending at origination: the mapping requires distinguishing loans which may have a loan commitment associated to them (e.g. credit line) from those which do not. For the latter, this variable is correctly captured by the 'commitment amount at inception'. When the instrument allows for a loan commitment, the variable can only be estimated by the attributes 'commitment amount at inception' and 'off-balance sheet amount'. These values can be further refined for loans granted after AnaCredit goes live in September 2018 by using the 'outstanding nominal amount' at the first reference date after the loan was originated.

- Current property value: an accurate mapping using the attributes 'protection value' and 'type of protection' to distinguish real estate collateral.

- Property value at origination: this variable can be accurately mapped by the attributes 'original protection value' and 'type of protection'.

- Loan service at origination: an estimate can be calculated on the basis of the 'interest rate', 'amortisation type' and the history of 'outstanding nominal amount' and 'accrued interest' reported.

- Total debt: out of scope

- Debt service: out of scope

- Disposable income at origination: out of scope (this variable is related to natural persons which are not in the scope of AnaCredit).

- Maturity at origination: this value can be accurately mapped by the attributes 'settlement date' and 'legal final maturity date'.

- Non-performing loans: this value can be accurately mapped by the attribute 'performing status of the instrument'.

- Loan-loss provisions: this value can be accurately mapped by the attribute 'accumulated impairment amount'.

- Loans in foreign currency: mapped by the attribute currency

The ESRB Recommendation also proposes a series of breakdowns which are partially available in AnaCredit.

- Buy-to-let: Out of scope (this variable is related to natural persons which are not in the scope of AnaCredit).

- Owner-occupied: Out of scope (this variable is related to natural persons which are not in the scope of AnaCredit).
- First time buyers: Out of scope (this variable is related to natural persons which are not in the scope of AnaCredit).
- Fully amortising / partially amortising: the attribute 'amortisation type' allows identifying the combination of these two categories. However, the separation of the two categories can only be estimated.
- Non-amortising: this value can be accurately mapped by the attribute 'end date of interest-only period'.
- Initial interest rate fixation period: this value can be accurately mapped by 'initial interest rate fixation period'.
- Renegotiation: this value can be accurately mapped by 'status of forbearance and renegotiation'.
- Property type: this value can be accurately mapped by 'type of protection'. However, one-to-one mapping is not available. Coarser categories have to be used (ESRB: office, retail, industrial, and other are mapped to CRE in AnaCredit and residential to RRE).
- Property location: this value can be accurately mapped by 'real estate collateral location'.
- Lender / investor type: this value can be accurately mapped by 'economic activity'.
- Lender / investor nationality: this value can be accurately mapped by 'address: country'.
- Property under development: this value can be estimated using the attribute 'purpose' with the value 'construction investment'.

The ESRB proposes the presentation of the distribution of some indicators on the basis of a fixed set of categories (e.g. 8 categories used for the maturity at origination of RRE loans). The use of AnaCredit data enables the calculation of the complete univariate distribution of any indicator calculated across the whole population or a specific subset of the population. Once the complete distribution is calculated, the user may choose to define different categories (e.g. percentiles) to describe its different areas or define statistics (e.g. standard deviation).

Moreover, the ESRB Recommendation also proposes joint distributions of indicators. In this area AnaCredit proves to be of great value as it allows the combination of as many indicators or variables as the user considers relevant for the analysis without pre-specifying any of those. Due to the potential exponential growth of indicators by combining different variables, the ESRB restricts the combination of indicators to two indicators (see for instance the joint distribution of loan-to-value vs. loan-service-to-income proposed in the ESRB Recommendation).

The ESRB Recommendation proposes two different data types to register their indicators, flows and stocks depending on the indicator. Stocks are directly captured in AnaCredit. As regards flows, the ESRB definition can be accurately matched in AnaCredit by using the attribute status of forbearance and renegotiation. AnaCredit makes no distinction and all indicators created can be defined in terms of stocks and flows without the need to make a distinction on the basis of the indicator. Moreover, the ESRB Recommendation contains three different indicator metrics, namely amount in national currency, number of contracts and average. The use of granular data to define metrics also proves to be more than sufficient as not only these three different metrics can be computed, but many others depending on the focus of the analysis.

The main purpose of this comparison is not to merely identify the loans in scope of for the ESRB Recommendation, but to stress the value of granular data in order to capture specific financial phenomena. Different users of credit data may require specific definitions which are costly to implement. This analysis shows that it is worth considering capturing the main elements of the financial intermediation and combining them in different ways to match the economic phenomena that are needed for analysis. On the other hand, this shows that an adequate exploitation of AnaCredit data requires a significant level of knowledge of the AnaCredit data model and the attributes and values therein.

4. Exploring indicators from the top down

The value of AnaCredit for macroprudential analysis does not only stem from the enhancement to track existing indicators or define new indicators, but also from exploring the economic phenomena highlighted by these indicators in more detail.

In practice, this inductive approach involves several steps. First, indicators are selected at highly aggregated levels. After identifying indicators of interest, the analyst may decide to delve into a particular indicator for one specific country for which the indicator shows particularly high potential risk. Focusing on one country, the analyst can look further at, for example, the distribution of the indicator across the population of credit institutions of the particular country at both group and individual level. The definition of the distribution allows the analyst to focus on the counterparties which concentrate the highest risk revealed by the indicator. The analyst may also abstract from the less risky counterparties and aim attention at the counterparties that pose the highest systemic risk.

A single indicator may only be a part of the puzzle and the user may need to quantify multiple indicators in combination. AnaCredit individual and granular information enables the user to calculate the matrix of correlations among different indicators which may allow the identification of relationships among different sources of risk that may otherwise go unobserved.

The identification of intra-group links on the basis of ownership relationships and inter-group connections due to inter-MFI transactions registered in AnaCredit allows the identification of networks. The identification and measurement of these connections enables the users to quantify how the identified risks may spread in the financial sector. This information may be of significant relevance for stress test exercises which can be enriched with contagion effects.

This represents only one way of how indicators can be explored from the top down with AnaCredit data.

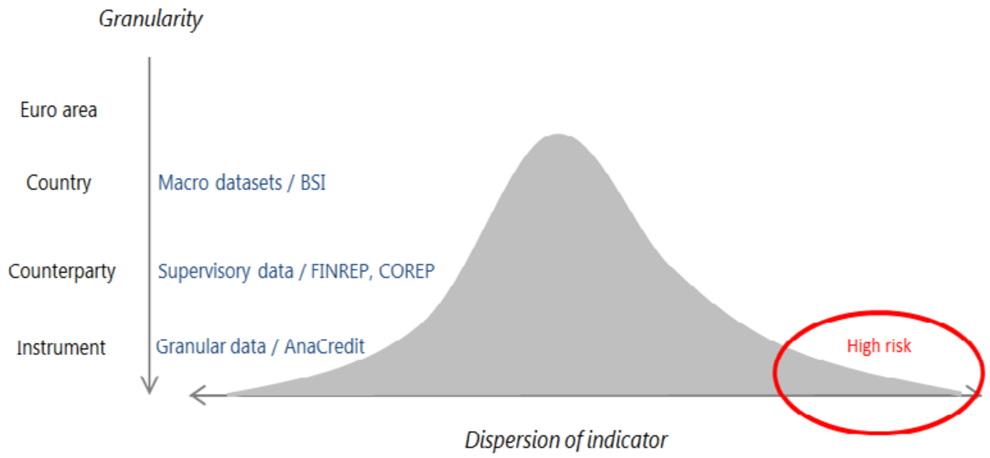


Figure 3. Granular datasets such as AnaCredit provide a zoom lens that can reveal specific instruments that generate the highest risk for the system as a whole. These sources of risk are often invisible when data is only available on an aggregate level.

More concretely, the analysis could focus, for example, on the indicator loan-to-value ratio. Depending on the purposes of the analysis, the definitions for the concepts of loan and value might be different. Using AnaCredit data, the amount of the loan may be calculated with the attribute 'outstanding nominal amount' when the focus lies on financial intermediation, or the 'carrying amount' when the interest lies on the credit risk for which the credit institution is currently exposed to. Similarly, the underlying value of the protection may be calculated in different ways depending on the target of the analysis, whether the assessment of the credit institution represented in the 'protection allocated value', or the maximum value of the protection that could be used to secure the instrument, which can be derived on the basis of the 'protection value' and the set of instruments secured by the protection.

Furthermore, the loan-to-value may be restricted to specific types of protections, e.g. real estate collateral, or take a more holistic view. Another relevant dimension that matters for the definition of loan-to-value ratios is the moment in time.

Also, if the analysis lies on the decision process of economic agents, it is of relevance to compute these indicators at the time when the decision was taken, i.e. at origination. However, if the analysis focuses on the status and evolution of the financial intermediation and the risks involved, then the current and historical values will be needed. AnaCredit allows both types of analysis as, in addition for the values to be reported for each reference date, AnaCredit also includes the main metrics at origination.

This breadth of options demonstrates the flexibility of using AnaCredit to conduct multiple types of analyses as it is evident from the use of different attributes to properly define the indicators that best represent the object of analysis. AnaCredit empowers the user providing the necessary data for her to take the final decision on what should be the adequate metric to be calculated.

Given a specified definition of the loan-to-value ratio, the AnaCredit user can decide in a flexible manner on the focus of the analysis. It might be sensible to focus on specific groups of entities, e.g. banking/corporate groups or SMEs. Alternatively, analysis may focus on the location of the creditor, the debtor or the real estate collateral securing a loan. Another perspective within the realm of AnaCredit would be to focus on the performance of instruments, e.g. to look at loan-to-value ratios specifically for non-performing instruments or counterparties. The benefit of the flexibility of the granular database is precisely that the user does not necessarily need pre-defined assumptions, but can instead let the data speak for itself given the various available dimensions and possibilities for combinations.

In the particular example of the loan-to-value ratio that the analyst might wish to explore, investigating the distribution of the indicator would be highly informative for financial stability purposes. AnaCredit allows the analyst to look at the distribution of the loan-to-value ratio across nearly the entire population. This reveals the degree of dispersion as well as those entities or portfolios with the highest loan-to-value ratios. More advanced analysis could involve the inclusion of more indicators and looking at the joint distributions. Valuable information may also be contained in correlations of loan-to-value ratios with, for example, non-performing loans.

Overall, drilling down from aggregate indicators at Euro Area or country level down to the level of the instrument has many benefits. It is the inductive, data-driven approach that will allow users to make maximum use of the information value of AnaCredit. This perspective underlines the potential of AnaCredit not only to provide macroprudential analysis with more detailed information, but also to allow analysts to see risks that would otherwise remain hidden.

5. Future enhancements

The AnaCredit Regulation sets up the first stage of AnaCredit and contains reflections on possible future enhancements in the recitals. Although each new reporting requirement would be subject to a dedicated merits and costs exercise according to standard practice within the ESCB, the Regulation explicitly mentions the following envisaged extensions:

- a reassessment of national discretion with respect to granting derogations for small reporting agents (Recital 11)
- an extension of the reporting population to non-deposit-taking institutions and other financial corporations in later stages to deposit-taking

corporations other than credit institutions, asset management vehicles and other financial corporations (Recital 12)

- an extension of the instruments to be reported to derivatives, other accounts receivable, off-balance-sheet items (such as financial guarantees) and credit extended to persons other than legal persons, including to sole proprietors (Recital 12)

- the requirement to report on a consolidated basis (Recital 12).

For our purposes, we will focus on four particular possible extensions. Firstly, the interoperability between AnaCredit and other databases could be enhanced. The connection of AnaCredit with other granular databases such as the Securities Holdings Statistics Database (SHSDB) and the Centralised Securities Database (CSDB) would significantly enhance the information value for macroprudential analysis. Moreover, connecting AnaCredit to other databases with data on the individual level would allow for an even broader perspective. This could include the iBSI, as well as FINREP and COREP data.

Secondly, AnaCredit could be extended by adding attributes on - or facilitating a connection to – complete balance sheet data of legal entities. This would allow inter alia a comprehensive view of the risks taken by banks. Analysis of credit intermediation would be enhanced by data on the sources of finance and leverage of the lenders. Assessing the total indebtedness of borrowers would furthermore require including data on off-balance sheet items such as loan commitments and guarantees as well as derivatives.

Thirdly, Regulation (EC) 2533/98 requires that the ESCB uses confidential statistical information, including AnaCredit, exclusively for the exercise of the tasks of the ESCB. The granular data will therefore not be accessible for the general public except for scientific research bodies which may be granted access provided the identification of counterparties is not possible. However, market participants may adopt the AnaCredit data model to collect granular credit and credit risk data and establish market-led initiatives for the sharing of granular data for other purposes.

Finally, enlarging the scope of AnaCredit would further enhance the flexibility of the database for financial stability purposes. In particular, there is a need for macroprudential policy to focus increasingly on shadow banking, i.e. banking activity conducted by non-banks (Constâncio, 2017). As demonstrated in the case study, other relevant counterparties include, for example, natural persons. This group represents a significant part of banks' portfolios. Additionally, the analysis of banks' exposures to households via deposits and mortgages is an important source of systemic risk that could be analysed in case natural persons are included in the scope of AnaCredit in the future.

6. Conclusion

Granular data captures the behaviour of economic agents closer to reality than traditional aggregate datasets. By modelling individual elements of the economy and explicitly taking into account the interaction between agents these novel databases provide new insights that can be used to enhance current analysis and to define new indicators for financial stability purposes and beyond.

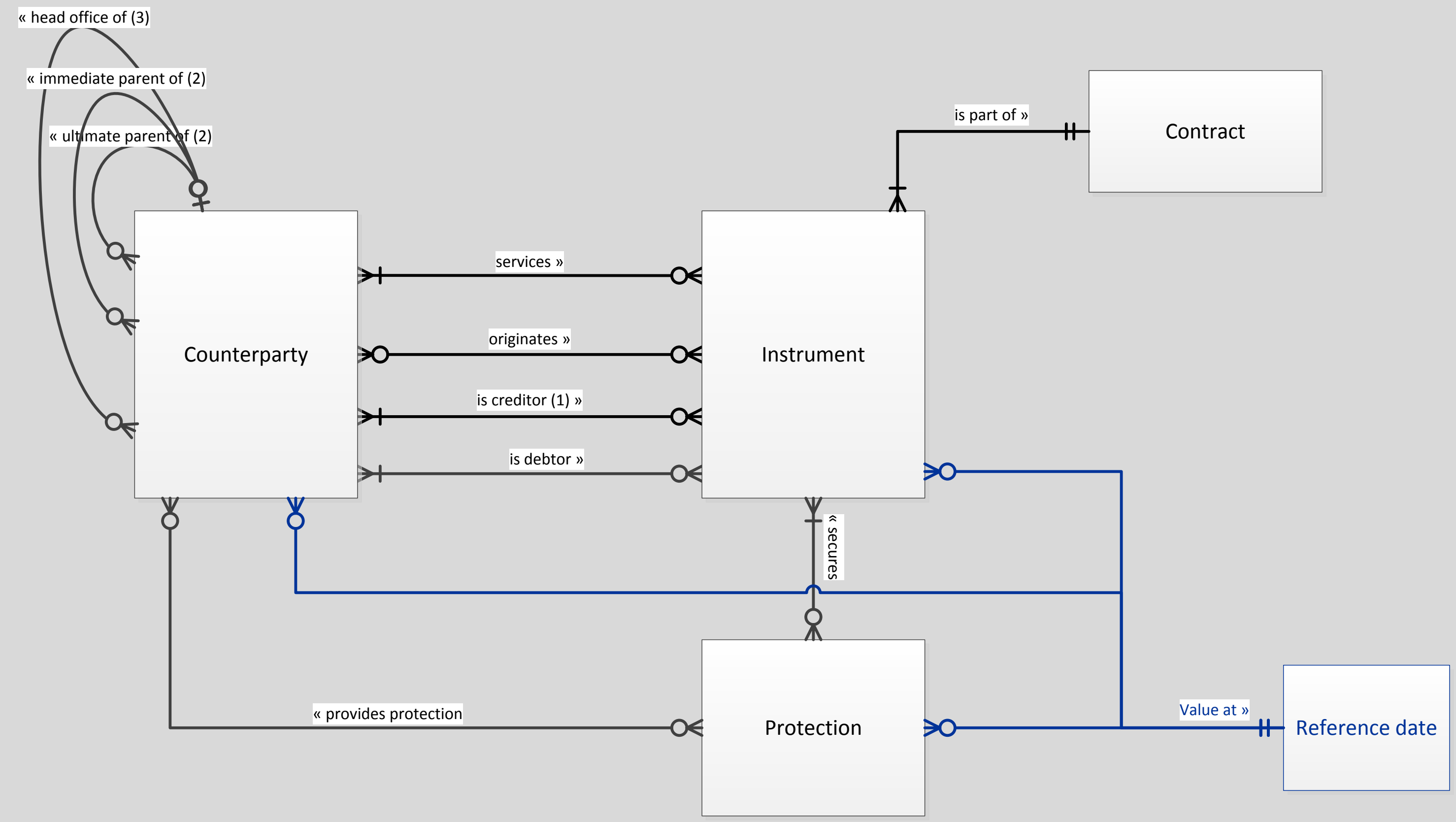
AnaCredit is an example of a granular database for credit intermediation, modelling credit on the basis of its main elements: instruments, counterparties and protection. The user of AnaCredit data can identify connections between these elements and conduct analyses at various levels, from the instrument and counterparty levels up to the aggregate for the Euro Area as a whole (bottom-up). In addition, high-level indicators previously available only as average figures can be analysed from the top-down without pre-defined assumptions.

Hence, macroprudential analysis can benefit from AnaCredit data in three ways. Firstly, it provides a higher level of detail to analyse credit intermediation at various levels. Secondly, networks of counterparties can be traced and constructed based on various dimensions. Thirdly, full distributions of indicators across nearly the whole population can be viewed and analysed.

As the case study of real estate data gaps has shown, granular data alleviates to a large extent the difficulty of having different definitions in different datasets. Indicators on loans, for example, might use varying definitions of a loan itself. The granularity of AnaCredit helps to overcome different definitions as they can be reconstructed by combining certain data attributes.

Ultimately, many indicators for financial stability purposes can be constructed with AnaCredit data. Not only will decision-makers have a more sophisticated view of credit intermediation, but also the effectiveness of policy tools might be enhanced as they can be used in a more targeted manner.

Annex 1: AnaCredit conceptual data model



Colours used in the diagram:

Main entities in the reporting and their relationships

Entities related to the reference date and their relationships

Symbols:

0..1

1

0..n

1..n

Minimum and maximum cardinality in the relationship

Notes:

(1) The observed agent, when reported as creditor, assumes the non-transferred risk. Any other creditor reported for an instrument assumes the amount reported as transferred risk.

(2) Only applies to debtors and protection providers

(3) Only applies to foreign branches, being debtors or protection providers

Bibliography

Constâncio, V. (2017, May 11). Macroprudential policy in a changing financial system (speech). Frankfurt am Main, Germany.

European Central Bank. (2016). Regulation (EU) 2016/ 867 of the European Central Bank - of 18 May 2016 - on the collection of granular credit and credit risk data (ECB/ 2016/ 13). *Official Journal of the European Union*.

European Central Bank. (2017). *AnaCredit Reporting Manual. Part I - General Methodology*. Frankfurt: European Central Bank.

European Central Bank. (2017). *AnaCredit Reporting Manual. Part II - Datasets and data attributes*. Frankfurt: European Central Bank.

European Systemic Risk Board. (2016). Recommendation of the European Systemic Risk Board of 31 October 2016 on closing real estate data gaps (ESRB/2016/14). *Official Journal of the European Union*.

Israël, J.-M., Damia, V., Bonci, R., & Watfe, G. (2017). The Analytical Credit Dataset - A magnifying glass for analysing credit. *ECB Occasional Paper Series*(187), 1-41.

Neudorfer, P. (2016). Multiple usage of the ESCB 'Register of Institutions and Affiliates Database' (RIAD) - features and challenges. *25th Meeting of the Wiesbaden Group on Business Registers*, (pp. 1-10). Tokyo.

Thijs, S., & Corvoisier, S. (2017). Integrating reference data for monetary policy and supervisory purposes - The European System of Central Banks (ESCB) experience. *IFC Bulletin. 43*, pp. 1-12. Basel: Bank for International Settlements.

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BANK FOR INTERNATIONAL SETTLEMENTS

IFC-National Bank of Belgium Workshop on "*Data needs and Statistics compilation for macroprudential analysis*"

Brussels, Belgium, 18-19 May 2017

AnaCredit: From broad to flexible macroprudential analysis [1]

Orestes Collazo Brananova and Gibran Watfe,

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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EUROSYSTEM

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Brussels, 19 May 2017

Disclaimer: The views expressed are those of the authors and do not necessarily reflect those of the ECB.

