Irving Fisher Committee on Central Bank Statistics

IFC Bulletin

No 45

Uses of Central Balance Sheet Data Offices' information

Proceedings of the IFC-ECCBSO-CBRT Conference in Özdere-İzmir, Turkey, on 26 September 2016

October 2017

BANK FOR INTERNATIONAL SETTLEMENTS

Contributions in this volume were prepared for the IFC-ECCBSO-CBRT Conference on "Uses of Central Balance Sheet Data Offices' information", co-organised by the IFC, the European Committee of Central Balance Sheet Data Offices (ECCBSO) and the Central Bank of the Republic of Turkey (CBRT) in Özdere-İzmir, Turkey, on 26 September 2016. The views expressed are those of the authors and do not necessarily reflect the views of the IFC, its members, the BIS and the institutions represented at the meeting.

This publication is available on the BIS website (www.bis.org).

ISSN 1991-7511 (online)

ISBN 978-92-9259-093-2 (online)

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Proceedings of the IFC-ECCBSO-CBRT Conference, co-organised by the Irving Fisher Committee on Central Bank Statistics (IFC), the European Committee of Central Balance Sheet Data Offices (ECCBSO) and the Central Bank of the Republic of Turkey (CBRT)

Özdere-İzmir, Turkey, 26 September 2016

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The growing use of Central Balance Sheet Data Offices' information in the wake of the Great Financial Crisis

Overview of the IFC-ECCBSO-CBRT Conference

Timur Hülagü and Bruno Tissot[1]

1. Introduction – Granular balance sheet information

Importance of analysing firm-level data after the Great Financial Crisis

If anything, the Great Financial Crisis (GFC) of 2007–09 highlighted the importance of looking at the financial exposures of economic agents. Since then a key focus has been to enhance the provision of National Accounts-based aggregated information on financial positions, particularly with respect to the development of integrated sectoral accounts.[2] The GFC also underscored the need for "going beyond the aggregates" to better analyse micro-level situations that could potentially have systemic implications.[3] One key reason is that financial stress experienced at the level of individual entities, transactions or instruments can quickly reverberate to the entire financial system.

Indeed, a key element of the policy response after the GFC was to fill the data gaps related to these two aspects. Following the initial recommendations of the Financial Crisis and Information Gaps report of 2009[4] – issued by the International Monetary Fund (IMF) and the Financial Stability Board (FSB) and endorsed by the G20 – the international Data Gaps Initiative (DGI) emphasised the need for a better understanding of the financial system at both the macro- and microeconomic levels. It explicitly recognised the importance of collecting more granular data to "*help*

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[2] See Tissot (2016): "Development of financial sectoral accounts: new opportunities and challenges for supporting financial stability analysis", *IFC Working Papers*, no 15, November.

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

[4] International Monetary Fund and Financial Stability Board (2009): "The financial crisis and information gaps", *Report to the G20 Finance Ministers and Central Bank Governors*, October.

straddle the divide between micro and macro analysis".[5] It also noted the challenges posed by the lack of data on non-financial corporates – with a specific recommendation (no 14) relating to "*data on non-bank corporations' cross-border exposures, including those through foreign affiliates and intra-group funding (…)*".

Central Balance Sheet Data Offices (CBSOs) can clearly play a major role in addressing such information needs. Although there are no unified practices or definitions, one will generally understand the expression "central balance sheet data" as the information covering **firms' individual financial statements**. Given that a large part of the financial sector (eg banks, insurance companies etc) is supervised and reports such data, the focus is usually on the balance sheets of **non-financial corporates**.

A number of countries have established CBSOs to collect, store, disseminate and analyse individual data on corporate balance sheets. Most of these CBSOs are located at the central banks and associated with their statistical functions. The **information collected** is usually derived from multiple sources, depending on national practices and/or institutional factors – related, in particular, to the legal framework governing the collection of firm-level information, the degree of confidentiality and the ability to share it among authorities. CBSO data may thus vary significantly from one country to another, in terms of periodicity, accounting consolidation and perimeter.[6] They can be derived from multiple sources, in particular administrative registers, statistical surveys and official financial reporting data sets. Reflecting this complexity, a growing number of central banks are exploring "big data" techniques to deal with the large amount and complexity of information that can be included in such databases.[7]

Not only do the statistics collected vary but their **usage** can also be very diverse. National experiences show that CBSOs comprise a wealth of information to support financial stability analyses, facilitating the understanding of financial linkages and the assessment of fragilities:[8] for instance, the importance of banks' credit exposures to non-financial corporates, the extent of firms' reliance on specific funding sources etc. They can also provide useful insights into the economic performance of the corporate sector, including, for instance, the impact of their foreign operations and investment decisions. Furthermore, they help to assess the impact of public policies, such as monetary policy measures targeting specific borrowing segments (eg SMEs), macroprudential tools or even fiscal policy actions.

5 International Monetary Fund and Financial Stability Board (2015): "The Financial Crisis and Information Gaps", *Sixth Implementation Progress Report of the G20 Data Gaps Initiative*, September.

6 In practice, CBSO data almost always include information on balance sheet positions and income statements derived from non-financial corporations' financial accounts. In several countries, this information is combined with various data sets, for instance those from central credit registers (information on loans granted by credit institutions to companies), business registers (providing general characteristics for each corporation) and other descriptive data about companies, such as information on group structures. For more details on national practices, see ECCBSO (2015): "Report 2015 – Products and services of the European CBSOs", December.

7 See IFC (2017): "Big data", *IFC Bulletin*, no 44, September.

8 As emphasised by Mario Marcel, Governor of the Central Bank of Chile in his opening remarks at the third meeting of the CEMLA Financial Information Forum held in Santiago on 4–5 October 2017 under the auspices of the Central Bank of Chile (www.cemla.org/actividades/2017/2017-10-iii-reunion-fif/2017-10-iii-reunion-fif0.pdf).

This last aspect has clearly increased since the GFC with the growing importance of evidence-based policies undertaken.[9]

The need for sharing national experiences

The issues just discussed clearly highlight the need for the sharing of information on national experiences relating to CBSO data, especially among central banks. At the European level, the European Committee of Central Balance Sheet Data Offices (ECCBSO) is a consultative body created in 1987 by a group of central banks managing a CBSO.[10] Its main objectives are to improve the analysis of non-financial corporate data, especially by exchanging relevant information, and to assess how the information could be used to accomplish central banks' functions in fields such as statistics, economic and financial research, financial stability, financial supervision and financial risk assessment.[11]

In response to an invitation by the ECCBSO, the IFC decided to co-organise with the Central Bank of the Republic of Turkey (CBRT) a workshop on these issues. A key objective was to present experience gained by the ECCBSO to the broader community of central banks involved in BIS/IFC activities. Another objective was to provide a global platform for the sharing of national experiences in collecting granular balance sheet-type information as well as to facilitate communication among the various stakeholders – especially between the producers of statistics at official institutions and the end-users of the statistics, in particular for policy purposes and academic research.

A key issue covered by the workshop related to the **value added** of central balance sheet information. While it is widely acknowledged that this information can help gauge company-level vulnerabilities – eg the relative strength of a specific firm, its default risk or its fragilities in terms of maturity and currency mismatches – there are also important data limitations, in particular with respect to availability, quality, frequency and timeliness.

A second issue has been the growing demand for CBSO-type information to **support public policies** in the aftermath of the GFC. As regards monetary policy, the various quantitative easing policies implemented have relied on the use of new, unconventional tools that often require access to firm-level data. As regards microfinancial supervision, there has been a growing focus by banking supervisors and other supervisory authorities on non-financial corporate information, not least to better understand the credit and counterparty risks borne by financial institutions. Similarly, the increasing importance of macroprudential policies and analyses has put a premium on a better monitoring of firm-level fragilities with potential system-wide implications. This often requires access to, and aggregation of, relatively granular data.

[9] See Tissot (2017): "Using micro data to support evidence-based policy ", International Statistical Institute 61st World Statistics Congress, July.

[10] ECCBSO members are largely made up of European central banks but they also comprise a significant number of statistical offices. They also include Cerved Group Spa, an Italian company that is one of the major credit rating agencies in Europe. Several international organisations, including the BIS, participate as observers. See https://www.eccbso.org/wba/default.asp.

[11] See ECCBSO (2015).

A third issue is whether CBSO-based information can be used for wider **research purposes**. In particular, there has been growing interest among academic circles for using firm-level data to explore the drivers of microeconomic performance, including, for example, the impact of leverage, the determinants of profitability and the assessment and management of exposures (eg hedging operations). However, such studies often depend on the ability to match CBSO information with other firm-level data sources, such as detailed loans and securities data.

A fourth issue is that the actual use of CBSO data can be constrained by **confidentiality** considerations. For instance, a large part of firm-level information cannot be accessed by the general public without being anonymised. Such considerations also constrain the ability of firms to conduct benchmark analysis for comparative purposes.

A last issue is how recent efforts to use CBSO data fit within related **international initiatives**, such as the DGI, the Statistical Data and Metadata Exchange (SMDX) standard[12] and the Legal Entity Identifier (LEI) project.[13] In particular, the more active use of granular balance sheet information is likely to depend on progress achieved in other areas, such as revisions to confidentiality rules, the sharing of data among domestic and international public authorities, the use of common identifiers and efforts to enhance the links between micro indicators and macro aggregates.

The main themes of the conference

Opening the meeting, Erkan Kilimci, Deputy Governor, CBRT, emphasised that the event was a **key opportunity** for connecting the producers and users of CBSO data. Bridging the gap between these two groups was essential since the GFC. His intervention focused on four themes. The first one was the importance of capturing non-financial institutions when conducting financial stability analysis, not least because of the importance of network and spillover effects. The second one was that there was always a financial dimension to "real economic issues", such as the determinants of investment, SME access to credit and productivity performance. The third was that traditional macro statistics were insufficient to understand fully the functioning of the global financial system, which required the integration of granular data into a system-wide perspective. Last, there was a need for greater cross-country harmonisation of firm-level databases, for instance, to get a better grasp of cross-border linkages and to conduct benchmarking exercises.

The meeting was fruitful in offering **various perspectives** on these issues, underscoring the importance of the burgeoning literature on the use of firm-level data. The first session presented data that could be extracted from CBSOs, based on various country experiences. The second session focused on how this information could be used to assess financial sector risks, especially with respect to the banking system (which could be heavily exposed to non-financial corporates). The third session focused on the non-financial sector, highlighting the opportunities provided

12 On the SDMX, see IFC (2016): "Central banks' use of the SDMX standard", March.

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

by CBSO information to analyse risks in the "real economy", for instance, to assess the creditworthiness of firms or their exchange rate exposures. The fourth and last session discussed the use of CBSO data for economic research and for the general assessment of financial stability issues.

2. A framework for collecting firm-level balance sheet data

The first session, chaired by Gülbin Şahinbeyoğlu, CBRT, provided a general overview of the **kind of firm-level balance sheet information** that was available in CBSO-type databases. A key difficulty was to cover the non-financial sector. This could be achieved by combining various sources of information – especially when there was no compulsory reporting of firms' financial data, as was the case in Germany, or when such a combination of statistical sources could significantly enhance the quality of the CBSO database maintained by the central bank, as in Portugal. Moreover, there were important efforts to coordinate data collection exercises across countries, especially in Europe, to better capture the global activities of corporate groups.

The first presentation, by the Deutsche Bundesbank, illustrated ongoing central bank initiatives – especially, but not only, in Europe – to set up large-scale and comprehensive CBSO databases. A main objective was to **collect individual records** on non-financial firms' financial accounts. But one had to deal with sensitive data protection issues, especially in Germany where there was no compulsory system for the collection of such information. This was a particular problem for small German firms as it was difficult to capture information on them. To address these challenges, a large "data pool" combining multiple statistical sources, including internal information derived from the central bank's own rating activities and commercial data sets, was constructed. Despite these efforts, small firms were under-represented and coverage of the service sector remained relatively weak. A second important aspect of the German experience was the initiative to facilitate information dissemination for scientific use. In particular, a secure research centre was established by the central bank to provide data analysis services for researchers – noting, however, that the internal data pool could not be directly accessed by these users and that balance sheet information had to be anonymised before being shared.

The second presentation, by the Bank of Portugal, also stressed the importance of matching firm-level databases but from a slightly different angle. While in the German case the focus was on improving the **coverage** of firms, in Portugal it was to enhance the **quality** of the information collected in the central bank's CBSO database. Matching CBSO data with other firm-level databases – available both within the institution (eg central credit registry data, securities statistics and information reported by monetary and financial institutions) and outside it (eg tax authority business information and wage and employment records) – was a way of controlling and improving the quality of the CBSO database. The central bank's experience underlined the need to apply careful and systematic quality checks when constructing micro databases, a task that was often underestimated by the users of such firm-level information.

The third presentation, by the National Bank of Belgium, described the collection of **pan-European firm-level information** in the context of the ERICA project.[14] The goal was to set up a common database for around 10 countries to monitor the adoption of the International Financial Reporting Standards (IFRS)[15] and analyse firms' financial statements (eg financial structure, sectoral diversification, profitability etc). Two benefits of this cross-country approach were highlighted. First, it allowed the capture of information on non-financial groups on a consolidated basis, which was becoming of increasing relevance with the development of Global Value Chains (GVCs)[16] and the expansion of the foreign operations of global groups (given that the use of "traditional" residency-based sources of firm-level information was increasingly showing its limitations).[17] Second, the pan-European nature of the database allowed for useful cross-country comparisons of key economic indicators, such as corporate profitability and financial structures, helping, in turn, to identify country- or sector-specific effects.

The last presentation, by the CBRT, provided a **wider perspective** on data collection efforts. As underlined by the GFC, it was essential to set up a proper macroprudential framework to analyse systemic risk from a holistic perspective. This called for a careful monitoring of systematically important institutions as well as of their interactions with each other – the so-called network effects. Doing so required looking at the wide range of potential linkages among economic units, including financial relationships, risk exposures, operational links etc. At the macro level, the aim was to develop integrated financial accounts so as to obtain a comprehensive picture of counterparty relationships within the economy. At the micro level, more granular information on the financial position of globally systemic entities was warranted. Post-GFC efforts had been devoted to the collection of such information for financial institutions, for instance, with the setting up of the International Data Hub hosted by the BIS in the context of the DGI (the trigger for which had been the publication of the "Top 50 Counterparty report").[18] More attention would need to be paid to the monitoring of non-financial corporates, for instance to assess the system-wide impact of their potential defaults, debt repayment failures and

[14] The ERICA Working Group of the ECCBSO focuses inter alia on the impact of the IFRS standards on European CBSO databases. To that end, the group created the ERICA (European Records of IFRS Consolidated Accounts) database, which includes around 1,000 non-financial listed groups in participating countries. For an example of recent work, see in particular ERICA Working Group of the ECCBSO (2017): *"European non-financial listed groups: analysis of 2015 data",* January.

[15] A vast majority of jurisdictions currently require the implementation of the IFRS for all or most domestic publicly accountable entities (for an assessment of progress relating to global accounting standards, see http://www.ifrs.org/use-around-the-world/use-of-ifrs-standards-by-jurisdiction/). In Europe, all publicly listed corporations are required to use IFRS (involving around 8,000 companies whose securities trade on a regulated market, with a few, temporary, exceptions).

[16] See BIS (2017): *87th Annual Report*, Chapter VI, "Understanding globalisation".