Contents

Granular data for macroprudential supervision

Past

Broad approach

- Aggregate indicators
- Constrained by *static definitions* and *complex relationships* between agents

Future

Top-down and bottom-up approaches with three advantages:

1. **Detail**: flexible definition of *indicators* (with back-casting) and calibration and *estimation of models*
2. **Networks**: *concentration of risk* and *contagion effects*
3. **Distributions**: rich analysis of the complete population with simulations

AnaCredit Data Model: representing reality

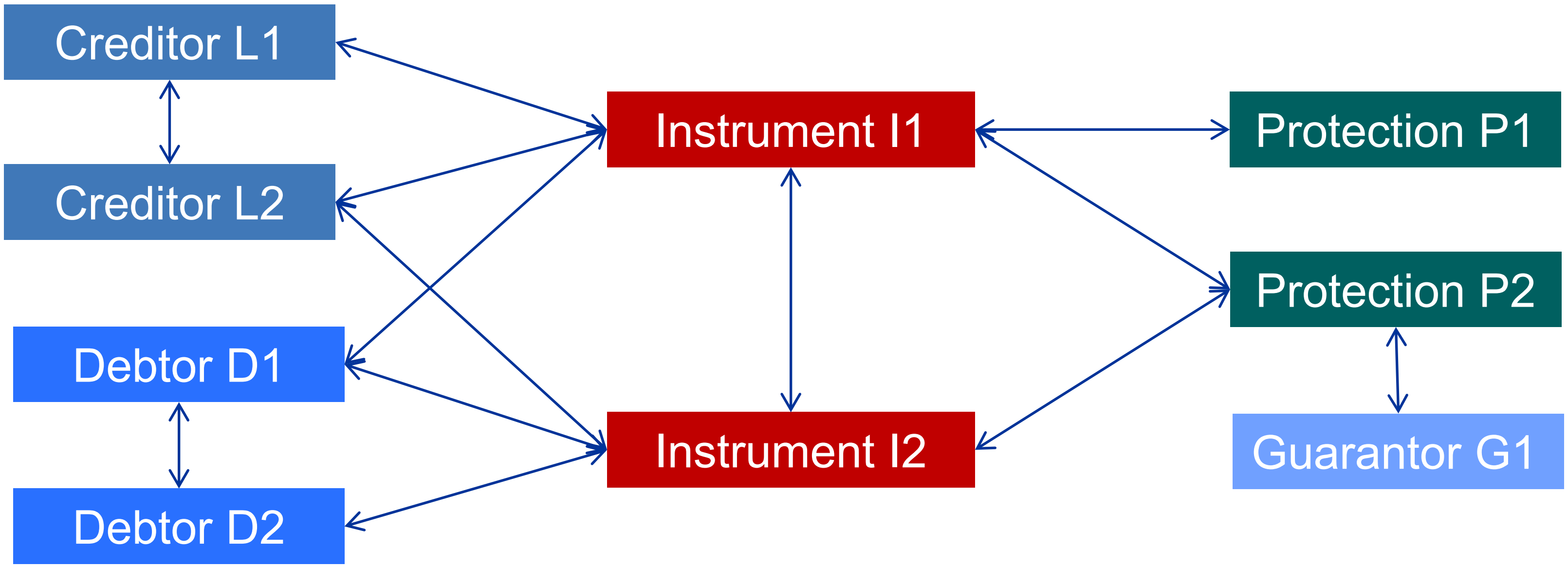
Financial intermediation is complex

- ***Instruments*** Multipurpose contracts
- ***Counterparties*** Creditor, debtor, protection provider, etc.
- ***Protection*** Collaterals and guarantees
- ***Relationships*** Banking groups / corporate groups

  Syndicated loans / joint debtors

  Umbrella contracts

  n-to-m instrument-collateral relationships



AnaCredit scope

AnaCredit Regulation (EU) 2016/867 adopted ***18 May 2016***

AnaCredit go-live: ***September 2018***

- Reporting population: credit institutions
  - Resident in the euro area
  - Includes all foreign branches
- Counterparties:
  - Creditors: credit institutions & other sectors (for loans serviced by CI)
  - Debtors: legal entities (including Government)
- Instruments (assets): loans (including inter MFI positions)
  - Serviced or held
- Threshold (creditor-debtor): EUR 25,000

88 attributes to assess credit intermediation

- Counterparties: → *Who is who?*
  - Identification of creditors and debtors
  - Characterisation: e.g. size, sector of economic activity
- Balance sheet status → *What?*
  - Classify exposures by type (e.g. type of product) and use (e.g. securitisation)
  - Needed for internal consistency: avoid double counting (e.g. joint liabilities)
- Exposure features → *What (in greater detail)?*
  - Classify the exposures for analytical purposes (e.g. maturity, interest rate)
- Risk measure → *Will it happen?*
  - Provide a forward-looking view (e.g. probability of default)
- Loss measure → *What would happen?*
  - Provide a backward-looking view (e.g. accumulated impairments)
- Valuation → *How much?*
  - Book values, nominal values, market values

AnaCredit for macroprudential analysis – use cases

➢ Four indicative use cases

\+ Examples for AnaCredit attributes that may be relevant

Concentration of risk

- Head office/immediate/ultimate parent identifiers
- Address: country
- Economic activity
- Outstanding nominal amount

Contagion

- Outstanding nominal amount
- Type of securitisation
- Type of protection
- Protection value

Level of exposure

- Enterprise size
- Outstanding nominal amount
- Off-balance sheet amount
- Probability of default

Losses

- Legal final maturity date
- Settlement date
- Arrears for the instrument
- Accumulated impairment amount

AnaCredit networks – counterparty relationships

- Banking groups
  - Pseudo-consolidation
  - Different levels of banking groups (e.g. national level, EU level)
  - Syndicated loans
- Corporate groups
- Location
- Sectors of activity
  - Institutional sector
  - NACE level 3
- Contagion
  - Inter MFI positions
  - Unique identification of counterparties
  - Banks with similar business models
- Extensibility via RIAD*

* RIAD: Register of Institutions and Affiliates Database

AnaCredit distributions

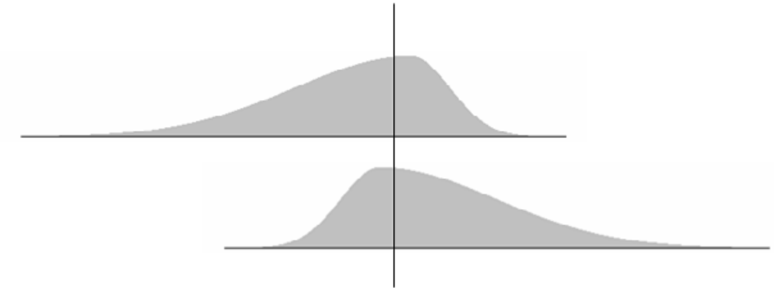
- Individual information
- Near complete population

→ Building the full distribution for all entities

- Describing the complete population
  - Average (traditional)
  - Additional descriptive statistics for the population
    - + Central tendency
    - + Dispersion
    - + Concentrations

→ e.g. focus on the tail
(entities that accumulate risk)

- Combining indicators
  - Loan-to-value - NPL ratio - bank size
  - Correlations



Case study: ESRB Real Estate Indicators

- Based on ESRB Recommendation (ESRB/2016/14)
- Two main loan portfolios: CRE* and RRE** loans
  - Different definitions of CRE and RRE
  - Combination of granular data allows for multiple definitions
  - Large reconciliation possible with current information
- Coverage:
  - CRE loans are captured (missing loans to natural persons for RRE)
  - Large coverage of main variables required to calculate the indicators
  - Many of the proposed breakdowns
  - All required distributions, indicator metrics and data types (flow/stock)
- AnaCredit allows analysing in detail the portfolio of CRE loans
  - Large set of indicators
  - Correlation with other indicators
  - Ex-post definition of indicators – not constrained to a fixed template

* CRE: Commercial real estate

** RRE: Residential real estate

Case study: ESRB Real Estate Indicators - CRE

ESRB indicator concepts	AnaCredit mapping
Lending – current	Outstanding nominal amount
Lending – at origination	Commitment amount at inception, off-balance sheet amount (requires estimate for credit lines)
Property value – current	Protection value, type of collateral
Property value – at origination	Original protection value, type of collateral
Maturity – at origination	Settlement date, legal final maturity date
Investment in CRE	Out of scope
Non-performing loans	Performing status of the instrument
Loan-loss provisions	Accumulated impairment

ESRB break downs	AnaCredit mapping
Property type	Type of protection (less detail in AnaCredit)
Property location	Real estate collateral location (Analyst must identify prime locations)
Lender type	Economic activity
Lender nationality	Address: country
Investor type	Economic activity
Lender nationality	Address: country
Property under development	Purpose with the value Construction investment

Exploring indicators from the top down

- Loan-to-value
- Different definitions can be specified
  - What is a loan? (outstanding amount, carrying amount?)
  - What is value? (protection value, amount of protection that secures the loan?)
    - + By type of protection: Financial / real estate / other
  - What time? (current, origination?)
- Defined at loan level –
  Focus of analysis can be defined ex-post based on available details:
  - Groups of entities
  - Location (creditor, debtor, real estate)
  - Performance
- Distribution
  - Focus on the least secured (highest loan-to-value) entities/portfolios
    - + Tail of the distribution
  - Joint distribution
    - + Correlation with other relevant indicators, e.g. non-performing loans

Future extensions

- Combine with information from other datasets
  - Granular data (SHSDB, CSDB)
  - Individual basis (e.g. iBSI, FINREP, COREP)
- Complete balance sheet*
  - Comprehensive view of risks taken by the bank
    - + Off-balance sheet items, e.g. loan commitments, guarantees provided
    - + Derivatives
  - Sources of finance and leverage
- Enlarge the scope*
  - Shadow banking
  - Other relevant counterparties, e.g. natural persons

* Not planned, based on user needs

Conclusion

- Granular data captures the behaviour of economic agents closer to reality

- Macroprudential analysis can benefit in particular from
  - The higher level of *detail*
  - The ability to trace and construct *networks of counterparties*
  - The possibility to analyse full *distributions* of indicators

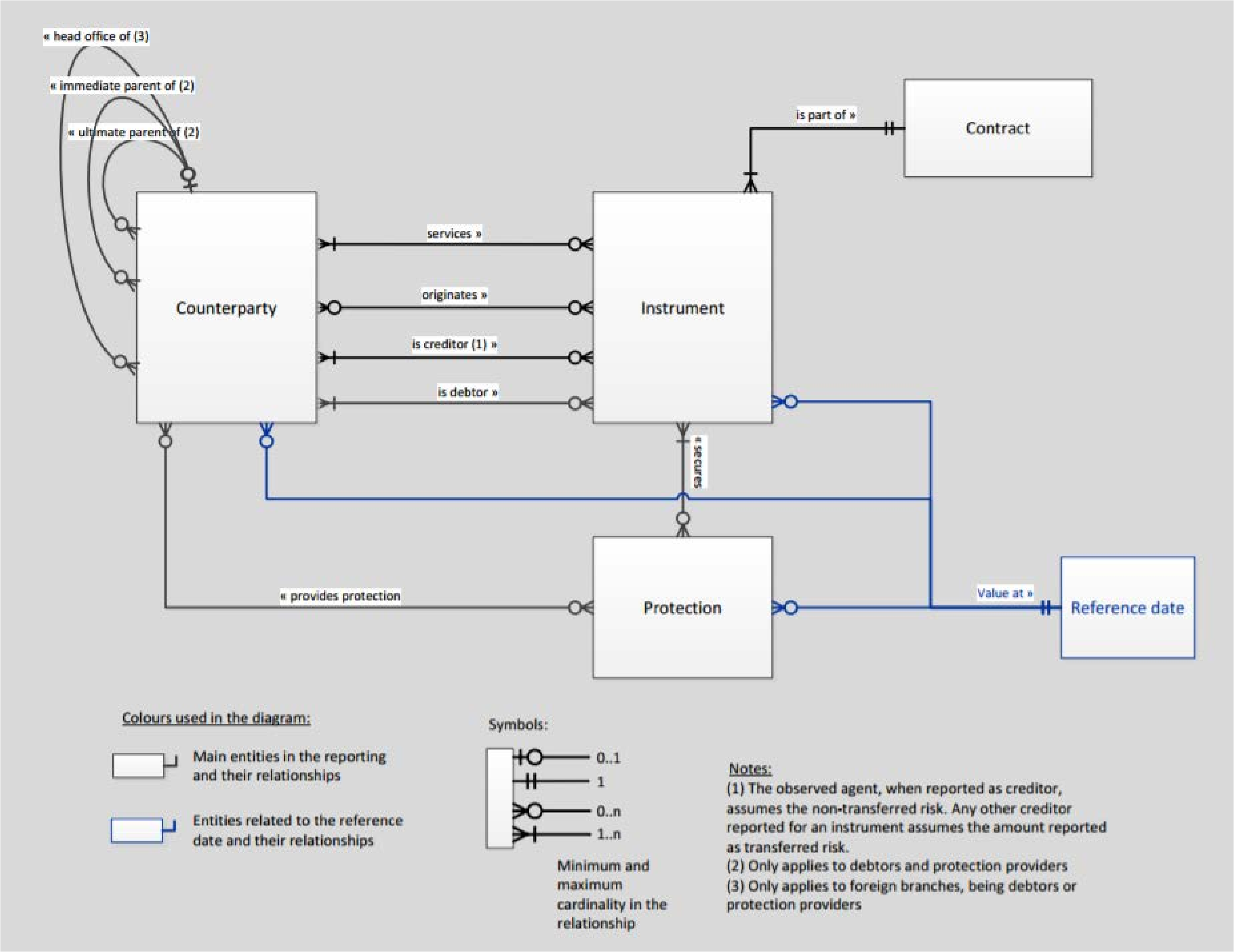
- Granular data alleviates discrepancy between different definitions

- Many economic & financial indicators can be constructed with AnaCredit
  - Drill-downs and distributions provide important *insights for analysis* where averages are insufficient and dispersion measures are needed

Annexes

AnaCredit data model: representing reality

Conceptual model



Logical data model

- 6 entity tables with one or more datasets each

Instrument entity table
instrument data, financial data, accounting data

Protection entity table
protection received data

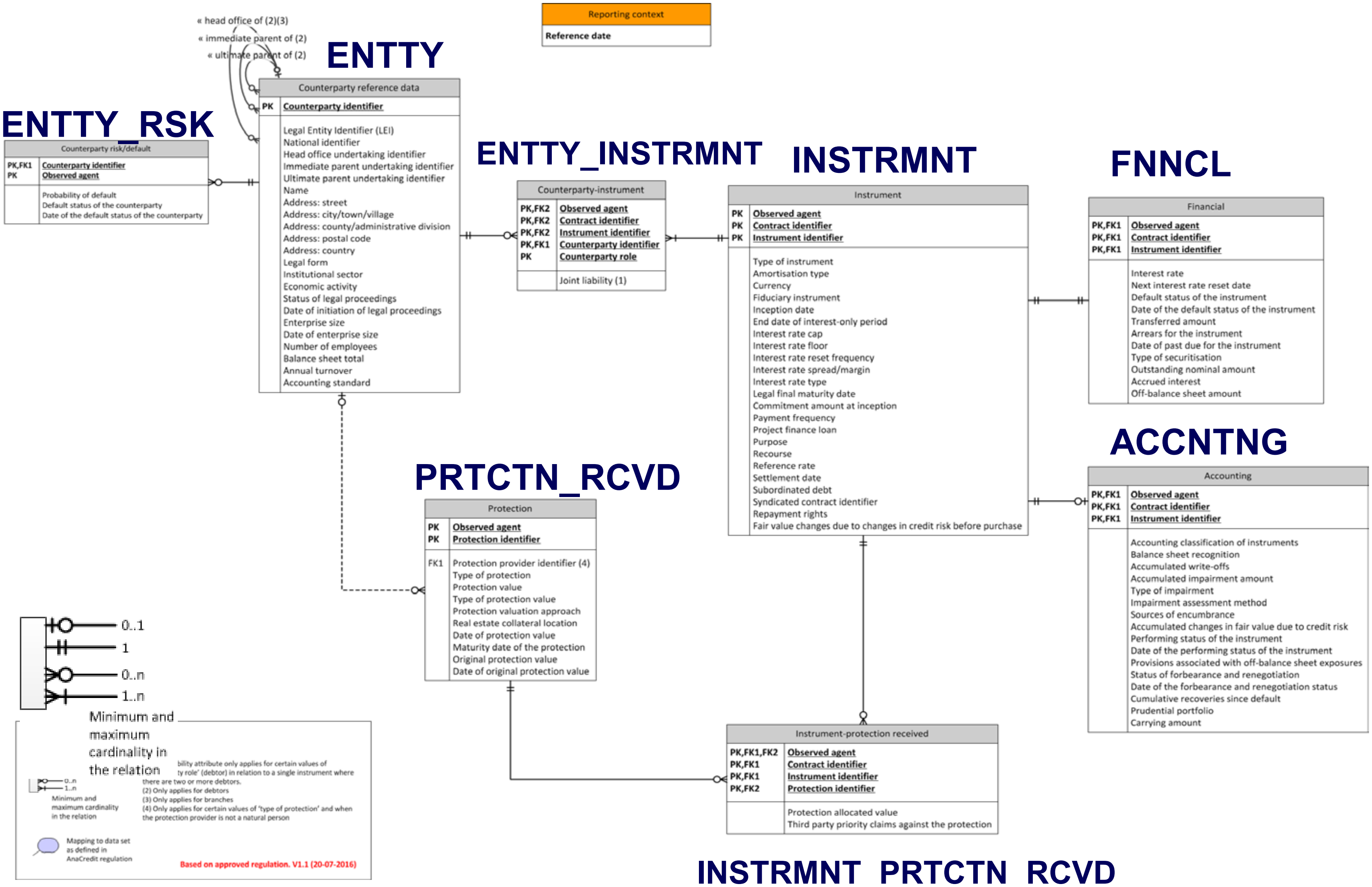
Instrument-protection received entity table
instrument-protection received data

Counterparty reference data entity table
counterparty reference data

Counterparty risk/default entity table
counterparty risk data, counterparty default data

Counterparty-instrument entity table
counterparty-instrument data,
joint liabilities data

Logical data model



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Non-financial sector's foreign exchange risk: new project of foreign exchange position monitoring system in Turkey[1]

Oya Gençay,
Central Bank of the Republic of Turkey

[1] This paper 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.

Non-Financial Sector's Foreign Exchange Risk: New Project of Foreign Exchange Position Monitoring System in Turkey[1]

Oya Gençay[2]

Abstract

Non-financial sector's net foreign exchange (FX) open position has risen gradually in Turkey since 2003. Despite the fact that the sector has a high open FX position on aggregate, natural and financial hedge management of firms are not at desired levels. As Turkish Lira (TL) depreciates, balance sheets worsen, which in turn threaten the financial sector, and the whole economy from counterparty and systemic risk perspective. At the Central Bank of The Republic of Turkey (CBRT), a new system that collects net FX and hedging positions of real sector firms is going to be established. One of the expected benefits of the project is to identify risky firms and sectors, i.e. those firms with unhedged open FX positions. This will also allow introducing regulations that would penalize unhedged open FX position and/or promote hedging with financial instruments, if necessary. This study discusses FX position reporting details and potential benefits of the new project from a macro-prudential perspective.

Keywords: credit registry data, net FX open position, FX risk of non-financial sector, hedging positions of real sector firms, natural hedge

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Contents

1. Introduction

The purpose of this paper is to analyze FX position of non-financial corporations (NFCs) in Turkey and present a new project which aims to monitor the FX position of those firms. In the paper, previous and current FX position of non-financial firms in Turkey and studies related to FX position are discussed. After giving an introduction about the general scope of the project, details of the project is discussed.

In Turkey, non-financial firms can hold FX or FX-indexed loans with some limitations. They can get loan from domestic banks or foreign banks directly or through domestic banks. According to Resolution 32 on Protection of Turkish Currency Value, firms without FX revenue are allowed to use FX loan over US$5 million and with at least 1 year average term. FX indexed loans on the other hand can be used for trade and professional purposes. This funding opportunity may result sudden increase in FX open position for the NFCs in case of FX rate fluctuations.

Both positive global trends in value of USD and inflation data resulted in higher USD/TL value between September 2016 and January 2017. In addition to that, geopolitical risks and downgraded rating of Turkey contributed depreciation of TL in this period. As a result, adverse signals started to come out of companies that had open position. This issue has come to the fore in the Financial Stability Committee which turned into «Systemic Risk Data Monitoring Model» and after couple of meetings with public authorities, the project was decided to be run by the Central Bank for the time being. Currently, the determination of the reporting details of the project has not finished yet, but a pilot period was run by Central Bank between April and June 2017.

In line with the developments in the international platform and the needs arising after the global crisis, the Financial Stability Committee, which is composed of the Undersecretary of Treasury and the Central Bank, Banking Regulation and Supervision Agency (BRSA), Capital Markets Board of Turkey (CMB) and Savings Deposit Insurance Fund (SDIF) Heads and whose main duties are monitoring and preventing systemic risk and ensuring the coordination of systemic risk management, has been established under the chairmanship of the Minister of the Treasury.

The duties of the committee are:

- To identify and monitor the systemic risks that may spread throughout the financial system and to propose the necessary measure and policies to reduce such risks,
- To make warnings about the systemic risks to the relevant units,
- To follow the applications related to warning and policy recommendations,
- To evaluate the systemic risk management plans to be prepared by the related institutions,
- To provide coordination regarding systemic risk management,
- Providing all kinds of data and information from public institutions and organizations in relation to the field of duty,
- Ensuring the coordination of policies and practices between institutions,
- Deciding on other issues authorized by legislation

It is a fact that the rapid increase in the FX rate has a significant negative effect on non-financial companies as well as financial sector. Monitoring and acknowledging non-financial sector in order to take required precautions have a huge positive role in preventing systemic crises and from financial stability perspective.

2. Existing Data Related to Open FX Position of Non-Financial Corporations under Turkish Credit Registry System and Central Bank

In this section of the paper, existing data related to FX position of non-financial companies is discussed in order to understand what the motivation behind the initiation of the new project was. It should be understood that currently we have some data related to analyze FX position of the real sector but some of them are not at the firm level. Even if we had all of the required data to calculate firms' open FX position, since different institutions own different part of the required data, compiling it from different institutions may result in mismatches or wrong results. Although it seems feasible, every institution has different regulations for the data content and description. In order to achieve consistency in firm based FX position data, ensuring the compilation of the data under one center is very important.

2.a. Dataset under Credit Registry

Credit registry in Turkey is run by The Banks Association of Turkey (BAT)-Risk Center. Banks Association of Turkey-Risk Center started its operation in June, 2013. Risk Center used to be run by CBRT from 1951 until the end of June 2013.

Risk Center is established as a part of the Banks Association of Turkey in order to gather risk information on customers of crediting institutions and other financial institutions that is approved by the Banking Regulation and Supervision Board, and to share such information with the said institutions and with natural persons or legal entities themselves or subject to prior consent thereof, with legal entities.[3] FX data gathered by BAT-Risk Center contains tax identification number, name of the firm, limit of the loan, maturity information, debt amount, sectoral codes (NACE Codes), type of the loan (cash, non-cash, non-performing, etc.), province and district code, financial institution's code and its name.

The BAT-Risk Center data covers all FX and FX indexed loans granted by domestic and foreign banks through domestic banks, but does not cover "direct external loans". And, this data by itself is not enough to calculate net FX position of NFCs as loans are just one component of liability side of a balance sheet. Additionally, limits and risk amounts within the scope of futures and options contracts and other similar contracts allocated to real and legal persons at banks are notified to Risk Center. However, derivative contracts between firms are not included in this dataset.

2.b. Dataset under the Central Bank of Turkey

According to the CBRT Law, it is authorized to collect data on economic issues and produce statistics by compiling and processing data. With the aim of monitoring the developments regarding real sector firms and providing the public with comprehensive and systematic information on the issue, the "Company Accounts" study has been prepared depending on the annual financial statements since 1990 with participation, cooperation and support of the real sector firms.

Balance sheets and income statements of enterprises on a solo basis prepared for corporate tax purposes in accordance with Tax Procedure Law of Turkey are used in the preparation of Company Accounts.[4]

[3] https://www.riskmerkezi.org

[4] Methodological Information on "Company Accounts Statistics", Statistics Department, Real Sector Data Division, http://www.tcmb.gov.tr

Despite of the annual information about FX loans in the balance sheets and income statements of the real sector firms, the total FX position of the real sector could not be reached due to the limited participation of these firms.

Regarding derivative transactions of the real sector firms aiming for the hedge of the on-balance sheet open position, banks report their customers' derivative operations on type and amount details to CBRT. However this dataset includes derivative transactions of the firms that subject to transaction only with banks over-the-counter and does not include all derivative agreements.

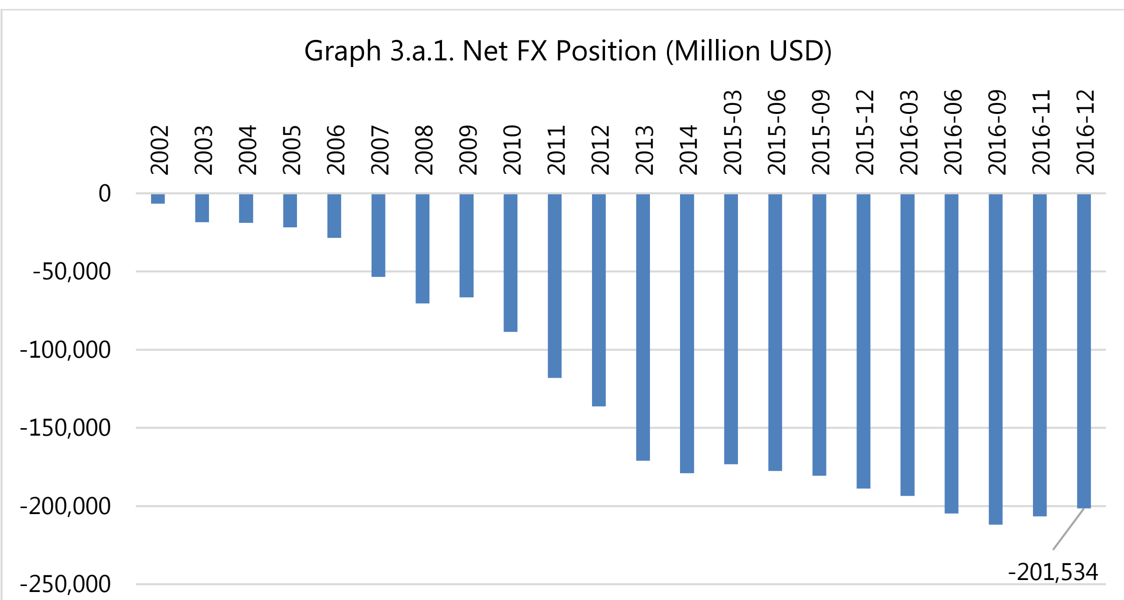
3. Net FX position of Non-Financial Sector in Turkey and Some Related Statistics

3.a. Net FX Position of Non-Financial Sector in Turkey

The net FX position could be defined as the difference between FX denominated assets and liabilities in the balance-sheet. As it shows the FX indebtedness of real sector, monitoring FX position is beneficial from macro-prudential perspective.

Turkey's non-financial firms' net FX position is probably the most cited risk factor recently. The main reason behind this concern is that the depreciation in TL would deteriorate balance sheets of NFCs which could result in mass bankruptcies.