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

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

difficulties in rolling over debt. Balance sheet information on the household sector was another important piece of the puzzle from this perspective.[19]

3. CBSO information to monitor risks in the financial sector

The second session, chaired by João Cadete de Matos, Bank of Portugal and Chair of the ECCBSO, dealt with the use of CBSO data for risk assessment, with a focus on the **creditor's perspective**. CBSO-type data sets on non-financial corporates could provide useful insights into the financial system's vulnerabilities because its exposures to the non-financial sector. In particular, it was key for assessing default risk, both at the firm and sectoral levels, and for understanding the risks borne by lending institutions as well as by central banks in their liquidity operations.

The first presentation, by the Bank of Italy, analysed risks to the Italian banking sector stemming from the **excessive provision of credit** to specific sectors. Granular information, combining bank supervisory data and borrower balance sheet data, allowed for the estimation of firm-level indicators of financial risk, such as probability of default (PD) and loss given default (LGD). In turn, such measures helped to assess the concentration of a given bank's credit exposure to specific sectors, for instance, to the construction sector, which appeared to be relatively more vulnerable because of the cyclicality of its activity, its higher risk profile and its correlation with other sectors. Such bank-level information on sectoral credit concentration was useful in gauging the stability not only of the lending institutions taken in isolation but also of the financial system as a whole. By identifying the contribution of the various sectors to systemic risk, the approach provided important insights for macroprudential authorities willing to take preventive actions against potential financial stability threats.

The second presentation, again by the Bank of Italy, also looked at the fragility engendered by the banking system's provision of credit but from a different angle. Instead of analysing the **individual default risk** characteristics of a bank's borrower, attention was put on the borrower's **repayment behaviour**. This issue had become particularly important in Italy, reflecting the important stock of non-performing loans (NPLs) accumulated in the aftermath of the GFC as well as slow insolvency and recovery procedures. The starting point was that borrowers tended to delay their loan repayments in a selective way, for instance, when a bank was perceived to be weak. This seemed to be particularly the case for large firms that borrowed from multiple banks. Moreover, such a selective behaviour appeared to have a local dimension, being more frequent in those regions where legal enforcement was weak. By matching balance sheet registry data (providing borrower-side information), supervisory bank level reports (providing lender-side information) and credit registry data (providing information on specific loans), one was able to assess the risk of such "borrower runs".

The third presentation, by the Bank of Spain, focused on the assessment of the risks posed to financial institutions by **SME lending**. The financing constraints of small firms had gained a lot of attention in Spain, following post-GFC public initiatives to facilitate SME access to bank credit. In particular, financial institutions

[19] See IFC (2015): "Assessing household financial positions in Asia", *IFC Bulletin*, no 40, November.

were required to provide (confidential) reports assessing the credit quality of particular SMEs in order to reduce information asymmetries. These reports were based on a wide range of firm-level data, including financial statements, central credit registry data, individual solvency and credit history information, credit ratings and the relative position of firms within a given sector. While this project was instrumental in providing standardised information on SMEs and facilitating banks' lending decisions, it also highlighted a number challenges posed by the use of granular, firm-level data (eg the treatment of anomalous data points, confidentiality issues and sample coverage).

The last presentation, by the Central Bank of the Republic of Austria and the Deutsche Bundesbank, reviewed the **in-house credit assessment systems** (ICAS) used by those central banks and, in particular, the Common Credit Assessment System (CoCAS) developed jointly by the two institutions. Central banks' rating activities have gained importance after the GFC with the general development of liquidity-based operations and the related need to assess the credit quality of eligible assets used as collateral. A proper credit assessment framework had to be set up for this task. It relied on the combination of granular balance sheet data, statistical models and expert judgement. These efforts also highlighted the importance of collaboration among central banks in order to adequately capture the characteristics of internationally-connected corporate groups and assess cross-country factors. Of note, this framework relied heavily on the use of CBSO-type data but also generated, in turn, a new source of firm-level information (ie internal credit ratings) that could be of use for policy.

4. CBSO information to assess vulnerabilities of non-financial corporates

The third session, chaired by Robert Kirchner, Deutsche Bundesbank, discussed the importance of CBSO information for the analysis of financial fragilities in the **non-financial corporate sector**. The various presentations showed that one could use firm-level information to better analyse default risks, capital structures, "access to finance" risks and trade credit-specific problems.

The first presentation, by the Bank of Portugal, showed how the **creditworthiness** of Portuguese firms could be measured by looking at granular firm-level information. In particular, one could compute the probability that a specific firm would default on its banking obligations or move between rating classes. This type of exercise was based on the matching of individual corporate balance sheet data (eg assets and liabilities, profit and loss statements and cash flow information) and central credit registry information on borrowers, especially NPL data. Significant cleaning work was required when using such micro data sets (eg need to deal with incoherent data points or minor banking relationships). Complex statistical techniques were also in demand – for instance, to select the most important explanatory factors among a vast range of available variables, group individual firms into homogeneous risk classes and produce synthetic risk indicators for policy use.

The second presentation, by the European Central Bank, showed the usefulness of granular balance sheet data to analyse the determinants of **corporate capital structures** and, in particular, the degree of leverage (ie total debt-to-asset ratios) and maturity structure of liabilities (ie importance of short- versus long-term debt).

Various factors had to be considered, including firm-specific ones (eg profitability, size) and also sectoral, regional and country ones.[20] In particular, growing attention was being paid in Europe to the role played by institutional factors and local environmental conditions in driving firm leverage. This, in turn, was facilitating the understanding of the drivers of microeconomic performance and monetary policy transmission. The analysis presented was based on cross-country granular balance sheet information collected from a number of European countries in a harmonised way – the Bank for the Accounts of Companies Harmonised (BACH) database.[21]

The third presentation, by the CBRT, emphasised the usefulness of CBSO information for assessing the vulnerability of non-financial firms in **emerging market economies** (EMEs). A key element was that their access to credit had been significantly eased, reflecting accommodative global liquidity conditions in the aftermath of the GFC, higher risk appetite in global financial markets and large capital inflows.[22] Granular balance sheet information was particularly useful to assess the fragilities that had developed in the corporate sector, the way these fragilities had been managed and how changes in economic conditions (eg tighter global financial conditions and sudden reversals of capital flows) could create new vulnerabilities. In particular, CBSO data helped to assess the weighted cost of firm capital (combining the costs of equity and debt funding), the degree of firm leverage (relative to an "optimal" financing structure) and foreign currency and debt rollover risks.

The last presentation, by members of the ECCBSO Financial Statement Analysis Working Group, showed how firm-level accounting information could be instrumental for analysing **trade credit**, which played an important role in the overall financing of European companies. While this information was often disregarded in financial statements, it could shed light on firms' payment behaviour: for instance, to analyse the time needed to settle transactions with customers (trade receivables) and suppliers (trade payables). The analysis emphasised: (i) the crucial role played by trade credit for the liquidity management of non-financial firms; (ii) the considerable disparities existing across countries as well as sectors as regards customer-collection and supplier-payment behaviour; and (iii) the variation over time of these effects, both at the country- and continent-wide levels.

5. CBSO information for general economic research

By contrast to the preceding two sessions, which mainly focused on the assessment of financial vulnerabilities in the financial and the non-financial sectors, the last session chaired by Bruno Tissot, BIS and IFC, showed how CBSO-type information could be mobilised to answer a variety of **general research questions**. In particular, the presentations stressed that such information could be quite useful for analysing

20 See ECB (2017): "Decomposition techniques for financial ratios of European non-financial listed groups", *Statistics Paper Series,* no 21, May.

21 See ECB (2015): "The Bank for the Accounts of Companies Harmonised (BACH) database", *Statistics Paper Series,* No 11, September.

22 For an illustration, see the Global Liquidity Indicators of the BIS at: http://www.bis.org/statistics/gli.htm?m=6%7C333.

the determinants of firms' exports, the benefits arising from foreign ownership, the impact of uncertainty on business activities and currency mismatches.

The first presentation, by the CBRT, showed how granular balance sheet information could explain firms' **export performance**. The data matched companies' financial statements with risk assessment information provided by banks, allowing for an analysis of the behaviour of almost 4,000 manufacturers classified by various characteristics – eg sector, import intensity, size, age and share of foreign currency debt. This information helped analyse a wide range of economic issues, such as firms' responses to exchange rate movements – which could vary depending, for instance, on the import intensity of exports, currency mismatches or firm size (reflecting the higher probability that large firms hedge against exchange rate movements). A key takeaway was that mature Turkish firms were well inserted in GVCs and appeared less sensitive to exchange rate movements.

The second presentation, by the Bank of Italy, started with the general finding that **foreign-owned firms** tend to perform better than domestic ones. This could reflect multiple factors, such as the fact that foreign parent companies tend to transfer superior technology and organisational practices to their local affiliates or the existence of a selection bias (when foreign firms select domestic companies they want to acquire). To better analyse these issues, one could compare the observed performance of a foreign-owned firm with a counterfactual scenario, that is, if the FDI operation had not taken place. Using a panel data set covering a large sample of Italian companies and comprising, in particular, firm-level balance sheet data, the study showed that the performance of Italian firms actually improved after an FDI operation. But this favourable "foreign ownership premium" was mainly concentrated in the service sector and differed depending on the origin of the parent company. In particular, it was estimated to be higher when the controlling parent was from an advanced economy while it was absent when the parent was a holding-type company located in an offshore financial centre.

The third presentation, by the CBRT, analysed the impact of **uncertainty** on firm performance. Traditional analyses of such effects relied on some kind of aggregate measures of uncertainty at the country level, say macro forecast errors or the variance of some financial market indicators. But the impact of economic uncertainty might differ at the level of individual firms, for instance, reflecting the importance of sunk costs, information asymmetries between borrowers and lenders or simply different degrees of risk aversion. To capture these dimensions, the study matched firm-level data on balance sheets and income statements with the CBRT's manufacturing sector business tendency survey. This latter source provided firm-specific information on the perception of uncertainty and its impact on individual prospects in terms of production, domestic demand and foreign demand. In particular, the survey allowed for the building up of an uncertainty indicator for any specific firm by comparing the survey's response on its current situation with its expected business conditions. The resulting database helped to estimate in a highly granular way the impact of uncertainty on employment growth, which appeared to depend on the specific characteristics of a given firm, such as its export orientation, its size or its credit constraints.

The last presentation, by the BIS, also stressed the importance of "going granular" when looking at corporate vulnerabilities. One telling example related to the measurement of **currency mismatches**. Traditional indicators relied on country-level aggregate measures of such mismatches, which were no longer a problem in most EMEs. But this was almost entirely due to the stronger foreign exchange position of the official sector – higher forex reserves and lower foreign currency government debt. Currency mismatches in the non-official sectors of EMEs were larger and had significantly increased in recent years. In addition, a significant proportion of EME foreign currency corporate bonds had been issued by financing vehicles located abroad and this borrowing was not captured by residency-based statistics. For this reason, usual measures could significantly understate the true size of the recent increase in currency mismatches for EME corporates. To address these issues, one would benefit from access to more granular, microeconomic data on corporate balance sheets. Yet such data might still not be sufficient to capture derivatives-related activity at the global, consolidated group level (ie with non-resident counterparties) as well as the full range of (untested) guarantees between the parent company and its offshore subsidiaries. From this perspective, there was a need for promoting more (granular) data sharing between national authorities.[23]

[23] See IFC (2016): "The sharing of micro data – a central bank perspective", December.

IFC / ECCBSO / CBRT Conference on "Uses of Central Balance Sheet Data Offices' information", CBRT Premises, Özdere-İzmir, 26 September 2016

Opening remarks by Erkan Kilimci, Deputy Governor, Central Bank of the Republic of Turkey

Welcome to the Central Bank of the Republic of Turkey premises in our beautiful city İzmir for the conference on "Uses of Central Balance Sheet Data Offices' information". It is a great pleasure for us to organize this conference jointly with the BIS-Irving Fischer Committee on Central Bank Statistics (IFC) and the European Committee of Central Balance-Sheet Data Offices (ECCBSO). I would like to congratulate these three organisations for the successful collaboration in organizing this event, which is extraordinary in the sense that it precedes the traditional ECCBSO annual plenary meetings and has the opportunity to connect both sides of the table: statistics producers and statistics users. The Central Bank of the Republic of Turkey aims to extend partnerships with distinguished researchers and encourage the usage of CBSO databases. So, I would like to extend my appreciation to all guests for contributing to this important conference.

The Great Financial Crisis of 2007-09 revealed the importance of a system-wide approach in sustaining financial stability and emphasized the role of non-financial institutions in the system. The financial system is global and the crisis showed the importance of cross-border linkages in today's closely integrated economies. This systemic orientation should focus on network effects and spillovers from advanced economies to emerging markets and within the country as well. International comparisons are crucial to understand the recent issues such as prolong growth slowdown in emerging markets. There are structural and cyclical factors that can be reasons for our current problems, such as weak world trade, low commodity prices, tightening financial conditions, access to credit problem for small and medium-sized enterprises or slowdown in productivity growth.

To overcome these problems, we need to better understand the reasons behind them and hence we need better and more comprehensive datasets. Conventional indicators for the macro understanding of the financial system, which employ macro statistics are insufficient in that framework. For in depth analysis of the systemic risks and assessing fragilities, more research is needed using granular datasets. National authorities – and here the central banks have a key role to play – should develop adequate frameworks to integrate granular data into a macro perspective. In this context, ECCBSO is a very important organization in the management of non-financial companies' databases harmonized across countries at the micro-level. Thanks to its study groups, financial information of non-financial companies that are commonly used for statistics or risk assessment purposes are investigated in more detailed way. In this understanding, CBRT will continue its full support to ECCBSO activities by actively participating the study groups, harmonizing and sharing its firm level data.

The conference is mainly organized in three parts. The first session introduces some CBSO databases and addresses several important issues such as how they are provided for research, matched across several data sources and consolidated in the company-group level. Second and third sessions consist of studies which assess the creditworthiness on the micro and macro levels by employing company's financial reports. Bank-firm relationship is under detailed investigation since the latest crisis. Excessive credit growth, credit concentration in some sectors and access to credit problem for SME's are also on our research agenda for more efficient allocation of credit risk in the entire banking system. Finally, the fourth session analyzes exchange rate risk in the sense of currency mismatches, implications of uncertainties firms face and the ownership structure role in firm performance. We are eager to watch fruitful discussions on these issues during the conference today.

The conference will be succeeded tomorrow with a trip to Ephesus, in which I hope you will enjoy the wonderful ancient city while extending the good networking opportunity.

While concluding my remarks, I especially thank João Matos, the chairman of the ECCBSO, and Bruno Tissot, the head of statistics at BIS, for their continuous belief and support to our local organizing team in pursuing this conference happen in Turkey. Finally, once again I would like to thank all participants here today for your support. I wish you a pleasant time for your entire stay.

IFC-ECCBSO-CBRT Conference on *"Uses of Central Balance Sheet Data Offices' information"*

Co-organised by the IFC, the European Committee of Central Balance Sheet Data Offices (ECCBSO) and the Central Bank of the Republic of Turkey (CBRT)

Özdere-İzmir, Turkey, 26 September 2016

Squaring the circle - providing annual account information for research in Germany

The annual accounts scientific database and its dissemination in the Deutsche Bundesbank[1]

Ulf von Kalckreuth, 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.

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Paper presented at the IFC / ECCBSO / CBRT Conference on "Uses of Central Balance Sheet Data Offices' information" in Ozdere-Izmir, 26 September 26 2016

Dr Ulf von Kalckreuth, Deutsche Bundesbank*

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Squaring the Circle – Providing Annual Accounts Information for Research in Germany

The Annual Accounts Scientific Database and its Dissemination in the Deutsche Bundesbank

Paper presented at the IFC / ECCBSO / CBRT Conference on "Uses of Central Balance Sheet Data Offices' information" in Ozdere-Izmir, 26 September 2016

By Dr Ulf von Kalckreuth, Deutsche Bundesbank[1]

1. Data confidentiality is important in Germany

Working with statistics that involve granular data in Germany entails several additional layers of complexity compared to other European countries. In principle, German confidentiality and data privacy laws are fully compatible with EU standards. But since the ruling of the German Constitutional Court concerning the 1983 census in West Germany, the right to data protection has been considered a "basic right", ie a constitutionally protected individual right that directly binds the legislature, the executive and the judiciary. The Constitutional Court blocked the 1983 census to prevent the infringement of this right. The census was consequently delayed until 1987, after which no census took place for another 24 years, although the reunification of Germany in 1991 created a major need for new census information. As a result, courts and all levels of administration treat data privacy issues in a very principled way.

Data protection issues have repercussions for corporate financial statements statistics on many levels. In Germany, there is no balance sheet office that is officially tasked with processing and publishing financial statements.[2] With regard to the publication of financial statements, there are numerous exemptions for smaller companies. Thus, statistical information on smaller firms is difficult to obtain and firm-level data needs to be collected from various sources, involving diverse formats and levels of detail. There is no unique identifier for non-financial firms in Germany. Therefore, in order to use data from different sources, much work has to be done to preclude double entries, ie the same annual account entering the statistical database more than once. This and other aspects of data quality management become especially cumbersome when a significant part of the financial statements have to be processed in anonymised format for data protection reasons. And finally, it was not until 2016 that a law was passed allowing the use of the Federal Business Register for statistical purposes at the Bundesbank.

2. A database for statistical purposes

As is often the case, specific limitations call for specific solution strategies. Traditionally, annual accounts statistics uses financial statements data from the rating activities of the Deutsche

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[1] Ulf von Kalckreuth is Head of Section and Deputy Head of Division and is responsible for corporate financial statements statistics at the Deutsche Bundesbank. Timm Körting is advancing this project. I thank him for indispensable and valuable input, also in the context of this presentation. E-mail: ulf.von-kalckreuth@bundesbank.de. Address: Deutsche Bundesbank, DG Statistics, Wilhelm-Epstein-Str. 14, 60431 Frankfurt am Main, Germany.

[2] The "Bundesanzeiger" is evolving in this direction, though.

Bundesbank. Before monetary union, the Deutsche Bundesbank bought commercial bills from commercial banks for refinancing purposes. Thus, for the year 1998, more than 60,000 balance sheets were available. After monetary union, the number of available annual accounts dropped sharply as a result of the new regime in refinancing. Thus, in 2005, a "pool" was created by merging balance sheets available from rating activities with those from external providers. Some of these are designated data providers selling identified annual accounts; others are private sector "pool partners" sharing anonymised balance sheet information. Today, the pool is the backbone of the statistical infrastructure on company finances at the Bundesbank.

3. Towards a database for scientific use

Since the inception of the pool, research activities at the Bundesbank and by outside researchers using firm-level data have become very important. The statistical database cannot be used directly for research purposes. Because the anonymous pool partner data are strictly confidential, they cannot be matched with external information such as ratings or direct investment activity.

Fortunately, during the last decade, the volume and share of data obtained from identified information from external information providers has increased dramatically. Together with the Bundesbank's data from rating activities, these provide a solid, stand-alone basis for research activities. In 2014, the Research Data and Service Centre (RDCS) was established as the Bundesbank's provider of micro data information for both analysis and (internal and external) research purposes. The RDCS provides a secure environment for the analysis of granular data. Within its confines, the balance sheet data collected from the Bundesbank's rating activities and from commercial data providers can be enriched using external information. The scientific data set is then anonymised and made accessible to researchers under close surveillance, making sure that no reidentification activity takes place. Everything is therefore in place: attractive granular information for researchers, a protocol to resolve confidentiality issues and the resources needed to make the data accessible in a safe way.

The database under construction is provisionally labelled *Ustan^{+}*, referring to an earlier and very successful scientific database called *Ustan* that was composed exclusively of data originating from rating activities; see Stöss (2001)[3] for a description and Chatelain et al. (2003)[4] for a usage example. From a technical point of view, Ustan^{+} will be realised by extracting data from the pool, which is composed of data from eight different providers.

4. Ustan^{+} at a glance

Ustan^{+} provides balance sheet and profit and loss account information from the non-consolidated financial statements of non-financial firms in Germany. It comprises three different data sources: the Bundesbank's refinancing operations and two commercial data providers, Bisnode and Creditreform. The data base is free of duplicates and the accounting information is provided in a unified format, with a common underlying set of definitions, making the data commensurable to the utmost extent.

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[3] Elmar Stöss, Deutsche Bundesbank's Corporate Balance Sheet Statistics and Areas of Application, Schmollers Jahrbuch 121 (2001), pp 131-137.

[4] Jean-Bernard Chatelain, Ignacio Hernando, Andrea Generale, Ulf von Kalckreuth and Philip Vermeulen, New findings on firm investment and monetary transmission in the Euro area. Oxford Review of Economic Policy, Vol. 19(1), 2003, pp 1-11.

Per financial year, the data base encompasses up to around 90,000 observations for the years from 1997 onwards.

The scientific dataset is based on non-anonymized data with firms' names and addresses. Thus, RDCS staff is able to enhance the financial information, matching it with complementary data sources. The first version of the database is expected to be ready for use by summer 2017. Afterwards, subsequent refinements involving external information and weights will be carried out.

Tables 1 and 2 give an overview of the size and composition of *Ustan⁺* with regard to sectors and firm size for the fiscal year 2013. *Ustan⁺* is compared to the statistical database, the pool, and the business register run by the German National Statistical Office as a proxy for the universe of non-financial companies in Germany.[5] There is little difference between *Ustan⁺* and the pool in terms of sector and size composition, concerning both number of firms and aggregate sales. A comparison with German business register data reveals a clear underrepresentation of micro firms with sales of less than €2 million. In terms of the number of firms, the manufacturing sector is overrepresented and the service sector is underrepresented. The same holds true – to a lesser extent – with regard to sales aggregates. Thus, in order to extrapolate on the aggregate, informative weights are important.

Table 3 demonstrates the panel structure of the new scientific data base, showing the number of observations per fiscal year, the number of observations with at least one predecessor (needed to calculate first differences or growth rates) and the number of firms that are part of a balanced panel that has observations for each year in the period from 2008 to 2013. Longer contiguous strings of observations are needed for many of the more elaborate techniques in panel econometrics. Starting from 1997 with 55,000 firms, the number of observations increases to up to 90,000 observations per year. As many as 35,000 firms are part of a balanced panel from 2008 to 2013. The reduction is even less pronounced when using sliding cylindered samples.

It is expected that *Ustan⁺* will quickly become an important part of the data infrastructure for research on financial structures and activity of companies in Germany and Europe.

[5] Due to lower thresholds concerning turnover and number of employees in the register, this is not entirely correct: in all of the data collections, a large number of very small firms is missing.

Number of Firms and Sales by Sector in Comparison (FY 2013)

Sector	*USTAN+* Number of Firms	%	*Data Pool* Number of Firms	%	*Company Register* Number of Firms	%
Mining & Quarrying	255	0.3	373	0.3	2.279	0.1
Manufacturing	18,396	20.5	23,487	19.7	248,135	7.0
Energy & Water	3,643	4.1	4,669	3.9	74,273	2.1
Construction	11,320	12.6	13,820	11.6	389,557	11.0
Trade	21,102	23.5	27,747	23.3	655,102	18.6
Transportation	4,659	5.2	7,381	6.2	119,016	3.4
Information & Communication	3,708	4.1	4,929	4.1	130,027	3.7
Business-related Services	8,260	9.2	10,871	9.1	685,547	19.4
Other	18,496	20.6	25,773	21.6	1,223,844	34.7
Total	89,839	100.0	119,050	100.0	3,527,780	100.0

Sector	*USTAN+* Sales € bn	%	*Data Pool* Sales € bn	%	*Company Register* Sales € bn	%
Mining & Quarrying	16	0.5	17	0.4	16	0.3
Manufacturing	1,385	38.1	1,566	37.9	1,988	33.9
Energy & Water	626	17.2	636	15.4	616	10.5
Construction	82	2.3	93	2.3	247	4.2
Trade	970	26.7	1,147	27.8	1,801	30.7
Transportation	130	3.6	150	3.6	264	4.5
Information & Communication	116	3.2	155	3.7	217	3.7
Business-related Services	87	2.4	100	2.4	371	6.3
Other	219	6.0	264	6.4	342	5.8
Total	3,632	100.0	4,127	100.0	5,861	100.0

Number of Firms and Sales by Size in Comparison (FY 2013)

Size Sales of …	*USTAN+*		*Data Pool*		*Business Register*	
	Number of Firms	**%**	**Number of Firms**	**%**	**Number of Firms**	**%**
< 2 m€	38,967	43.4	54,501	45.8	3,326,856	94.3
2 to 10 m€	23,729	26.4	32,767	27.5	150,146	4.3
10 to 50 m€	18,224	20.3	21,969	18.5	38,879	1.1
> 50 m€	8,919	9.9	9,813	8.2	11,899	0.3
Total	89,839	100.0	119,050	100.0	3,527,780	100.0

Size Sales of …	*USTAN+*		*Data Pool*		*Business Register*	
	Sales bn€	**%**	**Sales bn€**	**%**	**Sales bn€**	**%**
< 2 m€	27	0.7	37	0.9	694	11.8
2 to 10 m€	115	3.2	158	3.8	627	10.7
10 to 50 m€	417	11.5	494	12.0	810	13.8
> 50 m€	3,074	84.6	3,438	83.3	3,731	63.6
Total	3,632	100.0	4,127	100.0	5,861	100.0

Panel Structure: Number of Firms

Financial Year	*Unbalanced Panel*	*With Predecessor*	*Balanced Panel*
1997	55,146	.	.
1998	42,216	37,728	.
1999	36,765	31,748	.
2000	35,081	29,554	.
2001	36,038	28,028	.
2002	41,242	28,783	.
2003	51,458	33,566	.
2004	62,587	42,628	.
2005	72,198	49,275	.
2006	75,978	53,500	.
2007	70,268	51,673	.
2008	77,593	54,738	35,007
2009	83,129	61,130	35,007
2010	87,109	65,623	35,007
2011	89,941	68,780	35,007
2012	91,331	71,118	35,007
2013	89,674	71,096	35,007
2014	41,942	38,417	.

Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

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Squaring the circle - providing annual account information for research in Germany

The annual accounts scientific database and its dissemination in the Deutsche Bundesbank[1]

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The Annual Accounts Scientific Database and its Dissemination in the Bundesbank

Ulf von Kalckreuth, Deutsche Bundesbank, DG Statistics

IFC / ECCBSO / CBRT Conference on "Uses of Central Balance Sheet Data Offices' information" in Ozdere-Izmir, September 26th, 2016

Data confidentiality is important in Germany!

Confidentiality and data protection laws in Germany **in principle fully compatible with EU standards**

But: in Germany, right to data protection is considered a **fundamental individual right** by the powerful German Constitutional Court

- The Court blocked the 1983 census to make sure that this right was not infringed
- The census was carried out only in 1987 (Western Germany). After that, there was no census for 24 years!! (Reunification was in 1991).
- The first census after reunification was carried out only in 2011!

Courts, and – as a consequence – the administration treats data privacy issues in a rather principled way.

Doing statistics involving granular data is hard work in Germany!

Annual accounts information in Germany

Some consequences for annual accounts statistics

- No compulsory balance sheet central office that processes annual accounts (Though the “Bundesanzeiger” is evolving in this direction)
- Lots of exceptions from publication obligations for smaller firms
- **Statistical information for smaller firms hard to get**

Annual accounts information in Germany

Traditionally, annual accounts statistics uses data base from Bundesbank rating activities. Bundesbank was buying commercial bills from commercial banks for refinancing. In 1998, more than 60 000 balance sheets available.

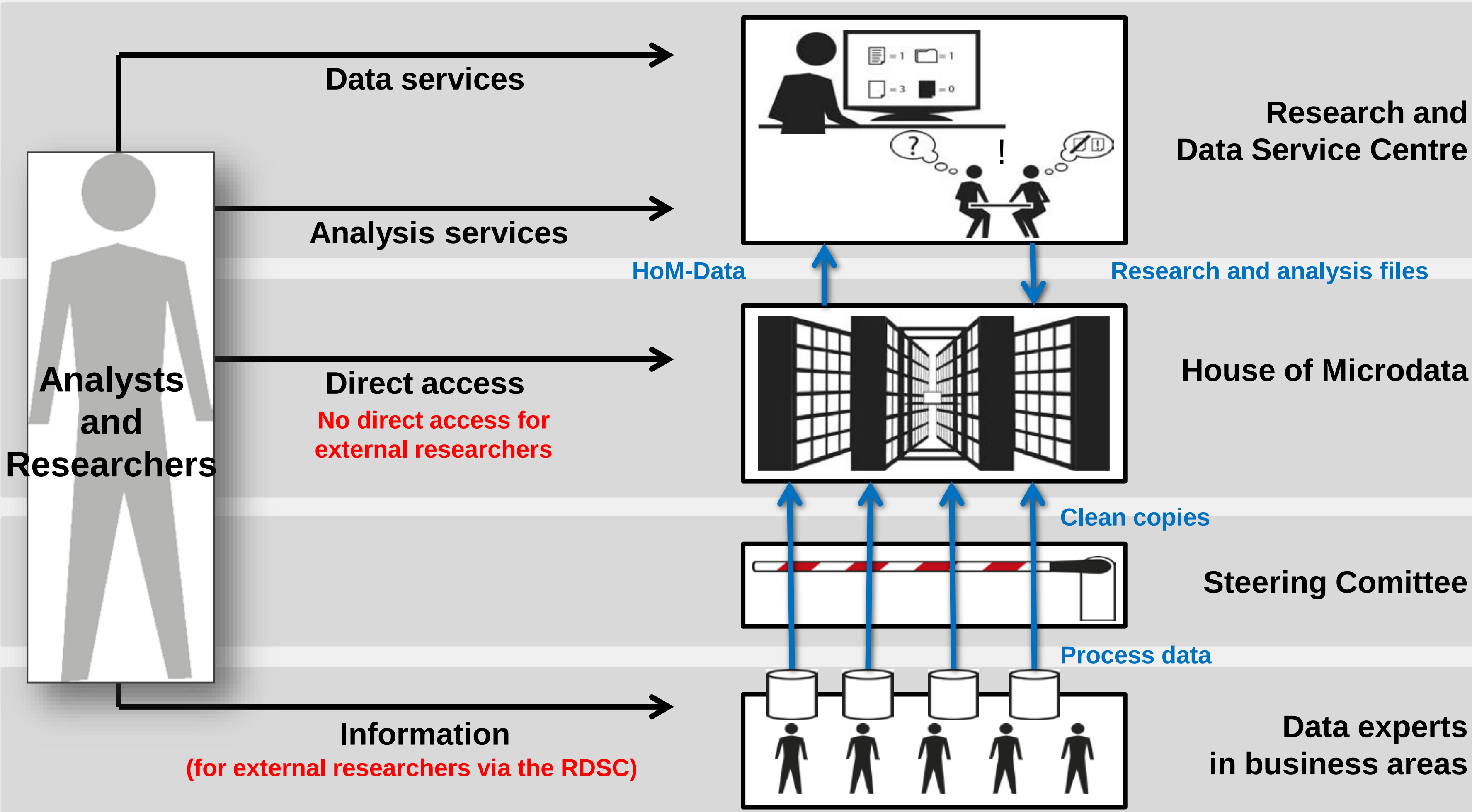
- After monetary union, number of available annual accounts drops sharply as a result of the new regime in refinancing
- In 2005, the **“Pool”** is created, from merging balance sheets available from rating activities with those from external providers.
- Some are designated data providers selling identified annual accounts, others are **“pool partners”**, sharing anonymised balance sheet information.
- **We must not disclose the accounts provided by the “pool partners”**