During the last 10 years, the FX open position of non-financial corporations in Turkey has increased dramatically (Graph 3.a.1). As a result of the liability dollarization, total FX-denominated debts of non-financial firms in Turkey are much higher than their FX-denominated assets.[5] The reason for companies' fragility is not just borrowing in terms of foreign currency but the existence of open position due to income, asset and liability mismatch.[6]



Source: CBRT

[5] Hülagü and Yalçın (2014)

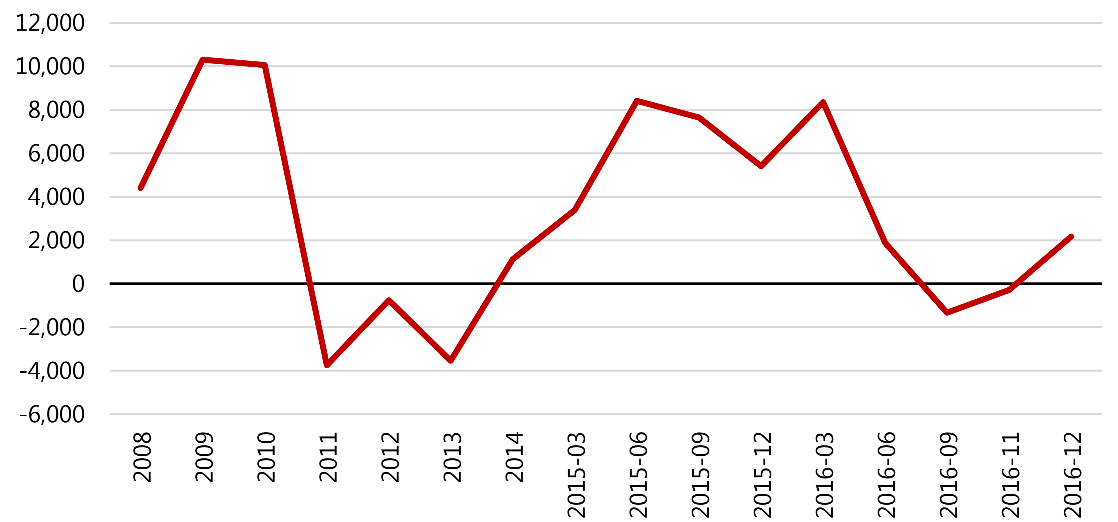
[6] Gençay (2007)

Net open FX position of non-financial companies in Turkey has reached to USD$201.5 Billion by the end of 2016. This open FX position has created some concerns in terms of macro-prudential perspective because of volatile exchange rates during the periods of uncertainty. Conversely, this mismatch could also make it possible for firms to grow at higher rates in normal times by easing the financial constraints of firms by serving the facility of borrowing in FX at longer maturity.[7] Besides past macroeconomic instability, due to the lack of financial depth for meeting the financial needs of them, non-financial corporations have intensely preferred to use FX loans in Turkey.[8] However, it should be kept in mind that high financial dollarization could result in a deeper economic crises.[9] As Krugman (1999) argued, the main reason behind the twin crises is open FX position in the real sector.

On the other hand, small firms without FX revenues could not accumulate debt in foreign currency according to current legislation on foreign currency loans in Turkey. Hence, firms with open FX position are generally large-scale firms either having a significant amount of export revenues or dealing with projects which have potential to generate FX revenues. This enhances the financial soundness of Turkey's real sector against FX fluctuations.

In contrast to ongoing negative net open FX position of non-financial corporations, short-term FX position of firms is positive. By December 2016, short-term FX position has reached over US$2 Billion (Graph 3.a.2). The fact that the short-term FX position is positive is an indicator in terms of the resistance of the firms to handle short-term currency shocks.[10]

Graph 3.a.2.Short Term Net FX Position (Million USD)



Source: CBRT

Özatay (2006) argues that good supervision of open FX position is very important. Non-financial companies need to be well-evaluated by the banks and only then loans should be granted. With the lack of open FX position supervision, rapid increases in exchange rate would disrupt balance sheets of firms and hence create a lower growth rate.

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[7] Hülagü and Yalçın (2014)

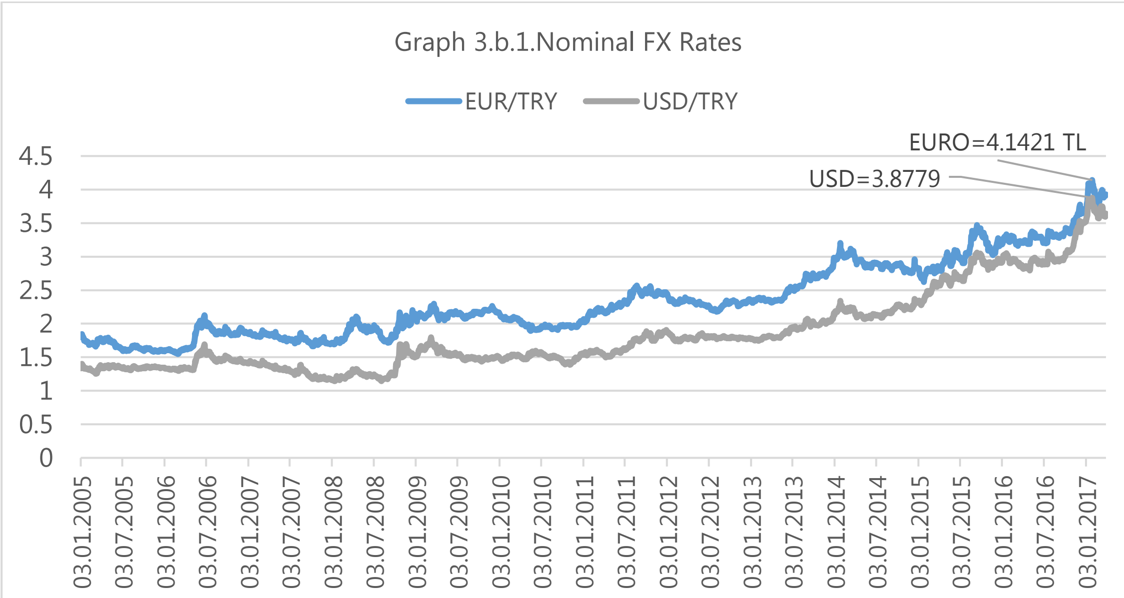
[8] Alp and Yalçın (2015)

[9] Rennhack and Nozaki (2006)

[10] Financial Stability Report, November 2016.

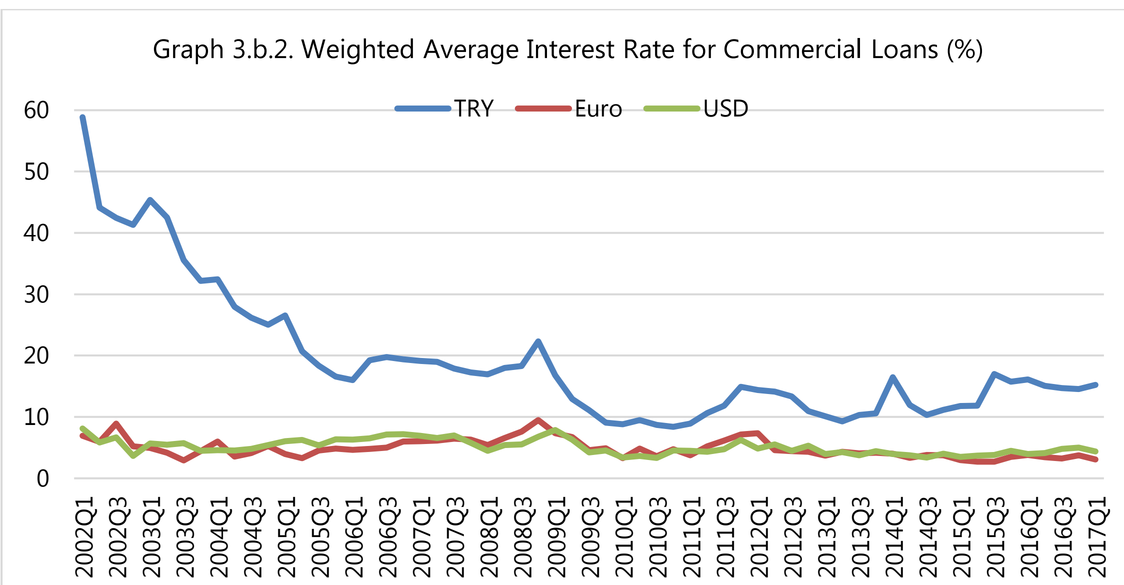
3.b. FX Rates and Weighted Average Interest Rates for Commercial FX Loans

In addition to the volatility in international markets, both geopolitical tensions and domestic uncertainties resulted in exchange rates in Turkey to be affected more adversely compared to other emerging economies during the last quarter of 2016 and reached to historical record levels in January 2017 (Graph 3.b.1).



Source: CBRT, Last data: 30.03.2017

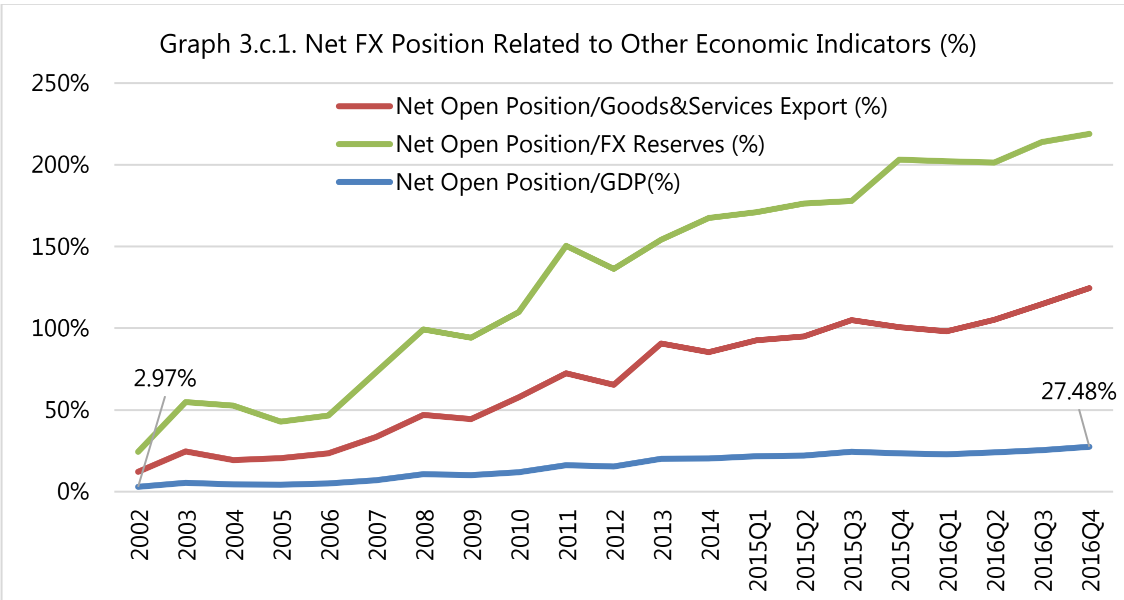
Progress in FX lending opportunities and lower interest rates of FX loans have been powerful motivations besides moderate exchange rate levels for firms to use FX loan in the past couple of years. Below weighted average interest rates of Euro and USD loans for commercial purposes are visualized (Graph 3.b.2). As it is seen from the graph, although the gap between TRY, EUR and USD interest rate lines narrows in time, TRY loan interest rate line never intersects with others. Another thing is that TRY line is always higher than those of other currencies.



Source: CBRT

3.c. Net FX Position Related to Other Economic Indicators

In order to better understand what the open position numbers mean in Turkey, net open position is compared to some macroeconomic indicators. Net open FX position in Turkey has reached to approximately 27% of GDP as end of 2016 due to the surge in FX debt stock. Export revenues provide natural hedge against FX fluctuations. Net open position to goods and services export ratio shows us to what extent open position can be covered by export revenue. It shows that export is not enough to cover open position as the ratio is around 120%. In the former years, natural hedge was high as the ratio was about 10%. Another ratio is open FX position to Central Bank gross FX reserves. This ratio also reached from 25% to 220% in the last 14 years (Graph 3.c.1).



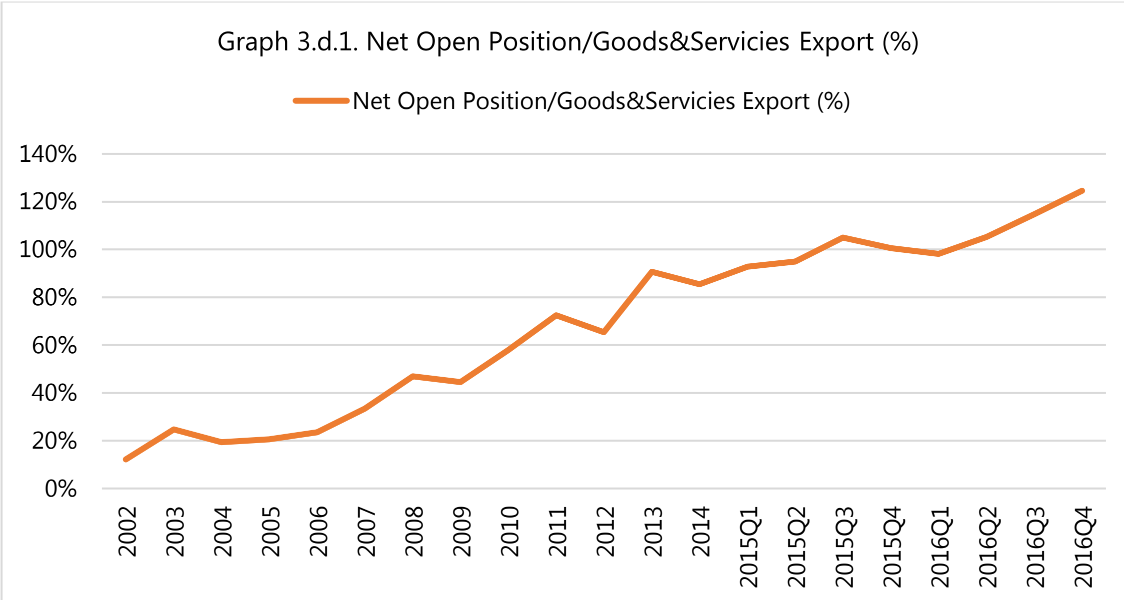
Source: CBRT

3.d. Natural Hedge

A natural hedge is the reduction in risk that can arise from an institution's normal operating procedures. A company with significant sales in one country holds a natural hedge on its currency risk if it also generates expenses in that currency.[11]

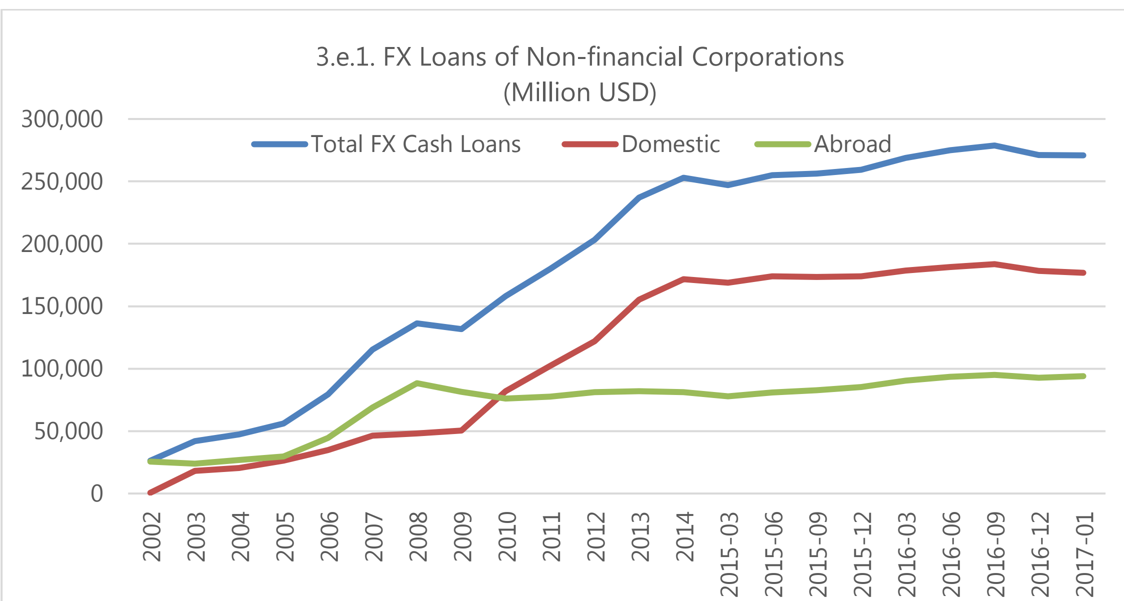
Export is a natural hedge for companies that borrow in other currencies. Natural Hedge position is represented as «a ratio of open FX position to goods and services export». Here it is aimed to see to what extent FX open position is covered by FX income through export of goods and services. As seen from the graph, natural hedge has diminished which means the ratio is increased over time which has climbed from 10%s to 120%s. This ratio tells us that in 2002 FX position was just 10% of goods and services export, but now it is 120% of the export (Graph 3.d.1).

[11] http://www.risk.net/definition/natural-hedge



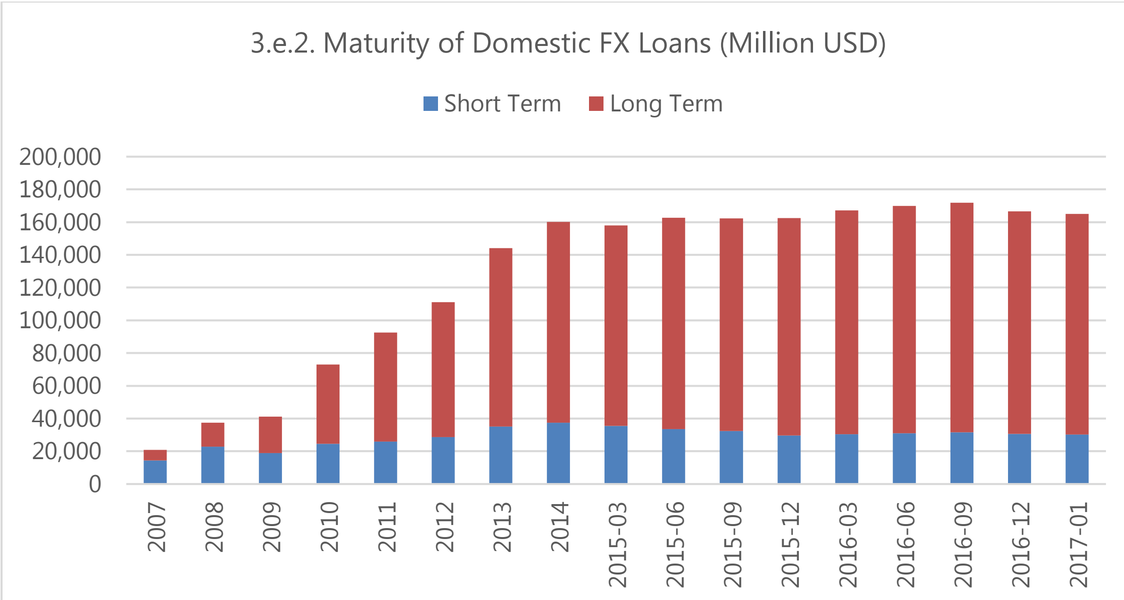
3.e. Total FX Loans and Maturity of Domestic FX Loans

Amount of total FX loan as a liability component has increased over time. Especially domestic FX loans exceeding external loans after 2010 is a striking development which has been one of the main reasons behind high open FX position (Graph 3.e.1).



Source: CBRT

On the other hand, from maturity perspective, long-term domestic FX loans have the highest share in the non-financial sector's FX debt distribution. It is worth to mention that FX loans having long term maturity is interpreted as a positive sign. Only about US$30 Billion (18%) of US$165 Billion outstanding loan amount has a short-term maturity as of January 2017 (Graph 3.e.2).



Source: CBRT

3.f. Financial Hedge Position

Though the risk management method of non-financial companies has been the topic of intense theoretical and empirical study, very little is known about the concrete hedging practices of firms.[12]

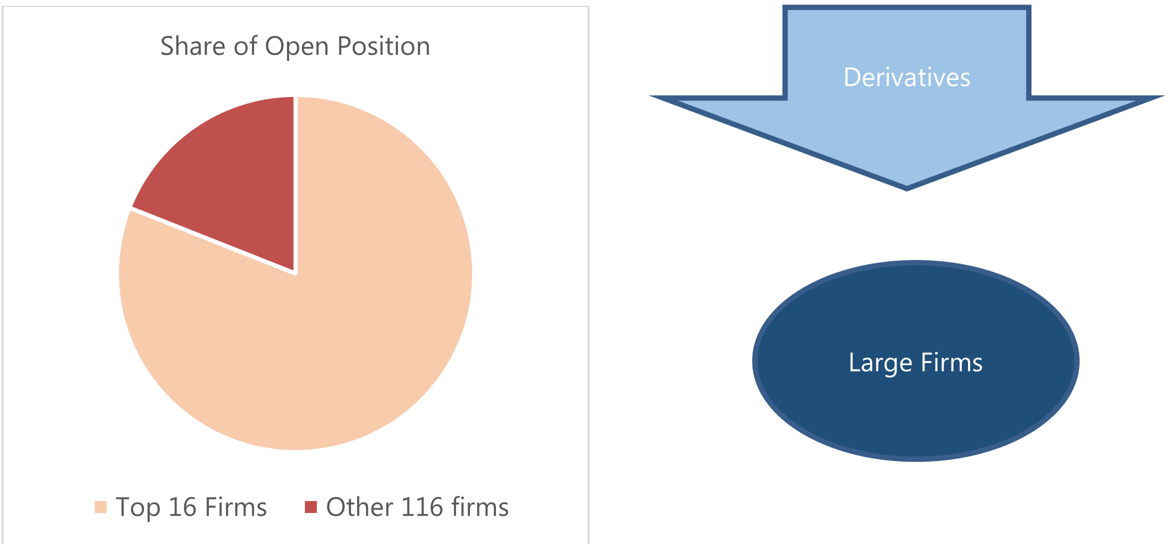
According to Financial Stability Report (November 2016) where 132 firms are analyzed[13];

- 81 percent of the FX open position belongs to the 16 largest firms by asset size (Figure 3.f.1).
- Protection of FX open position by derivative transactions rate is higher for large firms.
- The ratio of the derivative position/open position of the largest 10 percent of the companies included in sample is approximately 15 percent.
- The ratio of the derivative position/open position of the smallest 50 percent of the companies included in sample is very low, approximately 1 percent.
- For the total number of firms, this ratio is around 15%. So the hedging ratio of firms with derivative transactions is far from closing their open positions.
- Concentration of 80 percent of total open positions in large companies with relatively better protection in derivative transactions is considered positive in terms of financial stability.

[12] Brown G. W. (May 2001)

[13] Financial Stability Report (November 2016), Results for 132 firms. Last data: Q2.16.

Figure 3.f.1. Share of Open Position and Derivative Transactions



3.g. Results of Former Studies on FX Position of Real Sector Firms in Turkey

According to IMF country report dated April 2016; in Turkey, non-financial corporates have large FX exposures owing to borrowing from the domestic banking system and directly from abroad. Although external borrowing has weakened, there has been a rise in the total FX exposure as the increase in FX borrowing from the domestic banking system is higher than the fall in external borrowing.

Again in the same report, it is specified that credit risk and indirect credit risk connected with FX lending have increased. FX liquidity risk due to the realization of credit risk is important. Again, banks face indirect credit risk resulting from their FX and FX-indexed loans to non-financial corporations.

Reflecting the FX open positions, a scenario concerning depreciation of the Turkish Lira would significantly worsen the NFCs' balance sheet. A 20 percent depreciation of TL would result in an increase in the NFCs leverage by about 44 percentage points, to about 205 percent.

According to findings of Hülagü, T., and C. Yalçın (2014); 87 percent of firms in the dataset either do not borrow in FX or are naturally hedged with export revenues. Same study finds that 1/3 of firms without or limited FX revenue borrows in FX and this in turn generates currency risk. On the other hand; although classified as high risk group, they have higher average FX profits through FX-linked pricing in the domestic market. Even though we see high dollarization at sectoral level and no export as natural hedge, detailed analysis shows the other sources of FX revenues. Therefore, currency risk might be lower than macro aggregates' implications which urges the need for microdata.

Erdoğan (2016) examines the foreign exchange exposure and determinants of risk for different time horizons of Turkish firms from 1997 to 2011. The empirical findings of the study suggest a negative relationship between exposure and asset turnover ratio, and profit margin. However, this study finds a positive relationship between exposure and leverage besides proving connection between higher export rate and higher risk. Additionally, this study finds that large companies are subject to less risk in the short run.

4. Systemic Risk Data Monitoring Model

Foreign exchange position of the non-financial companies is manageable to a large extent. Especially short-term FX position is very well-balanced. Nevertheless, since we don't have detailed data, the comments made about foreign exchange debt of the real sector may affect the risk perception of Turkey negatively during the periods when there are fluctuations in exchange rates.

A 'Systemic Risk Data Monitoring System' is planned to be established so as to create a healthier surveillance against exchange rate risk. It is evaluated that it is beneficial from risk management perspective if there is a framework where foreign exchange position and foreign currency cash flows along with maturity mismatch data is compiled on the firm basis.

In the first phase of the project, companies with US$15 Million total FX loan will be covered which counts about 2000 real sector companies currently holding about 83 percent of total FX debt. A pilot study involving top 111 firms with the highest FX debt has already been started as the first stage of the project under the Central Bank of Turkey.

In the next phases of the project, 23 thousand companies with comparatively lower portion of foreign debt will be handled. As a result, the incentive and regulatory framework might be needed to be revisited in order to contribute to prudent borrowing and risk management.

Below are the important parameters in building the systemic risk monitoring model:

- Contents, quality, and frequency of data: Data must be detailed enough to give true picture of the sector by ensuring high quality on a timely manner.
- Collection of data and consolidation at one center: Consolidating data at one center ensures data consistency.

The examination of the data content to be reported by the accounting professionals will contribute to the data quality. As a result of the experience gained in the reports during pilot stage, it would be appropriate to establish solid reporting standards at the end of the pilot period.

4.a. Legal Issues

In order to run this model we have to look at the legal regulations whether Central Bank can collect data on FX position of non-financial corporations through bank or not. When we look at the regulation whether banks can get FX position of their customers, we see that it is possible according to Law: Article 52 of the Banking Law which is:

Banks are obliged to measure risks to be incurred due to their loans, regularly analyze and monitor the financial strength of the counterparty, provide necessary information and documents, and determine the basis for them. In this frame, loan customers are obliged to provide the necessary information and documents to the bank on consolidated and unconsolidated basis.

Additionally, according to Article 43 of the CBRT Law:

In order to be able to fulfill the duties assigned to it by this Law and legislation, the Bank (CBRT) is entitled to request all kinds of information and documents from the institutions and organizations mentioned in the first paragraph in the framework of the procedures and principles to be determined by itself. The institutions and organizations mentioned in the first paragraph are obliged to give the information requested from them within the time specified by the CBRT.

Acquisition of data collected by banks from their customers by CBRT is also possible. So there is no obstacle behind FX position collection by CBRT from banks.

If the CBRT needs to collect data directly from the companies, Resolution 32 on Protection of Turkish Currency Value includes the sharing of these data.

4.b. Calendar

Below table summarizes the meetings held by stakeholders regarding FX monitoring model. In March 2017 CBRT held a meeting with banks and other public authorities. Basic framework of the model was discussed and contribution of stakeholders has been taken into account to further develop the model and reporting details.

Table 4.b.1. Timeline for Systemic Risk Monitoring Model: Pilot Stage

March, 2017	April, 2017	May, 2017	June, 2017
1st Meeting w/related Banks Preparing FX position reporting form and documentation	Reporting Instructions to Banks Collecting firm-based data	Completing Pilot Period Data Collection	Pilot Term Report

4.c. Data Scope

Comprehensive information at micro level will be collected quarterly by CBRT in order to measure open FX position of real sector. The first phase of the project will include loans over US$15 Million which covers 2,000 firms. However, pilot stage in order to test the reporting details of the model included loans over 1 Billion TL covering 111 firms.

In order to measure net FX position, data scope for the new Project will cover FX assets and liabilities, along with past and future FX cash flows, income statement, and derivative transactions which will give us FX position and also the strength of a company to handle open position.

4.d. Loan Distribution of Firms

The BAT-Risk Center data used in this chart covers all FX and FX indexed loans granted by domestic and foreign banks through domestic banks, as of 30.09.2016.[14]

When grouped by amounts, total FX loan concentrates in firms with high-amounts of FX loan (Figure 4.d.1). Most of the FX risk is held by big firms. 1.100 firms hold 75% of FX loan and average maturity is more than 7 years for those firms.

[14] Financial Stability Report, November 2016

Figure 4.d.1. Loan Distribution of Firms

FX Loan Amount	Number of Firms
>1 Billion TL	105
100 Million - 1 Billion TL	1.009
50-100 Million TL	836
10-50 Million TL	3.833
0- 10 Million TL	20.779
Total	26.562

4.e. Pilot Practice

Pilot period has started in April 2017 for 111 firms which have more than 1 Billion Turkish Lira foreign currency denominated loan. The reason behind choosing 111 firms is because of their high portion in total FX loan which is approximately 38% as of December 2016 (Figure 4.e.1). In addition to that, keeping number of firms low makes it easier to compile data in a short period of time. During the pilot period, we expect to see possible obstacles that firms and banks face in filling out the FX position form.

Pilot period is expected to contribute methods for improving data quality and collection process as possible problems in reporting can be determined during this period.

Figure 4.e.1. Coverage of Pilot Stage Reporting

FX Loan Amount >1 Billion TL	Percentage of total FX loan: % 38	# of firms: 111

4.f. Reporting During Pilot Period

Data that is subject to reporting during pilot period is non-financial corporations' financials for the end of December 2016. Firms fill out the form and submit it to the pre-defined bank after necessary controls done by accounting department of the firm. Then, each bank is obliged to send the report of the firms to the CBRT.

5. Potential Benefits of the Project from Macro-prudential Perspective

The analysis of detailed data and the use of it as an input in surveillance processes will enable accurate calculation of risks and effective policy generation. Database will be created first, and then the regulatory bodies will decide on macro precautions if needed.

Another benefit of the project will be the true assessment of the currency risk. Through this reporting practice, we will see exporters which protect themselves against foreign exchange movements with natural hedge. In addition, companies that hedge themselves with derivative transactions will be revealed which are usually large corporations.[15] Therefore, companies that are either not exporting or having derivative transactions will be determined by the practice. So, it is very important to have detailed micro data for those firms which are at risk and as a final step to take precautions for them.

6. Conclusion

Non-financial sector's net FX open position levels have risen gradually in Turkey since 2003. Despite the fact that those companies have a high open FX position, their natural and financial hedge management are not at desired levels. As Turkish Lira depreciates, balance sheets worsen which in turn threaten the financial sector and the whole economy from counterparty and systemic risk perspective. With the leadership of the Central Bank of The Republic of Turkey, a new system that collects net FX, hedging positions and future cash flow of real sector firms is planned to be carried out. One of the expected benefits of the project is to identify the banks that extend loans to the customers with open positions and to introduce additional obligations if necessary. Macro-prudential precautions might come into force after the model establishments and analysis of data at firm-level have finished.

In this paper, FX position of non-financial corporations in Turkey is analyzed and the new project which aims to monitor the FX position of those firms is presented. In Turkey, non-financial firms can hold FX or FX-indexed loans with some limitations. They can get loan from domestic banks or foreign banks directly or through domestic banks. This funding opportunity may result FX open position for the NFCs.

Both positive global trends in value of USD and inflation data resulted in higher USD/TL value between September 2016 and January 2017. In addition to that, geopolitical risks and downgraded rating of Turkey contributed depreciation of TL in this period. As a result, adverse signals started to come out of companies that had open position. As this issue has come to the fore in the Financial Stability Committee, «Systemic Risk Data Monitoring Model» was decided to be run by the Central Bank of Turkey. Currently, the determination of the reporting details of the project has not finished yet, but a pilot period has been run by Central Bank since April 2017.

It is a fact that the rapid increase in the FX rate has a significant negative effect on non-financial companies as well as financial sector. Monitoring non-financial sector and having detailed data at firm level have a huge positive role from financial stability perspective.

When the open position is examined on an aggregate basis, it may be viewed as a risk factor; however, the impacts of these risks will depend on the financial structures of the firms, the maturity of the debt, their hedging position and their pricing power (FSR, November 2016). Therefore, having firm-level data enables true risk analysis and enables authorities to take macro-prudential precautions respectively.

[15] Financial Stability Report, November 2016.

References

Alp, B. and Yalçın, C. (2015). "Türkiye'de Şirketlerin Borç Dolarizasyonu ve Büyüme Performansı", Çalışma Tebliği No: 15/01. CBRT (in Turkish).

Brown, G.W. (May 2001). Managing Foreign Exchange Risk with Derivatives, Journal of Financial Economics, 60, 2-3, May 2001, 401-448.

CBRT. (2016). Financial Stability Report 23. Ankara.

Erdoğan, Mahmut (March 2016), Foreign Exchange Exposure and Hedging of Turkish Companies: Panel Data Evidence, International Business Research 9(6):44, http://www.ccsenet.org/journal/index.php/ibr/article/view/57858/32045.

Gençay, O. (February, 2007), Finansal Dolarizasyon ve Finansal İstikrar Arasındaki İlişki: Türkiye Değerlendirmesi (Expert's Thesis, Central Bank of the Republic of Turkey). Retrieved from http://www3.tcmb.gov.tr/kutuphane/TURKCE/tezler/oyagencay.pdf (in Turkish).

International Monetary Fund (IMF). 2016. "Turkey: 2016 Article IV Consultation-Press Release; Staff Report; and Statement by the Executive Director for Turkey." IMF Country Report 16/104, International Monetary Fund, Washington.

Hülagü, T., and Yalçın, C. (2014). Türkiye'de Firmaların Yabancı Para Borçluluğu ve Kur Riskine İlişkin Mikro Değerlendirmeler, CBT Research Notes in Economics 1413, Research and Monetary Policy Department, Central Bank of the Republic of Turkey (in Turkish).

Krugman, P. (1999). Balance Sheets, the Transfer Problem, and Financial Crises. Journal of International Tax and Public Finance, VI, 459–472. Access: 5.5.2017. http://www.princeton.edu/~pkrugman/krugmanbalance.pdf.

Özatay, F. (July, 31 2006). Verimlilik Artışı Sağlanmadan Bu İş Yürümez. Radikal. Access: 17.4.2017. http://www.radikal.com.tr/yazarlar/fatih-ozatay/verimlilik-artisi-saglanmadan-bu-is-yurumez-787499/ (in Turkish).

Rennhack, R. and Nozaki, M. (January 2006). "Financial Dollarization in Latin America". IMF Working Paper No: 6/7.

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BANK FOR INTERNATIONAL SETTLEMENTS

IFC-National Bank of Belgium Workshop on "*Data needs and Statistics compilation for macroprudential analysis*"

Brussels, Belgium, 18-19 May 2017

Non-financial sector's foreign exchange risk: new project of foreign exchange position monitoring system in Turkey[1]

Oya Gençay,

Central Bank of the Republic of Turkey

[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.

TÜRKİYE CUMHURİYET MERKEZ BANKASI

Non-Financial Sector's Foreign Exchange Risk: New Project of Foreign Exchange Position Monitoring System in Turkey

Oya Gençay
Central Bank of The Republic of Turkey
Statistics Department

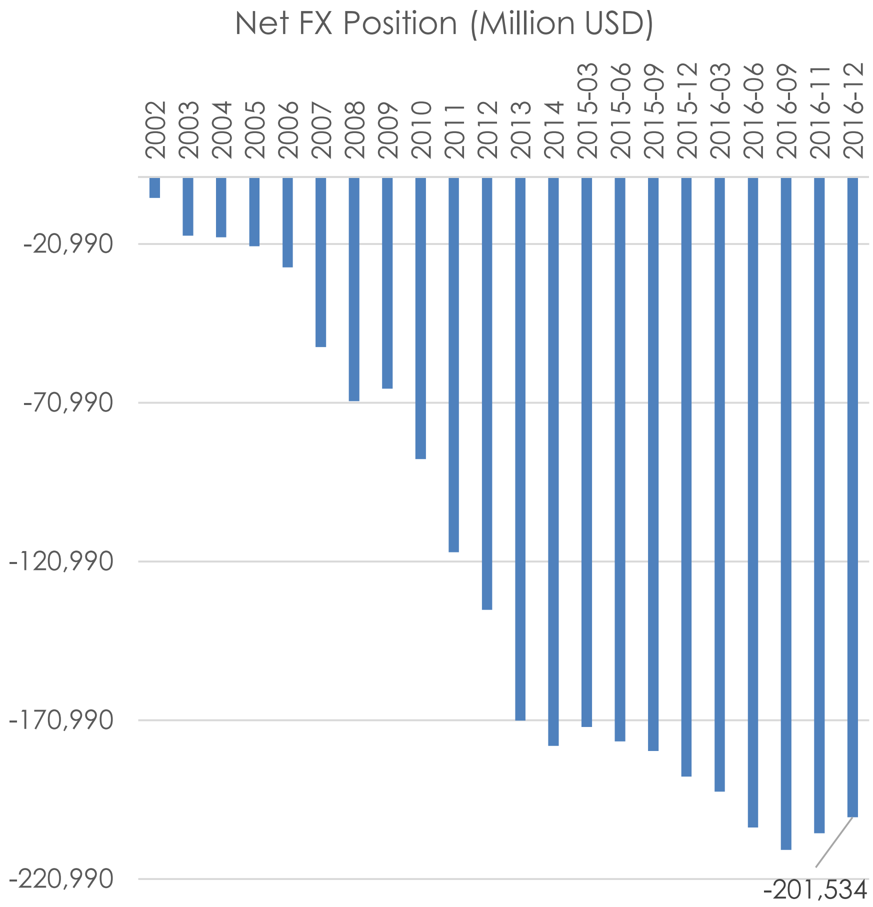
Data needs and statistics compilation for macroprudential analysis

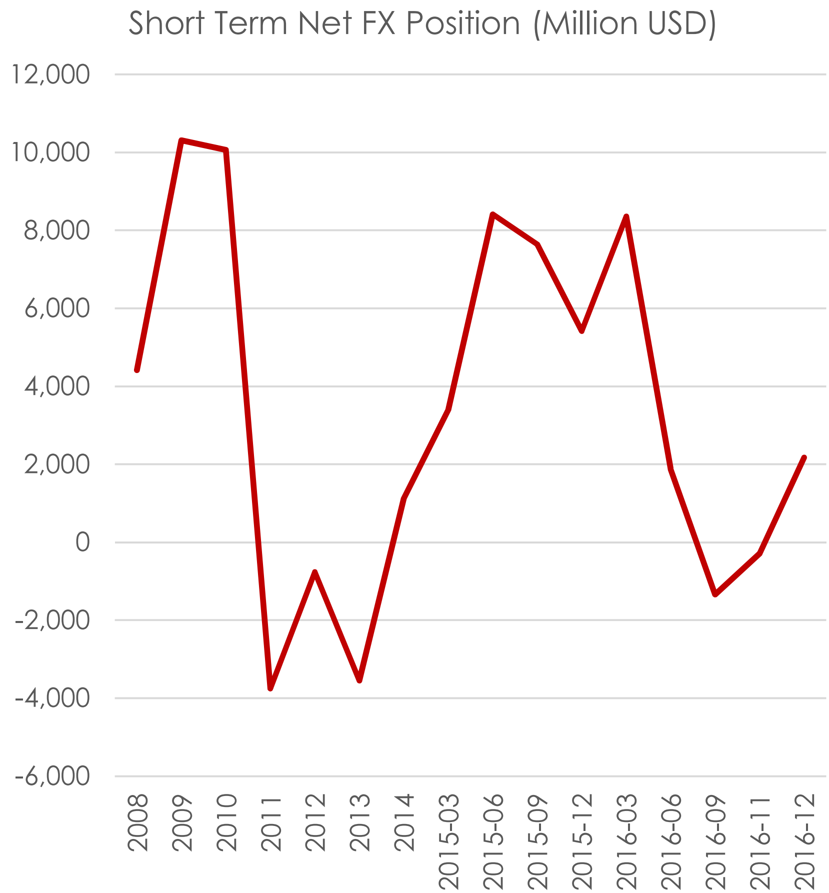
IFC / National Bank of Belgium Workshop, Brussels, 18-19 May 2017

Outline

- Information on FX position of non-financial sector in Turkey and related statistics
- **«Systemic Risk Data Monitoring Model»**

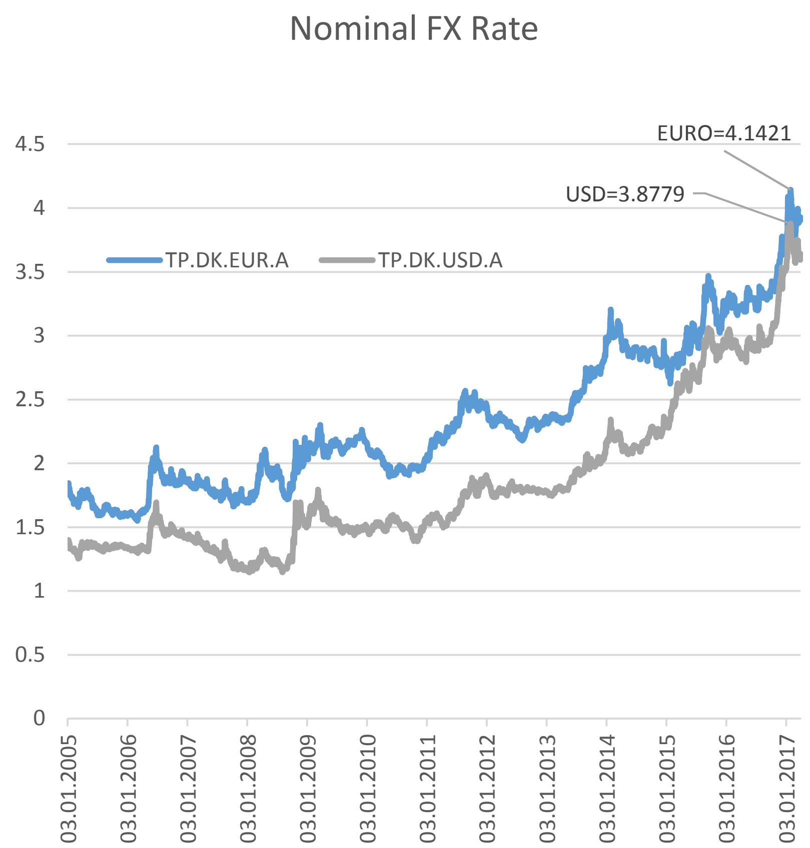
Net FX Position of Non-Financial Sector in Turkey

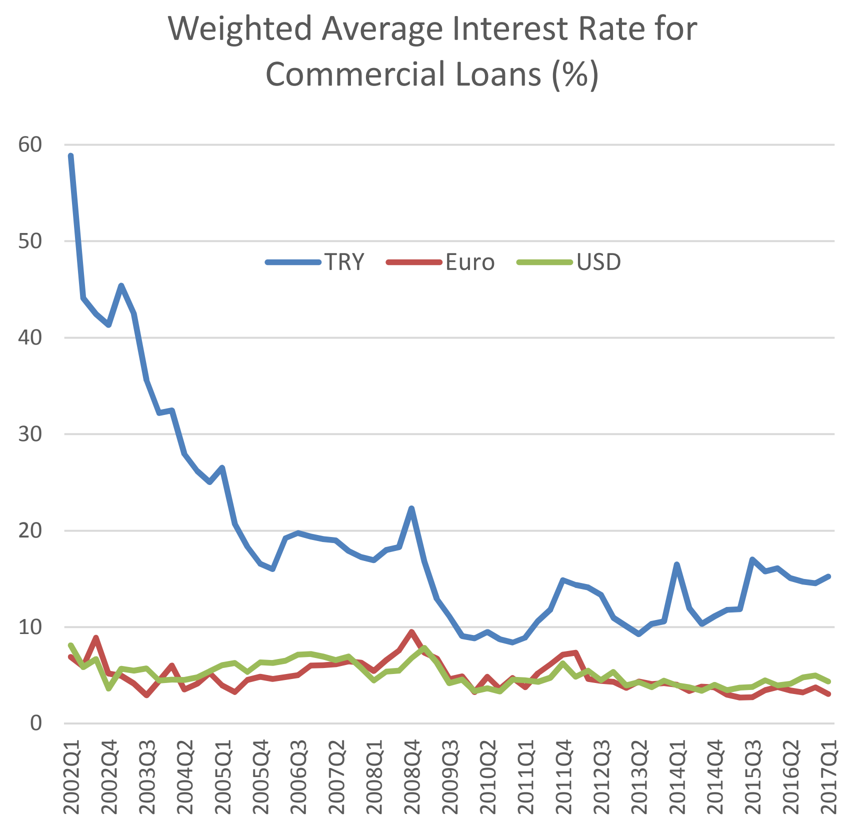




Source: CBRT

FX Rates and Weighted Average Interest Rates

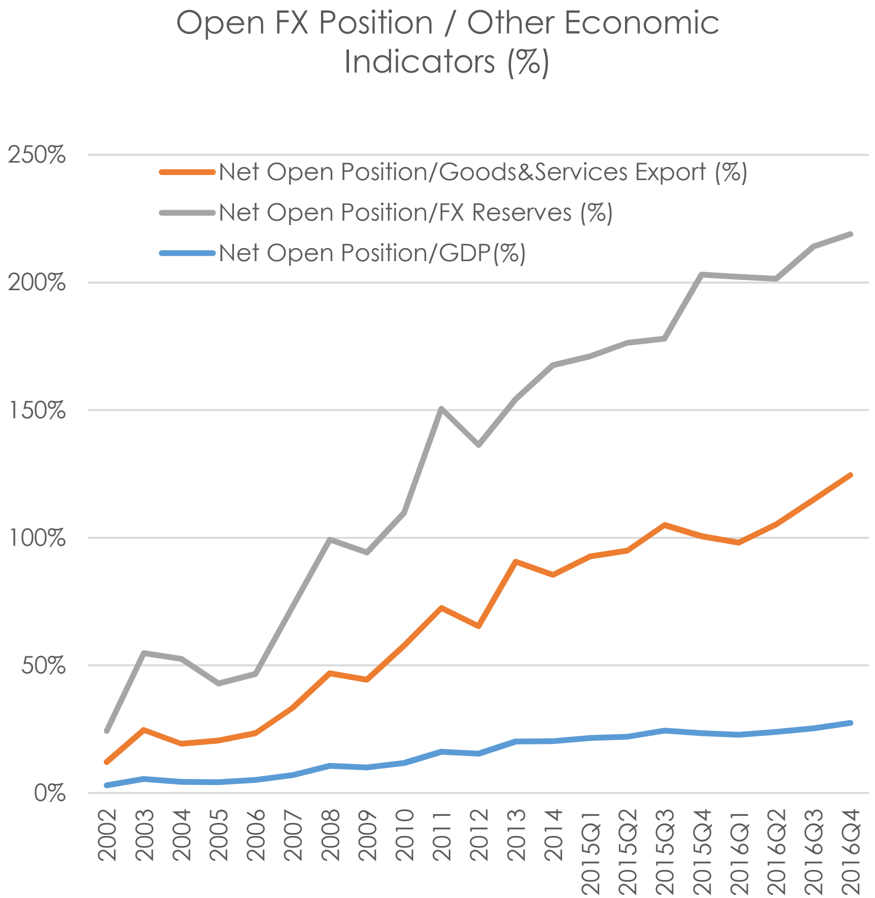


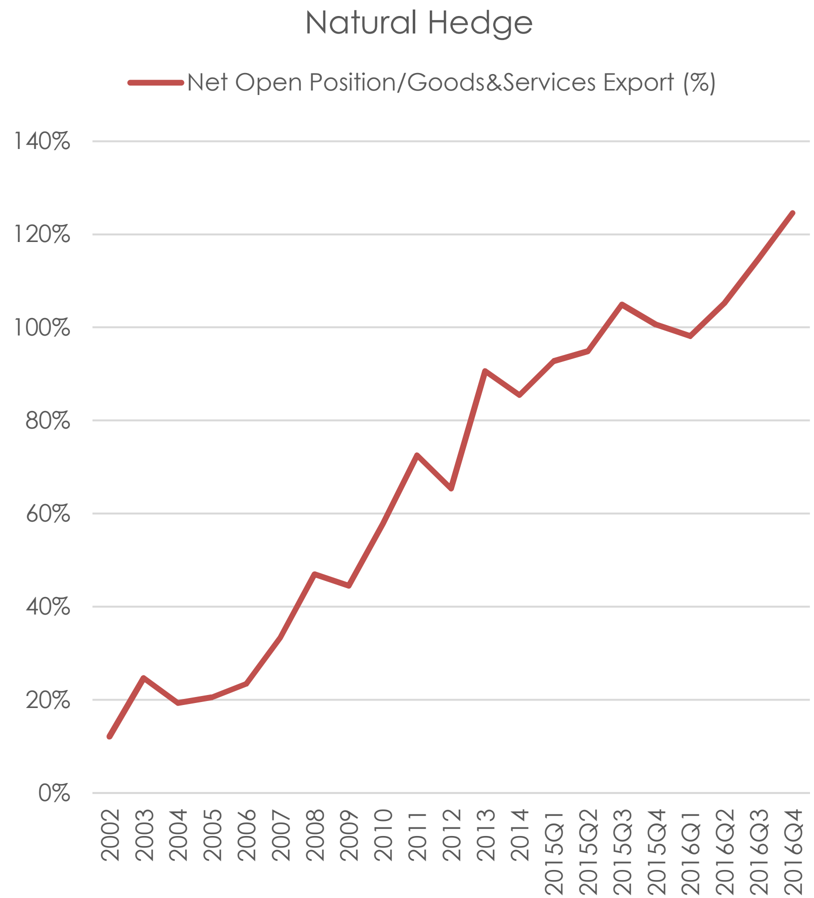


- Euro: 4.14 TRY, USD: 3.87 TRY (30.1.2017). Euro rate increased by 22%, USD rate increased by 27% in the last year.
- Although the gap between TRY weighted average interest rates and other currency interest rates narrows in time, the TRY lines do not intersect with others.