Towards a data set for scientific use

Since then

- Research activities in the Bundesbank and from outside researchers using Bundesbank data become very important
- Data pool not directly useable due to confidentiality and the missing possibility to match external information (such as rating or direct investment activity)
- Volume of data from outside information providers increases dramatically
- In 2014 Research Data and Service Centre (RDCS) founded as a Bundesbank provider of micro data information for analysis and (internal and external) research
- **Will provide safe environment for data analysis**

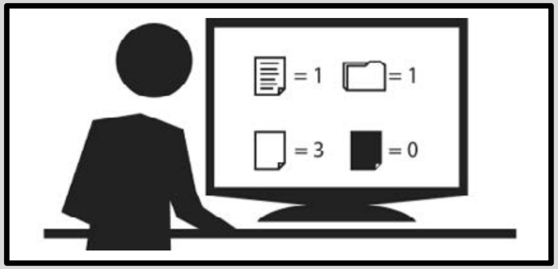
House of Microdata and RDCS – Value added for analysts and researchers



Research Data and Service Centre (RDSC)
Services for internal and external users

Data services

• Research and analysis files
• Documentation
• Tabulation
• Matching and merging
• Reference data administration



Analysis services

• Advice
• Clarification of access rights

Internal users
• Guidance
• Ad-hoc evaluations on analysis files

External Users
• Processing of applications
• Dissemination of data, making available on-site
• Output control and clearing

Towards a data set for scientific use

USTAN+

- Combines the Bundesbank rating data with the information from 2 commercial data providers
- Name refers to the old information data base USTAN that has gained a high reputation
- **Realised as extraction from data pool (itself consisting of 8 data sources)**

USTAN+ --- Basics

Overview

- Non-consolidated financial statements of non-financial firms in Germany
- 3 different data sources: Bundesbank's refinancing operations and two commercial data providers (Bisnode and Bureau van Dijks DAFNE database)
- Free of duplicates and a common structure
- Up to around 90.000 observations per year
- From 1997 onwards
- Non-anonymized data, i.e. containing firms' names and addresses
- Matching with complimentary data sources possible
- Data base expected to be usable in early spring 2017
- Afterwards refinements: matching, weights.

USTAN+ --- Structure (1)

Number of firms by sector in comparison (FY 2013)

	USTAN+		*Data Pool*		*Company Register*	
Sector	**Number of Firms**	**%**	**Number of Firms**	**%**	**Number of Firms**	**%**
Mining & Quarrying	255	0.3	373	0.3	2.279	0.1
Manufacturing	18,396	20.5	23,487	19.7	248,135	7.0
Energy & Water	3,643	4.1	4,669	3.9	74,273	2.1
Construction	11,320	12.6	13,820	11.6	389,557	11.0
Trade	21,102	23.5	27,747	23.3	655,102	18.6
Transportation	4,659	5.2	7,381	6.2	119,016	3.4
Information & Communication	3,708	4.1	4,929	4.1	130,027	3.7
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Other	18,496	20.6	25,773	21.6	1,223,844	34.7
Total	89,839	100.0	119,050	100.0	3,527,780	100.0

USTAN+ --- Structure (2)

Sales of firms by sector in comparison (FY 2013)

	USTAN+		*Data Pool*		*Company Register*	
Sector	**Sales € bn**	**%**	**Sales € bn**	**%**	**Sales € bn**	**%**
Mining & Quarrying	16	0.5	17	0.4	16	0.3
Manufacturing	1,385	38.1	1,566	37.9	1,988	33.9
Energy & Water	626	17.2	636	15.4	616	10.5
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Business-related Services	87	2.4	100	2.4	371	6.3
Other	219	6.0	264	6.4	342	5.8
Total	3,632	100.0	4,127	100.0	5,861	100.0

USTAN+ --- Structure (3)

Number of firms by size in comparison (FY 2013)

Size Sales of …	*USTAN+* Number of Firms	%	*Data Pool* Number of Firms	%	*Business Register* Number of Firms	%
< 2 m€	38,967	43.4	54,501	45.8	3,326,856	94.3
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Total	89,839	100.0	119,050	100.0	3,527,780	100.0

USTAN+ --- Structure (4)

Sales of firms by size in comparison (FY 2013)

Size	*USTAN+*		*Data Pool*		*Business Register*	
Sales of …	**Sales bn€**	**%**	**Sales bn€**	**%**	**Sales bn€**	**%**
< 2 m€	27	0.7	37	0.9	694	11.8
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> 50 m€	3,074	84.6	3,438	83.3	3,731	63.6
Total	3,632	100.0	4,127	100.0	5,861	100.0

USTAN+ --- Structure (5)

- **Little difference between USTAN+ and Data Pool** in terms of sector and size composition, concerning both number of firms and aggregate sales
- Comparison with German Company Register data (a proxy to the full population) reveals **underrepresentation of micro firms** with sales of less than 2 m€
- In terms of number of firms, an **overrepresentation of manufacturing sector** at the expense of **underrepresentation of the service sector**
- The same holds true – to a lesser extent – in terms of sales aggregates

USTAN+ --- Panel Structure

Number of Firms

Financial Year	*Unbalanced Panel*	*With Predecessor*	*Balanced Panel*
1997	55,146	.	.
1998	42,216	37,728	.
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2011	89,941	68,780	35,007
2012	91,331	71,118	35,007
2013	89,674	71,096	35,007
2014	41,942	38,417	.

USTAN+ --- Panel Structure

- Starting from 1997 with 55.000 firms, the number of observations increases to up to 90.000 observations per year.
- Mainly due to the growing volume of the DAFNE database – particularly since 2006
- Number of firms drops to 35.000 when using a balanced panel from 2008 to 2013.
- Reduction is less pronounced when using sliding cylindered samples

THANK YOU!

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Matching firm-level data sources at the Statistics Department of Banco de Portugal[1]

Paula Casimiro, Ana Bárbara Pinto and Tiago Pinho Pereira,
Bank of Portugal

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

Matching firm-level data sources at the Statistics Department of Banco de Portugal

Paula Casimiro

Banco de Portugal and Chair of the BACH Working Group, ECCBSO

Ana Bárbara Pinto

Banco de Portugal and ERICA Working Group, ECCBSO

Tiago Pinho Pereira

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Abstract

Matching data from the Central Balance Sheet Database (CBSD) with other firm-level data sources for quality control (QC) purposes has been a common practice at the Statistics Department of Banco de Portugal. Data from annual and quarterly surveys of non-financial corporations (NFC) available in CBSD were matched with internal and external firm-level data sources. As internal data sources we have used bank loans granted by resident financial institutions from Central Credit Register (CCR), securities issues from the Securities Statistics Integrated System (SSIS), Monetary and Financial Institutions (MFIs) Interest Rates (MIR), and bank loans granted by non-resident financial institutions and group companies, exports and imports, and trade credits from Transactions and Positions with Non-Residents (*COPE)*, database. As external data sources we have used exports and imports and information related with business demography from Tax Authority and number of employees and wages paid from Ministry of Social Security. Despite some methodological issues that avoid a full comparison between the different sources of information, all sources of information benefit from the cross checking of firm-level data sources. We concluded that matching data from firm-level data sources is of utmost importance to assure the accuracy and reach a high level of quality of the NFC information, which allows Banco de Portugal to publish useful information for firms' decision making such as the Enterprise and Sector Tables and the Central Balance Sheet Studies.

Keywords: firm-level databases, non-financial corporations, data matching

JEL classification: C81

Contents

1. Introduction

Matching data from the Central Balance Sheet Database (CBSD) with other firm-level data sources for quality control (QC) purposes is a common practice at the CBSD of Banco de Portugal.

Every year, data from both the annual and the quarterly survey of non-financial corporations (NFC) are matched with the Central Credit Register (CCR), the Securities Statistics Integrated System (SSIS), the data from Transactions and Positions with Non-Residents (*COPE*, *Comunicação de Operações e Posições com o Exterior*, in the Portuguese acronym) - and the Monetary and Financial Institutions (MFIs) Interest Rates (MIR) in order to assure the accuracy of the information reported by the NFC.

The CCR database contains information about all the loans above 50 Euros granted by resident financial institutions, while the SSIS database contains detailed data on issues and portfolios on a "security-by-security" and "entity-by-entity" basis. The COPE database contains information of flows and positions reported by resident legal entities with yearly transactions with the rest of the world above 100.000 Euros.

During the QC process of the annual and quarterly surveys of NFC, loans reported by firms in their balance-sheets are compared with the information available at the CCR, the SSIS and the COPE databases, while exports and imports of goods and services are compared with the COPE database. This comparison has been very useful for CBSD, although there are some methodological issues that do not allow for a complete matching of the data, especially in the case of the COPE database.

Regarding loans, benefits from the CCR and the SSIS database are twofold: on one hand, they allow the distinction between bank loans and bonds when firms do not specify the sources of their funding; on the other hand, in the case of bank loans, since the CCR only contains loans from resident financial institutions, it is possible to obtain, by a residual approach, the amount of loans granted by non-resident financial institutions to Portuguese NFC. The amount of loans granted by non-resident financial institutions can also be obtained directly from the COPE database. Usually, data on loans granted by non-resident financial institutions obtained by the residual approach matches the data obtained from the COPE database. It is also possible to obtain from the COPE database the intra-group loans from non-resident firms.

With respect to exports and imports of goods and services, the existence of data from COPE for a company that does not report exports and imports of goods and services in the CBSD surveys possibly allows to fill a gap in the CBSD database. However, there are several explanations for the absence of a complete matching between COPE and CBSD database, such as the existence of trade credits, business group relationships or cash pooling.

Monetary and Financial Institutions' (MFIs) statistics have detailed data on new, renegotiated and outstanding loans granted by monetary financial institutions on a "loan-by-loan" and "entity-by-entity" basis. Hence, it is possible to match this information with the implicit interest rates on the accounting information sent by NFC to the CBSD.

Data from Tax Authority includes information on intra-European Union (EU) and extra-EU exports and imports of goods and services, total sales and value added taxes (VAT), R&D tax incentives (deductions to R&D expenditures), business register for VAT purposes, income paid to or received from non-resident entities and interest paid or received by natural resident people.

Finally, data from the Ministry of Social Security contains the number of employees and the wages paid, by firm, on an annual basis.

Throughout the paper, we provide an integrated time series analysis of CBSD, CCR, SSIS, MIR and COPE databases from 2011 to 2015, as well as additional comments on matching databases.

2. Firm-level data sources

2.1. Internal data sources

Statistics based on the CBSD, CCR, SSIS, MIR and COPE databases are regularly published on the Statistical Bulletin and on the BPstat | Statistics Online, the interactive dissemination database available at Banco de Portugal website. In this section, we provide a brief description of each one.

- Central Balance Sheet Database (CBSD)

CBSD exists since 1983, based on accounting data of individual firms. From 2006 onwards, annual CBSD data has improved considerably and has been based on obligatory financial statements, which allowed the monitoring of almost all Portuguese NFC (about 370.000), instead of only a sample of them.

The major goal of the CBSD is to contribute to a better understanding of the operating and financial performance of NFC. CBSD data are useful to produce statistics about NFC, to derive the NFC sector for National Accounts, to estimate several items for Balance of Payments (BoP), to update business registers, and to produce sectoral benchmarks, namely Sector Tables and Enterprise and Sector Tables (Brites, 2013).

Yearly data of the CBSD database is obtained from *Informação Empresarial Simplificada* (IES). IES is a mandatory annual report through which NFC submit their annual accounts (balance-sheet, income statement, statement of changes in equity, cash flow statement and the annex to the financial statements) simultaneously to the Tax Authority, Ministry of Justice, Banco de Portugal and Statistics Portugal.

IES is reported within six and a half months of the economic year end, which, for most enterprises resident in Portugal, corresponds to 15 July of the year following the reference year.

Data reported by enterprises through IES is subject to QC by Banco de Portugal mainly to ensure that the accounting information for the economic year is coherent and complete and that the main aggregates are consistent throughout the years.

QC comprises the matching of data reported through IES with other internal data sources of Banco de Portugal, such as CCR, SSIS, MIR and COPE, as well as with external data sources, such as Tax Authority and Social Security.

- Central Credit Register (CCR)

Following Casimiro (2013), the Portuguese CCR database was launched in 1978, first including only the credit liabilities of NFC and, from 1993 onwards, also the credit liabilities of households.

Reporting institutions to the Portuguese CCR are banks, savings banks and mutual agricultural credit banks (MFIs), other non-monetary financial institutions and public agencies that grant credit, and NFC buying loans from the resident financial sector.

The main purpose of the CCR is to contribute for the financial stability by helping financial institutions in assessing the credit risk of their current or new credit clients, since they can access CCR data. Insurance companies undertaking credit and bond insurance can access CCR data, although they do not report it.

Data reported to Portuguese CCR include the borrowers ID (for residents, the tax identification number is used), the credit drawn (amounts outstanding at the end of the month), credit undrawn (irrevocable credit commitments), personal guarantees (potential credit liability), type or purpose of the loan, collateral (type and value), periodic repayments (for some types of loans granted to private individuals), original and residual maturities, credit defaults and write-offs, and specific flags for Banco de Portugal internal use of the data (e.g. securitized loans and loans used as collateral in Eurosystem financing operations).

- Securities Statistics Integrated System (SSIS)

The SSIS of Banco de Portugal was established in 1999. It was created to store, manage and explore data on securities issues and portfolios on a "security-by-security" and "investor-by-investor" basis, excluding investors in the households sector, whose data are aggregated by the investor's country. This database comprises securities other than shares and shares and other equity. The assembled data include, on a monthly basis, stocks and transactions, with the ISIN code being used for the identification of the securities (Dias, 2013).

Regarding issues, the SSIS collects data on securities issued by resident entities in Portugal, irrespectively of the fact that those issuances take place in the Portuguese market or in external markets. A multiplicity of sources are used such as the Lisbon Stock Exchange, the Portuguese Securities Market Commission, the Portuguese Treasury and Debt Management Agency and commercial databases.

In the case of portfolios, comprehensive information on holdings of domestic and foreign securities by resident investors and holdings of domestic securities by non-resident investors is collected. Data are reported mainly by custodians (e.g. banks, dealers and brokers). Direct reporting by resident investors with relevant portfolios deposited abroad is also applicable.

The leading aim of SSIS is the production of statistics on issues and portfolios of securities, the design of "from-whom-to-whom" tables crossing issuers and holders, and the supply of input data for MFIs, BoP and National Accounts statistics.