Source: CBRT
Last Data: 30.3.2017 for FX rates

Net FX Position Related to Other Economic Indicators

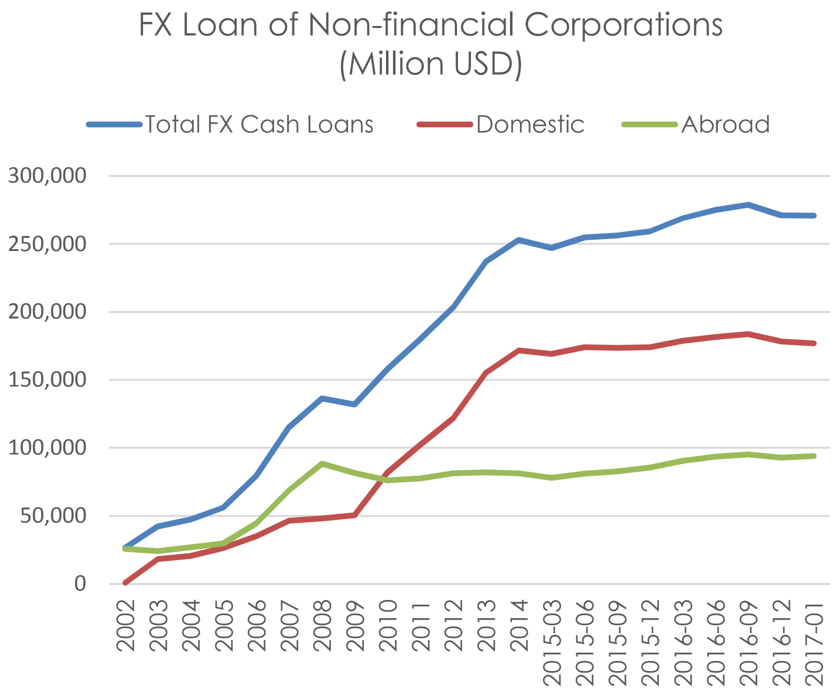


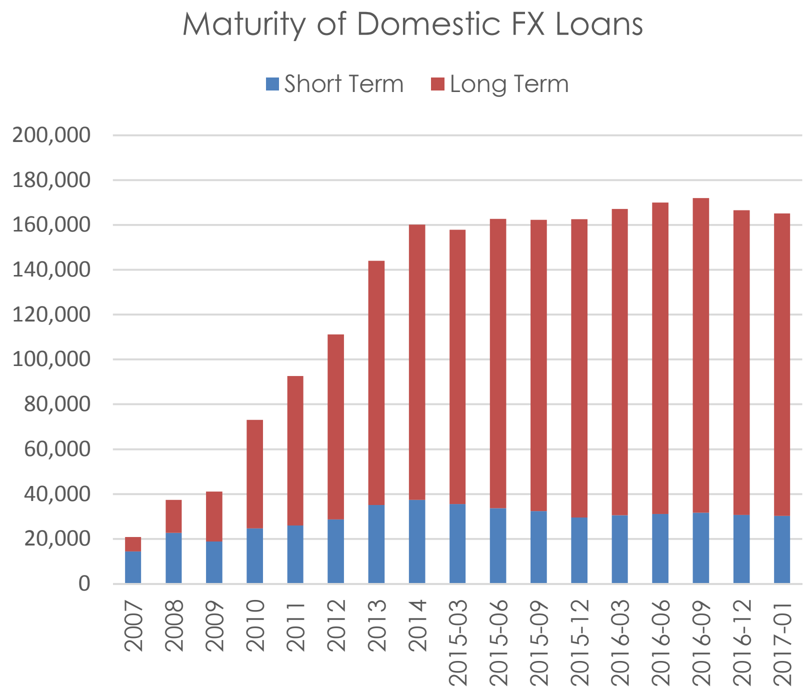


- Net FX position related to some economic indicators has increased over time as open position widens.
- Export of goods and services serves as a natural hedge for FX liabilities. Open position to goods and services export ratio exceeds120% by 2016.

Source: CBRT

Total FX Loan and Maturity of Domestic FX Loans



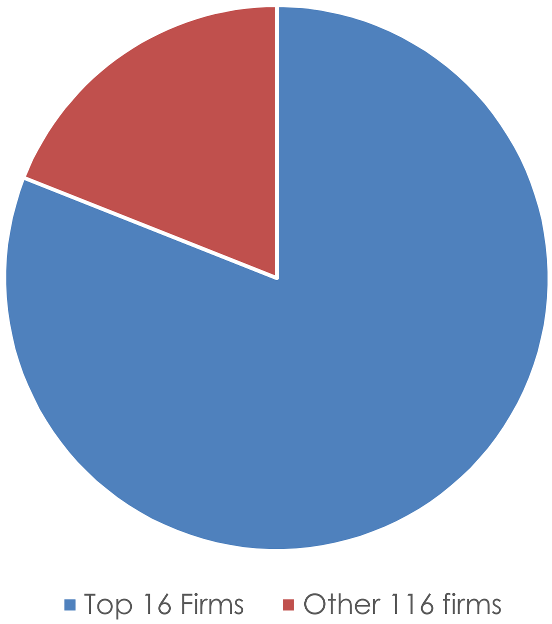


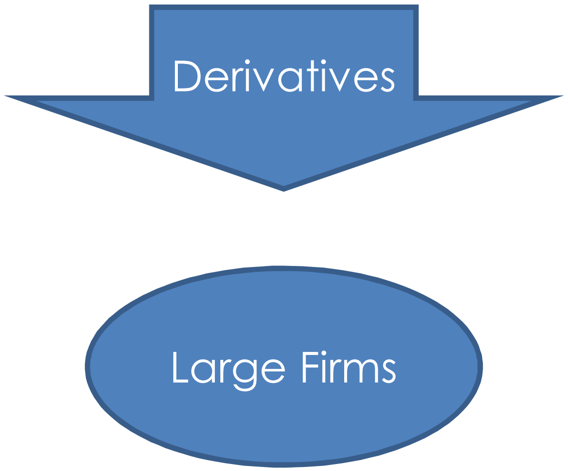
- Total FX loan has increased over time. Especially domestic FX loan exceeded FX loan from abroad after 2010.
- Long-term domestic FX loans have the highest share in the non-financial sector's FX debt distribution

Source: CBRT

Financial Hedge Position*

Share of Open Position





- 81 percent of the FX open position belongs to the 16 largest firms by asset size.
- Mostly large firms have derivative transactions.

*Results for 132 firms. Last data: Q2.16
Source: Financial Stability Report (November 2016)

Financial Hedge Position*

Top 10% of companies;

Derivatives / Open Position-15%

Smallest 50% of companies;

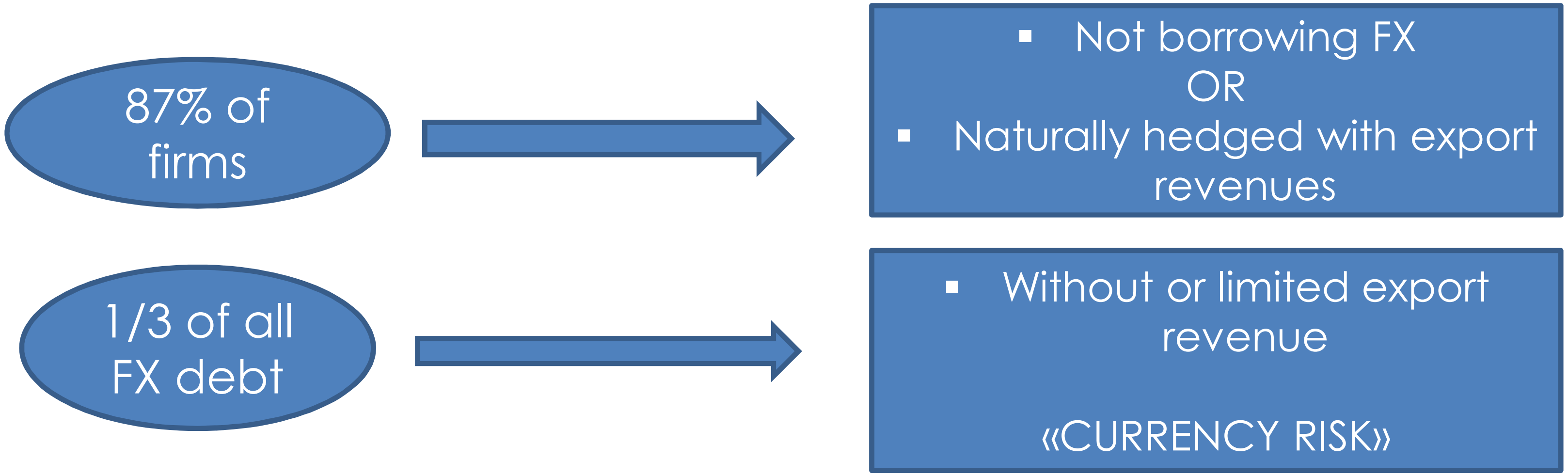
Derivatives / Open Position-1%

Hedging of FX open position by derivative transactions is higher for large firms: positive implication for financial stability since they hold big portion of open position.

*Results for 132 firms. Last data: Q2.16
Source: Financial Stability Report (November 2016)

Results of a Former Study on FX Position of Firms in Turkey-1

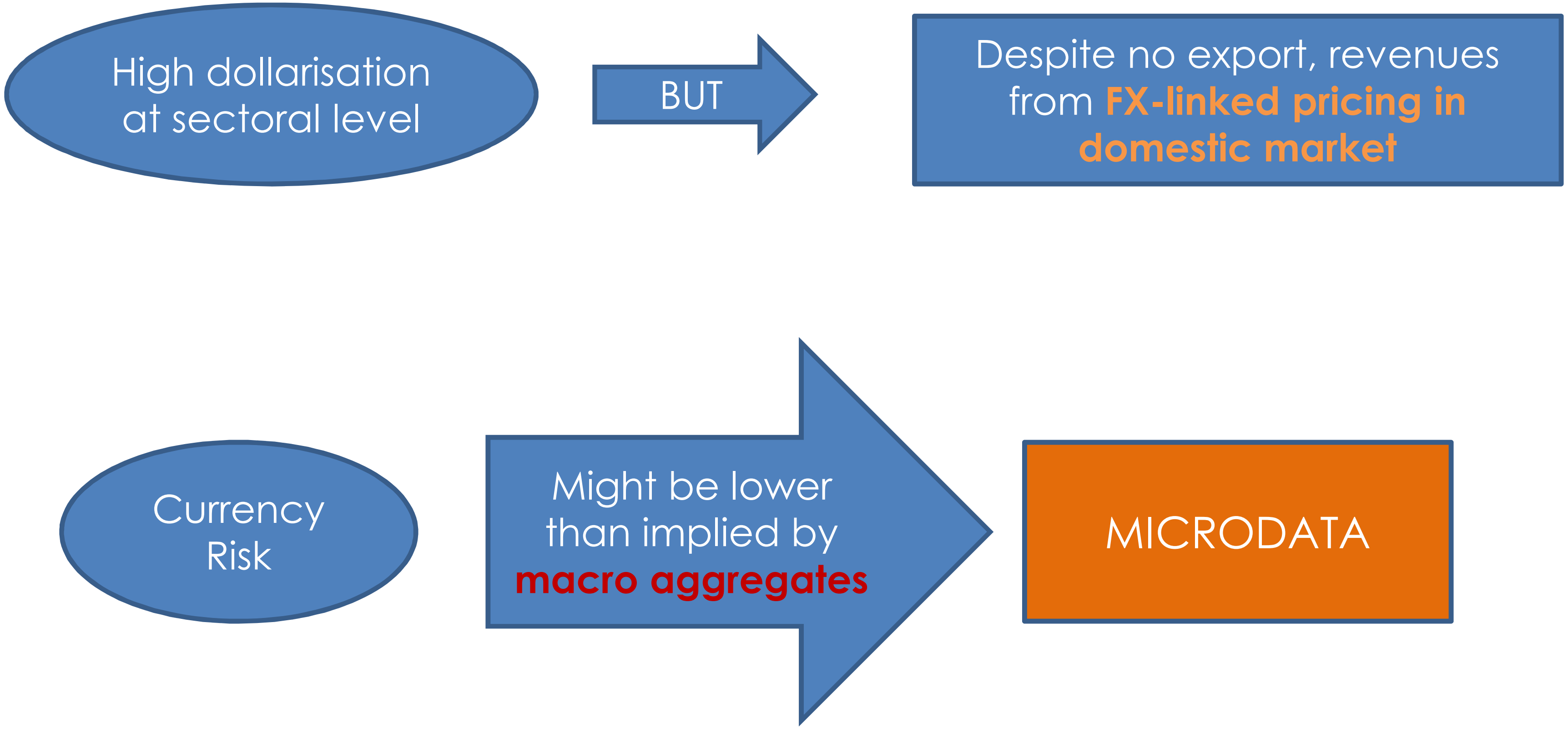
According to findings of Hülagü, T. and C. Yalçın (2014);



On the other hand;

Data: 31.12.2013

Results of a Former Study on FX Position of Firms in Turkey-2



Source: Hülagü, T., and C. Yalçın (2014);

Systemic Risk Data Monitoring Model

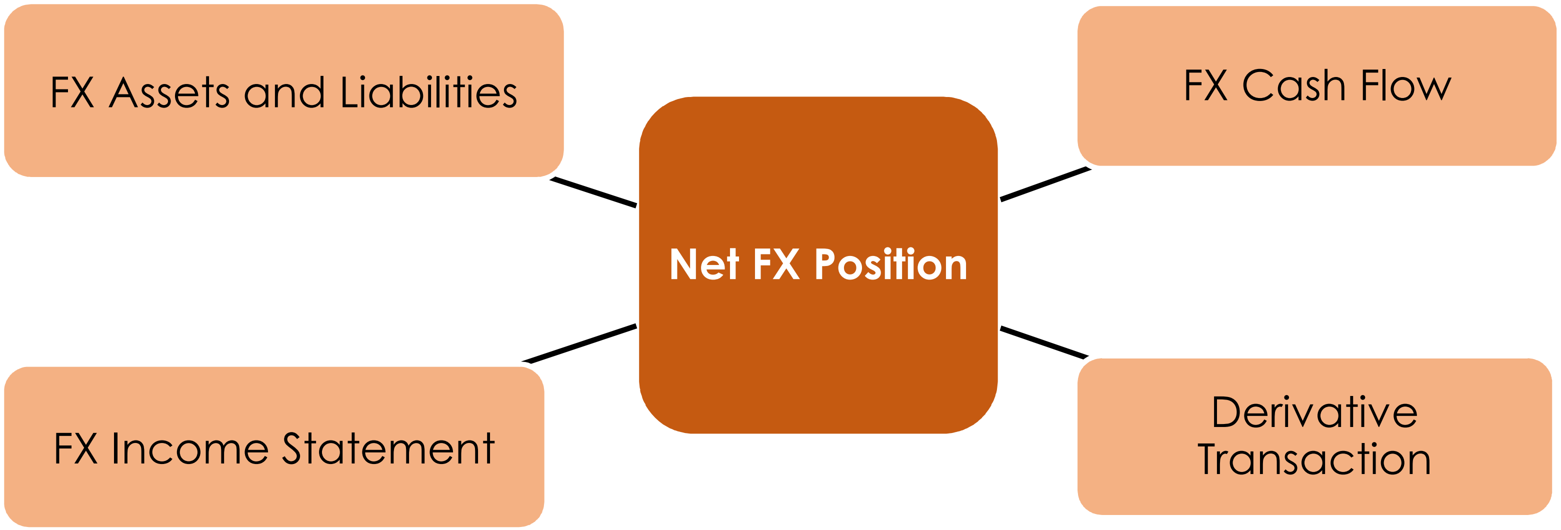
Comprehensive information at micro level

Quarterly data collection by CBRT

1st stage >50 million TL total FX loan: 2000 firms

Pilot stage > 1 billion TL total FX loan: 111 firms

Data Scope


FX Assets and Liabilities
FX Cash Flow
Net FX Position
FX Income Statement
Derivative Transaction

Loan Distribution of Firms

FX Loan Amount	Number of Firms
>1 Billion TL	105
100 Million - 1 Billion TL	1009
50-100 Million TL	836
10-50 Million TL	3833
0- 10 Million TL	20779
Total	**26562**

1100 firms hold 75% of FX loan

Average maturity > 7 years

- Grouped by amounts, total FX loan concentrates in firms with high-amounts of FX loan.
- Most of the FX risk is held by big firms.

Source: BAT Risk Center data used in Financial Stability Report, November 2016.
Data: 30.09.2016

Pilot Practice

FX Loan Amount >1 Billion TL	Percentage of total FX loan: % 38	# of firms: 111

Pilot Practice

Contribute →
- Data Quality
- Collection Process

Started → April 2017

Source: BAT Risk Center
Data: 31.12.2016

Reporting During Pilot Period

Firms

Banks

For the pilot period, firms report their financial data by December 2016

TÜRKİYE CUMHURİYET MERKEZ BANKASI

Non-Financial Sector's Foreign Exchange Risk: New Project of Foreign Exchange Position Monitoring System in Turkey

Oya Gençay

(Central Bank of The Republic of Turkey)

Data needs and statistics compilation for macroprudential analysis

IFC / National Bank of Belgium Workshop, Brussels, 18-19 May 2017

Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

IFC-National Bank of Belgium Workshop on "*Data needs and Statistics compilation for macroprudential analysis*"

Brussels, Belgium, 18-19 May 2017

The Portuguese Central Credit Register as a key input to the analysis of financial stability … and beyond![1]

João Cadete de Matos and André Cardoso 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.

The Portuguese Central Credit Register as a key input to the analysis of financial stability… and beyond![1,2]

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The Portuguese Central Credit Register (CCR) is a powerful multi-purpose tool, which contains monthly granular information on credit on a borrower-by-borrower basis and that includes, in some cases, details that provide loan-by-loan information with a virtually complete coverage. These features have enabled the *Banco de Portugal* to use its CCR data for a variety of purposes, from, *inter alia*, the compilation of very comprehensive and detailed statistics on credit, to the promotion of a better understanding of the risks underlying banks' balance sheets.

In this paper, we explore the richness of the Portuguese CCR, which is leveraged by its integration with other large granular datasets managed by *Banco de Portugal* (*e.g.* the data from the Bank's Central Balance Sheet Data Office). Furthermore, we highlight the way its features and ongoing reformulation – to meet the reporting requirements set by the AnaCredit Regulation and to fulfil additional data needs – have been key to monitor monetary and financial phenomena and to help the *Banco de Portugal* in meeting its mandate of ensuring the stability of the national financial system.

Keywords: Credit register data; AnaCredit Regulation; Macroprudential analysis; Microdata

JEL classification: C80; E50

[1] The analysis, opinions and findings of this paper represent the views of the author, which are not necessarily those of the *Banco de Portugal* or of the Eurosystem.

[2] The authors would like to thank to Marta Veloso, Flávia Serras and Rita Biscaya for their valuable insights and suggestions.

Contents

1. Introduction

The Portuguese Central Credit Register (CCR) is an information system managed by the Statistics Department of the *Banco de Portugal* (hereafter referred to as "the Bank"), which contains granular information on credit granted by the institutions participating in the system – all resident credit-granting institutions – on a borrower-by-borrower basis and that includes, in specific cases, details which provide loan-by-loan information, with a virtually complete coverage.

It is currently regulated by the Decree-Law no. 204/2008, by the Bank's Instruction no. 21/2008, and it is also mentioned in the Bank's Organic Law (Art. 17º - 1). The use and access to CCR data is compliant with the provisions laid down in specific data protection and use laws emanated by the Portuguese Parliament and by the National Commission for Data Protection (by National Commission for Data Protection's Authorization no. 4241/2011).

CCR data is used by the Bank not only for the compilation and dissemination of statistics, but also for a multitude of other purposes, such as for microprudential supervision of credit institutions, for monetary policy making, for economic research and for the macroprudential analysis and policymaking. In this context, this paper seeks to explore the richness and the usefulness of the Portuguese CCR in meeting these tasks, with a special focus on its role in the tasks pertaining to financial stability.

To that extent, this paper is organised as follows: the next section presents an overview of the Portuguese CCR and how its data are being used by the Bank for the compilation of statistics, monetary policy making, economic research and microprudential supervision; section three focuses on the role of the CCR in supporting the Bank in macroprudential analysis and policymaking; section four highlights the premises and the expected results of the ongoing CCR reformulation and its connection with the AnaCredit project; lastly, section five concludes.

2. The Portuguese CCR at a glance

2.1 Overview

The main purpose of the CCR is to offer its participants relevant data for their assessment of the risks underlying the provision of credit – *i.e.* aggregate information on the credit responsibilities of each client (borrower) *vis-à-vis* the participant institutions as a whole.

The CCR was firstly established in 1978 and initially it covered only the credit liabilities of non-financial corporations (NFCs). Later on, in 1993, began the collection of the same data for households and thereafter, in 1996, was issued an authorization for the compilation of statistics on credit based on the CCR. Subsequently, in 1999, the Statistics Department of the *Banco de Portugal* was assigned the responsibility for the management of this database and of all its related services.

Since 1999, a number of significant developments were introduced aiming at further improving the CCR's coverage and usability, namely: *(i)* the establishment of a bilateral exchange of individual credit data among the 7 signatories of the respective

Memorandum of Understanding (in 2005),[3] *(ii)* the incorporation of the potential credit liabilities of personal guarantors (in 2007) [4], and *(iii)* the implementation of a new information system that introduced additional breakdowns at the level of credit data and a greater efficiency in identifying private individuals (in 2009).

More recently, the *Banco de Portugal* has also successfully implemented a number of changes to the CCR which are equally worth highlighting:

a. Its coverage was expanded to cover new reporting institutions (*e.g.* NFCs that buy credit portfolios to the resident financial sector);
b. A new analytical data system for data analysis and exploration was developed;
c. Additional details were included to allow for the individual identification of the loans used as a collateral in the Eurosystem's monetary policy operations; and
d. Additional breakdowns were introduced (e.g., new collateral types, original and residual maturity brackets, special characteristics on non-performing loans and restructured loans).

Against this background, the entities that currently participate in the CCR are all the resident financial institutions granting credit – *i.e.*, banks (including savings and mutual agricultural credit banks) and other credit institutions (e.g., financial leasing companies, factoring companies, credit financial companies and credit-purchase financing companies) . Concomitantly, the borrowers registered are resident or non-resident entities, both private individuals and legal persons, to whom credit has been granted by the participant institutions. In this system, resident borrowers are uniquely identified through their tax payer number, while non-resident borrowers are identified through a set of elements provided by the participant entities, which include a code – unique for each borrower in each reporting institutions – and the name, country of residence and identification document of the non-resident borrowing entity.