- Monetary and Financial Institutions (MFIs) Interest Rates (MIR)

Besides micro data regarding the end-of-month balance-sheet of MFIs (mainly deposits received and loans granted), these institutions also communicate individual information concerning banking interest rates on new and renegotiated loans to NFC.

According to Santos (2013), Banco de Portugal created this new requirement in June 2012 with the aim of obtaining representative data on new loan operations, in a context of financial stability assessment. This new requirement only applies to MFIs granting at least 50 Million Euros per month in new loans to NFC. Furthermore, solely euro denominated operations and loans to euro area resident entities are taken into account.

Reported data includes the date of the operation, maturity of the loan, initial period of interest rate fixation, amount, annualized interest rate, the existence or not of collateral, the nature of the loan (new or renegotiated), borrower ID and residence.

Information on the interest rates of outstanding loans is also available.

- Transactions and Positions with Non-Residents (COPE)

According to Marques (2011), the collection and compilation of BoP data was set in 1993, based on monthly reports by resident banks, which communicated and classified transactions with non-residents on their own behalf and on behalf of their customers. Also, the report of transactions with non-residents settled without the intermediation of the resident banking system was mandatory and it was done by direct reporting to Banco de Portugal.

From 2013 onwards, the system of communication to Banco de Portugal changed, giving rise to direct reporting by economic agents on monthly transactions and positions with non-resident counterparts (so-called *COPE*, *Comunicação de Operações e Posições com o Exterior*, in the Portuguese acronym). Entities with transactions with non-residents above 100.000 Euros per year started to report and classify their transactions and positions with non-residents directly to Banco de Portugal, even if they have the intermediation of the resident banking system. Reports by resident banks without the classification of transactions are now only used to validate information submitted by entities.

Reported data is very granular and includes exports and imports of goods and services (including travel and tourism), rights and operations over tangible and intangible assets, unilateral transfers, real estate investment, shares, units of participation and other equity securities, debt securities, performing and non-performing loans, trade credits, bank deposits, margin accounts, financial derivatives and employee stock options and transfers between accounts breakdown by nature (asset or liability), maturity (short or long term), direct investment relationship (no relationship, voting rights lower than 10% or voting rights greater or equal than 10%), and transaction type (capital or income).

2.2. External data sources

- Tax Authority

Banco de Portugal has been receiving firm-level data from the Tax Authority since 2014, in the sequence of an information exchange agreement. Data is sent four-times a year and it is available from 2006 onwards.

This database includes the monthly amount of extra-EU exports and imports of goods and services, the quarterly amount of intra-EU exports and imports of goods and services, the fields of the VAT return (e.g. amount of sales, intra-EU imports of goods and services and other operations that originate VAT), the annual amount of tax incentives for R&D, the register of active companies for VAT purposes, with the date of beginning and end of activity, income paid to non-resident entities, interest on savings paid to resident natural persons, and income obtained from non-resident entities.

- Social Security

Data from Social Security was available until 2013 and comprised the annual number of employees and wages paid by firm.

3. Results

In this section, we provide some examples of data matching and how it improves the quality of the databases. The QC process of the CBSD occurs every year and quarter according with the periodicity of the data sources. Annual QC is done after the submission of the IES and it involves not only human resources from Banco de Portugal but also a group of undergraduate students that manually validate the information sent by a sample of NFC[1].

3.1. Borrowings structure and their sources

Chart 1 below shows the total borrowings structure of the Portuguese NFC in 2015, breakdown by sources. For total borrowings we mean the sum of bank loans, debt securities issued, loans from group companies and other loans. During the QC process, data on bank loans, debt securities and intra-group loans is matched with the CCR, the SSIS and the COPE databases, which explains the differences between the initial and the present situations. The CCR database provides information on loans granted by resident financial institutions, while SSIS database provides data on debt securities issues and COPE database on non-resident banks and intra-group loans.

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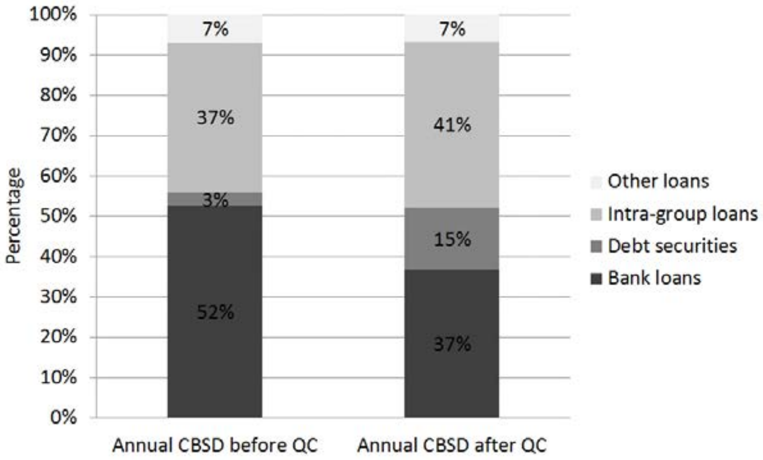
1 This sample is generated from the universe of more than 370.000 companies, according to some criteria. Usually, the final sample of validated companies represents more than 1% of the universe and more than 50% of the turnover of Portuguese NFC.

Chart 1: Borrowings structure of NFC (2015)

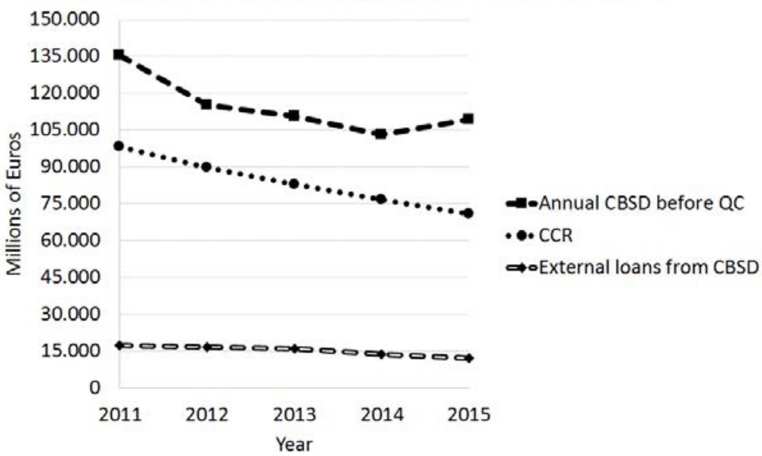


3.2. CBSD vs. CCR database

Chart 2 shows the amount of loans granted by financial institutions in the CBSD before QC and in the CCR database, as well as loans granted by non-resident financial institutions[2] from the CBSD, which are not available at the CCR database. External loans usually account for 15% of the loans granted by financial institutions and for 5% of total borrowings.

As it can be observed, loans granted by financial institutions in the CBSD before QC are higher than in the CCR database. This happens because of the existence of external loans and because NFC usually do not detail their sources of financing and include all of them in a single item, which is loans from financial institutions. External loans can be obtained through the comparison with the COPE database or the NFC' annual report, if available. Otherwise, NFC can also be contacted to clarify the data.

Chart 2: Loans granted by financial institutions before QC



[2] Also denoted as "external loans" throughout this paper.

Chart 3 shows the situation after QC. As it can be seen, the amount of loans granted by financial institutions at the CBSD moves closer to the amount in the CCR database and, if we deduct to this amount the value of external loans we can observe an almost perfect matching between databases.

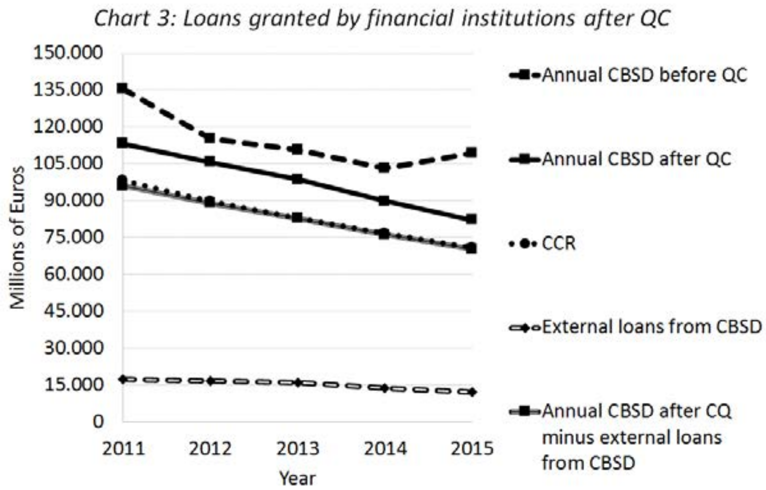


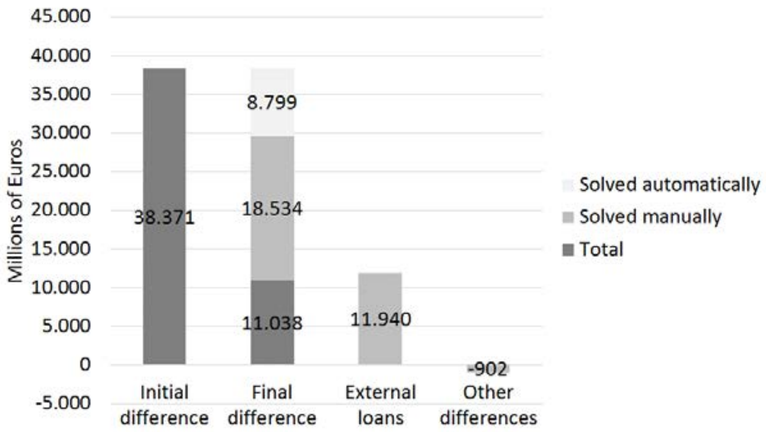
Chart 4 shows initial and final differences between the CBSD and the CCR database before and after QC.

In a first stage, NFC with large differences between the CBSD and the CCR databases and without external loans in the previous years in the CBSD[3], and for which the amount of loans outstanding in the CCR database is less or equal than the borrowings reported through IES are treated automatically, with the amount of loans outstanding in the CCR database being incorporated in the CBSD. According to Chart 4, this automatic procedure solved about 23% (corresponding to 8.799 Millions of Euros) of the initial difference between the databases.

In a second stage, NFC with large differences regarding CCR database which are not solved automatically are distributed for manual QC. Manual matching solved around 48% (corresponding to 18.534 Millions of Euros) of the initial difference between the databases. At the moment, the difference between the two databases remains at 11.038 Millions of Euros (29% of the initial difference), which corresponds approximately to the amount of external loans (11.940 Millions of Euros). As pointed out before, these loans are not generally covered by the CCR and are manually inserted according to firms' annual reports, direct contact or matching with COPE database.

[3] NFC with external loans in the previous years are distributed for manual QC.

Chart 4: Initial and final differences between CBSD and CCR databases (2015)

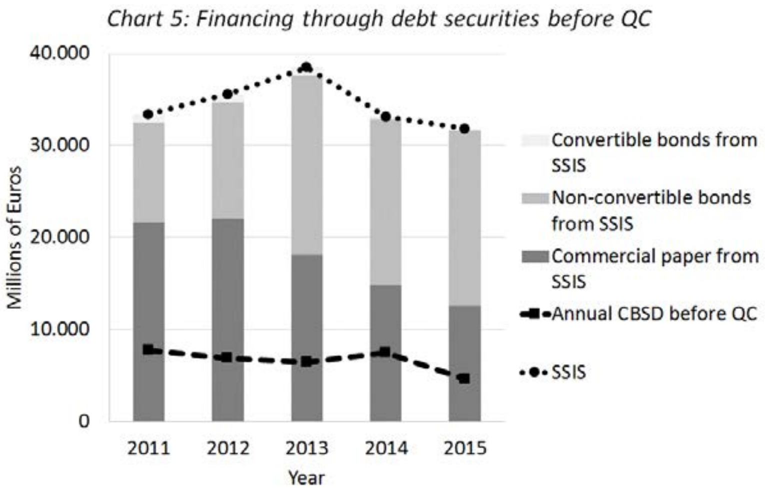


Besides external loans, there is a fraction of the final difference that is explained by specific circumstances such as time lags between the CBSD and the CCR databases, bankruptcy[4] or lawsuits against banks (Other differences, which represent 2% of the initial difference in absolute value). Also, there will always be a small difference between databases, even after QC, because only firms with material differences between CBSD and CCR database are distributed for manual QC.

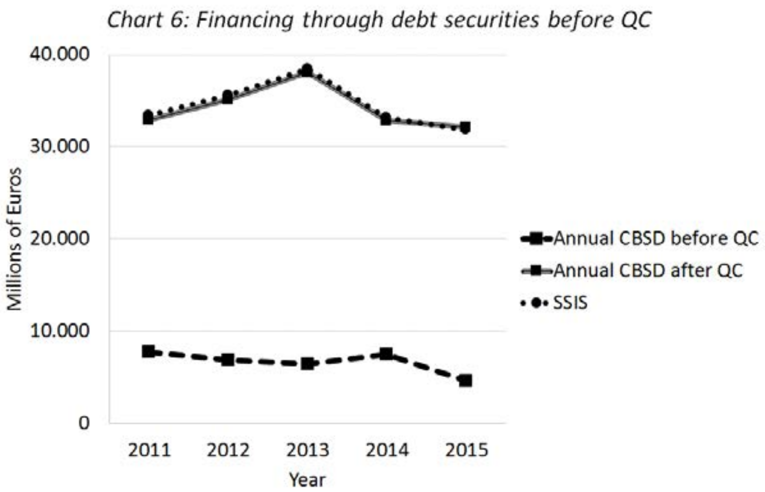
3.3. CBSD vs. SSIS database

During the QC process, matching with SSIS database is also done. Chart 5 shows the comparison between the outstanding amount of debt securities in the CBSD and in SSIS database. The amount from SSIS is generally much greater given that NFC incorrectly recognize the majority of their funding as loans from banks. On one hand, NFC usually do not detail their sources of financing and include all of them in a single item, which is loans from financial institutions. On the other hand, there are cases in which firms contact a bank to contract a loan, the bank agrees, and then securitizes the loan due to tax advantages. This loan will be consider by the firm as bank loan but in fact in a debt security.

4 Bankrupt firms usually submit their IES with many figures equal to zero, namely loans granted by financial institutions, while in the CCR database these loans remain. This happens because banks that report to the CCR continue to recognize these loans in their balance-sheets.



After QC, the amount of outstanding debt securities at the CBSD nearly overlaps the amount at the SSIS database (Chart 6). Here, the QC is also organized at two stages. First, for NFC with large differences between the CBSD and the SSIS database and for which the amount of outstanding debt securities in the SSIS database is less or equal than the borrowings reported through IES, automatic matching with the SSIS database is done. Then, the remaining situations are distributed for manual validation.



It should be stressed that automatic matching of CCR and SSIS database is done simultaneously to prevent unbalanced balance-sheets. Every year and quarter there is automatic incorporation in the CBSD of data from other sources namely CCR and SSIS databases, as well as bank and group loans from COPE database. As a result of this incorporation, the new total borrowings of CBSD could go above or go below the original ones, generating unbalanced balance sheets.

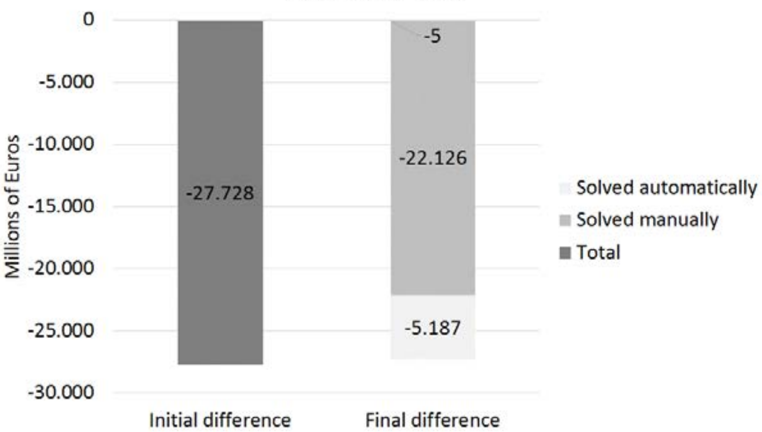
If, after matching the data from other data sources with the CBSD, the new total borrowings of CBSD go above the original ones and this excess is due to the original Other loans item of total borrowings, then the Other loans are adjusted to make the new total borrowings equal to the initial ones. If adjusting the initial Other loans item of total borrowings does not solve the unbalance, empirical evidence tells us that firms recognize borrowings in other liabilities' items which not total borrowings. Hence, the automatic procedure will take values from these other liabilities' items to total borrowings in order to match the data available from the other sources and will solve the unbalance.

In the cases that unbalance could not be solved acting this way, data from other sources is only automatically matched until the amount that prevents unbalanced balance-sheets and that respects the maximum difference allowed between CBSD and the other sources. The firms which are not solved automatically are distributed for manual validation.

If the new total borrowings go below the original ones, original total borrowings are kept equal, with the bank loans being matched with the CCR and the COPE databases, intra-group loans with the COPE database, and the loans through debt securities matched with the SSIS database. The excess in the original total borrowings is distributed for intra-group loans and other borrowings, according to the borrowings structure of the previous year.

Chart 7 shows initial and final differences between the CBSD and the SSIS database before and after QC. From the initial difference of -27.728 Millions of Euros (SSIS greater than CBSD), almost 80% (corresponding to 22.126 Millions of Euros) were manually inserted and 19% (corresponding to 5.187 Millions of Euros) were automatically inserted into CBSD after consultation of the SSIS database. In the end of the QC, the two databases are almost fully matched, with the amount of outstanding debt securities in CBSD being slightly greater than in SSIS database (which means a final difference of -5 Millions of Euros, 0,02% of the initial difference in absolute value).

Chart 7: Initial and final differences between CBSD and SSIS databases (2015)



As in the case of comparisons with the CCR database, a complete matching is not possible mainly because some firms report liquid (deducted of fees) or mark-to-market values to the CBSD database while in the SSIS database figures appear at their gross or nominal value.

On the other way around, SSIS database also benefits from inputs of the CBSD. For example, in the case of debt issuance by companies belonging to the same business group, the consultation of the annual reports of companies during the QC of the CBSD annual data allows the identification of the correct issuer, which sometimes is incorrectly identified at the SSIS database. If non-resident companies are, indeed, those which issue the securities, the issue should not be considered at the SSIS, since they are non-resident. However, during the QC process of the CBSD, if the consolidated annual report indicates that securities are, actually, issued by a domestic firm of the group, contacts between the two areas are made and SSIS database is updated if necessary.

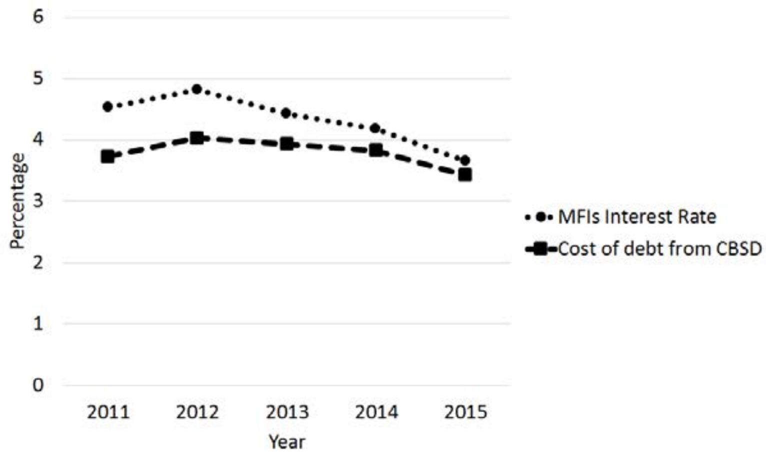
3.4. CBSD vs. MIR database

MIR database is used in the QC process of CBSD to detect eventual cases of a wrong report by firms. Chart 8 illustrates the interest rate of outstanding loans granted by MFIs to NFC, as well as the cost of debt from CBSD, defined as the interest paid divided by total borrowings.

Although this cost of debt contains other sources of financing besides loans from banks (and eventually with lower interest rates) it is a proxy for the interest rates that are actually paid by firms and, thus, it can be compared with MFIs' interest rates.

As it can be observed, in recent years, the overall cost of debt of NFC is not too far from the interest rates that are actually paid by NFC to MFIs.

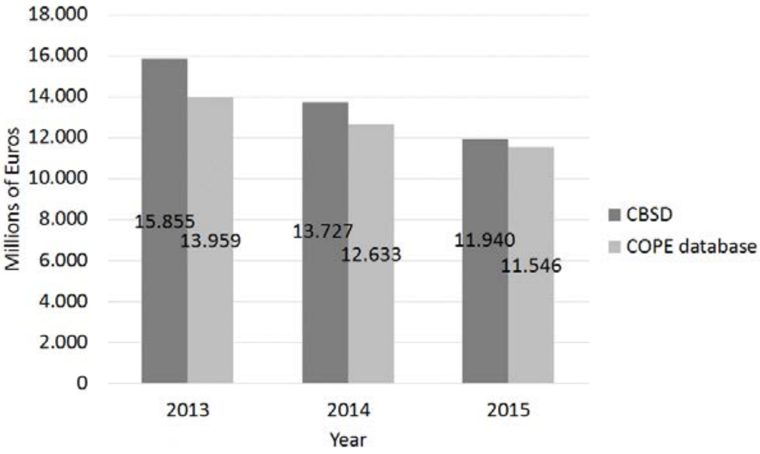
Chart 8: Cost of debt of NFC



3.5. CBSD vs. COPE database

Chart 9 shows the amount of external loans in the CBSD and COPE database. As it can be seen, external loans in the two databases are almost completely matched, which is not a surprise given that, on the one hand, COPE database is one of the sources used to fill the gaps regarding external loans in the CBSD, and, on the other hand, information from the CBSD is also used by BoP for QC purposes.

Chart 9: External loans in the CBSD and COPE database



On the other hand, comparisons between the amount of exports and imports of goods and services from the CBSD and the COPE and the Tax Authority databases are also made during the QC of the CBSD annual data. Contrarily to what happens with the CCR and SSIS databases, an almost complete matching is not possible because there are several methodological differences between the databases. However, information is used in the CBSD whenever it is needed to fill in missing values or confirm non-expected values according to the historical data for a given firm.

First, not all of the amounts recognized in the income statement correspond to effective financial flows. There are fractions of exports and imports that are not immediately paid. CBSD works according to an accounting perspective, while COPE database only recognizes exports or imports when there are financial flows. Hence, one of the sources of differences between the two databases is the existence of trade credits. Indeed, if we subtract the amount of trade credits to the exports and imports of the CBSD, there is an approximation to the COPE figures (Charts 10 and 11).

Besides trade credits, causes for an incomplete matching between CBSD and COPE database include the existence of transactions with resident branches of non-resident firms and with non-resident branches of resident firms[5], intra-group cash pooling, misclassification of transactions, time lags between the two databases, same operations reported in different companies of the same business group in each of the two systems, and the utilization of non-resident bank accounts owned by resident firms.

Regarding Tax Authority data, information sent to Banco de Portugal is divided by intra-EU and extra-EU trade. However, it was detected for some companies a duplication of values, given that transactions for which the goods are sent to an extra-EU location, but the counterpart is an intra-EU company were considered in both extra-EU and intra-EU systems by the Tax Authority. Also, non-resident branches of resident firms are treated by the Tax Authority as non-resident entities, while in accounting they are included in the report of resident firms. Anyway, this information is used in certain situations as a reference for CBSD QC.

[5] Non-resident branches of resident firms are considered by COPE database as non-resident entities, while in IES an accounting perspective prevails and they are considered as part of the resident firm.

Chart 10: Exports of goods and services from CBSD and COPE database

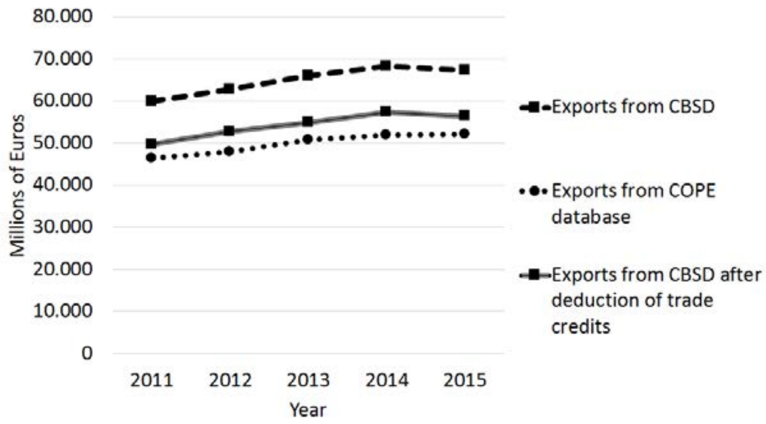
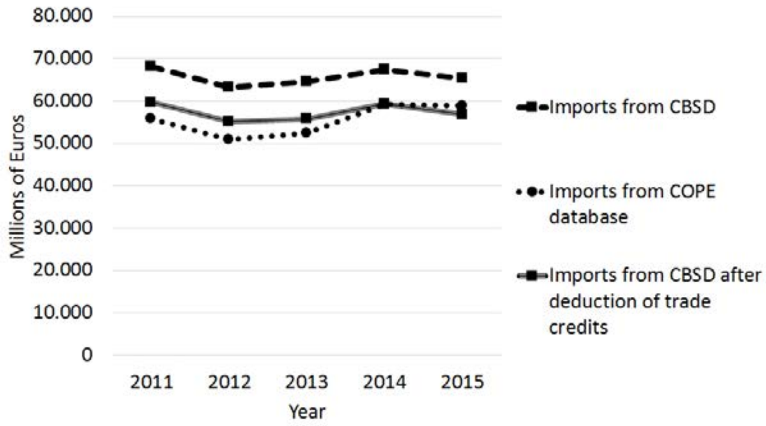


Chart 11: Imports of goods and services from CBSD and COPE database



3.6. CBSD vs. Social Security data

Social Security data used at the CBSD were a result of a pre-processed query to the original Social Security data. From this query, only a file with the total number of employees and their wages by firm and year was made available to the CBSD. As a result, some differences arouse, especially regarding the number of employees, given that, through IES, firms report their average number of employees during the year and not the total one, as in the pre-processed file from the Social Security data.

Consequently, the number of employees from the Social Security data is greater than the CBSD. However, the trend is very similar as it can be seen in Chart 12. Wages from the CBSD and the Social Security are presented in Chart 13.

Chart 12: Number of employees from the CBSD and the Social Security databases

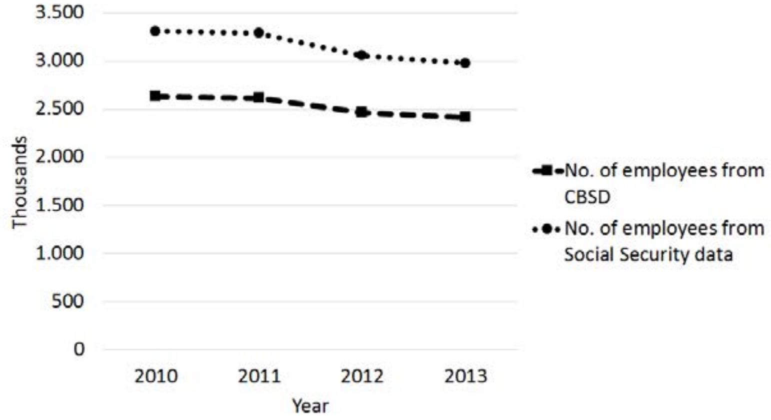
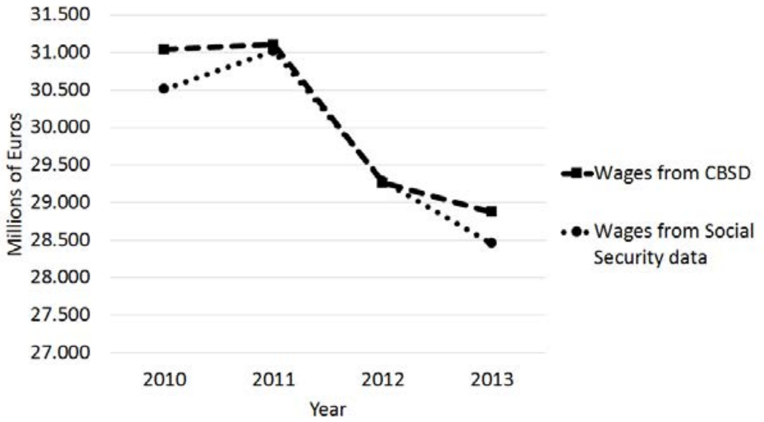


Chart 13: Wages from the CBSD and the Social Security databases



4. Conclusions

Matching firm-level databases is essential to ensure the quality of statistics. This paper presents the specific case of the CBSD of Banco de Portugal, which benefits from the existence of both internal and external databases that allow filling the gaps of the information submitted by NFC.

The Statistics Department of Banco de Portugal manages several databases, namely the CBSD, the CCR, the SSIS, the MIR and the COPE databases. Besides internal databases, the CBSD also has or had access to external data sources such as the exports and imports from the Tax Authority and the number of employees from Ministry of Social Security. Every year, during the QC process of data sent by NFC, the Central Balance-Sheet Office uses information of these sources to improve the quality of its data.

It is important to stress that not only the Central Balance-Sheet Office, but also all the other divisions benefit from the integration and interchangeability of the databases managed by the Statistics Department of Banco de Portugal. Frequently, inputs from one division are used for other divisions to improve their data, by matching or by validation of their own reports.

Data from the CCR and the COPE databases on loans granted by financial institutions and group companies, and from the SSIS on debt securities issued by NFC are automatically and manually matched with the CBSD, overcoming misclassifications in the reported data that otherwise would only be solved by direct contact to firms, which would be a very slow process.

Sometimes, it is not possible to fully match the databases. If, in the case of CCR, nearly all the amount that is not matched derives from external loans, which are usually available from the COPE database, in the case of exports and imports the sources of differences between CBSD and COPE database is broader. Trade credits are the main justification, but there are many others such as transactions with resident branches of non-resident firms or between non-resident accounts, intra-group cash pooling and equal operations reported in different companies of the same business group.

It was also illustrated that independently of the database used, the trends are fairly the same, which is important in the sense that, even in the absence of some source, the other sources available allow the characterization of a given phenomenon.

To sum up, manage and match several databases contributes to improve the quality of statistics. In the particular case of the CBSD, it was demonstrated that matching databases allows filling the gaps of NFC reports, although there are some methodological differences, whose knowledge also contributes to better understand the boundaries of each data source.