Moreover, to ensure a level playing field between all the participating entities, the Bank guarantees that these institutions are entitled to access aggregate information on the credit liabilities of each borrower[5] *vis-à-vis* the CCR's reporting institutions as a whole. Concurrently, the borrowers also have the legal right to access their own information stored in the CCR and, in case of missing or wrong information, they must address the reporting institution to change or update their information, since the Bank is not legally authorized to correct the information by itself.

[3] The seven initial Signatories of the 2005 Memorandum of Understanding on the exchange of information among CCRs were the National Central Banks (NCB) of Austria, Belgium, France, Germany, Italy, Portugal and Spain. A few years later, the NCBs of the Czech Republic and Romania also joined this group.

[4] The CCR database contains information on the actual and potential credit granted by its participants (mainly resident financial institutions) to borrowers. Actual credit includes all the loans granted by the participants and truly taken up – *inter alia*, loans for house purchase, loans to purchase cars, furniture and other consumer goods or services, loans for the acquisition of shares or bonds, payment of bills of exchange or other commercial bills, overdrafts, leasing or factoring operations, and balances on credit card transactions. Potential credit encompasses all the irrevocable commitments by participants, such as available credit on credit cards, credit lines, pledges granted by participants and other credit facilities which may become actual credit.

[5] Or of each potential client, when such client asks for a loan or explicitly authorizes the entity to access its information.

In this framework, the CCR's participants have to report their borrower's loans according to a predefined list of attributes and dimensions, using the following variables:

a. Type of liability of the borrower – identifies the type of commitment the borrower has *vis-à-vis* the credit institution (*e.g.* individual credit, joint credit, personal guarantee);

b. Status of the loan – shows the type of liability underlying the relation between the participant and the borrower and to what extent the repayment schedule is being respected (*e.g.*, drawn credit in a regular situation, undrawn credit, overdue loans, written-off loans);

c. Type/purpose of the loan – identifies the credit instrument used and, in some cases, its end-purpose (*e.g.*, consumer credit and car credit, credit card, factoring with or without resource, housing loans);

d. Original and residual maturity – classified according to a list of predefined brackets;

e. Number of days the loan is past due – in the event of a default, this variable shows the number of days since the loan has defaulted in accordance with a list of predefined brackets;

f. Currency – *i.e.* the currency in which the loan is denominated;

g. Type and value of the collateral or guarantee securing the loan (if it exists);

h. Identification of relevant special characteristics underlying the loan – this information is reported with a view to be used internally by the Bank in the identification of, *inter alia*, securitised loans (derecognized and non-derecognized), syndicated loans, loans used as collateral for monetary policy operations, non-performing loans;

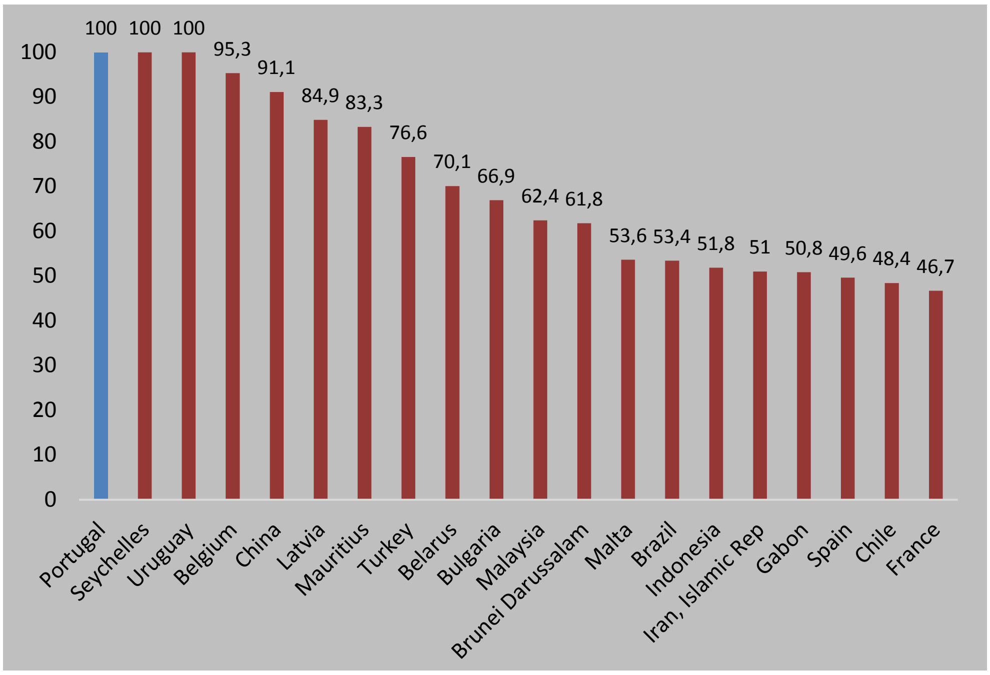
i. Value of monthly repayments – reported exclusively for specific types of personal loans.

Apart from this information reported by the participants, this system also collects data on the insolvency status of the borrower – for private individuals, companies or other legal entities – which is provided by the Portuguese Courts of Law.

All things considered, the aforementioned data is reported by the participants to the CCR on a monthly basis – until the 6th working day after the end of the reference period – for all the credits where the outstanding amounts of the borrower's actual or potential liabilities exceed fifty euros. This very low threshold, together with a full coverage in terms of participants and borrowers, has allowed the Portuguese CCR to lead the world ranking of public credit registries in terms of their coverage[6] (please see Figure 1).

[6] The credit registry coverage reports the number of individuals and firms listed in a credit registry's database as of 1 January 2016, with information on their borrowing history within the past five years, plus the number of individuals and firms that have had no borrowing history in the past five years, but for which a lender requested a credit report from the registry in the period between 2 January 2015 and 1 January 2016. The number is expressed as a percentage of the adult population, according to the World Bank's World Development Indicators. A credit registry is a database managed by the public sector that collects information on the creditworthiness of borrowers (individuals or firms) in the financial system and facilitates the exchange of credit information among banks and other regulated financial institutions. For more details on the methodology underlying the calculation of the credit registry coverage, please consult http://www.doingbusiness.org/data/exploretopics/getting-credit/faq

Figure 1: Credit registry coverage (as a % of the adult population)



Source – Doing Business 2017, World Bank

At the current juncture, the CCR processes over 20 million records in each reporting period which pertain to approximately 6.2 million borrowers with either actual or potential credit data and are drawn from 185 reporting institution.

Having thoroughly described the CCR's framework and the data it contains, it is now pertinent to ascertain to what extent it is used by the Bank and its relevance in meeting its mandate.

2.2 Using the CCR in meeting the Bank's mandate

2.2.1. Compilation and dissemination of statistics

The above mentioned authorization issued in 1996 reflected one of the main goals foreseen for the CCR: the compilation of comprehensive statistics on credit granted. Bearing in mind this objective, several credit instruments and other variables related to the classification of loans were defined, in such way that they are meaningful for economic analysis. In addition, the database also included a classification of borrowers classified according to appropriate statistical criteria[7] (*e.g.*, by sector of economic activity, by institutional sector, by corporation size and by region of residence).

Currently, the statistics compiled by the Bank based on the CCR data, whose main focus is the loans granted by the resident financial CCR's participants to the resident entities classified as NFCs, non-profit institutions serving households and households (NPISH), are made available to the public at large on a monthly or quarterly basis,

[7] Since the participating institutions only report the borrowers' identifications (*i.e.*, their taxpayer numbers), the statistical classification of the resident borrowers is made in the Bank, mostly by means of a business register managed by the Statistics Department.

depending on the statistics involved. Indeed, the set of statistical indicators published by the Bank on a monthly basis includes:

a. The outstanding amounts of the loans granted and their correspondent annual rate of change;

b. The ratio of overdue[8] loans.

c. The percentage of borrowers with overdue loans.

Such indicators are compiled for borrowers belonging to the NFCs, NPISH and households institutional sectors. Moreover, for the NFCs sector, this information is also broken down by corporation size[9] (micro, small, medium-sized and large corporations), by corporation statute (public and private corporations) and also made available for private exporting corporations[10]. For households, the statistics compiled also include a breakdown according to the purpose of their respective loans.

On a quarterly basis, the Bank publishes more detailed statistical information based on its CCR, both for NFCs and for the households sectors. In the case of NFCs, statistical data is broken down by:

a. Region, according to the NUTS II and III classification[11] of the NFC's headquarter;

b. Economic activity sector (according to NACE[12] sections, with further detail for the manufacturing industry);

c. Corporation size;

d. Financial product of the loan

e. Brackets of credit amount, for the level of indebtedness of the NFCs *vis-à-vis* the resident financial sector;

f. Original and residual maturity;

g. Type of guarantee.

As for the Households sector, statistical data is available with the following breakdowns:

a. Region breakdown, according to the NUTS II and III classification and, for some indicators, by municipality;

b. Purpose and financial product of the loan;

c. Brackets of credit amount, for the level of indebtedness of the debtors classified in the households sector *vis-à-vis* the financial sector;

d. Original and residual maturity;

[8] Overdue loans correspond to the outstanding amount of loans which were contractually due and have not been paid (past due).

[9] This classification is based on the European Commission's Recommendation 2003/361/EC of 6 May 2003, which addresses the definition of micro, small and medium-sized enterprises.

[10] The definition of "exporting corporations" is applied to all enterprises who meet the following criteria: a) at least 50% of their turnover comes from the export of goods and services or b) at least 10% of their turnover comes from the export of goods and services being the value more than 150 thousand euros.

[11] Nomenclature of Territorial Units for Statistics.

[12] Statistical Classification of Economic Activities in the European Community.

e. Type of guarantee.

In general, five indicators are published regularly for both institutional sectors: the outstanding amounts of the granted loans, the amount overdue loans, the ratio of overdue loans, the number of borrowers and the percentage of borrowers with overdue loans. As for the data broken down by original and residual maturity, it is only made available the amounts outstanding of loans granted, for each bracket of maturity; concurrently, for the type of guarantee breakdown, the Bank only releases the percentage of credit amount of each type of guarantee in the total loans granted.

In addition, on an annual basis, some additional indicators on the relationship of the borrowers with entities belonging to the financial sector – within the loans context – are published. Such indicators are presented both for the households sector and for the NFCs sector (which are also further broken by corporation size). Such indicators are:

a. The average number of entities belonging to the financial sector with which each credit client has credit relations;

b. The average percentage of loans granted by the entity with the largest share;

c. The average indebtedness of the credit clients.

Apart from being able to produce high quality fit-for-policy statistics, the CCR has also been able to bring about a reduction of the reporting requirements underlying the Bank's data collection for Monetary and Financial Statistics (MFS), thus alleviating the participants' reporting burden and curtailing data redundancy. Indeed, a good example of such feature was the source used for the breakdown by branch of economic activity of the credit granted to NFCs. From 1990 to 2002, this breakdown was included in the MFS reporting requirements, but the data collected showed a number of quality weaknesses, which were due to the need to aggregate the information according to several statistical criteria prior to its submission to the Bank by the reporters. Against this background, and since the CCR, as mentioned above, also provides an alternative source for the same data, but with higher quality – given that it is a micro data based system –, the Bank decided, in 2003, to discard this breakdown in the MFS data collection system and use exclusively the data of the CCR for this purpose.

Having thoroughly discussed the statistical potentialities of the CCR, it is now pertinent to discuss to what extent this data can be used for other tasks of the Bank and its impact. Concomitantly, in the next sections we discuss how the CCR's data has been used for economic research, monetary policy making and banking supervision purposes and some of the findings that it has enabled.

2.2.2. Economic research

Article 12 e) of the Bank's Organic Law states that the Bank is incumbent to "*Advise the Government in the economic and financial fields [...]*". In this capacity, the Bank's economic researchers have been using the CCR's micro data for several technical papers and empirical analysis, by, *inter alia*, regularly bringing together this data with other micro data sources as, for example, the Bank's Central Balance Sheet Database (CBSD).

Indeed, a good example of this exercise is the combination of CCR data with firm-by-firm accounting information drawn from the Central Balance Sheet Database, for internal research purposes pertaining to the analysis of the drivers of credit risk for non-financial corporations. Moreover, even though the study of household data is severely more restricted by legal constraints, there have also been significant efforts to identify what drives households to default.

In the same vein, another notable example on the utility of the CCR's data for economic research is found in Augusto & Félix (2014). In this paper, the authors investigated the impact of the recent bank recapitalization on the firms' access to credit between the first quarter of 2010 and the fourth quarter of 2013. Since the main dataset used for this study was the Bank's CCR, its granularity allowed the usage of sophisticated micro-econometric approaches to find the effects of the bank recapitalizations on the supply of credit. To that extent, the study included two firm distress indicators based on the firms' overdue credit (as reported to the CCR) and a sample of 201,768 non-financial corporations and 327,777 loans (firm-bank pairs). The results suggested that firms have on average two banking relationships and that that bank bailouts fostered an increase in the supply of credit and that this effect, which was verified for the sectors of manufacturing and trade, was negatively connected with the capital buffer of recapitalized banks. Moreover, the paper found no evidence that the bank recapitalizations contributed to a more selective behavior in granting credit to towards distressed firms when compared to other firms.

In a similarly minded study, Farinha & Félix (2014) studied the importance of credit demand and credit supply-related factors in explaining the evolution of credit granted to Portuguese small and medium-sized enterprises (SMEs). The findings of their study indicated that the interest rate is a strong driver of the demand for credit of SMEs, as well as their internal financing capacity. Moreover, it was found that the credit supply to SMEs mostly depended on the firms' ability to generate cash-flows, to repay their debt and on the amount of assets available to be used as collateral. To achieve such findings, a model was estimated for the period between 2010 and 2012, and its estimated coefficients were then used in the computation of the probability of credit rationing. In addition, the model produced in the study also suggested that a considerable fraction of Portuguese SMEs were affected by credit rationing in the surveyed period.

2.2.3. Monetary policy making

In light of the monetary policy making duties conferred by the Bank's organic law, the Bank has been using the CCR as an auxiliary tool for the identification of loans used as collateral in the Eurosystem's financing operations, since the CCR collects the necessary information to evaluate the risks associated with the acceptance of bank loans as collateral in monetary policy credit operations.

Indeed, the general documentation of the Eurosystem's monetary policy instruments and procedures requires that:

a. All Eurosystem credit operations are based on adequate collateral;

b. Such collateral assets fulfill a number of criteria in order to be eligible to be used in the Eurosystem's monetary policy operations;

c. A single framework for the definition of collateral eligibility is common to all Eurosystem credit operations.

In this context, such single framework encompasses two distinct asset classes:

a. Marketable assets;

b. Non-marketable assets (*e.g.*, credit claims).

Since February 2012, the NCBs are temporarily allowed to accept as collateral for Eurosystem credit operations additional performing credit claims. Such credit claims shall also meet specific eligibility criteria proposed by the NCBs and approved by the ECB's Governing Council.

Currently, each NCB is responsible for the eligibility assessment of a subset of assets. To this extent, the Bank is responsible for the eligibility assessment of the marketable assets traded in Portugal and of the non-marketable assets granted by domestic counterparties and presented as collateral to the Bank.

To meet such endeavor, the Bank is using its CCR on the eligibility assessment (and *ex post* verification) of credit claims – *i.e.* verifying the existence and confirming the major characteristics of such credit claims –, on the elaboration of collateral generation capacity estimates of domestic counterparties for credit claims, asset backed securities (ABS) and covered bonds, and to simplify the report for monetary policy purposes.

2.2.4. Microprudential supervision

Pursuant to its attributions in the field of micro-prudential supervision, the Bank has also been using the CCR's data in the evaluation of credit risk and of the concentration of risk exposures, both at micro and macro level, as well as for the improvement of the effectiveness of on-site inspections.

However, it is also relevant to mention the Bank's work in developing an Early Warning System (EWS), whose aim is to find companies evidencing a high likelihood of defaulting as a result of an excessive level of indebtedness. This system seeks to encourage credit institutions to be more proactive in identifying and setting forth the appropriate procedures and solutions in the treatment of the companies in such situations.

This EWS, which assesses the ability of the company to generate cash flows and its existing capital structure, incorporates information available on the Portuguese CCR and on the CBSD in the calculation of a set of five financial ratios, which are computed for each company, irrespectively of their industry or sector:

a. Two financial ratios (Total Debt to EBITDA[13] and the EBITDA Interest Coverage), which are classified as core ratios, in accordance with Standard & Poor's Corporate Ratings Framework;

b. Three additional supplementary ratios are considered, since they promote a better understanding of the company's financial risk profile and capture other critical risk dimensions, such as its profitability and leverage : FFO to Total Debt[14], Gearing, Return on Capital.

Having thoroughly discussed the current uses of the CCR for the compilation of statistics, economic research, monetary policy making and micro-prudential supervision, it is now pertinent to focus with greater detail to what extent the CCR's data is employed to ensure financial stability.

[13] EBITDA is an acronym for "Earnings Before Interest, Taxes, Depreciation and Amortization".

[14] FFO ("Funds from Operations") is given by (EBITDA - Net Interest - Income Taxes).

3. Using the Portuguese CCR to ensure financial stability… and beyond

In the previous section, we discussed the nature of the Portuguese CCR and how the Bank has been leveraging this tool to meet its tasks pertaining to the production of official statistics, economic research, monetary policy and microprudential supervision. However, one of the most relevant tasks entrusted to the *Banco de Portugal* through its Organic Law is ensuring "*the stability of the national financial system, performing for this purpose, in particular, the functions of lender of last resort and national macro-prudential authority*" and participating "*in the European system for the prevention and mitigation of risks to financial stability and in other bodies pursuing the same goal*". To meet this challenge, the Bank resorts to a number of different inputs and techniques that allow for a systemic view of the financial systems and of the build-up of systemic risks.

In this context, the above exposed statistics based on the CCR are an instrumental input and extensively used, since they allow for a crucial crossing and analysis of the various dimensions and characteristics attached to the loans, debtors and/or creditors. Indeed, in light of its intrinsic homogeneity and of the possibility to compare its data with other databases, the CCR data allows for a complementary analysis to the "traditional" aggregated data by providing the underlying distribution measures and by enabling the enhancement of the testing and monitoring (*e.g.*, stress testing) of the banks' results in ever-changing and increasingly complex scenarios.

Concretely, these data are used, *inter alia*, in the support to the following tasks:

a. Assessment of the risks stemming from the household and NFCs sectors, through the examination of the distribution measures of the loan/debtor classes, according to, when applicable, their economic activity sector, type and number of guarantees, exposure size, firm size, performing/non-performing status and other characteristics;

b. Identification of the financial situation of NFCs, by distinguishing the different financial situation of NFCs through their positive, null or negative changes in borrowing. The CCR is also used in the support to this task to allow for a breakdown by economic activity and by firm size and it is also complemented and cross-checked with data from the Bank's CBSD;

c. Analysis of the NFCs' credit performance in the wake of credit restructuring;

d. Evaluation of the effects of the age of the NFCs on their credit spreads – in this case, the CCR is also complemented by the Bank's interest rate statistics database;

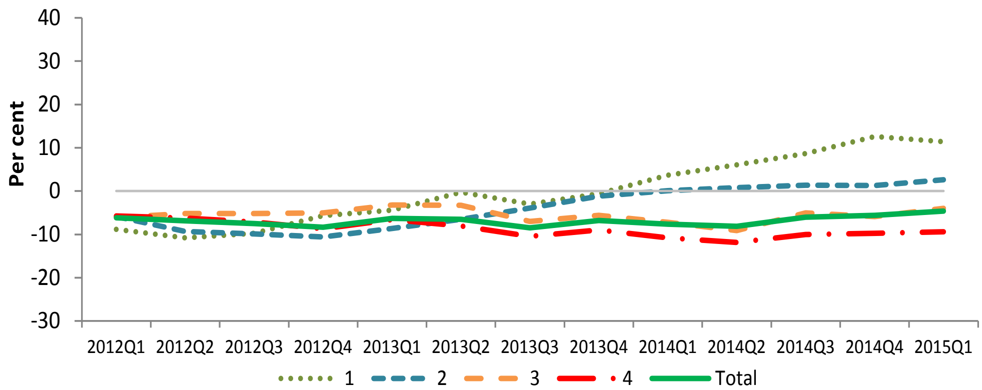
e. Monitoring of the credit tendencies of the largest indebted NFCs;

f. Exploration of the credit history of high growth corporations.

Indeed, Lima & Drumond (2015) discussed the insufficiencies attached to aggregated data when assessing financial stability and showed how microdata databases, such as the CCR, enable an assessment of the causes of the movements behind the aggregates and thus uncover the potential buildup of imbalances. Moreover, they also recognize that some macroprudential tools require specifically the use of characteristics that are only available in granular datasets – such as the collateral amount of real estate and debt instalments.

Using data drawn from the CCR, the authors concluded that the credit granted by Portuguese banks to non-financial corporations during the recent crisis diminished more significantly in the non-tradable sectors, whereas the credit granted to exporting firms, which are less dependent on the domestic economic recovery, increased. The authors then went on to estimate a z-score model, based on data from the CCR and from the CBSD, which then allowed to conclude that the most of credit granted was being channelled to less risky firms and that the underlying interest rates were decreasing both for high and low credit risk NFCs.

Figure 2 - Total loans granted by risk category/ year-on-year growth rate by risk classes (1 – less risky firms, 4 – riskiest firms)



Source: Lima & Drumond (2015)

Notwithstanding, to assess the necessity of additional prudential measures to increase the pace of the deleveraging of NFCs, Lima & Drumond (2015) argued that additional micro data, which also focuses on the credit institution's balance sheets, are needed. To that extent, the authors underline, yet again, the importance of the CCR and of the Bank's Large Exposure Database to assess the coverage rate of non-performing loans (NPL) in the credit institutions' balance sheets and to estimate the potential impact of writing of such loans on their capital position, while emphasizing the role of the "Corporate Debt Restructuring Monitor" in the assessment of the developments of the NFCs' indebtedness and NPLs.

Another good example of the usefulness of the CCR in meeting the Bank's financial stability mandate is its role in supporting the systemic analysis expressed in the Bank's biannual Financial Stability Report. For instance, the latest version of such report – published in November of 2016 – even included a special section on the recent developments in consumer credit, in light of the systemic impact that excessive credit growth and leverage can exert on an economy.

For this study, the Bank's researchers resorted to the Bank's CCR in order to examine the loans broken down by loan segment[15] and type of institution granting the credit, on a quarterly basis. The results have shown that, while the share of loans for consumption and other purposes in total household debt is relatively low – below 20% –, its recent increase was mainly driven by car loans (Figure 3 and 4), which reflected the effect of the anticipation of the decision to buy a car, in the wake of the entry in force – in April of 2016 – of an increase in the Vehicle Tax. Moreover, this analysis has also uncovered that such loans were mainly taken from credit institutions not belonging to the eight largest banking groups and were mainly granted to

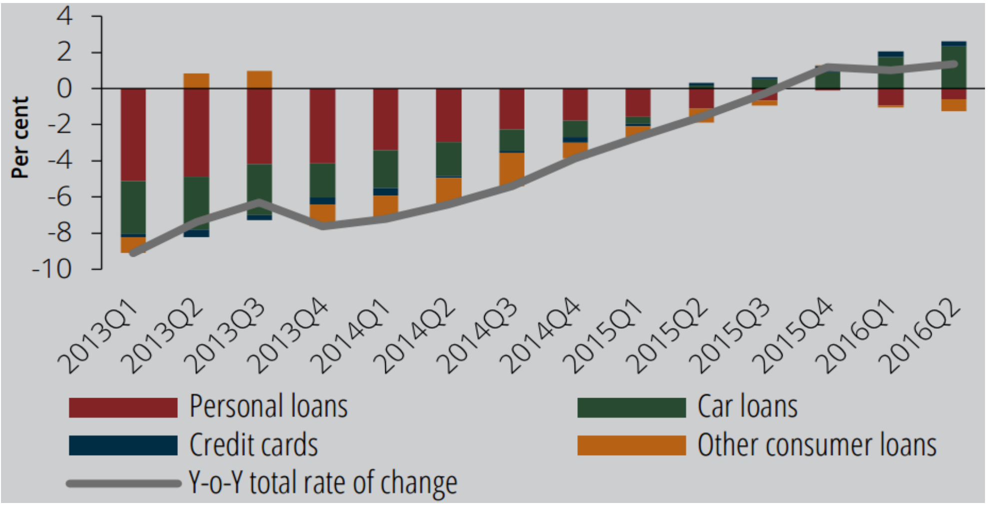
[15] Four segments of consumer loans were taken into account: (i) personal loans; (ii) car loans; (iii) credit cards; and (iv) other consumer loans.

households whose total indebtedness was less than € 50.000 (Figure 5). This observation also allowed to infer that the greater access to credit of households with little or no credit could stem from two causes: (i) such households were previously refused in their attempts to seek and were now being funded by credit institutions; or (ii) such households did not seek or need credit in the past.

Figure 3- Contributions to the year-on-year rate of change in new consumer loans (flows), by consumer loan segment

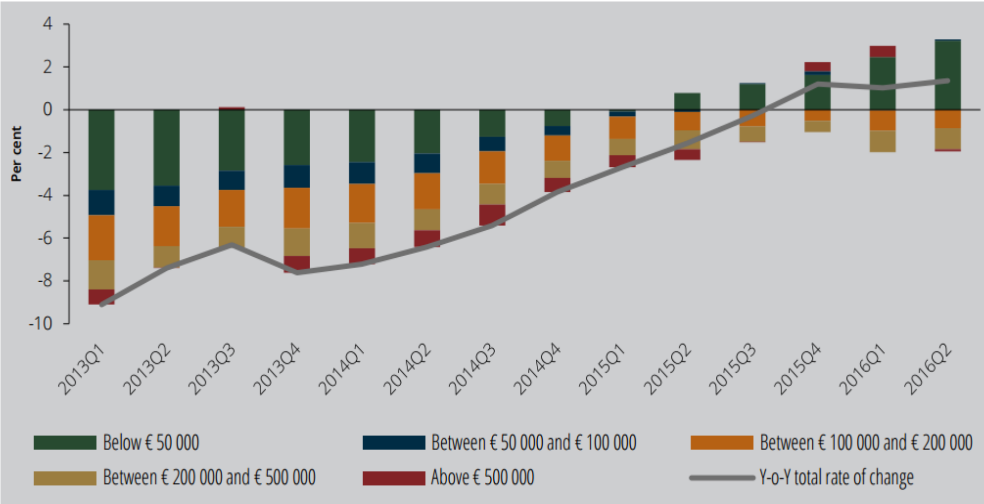
Source – Banco de Portugal | Financial Stability Report – November 2016

Figure 4- Contributions to the year-on-year rate of change in the stock of consumer loans, by consumer loan segment



Source – Banco de Portugal | Financial Stability Report – November 2016

Figure 5- Contributions to the year-on-year rate of change in the stock of consumer loans, by class of total household indebtedness



Source – Banco de Portugal | Financial Stability Report – November 2016

All in all, the study concluded that the recent increase in consumer credit, and particularly car loans, was likely to be interconnected with temporary factors and targeted to lowly indebted households and that, taking into account the relatively low importance of consumer credit in the household's and banking system's balance sheets, there was no expected increase in the risk to financial stability on the short run.

3.1. The In-house Credit Assessment System

The different microdata databases currently available at the Bank and the choice for an integrated management of information model has, as Lima & Drumond (2015) argue, allowed the Bank to meet the needs of its ever-challenging statistical stakeholders and enabled the Bank to go beyond the aforementioned tasks, by supporting and participating in a set of new initiatives at the Eurosystem level.

Indeed, in the framework of the European Credit Assessment Framework, the Bank has set up an In-house Credit Assessment System (ICAS), by further exploring the informational potential of the CCR and of its CBSD.

In the wake of the recent economic and financial crisis and inherent shortage of assets eligible to be used as collateral in monetary policy operations, these systems have been gaining importance in the Eurosystem, as shows the increasing number of Eurosystem NCBs who have either introduced them or are planning to introduce in the near future[16]. The Bank's ICAS, which was formally made available to credit institutions on November of 2016, provides the Bank with its own internal credit risk assessment system, thereby curtailing its dependence on external credit assessment providers.

At the current juncture, a more compelling use case for ICASs is related to monetary policy making, for which the ICAS will provide an evaluation of NFCs credit notation, to assess whether the debt issued by such entities is eligible to be used as collateral in the Eurosystem's monetary policy operations. However, the merits of such a system

[16] Currently, eight Eurosystem NCBs have their own ICASs: Belgium, Germany, Ireland, Spain, France, Italy, Austria, Portugal and Slovenia.

are not exclusively related to monetary policy making, as there are a number of advantages that this system offers to different business areas, especially those connected to micro and macroprudential supervision.

In the field of microprudential supervision, the credit notations derived from the ICAS can be used not only as a benchmark for those provided by credit institutions – which are obtained through their own internal assessment systems –, but also as a method to assess the quality of each credit institution's credit portfolios, while contributing to the early identification of specific risks to which these institutions may be exposed to. Furthermore, the ICAS can also support the identification and analysis of the risks and weaknesses attached to different economic sectors and assist in the preparation of the Portuguese financial sector's response to them, hence proving as an important input for stress-testing.

Concurrently, in the domain of macroprudential supervision, the data stemming from the Bank's ICAS can also be employed as a tool to monitor the developments the non-financial sector and their associated potential build-up of imbalances. This is done not only through the credit risk indicators on non-financial corporations generated by the ICAS, but also interconnected with the judgement of the Bank's risk assessment experts. To this extent, the purpose of this tool is twofold: on the one hand, to evaluate the frailty of specific economic activities through the economic and financial analysis of the companies that constitute them; and, on the other hand, to support the assessment of other systemic risks building-up in the NFCs sector, thus providing additional insights on the main risks and threats to financial stability.

To this extent, the CCR's data is a quintessential input in allowing the ICAS to fulfil its potential uses, as the default observations used in the ICAS are determined using the CCR and are in line with the Basel III default definition (and its guiding principles for the identification of defaults). Moreover, the CCR's data is also a key input for the calibration of the econometric models developed for the ICAS and also to assess the firm's scoring performance. Concretely, the CCR data that assists the ICAS is, *inter alia*:

a. Data on legal proceedings (legal defaults);

b. Data on all remaining elements of the reference default definition.

In addition, the remaining standard credit information expressed in section 2 (*e.g.*, non-performing loans, loan volume, number of banks and write-offs) is also used by the ICAS's analysts to feed their qualitative analysis on the NFC's creditworthiness, which then allows to support their decision to revisit (or not) the company's rating upwards or downwards.

Finally, after carefully discussing how the CCR is used to support the fulfilment of the Bank's mandate, it is now pertinent to understand how the ongoing CCR reformulation will add value to the existing data solutions and deepen the support that it provides to such areas of the Bank.

4. The new CCR

As discussed in the previous sections, central credit registers, such as the CCR, are a crucial tool for Central Banks that allow to monitor and manage credit risk, while providing provide a thorough description of the credit exposures and the level of indebtedness of both resident and non-resident borrowers *vis-à-vis* the national financial intermediaries.

Having recognized the importance of such tools, and in order to grasp an enhanced overview of the level of indebtedness of the borrowers across the Member-States of the European Union (EU), the European System of Central Banks (ESCB) has been exploring, since 2007, the potential statistical use of CCRs at the EU level. Particularly, it sought to understand the content of national CCRs could be enhanced and adapted to euro area and European Union statistical needs, such that it fostered the reduction of the reporting burden of the participants and promoted an increase in transparency.

Against this background, the European Central Bank (ECB) launched, together with experts from both the statistical and credit registers' areas of a number of euro area and non-euro area NCBs, the so-called AnaCredit[17] project in 2011. This project will create a new database which will be fed from new or already existing data in NCBs, that will allow to generate a harmonised repository of credit information to support the main central banking functions, in particular, monetary policymaking and macroprudential supervision.

The recent crisis showed how important good and detailed statistics are as a basis for decision making process, by giving more transparency for all the stakeholders. Therefore, AnaCredit will improve the statistical information basis for the Eurosystem in a significant way.

To fulfil the AnaCredit requirements, the CCR is currently being redesigned and will adopt a new philosophy: a loan-by-loan basis. Although the first stage of AnaCredit will only consider loans granted by credit institutions to legal entities, the CCR will keep its current extensive coverage, both in terms of its participating institutions and borrowers, in an attempt to cover all the attributes for nearly all this universe.

The implementation of the new CCR information system has already been initiated and is also taking into careful account other data needs (non-related with AnaCredit) and specific functionalities identified as relevant by its participant institutions and users. The resulting new data model will include not only the 94 attributes requested by AnaCredit but also other credit data needed by the Bank internal users, which will lead to a rationalization of the data requests to financial intermediaries, through the usage of a single entry point in the Bank for credit data, thus achieving a high standard of data integrity.

Concomitantly, the new CCR retains some rules of the current CCR: *(i)* different reporting rules for static and dynamic data; *(ii)* identification of borrowers through a unique code (the use of the taxpayer number will continue to be mandatory for residents in Portugal); *(iii)* statistical classification of borrowers will be made in the Bank through its business register; *(iv)* the monthly backflow data to the financial system will be approximately the same; *(v)* corrections to reported data will be made only by the reporting institutions; and *(vi)* the system itself should be composed by two components (transactional and analytical).

In order to improve the performance of the Bank's tasks related with monetary policymaking, risk management, statistical compilation, supervision and financial stability, the new CCR will cover more than 180 attributes. This means that when a loan is eligible to report to the CCR (the 50 euros threshold will be kept), the participant institutions will have to report information on the instrument, the debtor(s), the protection/guarantees, the accounting and risk information. Moreover, to meet a need of the financial intermediaries, the CCR will also deal with daily data

[17] The name AnaCredit stands for "Analytical Credit Datasets".

on relevant credit events, thus fostering a better evaluation of the credit risk of the credit clients and also enabling the Bank to follow the credit evolution on the financial system with a much smaller time lag.

The new CCR system is expected to “go live” in June of 2018, one quarter before the beginning of the AnaCredit reporting reference period. There will be no overlap with the current system since a test phase is planned to be included in the project development.

5. Concluding remarks

Upon its creation, the main objective of the Portuguese CCR was the provision of relevant information to better understand the risk attached to granting specific credit contracts or to specific borrowers. However, over time, the CCR has also shown a significant potential and usefulness to support other central bank’s purposes, such that the current CCR legal framework already foresees that this data can be used in meeting the tasks entrusted to the Bank, such as the compilation of official statistical, micro and macroprudential supervision, economic research and monetary policymaking.

Indeed, the use of CCR data for statistical purposes has allowed, *inter alia*, the improvement of the quality of monetary and financial statistics (MFS), namely in balance sheet statistics, since the CCR fosters a greater accuracy in the institutional classification of the counterparties receiving credit form monetary and financial institutions’ (MFI). Furthermore, in this statistical domain, the use of CCR data has been facilitated, due to the fact that: *(i)* both the CCR and the MFS domains share the same reporting institutions; *(ii)* the content of the reported information is coherent; and that *(iii)* they both share identical reporting frequencies and timeliness.

Notwithstanding, the CCR has also enabled a better assessment of credit developments, while also increasing the analytical possibilities at the disposal of the Bank by enabling a thorough evaluation through several different breakdowns. New statistical products have also been developed – without imposing further reporting requirements and intensifying the respondents’ burdens – and new statistical capabilities are planned within the CCR’s reformulation horizon.

In the domain of micro and macroprudential supervision, the CCR has been extensively used in the assessment of the risk of the credit granted by credit institutions to non-financial corporations and of the concentration of such risk exposures, both at micro and macro level. Furthermore, the CCR has also proved to be particularly useful in improving on-site inspection practices and to assess the need for prudential policy making. Concurrently, the CCR has also been a source extensively used by the Bank’s economic researchers, as its microdata, often combined with other microdata databases available at the Bank (*e.g.* the CBSD), have fuelled several research papers and analysis. Concomitantly, within the monetary policy framework, the CCR has been employed in the identification of the loans used as collateral in the Eurosystem’s financing operations.

In the future, as today, the CCR will surely continue to be of utmost importance to fulfil the Bank’s mandate. Notwithstanding, when taking into account the new data model arising from the CCR’s reformulation and the Bank’s information model, which fosters the combination of its data with other microdata databases available at the Bank (namely the securities holdings and issues and corporate balance-sheet data), it will be possible to develop and produce new statistics, thus increasing the contribution of the Bank to the official statistics universe.

Bibliography

Almeida, A. & Damia, V. (2013), "Challenges and prospects for setting-up a European Union shared system on credit". Workshop on Integrated Management of Micro-databases, Porto, 2013.

Augusto, F. & Félix, S. (2014), "The impact of bank recapitalization on firms' access to credit: evidence from Portugal". *Banco de Portugal*, Financial Stability Papers 2|2014.

Banco de Portugal (2016), Financial Stability Report, November 2016

Cadete de Matos, J. (2014) "The information model at *Banco de Portugal*: innovative and flexible data solutions". Meeting on Financial Information Needs for Statistics, Macroprudential Regulation and Supervision in Central Banks of Latin America and the Caribbean, CEMLA and *Banco de México*, Ciudad de México, May 2014.

Cadete de Matos, J. (2015a), "Reaping the Benefits of Using Integrated Micro-Data for Statistical Purposes… and Beyond". STATISTIKA – Statistics and Economy Journal, Vol. 95 (3) 2015.

Cadete de Matos, J. (2015b), "The Portuguese Central Credit Register: a powerful multi-purpose tool, relevant for many central bank's functions", IFC Workshop on *Combining micro and macro statistical data for financial stability analysis. Experiences, opportunities and challenges.*

Casimiro, P. (2013), "A flexible approach to credit statistics: The use of the Portuguese Central Credit Register for statistical compilation". Workshop on Integrated Management of Micro-databases, Porto, June 2013.

D'Aguiar, L., Almeida, A. & Casimiro , P., "Promoting enhanced responsiveness to users' data needs: the experience of the Banco de Portugal in exploring the statistical potential of micro-databases". 58th World Statistics Congress, Dublin, August 2011.

Farinha, L. & Félix, S. (2014), "Credit rationing for Portuguese SMEs". *Banco de Portugal*, Financial Stability Papers 3|2014.

Lima, F. & Drumond, I. (2015) "How to keep statistics' customers happy? Use micro-databases!", IFC Workshop on *Combining micro and macro statistical data for financial stability analysis. Experiences, opportunities and challenges.*

Neves, P. D. (2014), "Enhancing the synergies between the SSM and statistical reporting". Seventh ECB Statistics Conference "Towards the banking Union. Opportunities and challenges for statistics", Frankfurt am Main, October 2014.

Supplement 1/2005 to the Statistical Bulletin, "A New Source for Monetary and Financial Statistics: the Central Credit Register". *Banco de Portugal*, April 2005.

Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

IFC-National Bank of Belgium Workshop on "*Data needs and Statistics compilation for macroprudential analysis*"

Brussels, Belgium, 18-19 May 2017

The Portuguese Central Credit Register as a key input to the analysis of financial stability ... and beyond![1]

João Cadete de Matos,
Bank of Portugal

[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.

The Portuguese Central Credit Register as a key input to the analysis of financial stability… and beyond!

BANCO DE PORTUGAL
EUROSYSTEM

João Cadete de Matos

Director • Statistics Department

IFC – National Bank of Belgium
Workshop on "Data needs and Statistics compilation for macroprudential analysis"
Brussels, Belgium| 18 – 19 May, 2017

Outline

1. **The Portuguese CCR at a glance**
   a) Overview
   b) Using the CCR in meeting the *Banco de Portugal*'s mandate
      i. Compilation and dissemination of statistics
      ii. Economic research
      iii. Monetary policy making
      iv. Microprudential supervision
2. **Using the Portuguese CCR to ensure financial stability… and beyond**
3. **The ongoing CCR reformulation**
4. **Concluding remarks**

A brief overview of the Portuguese CCR

- The **Portuguese Central Credit Register (CCR)** is an **information system** managed by the **Statistics Department of the *Banco de Portugal;***
- Contains **granular information on credit granted by resident credit-granting institutions (the participants) to individuals and legal entities;**
- Has a **very low reporting threshold (50€),** which allows it to have a **virtually complete coverage.**
- Currently **on a borrower-by-borrower basis;**

Main Purpose: offer its participants relevant data for their assessment of the risks underlying the provision of credit

A brief overview of the Portuguese CCR

20 Million records monthly

6.2 Million private individuals

289 Thousand corporations

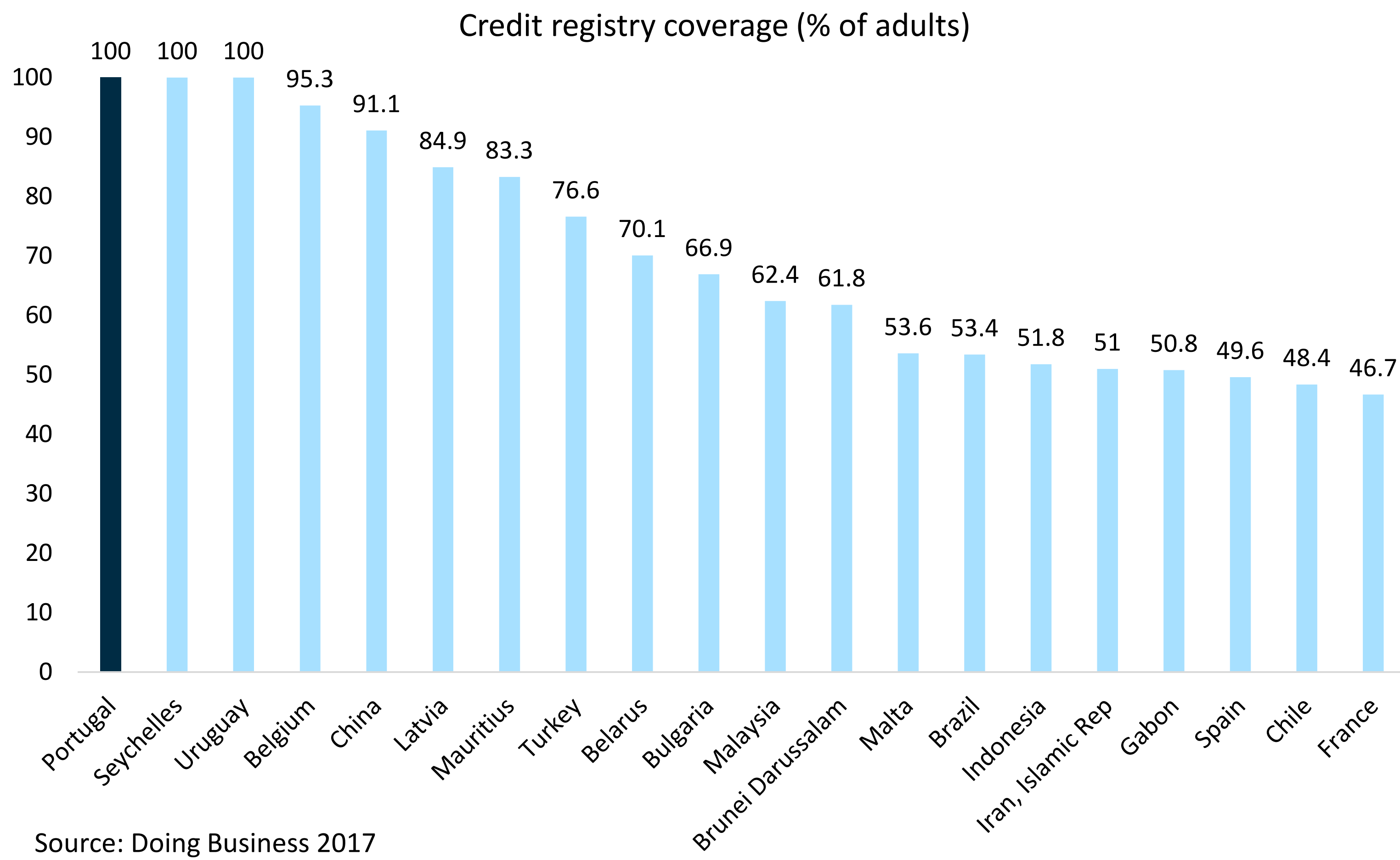
185 Reporting Agents

15 different types of loans

50€ threshold

6 Working Days deadline for reporting 16h/7 days a week

A brief overview of the Portuguese CCR



Source: Doing Business 2017

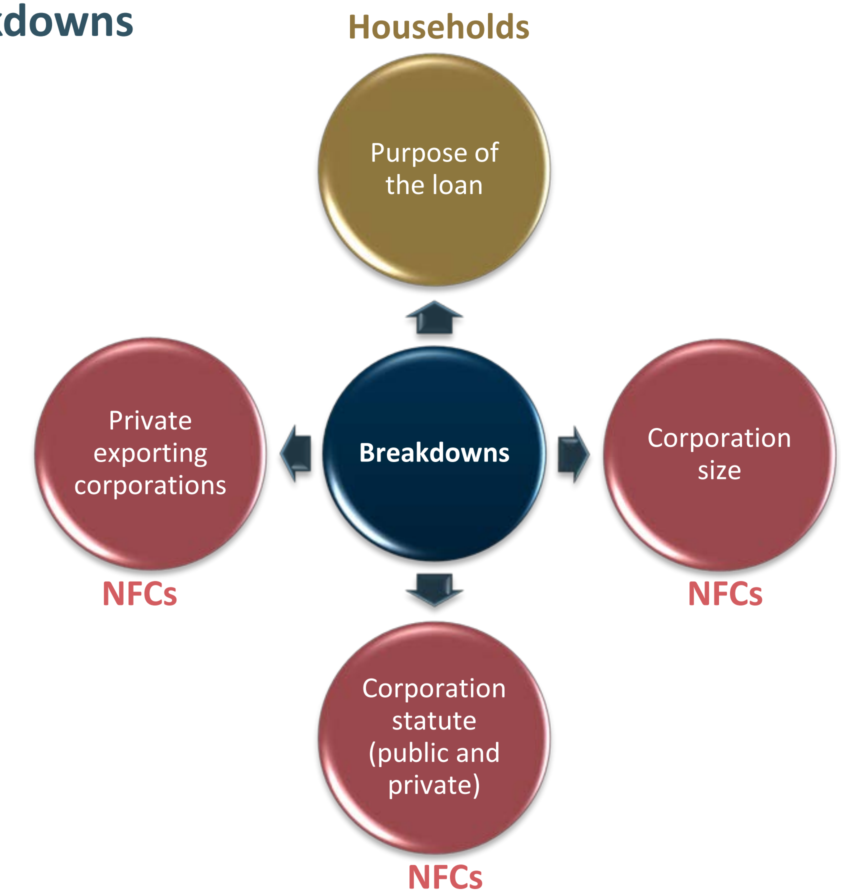
Using the CCR to compile and disseminate official statistics

The CCR allows to **compile very comprehensive statistics** on several credit related indicators and **with several breakdowns**

On a monthly basis, for NFCs, NPISH and Households sectors…

Indicators

- Outstanding amounts of the granted loans
- Annual rate of change
- Overdue loans ratio
- Percentage of borrowers with overdue loans