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Özdere-İzmir, Turkey, 26 September 2016

Matching firm-level data sources at the Statistics Department of Banco de Portugal[1]

Paula Casimiro, Ana Bárbara Pinto and Tiago Pinho Pereira,

Bank of Portugal

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

Matching firm-level data sources at the Statistics Department of Banco de Portugal

BANCO DE PORTUGAL
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Ana Bárbara Pinto • Banco de Portugal and member of the ERICA Working Group, ECCBSO

IFC / ECCBSO / CBRT Conference on "Uses of Central Balance Sheet Data Offices' information"

Özdere-İzmir, September 26th, 2016

1. **Firm-level data sources at the Statistics Department of Banco de Portugal**

   a. **Internal data sources**
      i. The Central Balance-Sheet Database (CBSD)
      ii. The Central Credit Register (CCR)
      iii. The Securities Statistics Integrated System (SSIS)
      iv. Monetary and Financial Institutions (MFIs) Interest Rates (MIR)
      v. Transactions and Positions with Non-Residents (COPE)

   b. **External data sources**
      i. Tax Authority
      ii. Social Security

2. **Some results from matching firm-level data sources**

3. **Conclusions**

Internal data sources

Central Balance-Sheet Database (CBSD)

- Created in 1983
- Contains **individual and consolidated (IFRS and National GAAP) accounting data on non-financial corporations** (NFC)
- Useful for the production of **statistics about NFC and sectoral benchmarks**, the derivation of **NFC sector for National Accounts**, the **estimation of several items for BoP**, for **updating business registers** and **risk assessment**

Central Credit Register (CCR)

- Launched in 1978
- Contains information about all the **loans above €50 granted by resident financial institutions** (e.g. borrowers and lenders ID, amount, guarantees, maturity)
- Contributes for the financial stability by **helping financial institutions in assessing the credit risk** of their current or new credit clients

Internal data sources

Securities Statistics Integrated System (SSIS)

- Established in 1999
- Contains detailed data on **issues** and **portfolios** on a **"security-by-security"** and **"entity-by-entity"** basis
- Allows the production of **statistics on issues and portfolios of securities**, the design of **"from-whom-to-whom" tables crossing issuers and holders**, and the supply of **input data for MFIs, BoP and National Accounts** statistics.

MFIs Interest Rates (MIR)

- New requirement created by Banco de Portugal in June 2012, with the aim of obtaining **representative data on new loan operations**, in a context of financial stability assessment
- Applies to MFIs granting at least 50 million euros per month in new loans to NFC resident in the euro area
- Reported data includes the **maturity** of the loan, **initial period of interest rate fixation**, **amount**, **annualized interest rate**, **borrower ID** and **residence**

Internal data sources

Transactions and Positions with Non-Residents (COPE)

- Set in 1993, based on monthly reports by resident banks and directly from some large entities
- Since 2013, all entities with yearly transactions with the rest of the world above €100.000 started to report and classify their **transactions and positions with non-residents** directly to Banco de Portugal
- Reported data includes **exports and imports** of goods and services, **loans**, **trade credits**, and several other operations and its breakdown by nature, maturity, direct investment relationship and transaction type

External data sources

Tax Authority

- Received at Banco de Portugal since 2014
- Contains **data from 2006 onwards**
- Includes, among others, **extra-EU and intra-EU exports and imports** of goods and services, the fields of the VAT return, the annual **amount of tax incentives for R&D**, and the **register of active companies** for VAT purposes, with the date of beginning and end of activity

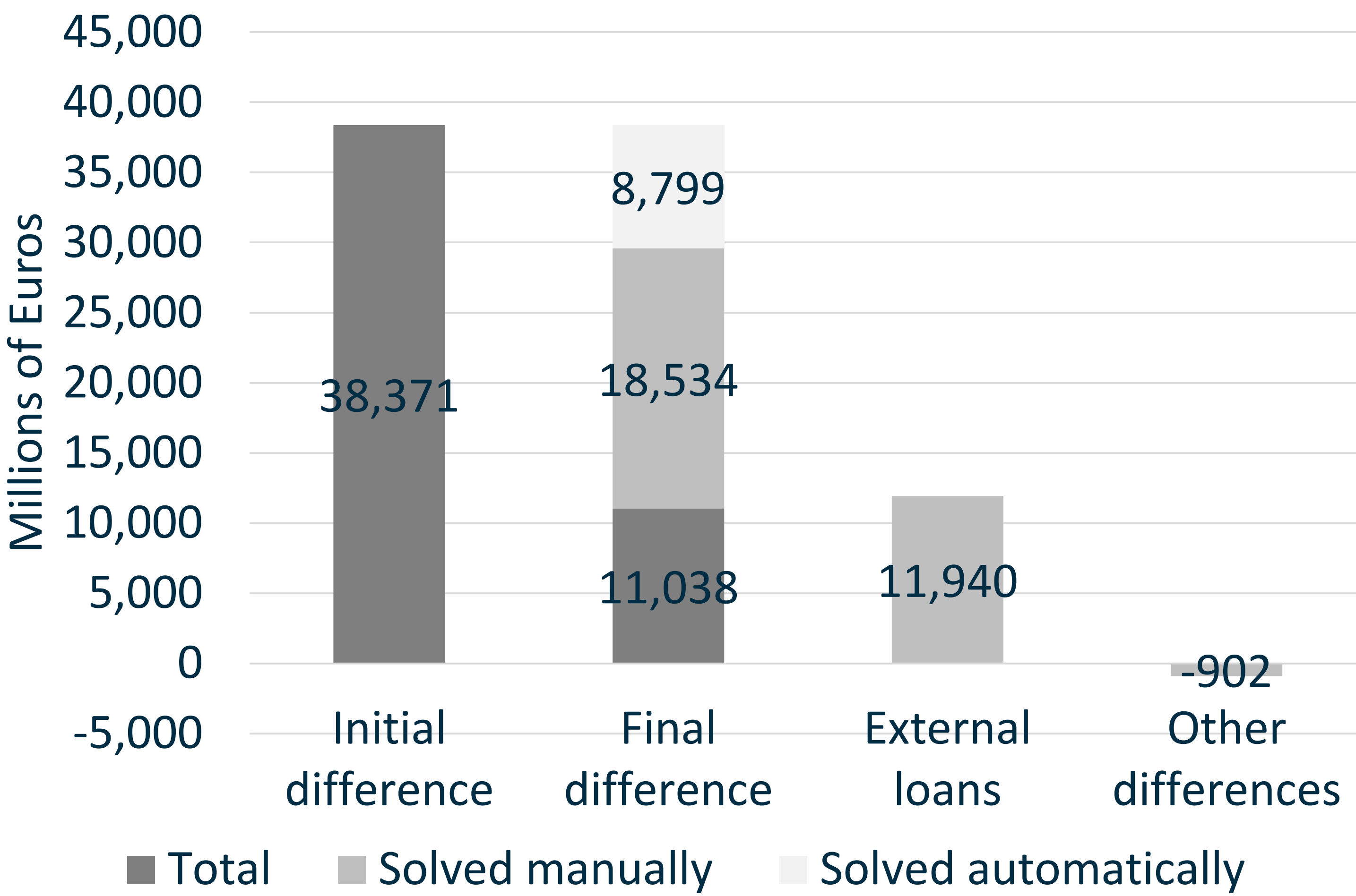
Social Security

- Received at Banco de Portugal until 2013
- Contains data on the **annual number of employees** (paid and unpaid), **number of hours worked**, and the **amount of wages paid** by firm

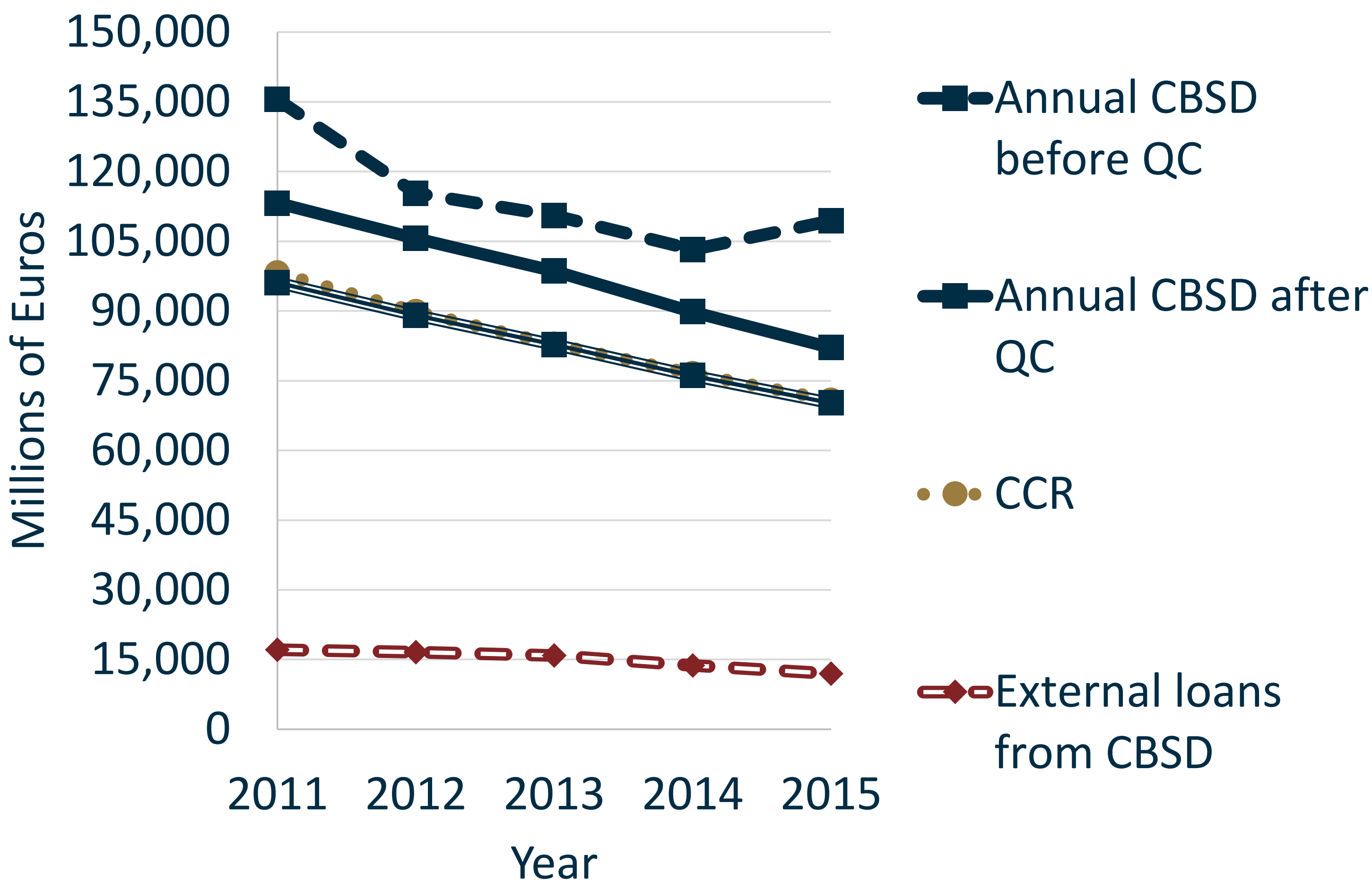
Results

- **Every year, data submitted by NFC to the Central Balance-Sheet Data Office of Banco de Portugal is subject to a quality of control (QC) process**
- **In this process, data from the firm-level data sources previously identified are matched with the CBSD and contribute to fill the gaps of CBSD**

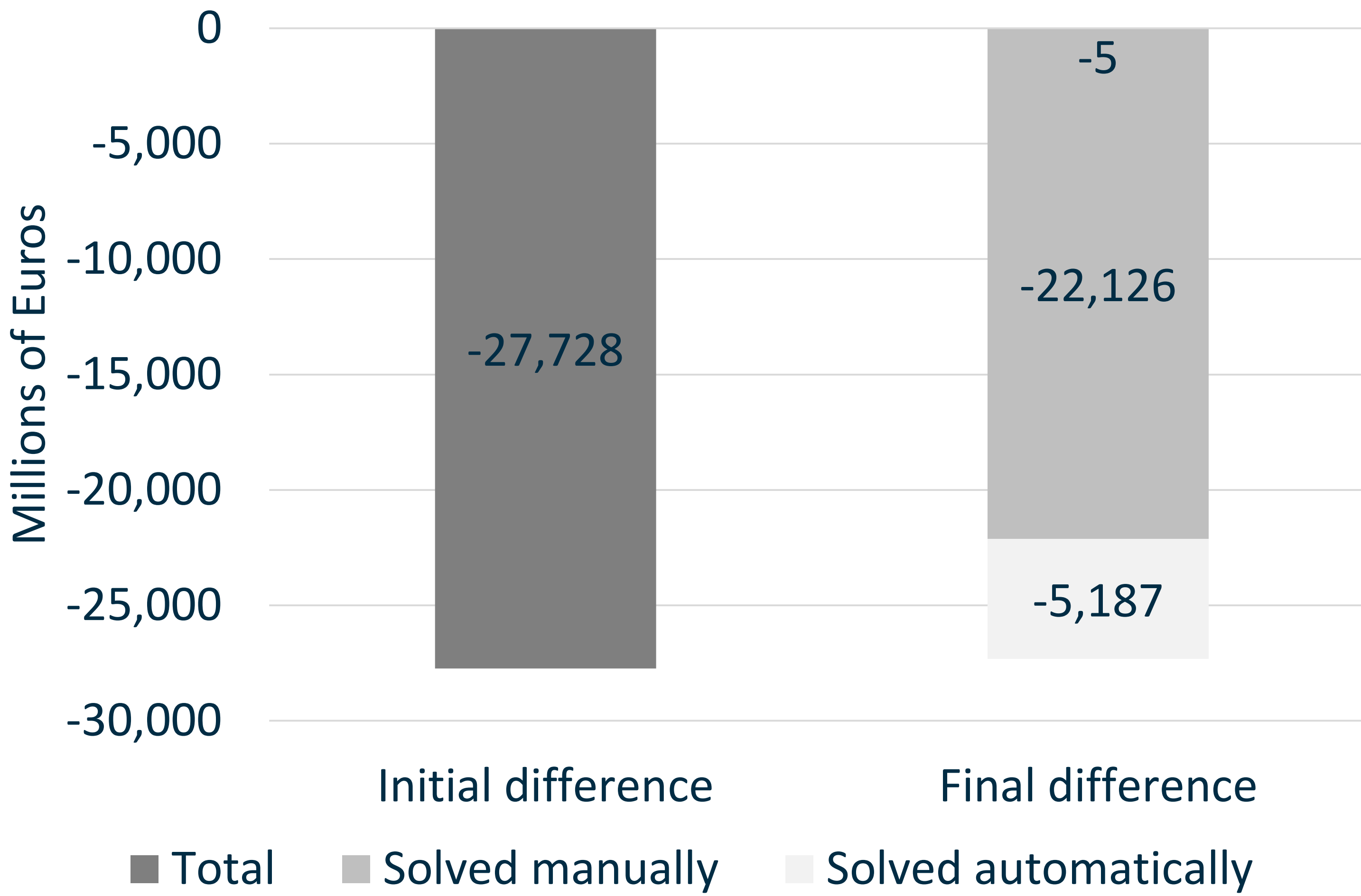
Results: CBSD vs. CCR database (2015)