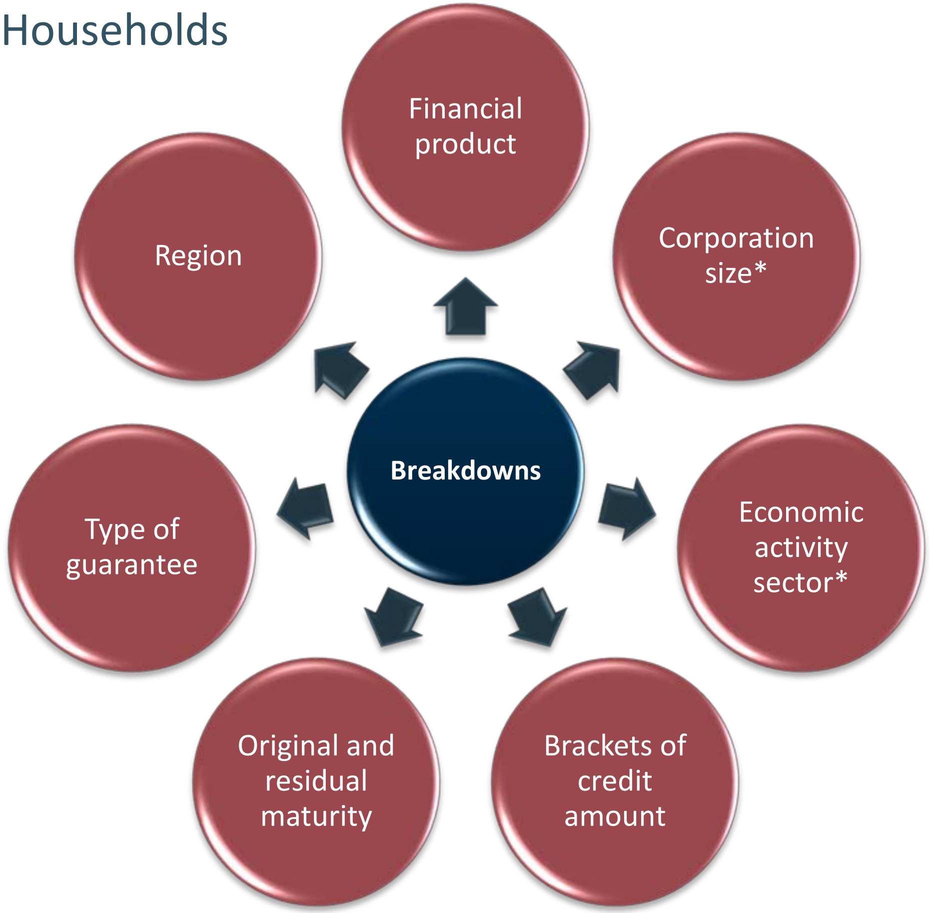


Using the CCR to compile and disseminate official statistics

On a quarterly basis, for NFCs and Households sectors…

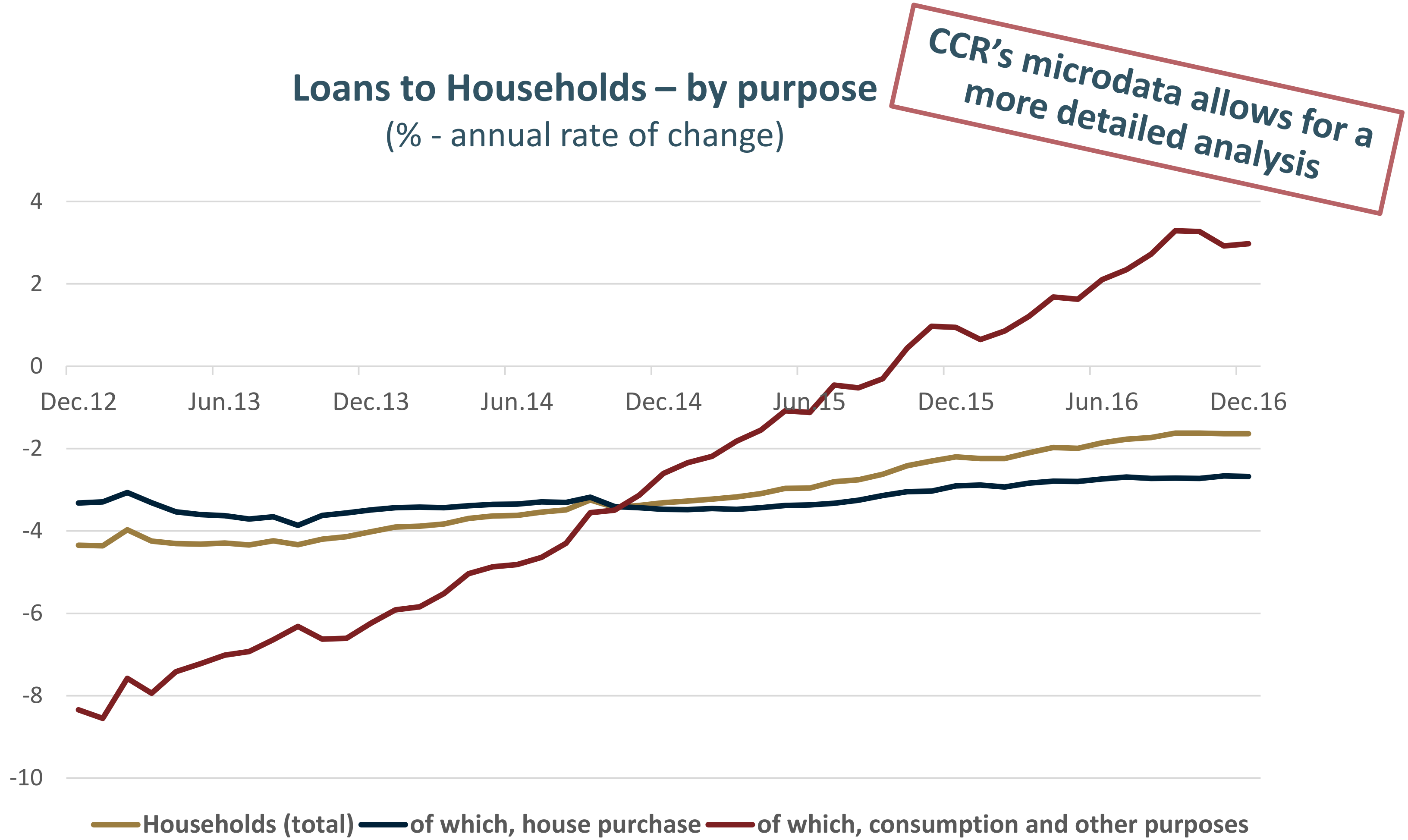
Indicators

- Outstanding amounts of the granted loans
- Overdue loans
- Overdue loans ratio
- Number of borrowers
- Percentage of borrowers with overdue loans



* Only for NFCs sector

Using the CCR to compile and disseminate official statistics



Using the CCR for economic research

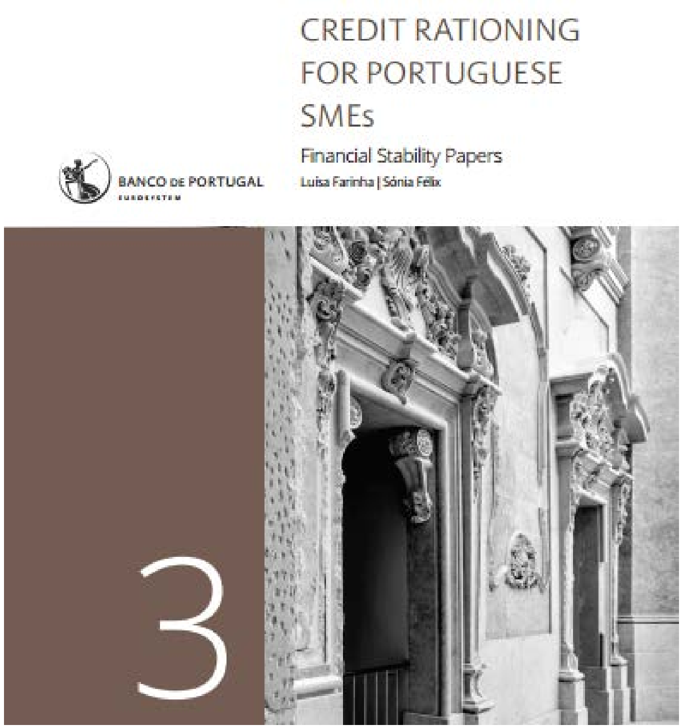
CCR

CCR's micro-data

Research community

Studies

Using the CCR for economic research



[…] The results suggest that a considerable fraction of Portuguese SMEs [Small and medium enterprises] were **affected by credit rationing** in this period [2010–2012].

In Farinha & Félix (2014)

Using the CCR for monetary policy making

CCR data is used:

As an auxiliary tool in the identification of loans used as collateral in Eurosystem financing operations

To evaluate the risks associated with the acceptance of bank loans as collateral of monetary policy credit operations

Using the CCR for monetary policy making

CCR is also relevant for:

Eligibility assessment (and *ex post* verification) of credit claims

Collateral generation capacity estimation of domestic counterparties on credit claims, asset back securities and covered bonds

Using the CCR for microprudential supervision

CCR data is used for the:

- Assessment of credit risk
- Evaluation of the concentration of risk exposures
- Improvement of on-site inspection practices

Using the CCR for microprudential supervision

The CCR is also used in the *Banco de Portugal*'s **Early Warning System (EWS)**, which aims at **finding companies evidencing a high default probability as a result of excessive indebtedness**

EWS

Two core ratios in accordance with Standard & Poor's Corporate Ratings Framework:

- **Total debt to EBITDA**
- **EBITDA Interest Coverage**

To foster the **understanding of the company's financial risk profile, three additional supplementary ratios:**

- **Funds From Operation to Total Debt**
- **Gearing Ratio**
- **Return on Capital**

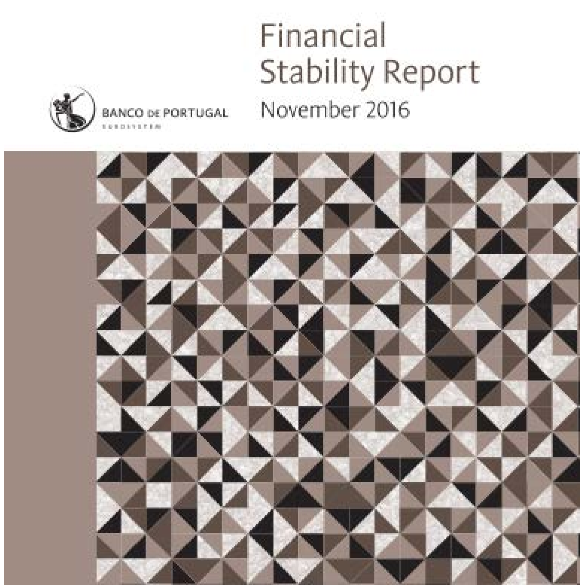
Using the Portuguese CCR to ensure financial stability… and beyond

The CCR enables…

- Assessment of the risks stemming from the household and NFCs sectors, through the examination of the distribution measures of the loan/debtor classes
- Identification of the financial situation of NFCs, by distinguishing different financial situations of NFCs through their positive/null/negative changes in borrowing
- Analysis of the NFCs' credit performance in the wake of credit restructuring
- Evaluation of the effects of the age of the NFCs on their credit spreads – in this case, the CCR is also complemented by the Bank's interest rate statistics database
- Monitoring of the credit tendencies of the largest indebted NFCs
- Exploration of the credit history of high growth corporations

Using the Portuguese CCR to ensure financial stability…

A **good example** of the usage of the CCR to assess financial stability: the **Financial Stability Report**



Contents:

1. **Financial stability: Vulnerabilities and risks (Vulnerabilities, risks, macroprudential policy)** **CCR Data!**
2. **Financing of the Economy** **CCR Data!**

   (Financial Markets, Households, Non-financial Corporations, General Government, Financial Corporations, External Sector)
3. **Banking Sector** **CCR Data!**
4. **Special Issues** **CCR Data!**

Using the Portuguese CCR to ensure financial stability…

A **good example** of the usage of the CCR to assess financial stability: the **Financial Stability Report**

Special issues 65

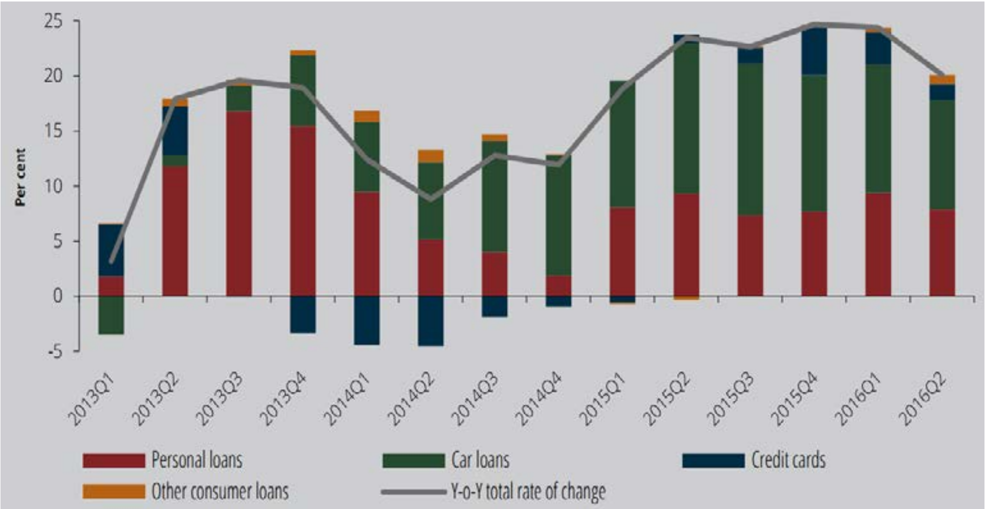
1. Recent developments in consumer lending: A macroprudential approach

"[…] one of Banco de Portugal's **responsibilities**, is the **mitigation and prevention of excessive credit growth** and leverage of the economy. Thus, when **assessing risks to financial stability**, as undertaken by Banco de Portugal, **monitoring the evolution of credit to the economy is of the utmost importance**.[…]"

Using the Portuguese CCR to ensure financial stability…

"[…] the **upward path recently shown by consumer credit is analysed,** […, since] **this segment** of the lending market **presents a significant default risk**, and its **persistent high growth could also lead to an increase in vulnerabilities**, both for households and the banking system.[…]"

Contributions to the year-on-year rate of change in new consumer loans (flows), by consumer loan segment

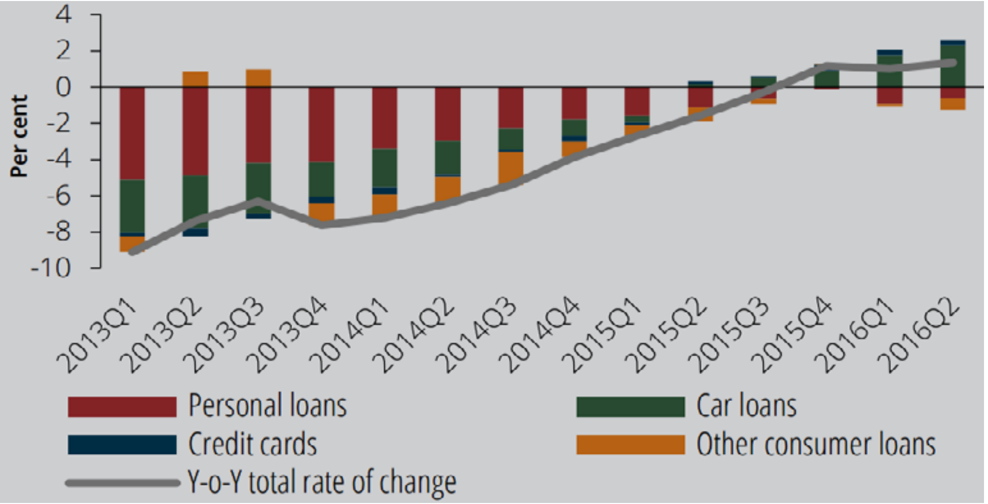


CCR's microdata allows for a more detailed analysis

Using the Portuguese CCR to ensure financial stability…

"[…] The recent **increase in consumer credit was mainly driven by car loans**, and was mostly **associated with the effect of the anticipated purchase of cars** as a result of the **announcement of an increase in Vehicle Tax** that came into force in April 2016. […] this evolution is **expected to be of a temporary nature**. […] Therefore, given the **reduced relative importance on households' balance sheets** and the resident financial system, there is **not expected to be a significant increase in risk to financial stability**. "

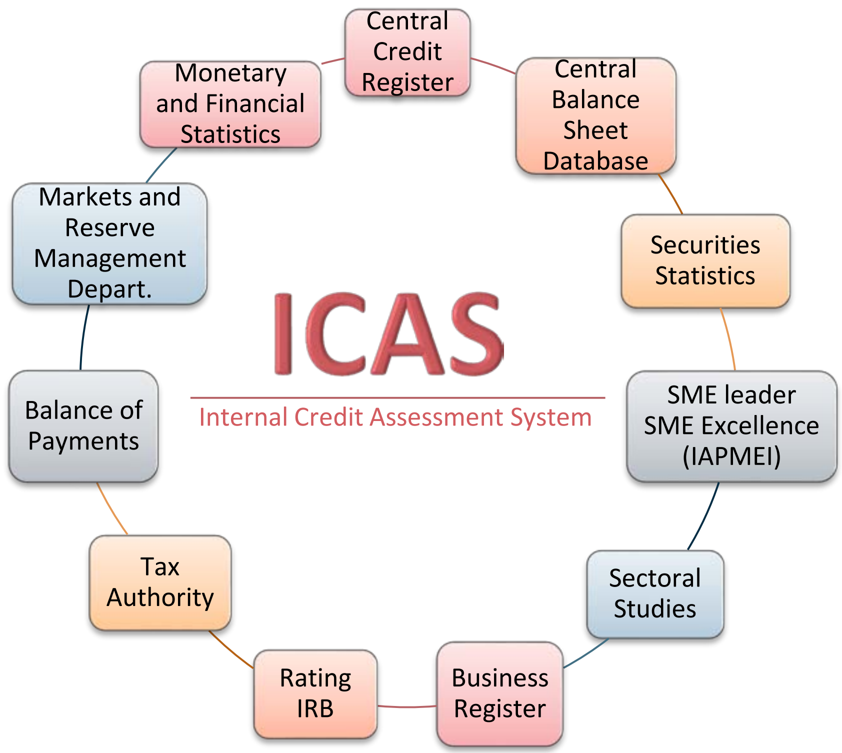
Contributions to the year-on-year rate of change in the stock of consumer loans, by consumer loan segment



CCR's microdata allows for a more detailed analysis

Using the Portuguese CCR to ensure financial stability… and beyond!

The **In-House Credit Assessment System** (ICAS): a new credit-rating tool developed by *Banco de Portugal* to support many of its key tasks



Using the Portuguese CCR to ensure financial stability... and beyond!

ICAS

Main purpose: Assessing the **creditworthiness of non-financial corporations**, with a view to determine the **eligibility of the debt issued by such corporations as collateral in monetary policy operations**

Additional uses:

Microprudential supervision:

- **Benchmarking the credit notations** provided by ICAS against those of the supervised institutions

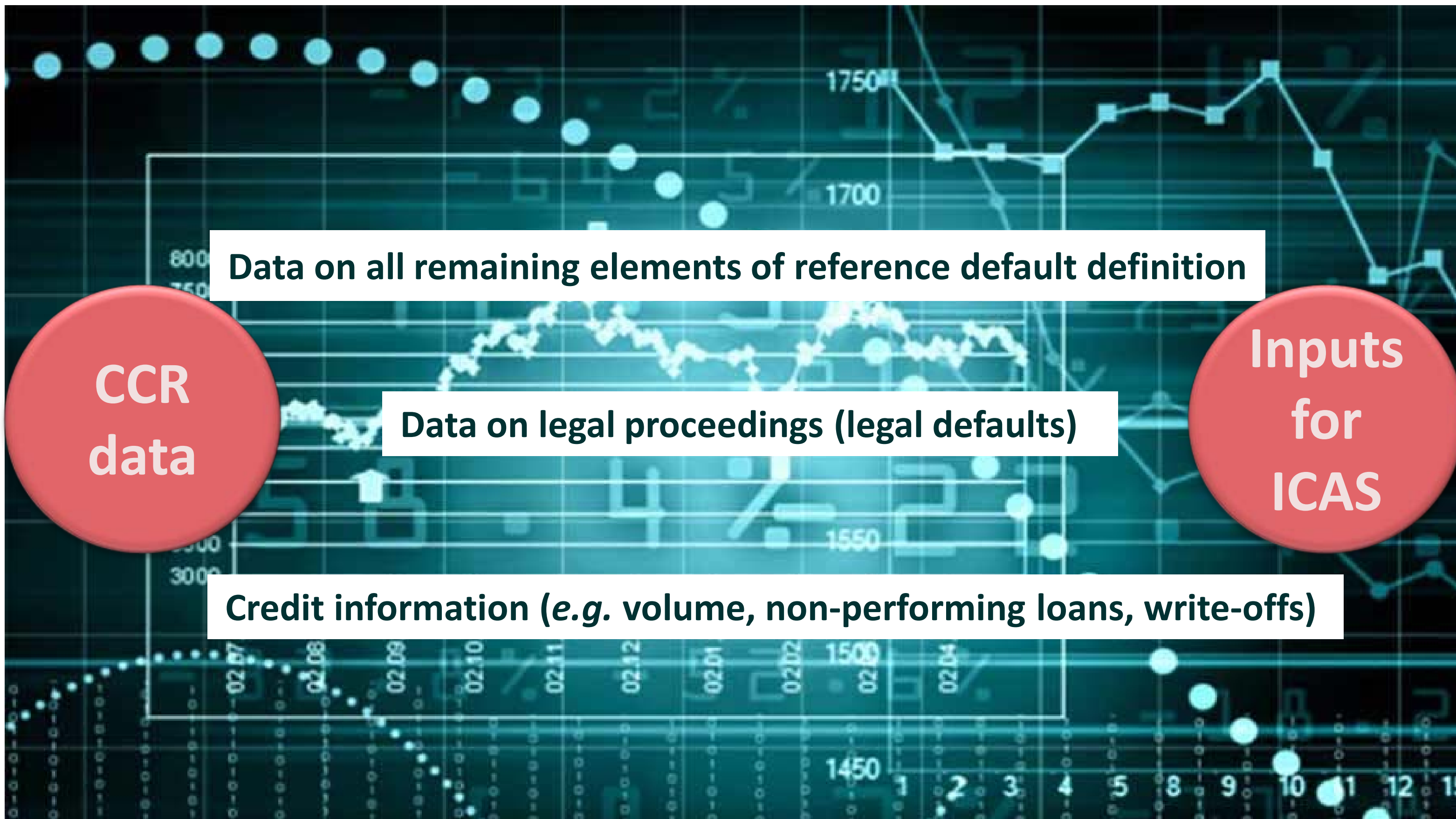
- Computation of **sectoral default probabilities** (input **for stress testing**)

Macroprudential supervision:

- **Identification of potential financial fragilities** in a set of companies and / or economic sector

- Assessment of **other systemic risks stemming from the non-financial corporations sector**

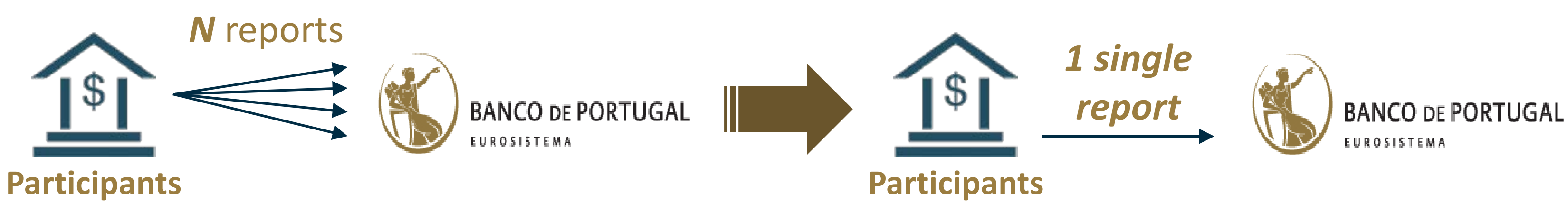
Using the Portuguese CCR to ensure financial stability… and beyond!



The ongoing CCR reformulation

The *Banco de Portugal* is currently undertaking a **significant reformulation to its CCR**. This project was developed due to the **need to**:

- Meet the forthcoming **AnaCredit requirements**
- **Rationalize the participant's reports to the CCR**, thus **integrating** other credit reports **in the CCR**



- **Improve the service** that the CCR offers to the financial system and to the public at large
- Include **new internal data needs**

The ongoing CCR reformulation

New CCR perspective: Loan-by-loan basis

Current CCR		New CCR
Information on **credit liabilities**	→	Information on **credit liabilities** and **credit risk**
Borrower-by-borrower basis	→	**Loan-by-loan basis**

Current CCR **24 variables** + AnaCredit Around **70 variables** + Other Instructions and reports Around **50 variables** + Other requisites Around **40 variables** = New CCR Around 184 variables

Concluding remarks

- The Portuguese Central Credit Register (CCR) is **truly a multi-purpose tool**, which **supports the fulfillment of several tasks entrusted** to the ***Banco de Portugal***
- It is particularly **useful to assess credit developments** with great detail, by offering a multitude of different breakdowns of analysis which are only possible due to its microdata reporting basis
- It has proved to be **a key input to the development of innovative initiatives**, such as **the establishment of the Bank's Internal Credit Assessment Framework**
- In the near future, it will experience **a deep reformulation to meet the AnaCredit requirements (and beyond),** which **will reinforce its supportive power**

Thank you for your attention!

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