Results: CBSD vs. CCR database

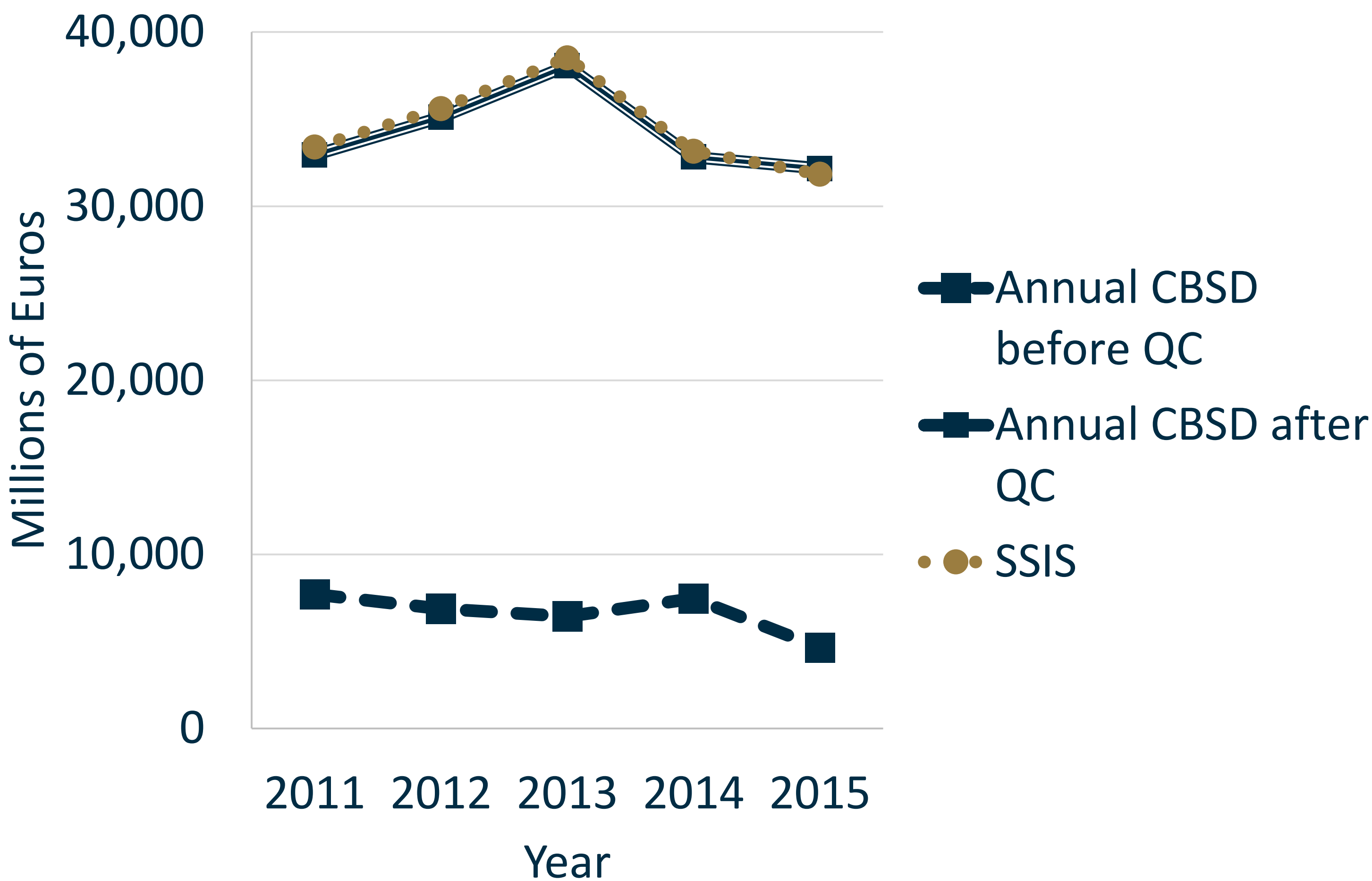


Results: CBSD vs. SSIS database (2015)

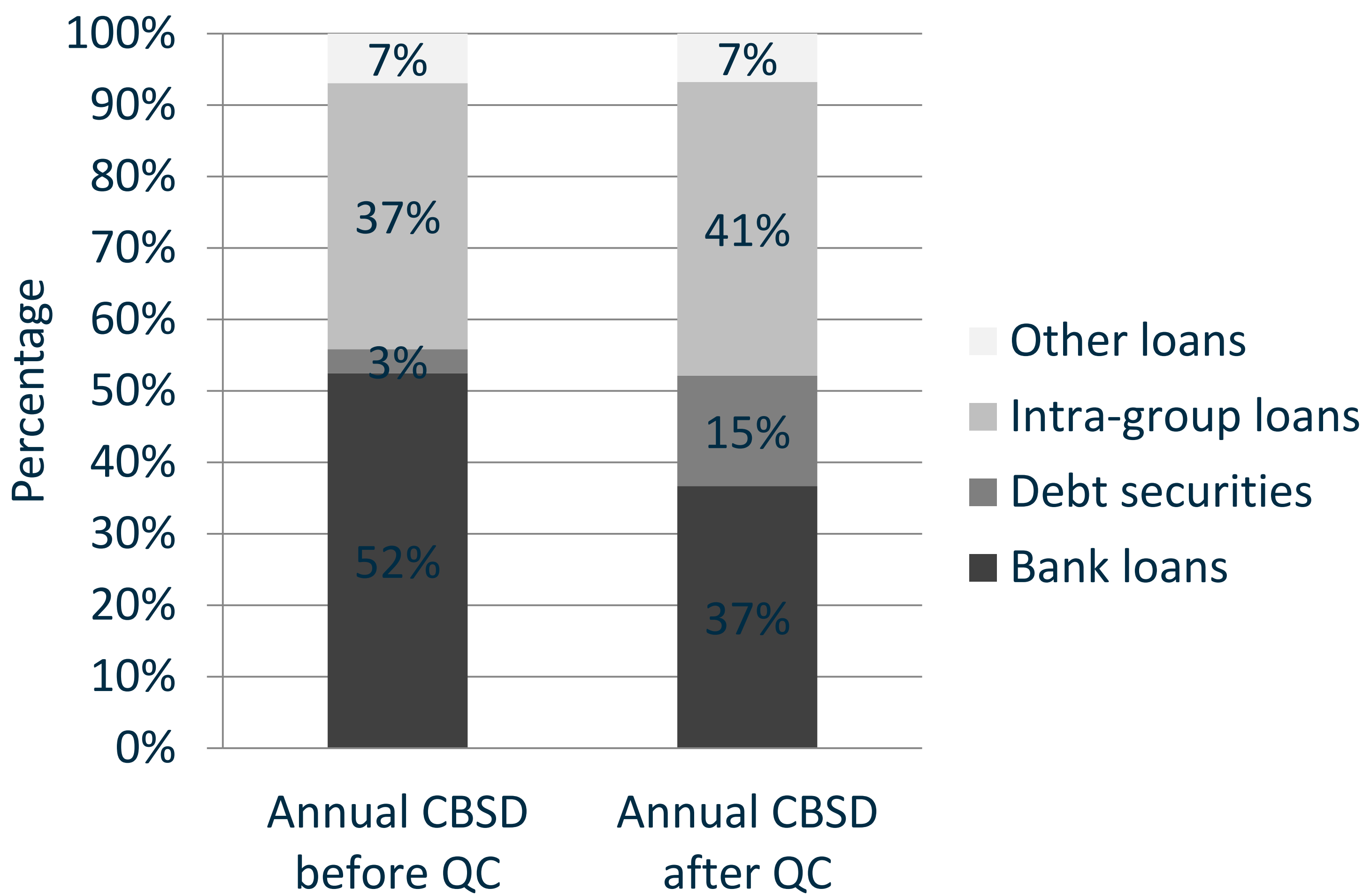


BANCO DE PORTUGAL
EUROSISTEMA

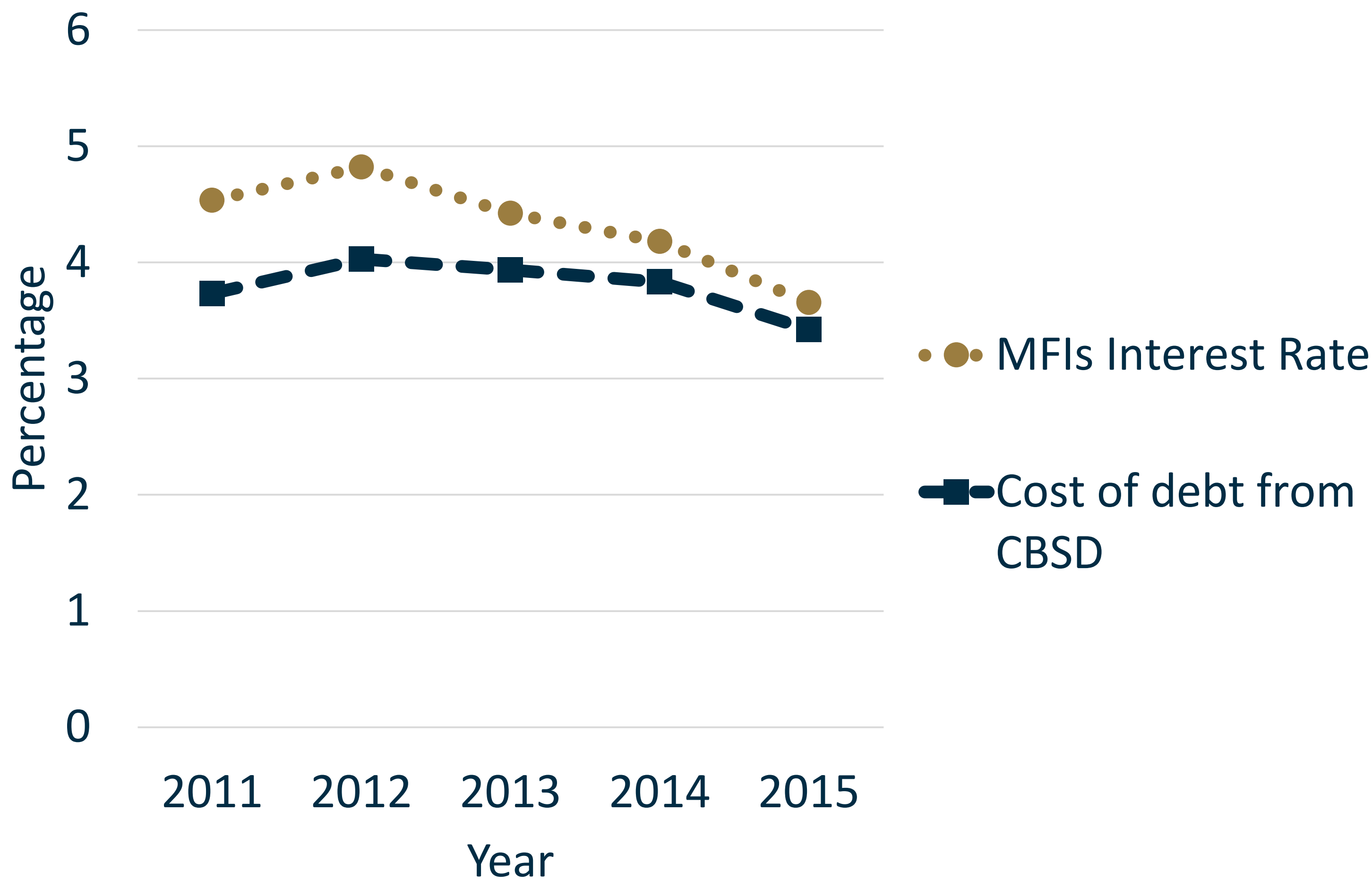
Results: CBSD vs. SSIS database



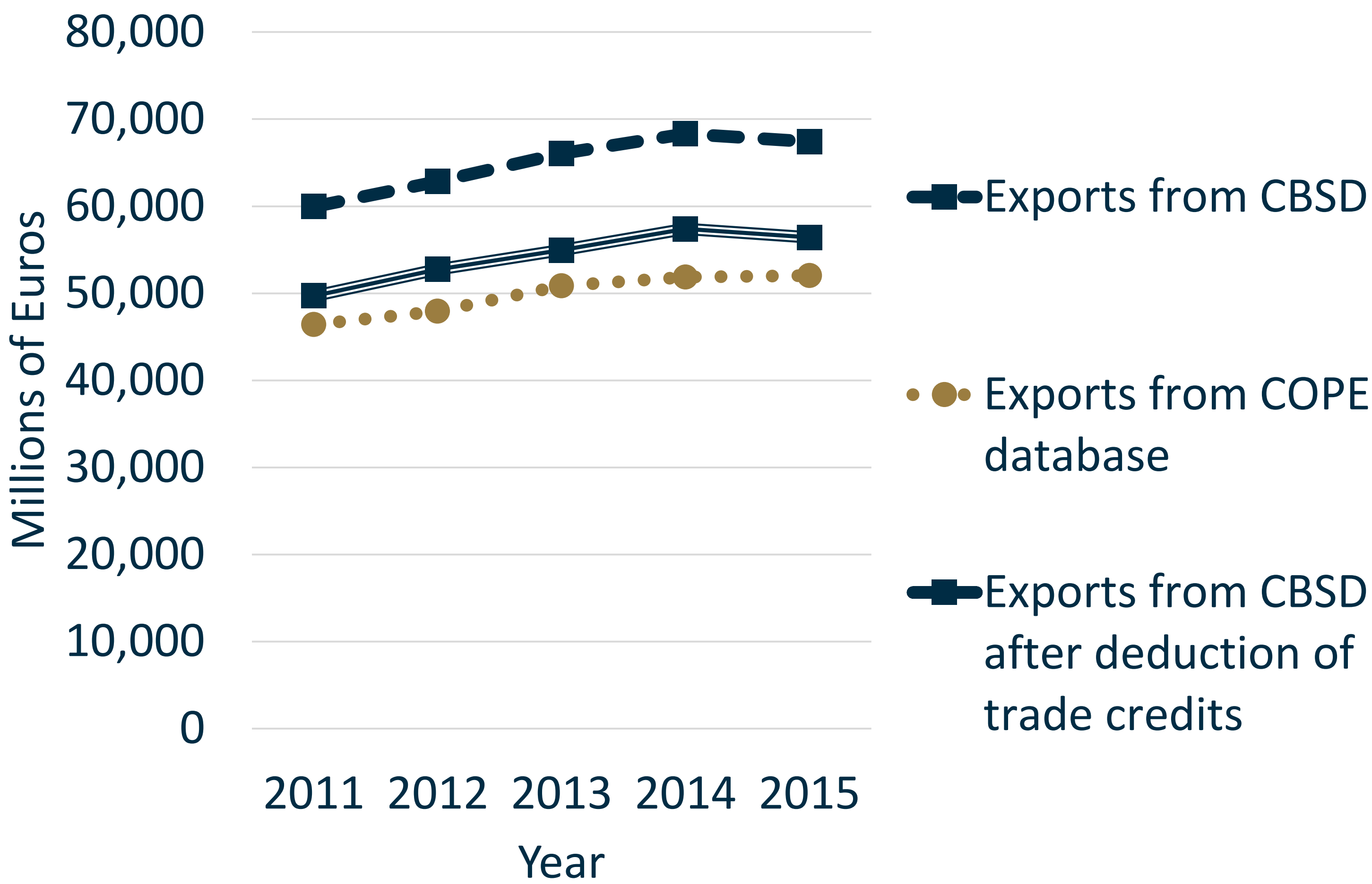
Borrowings structure of NFC (2015)



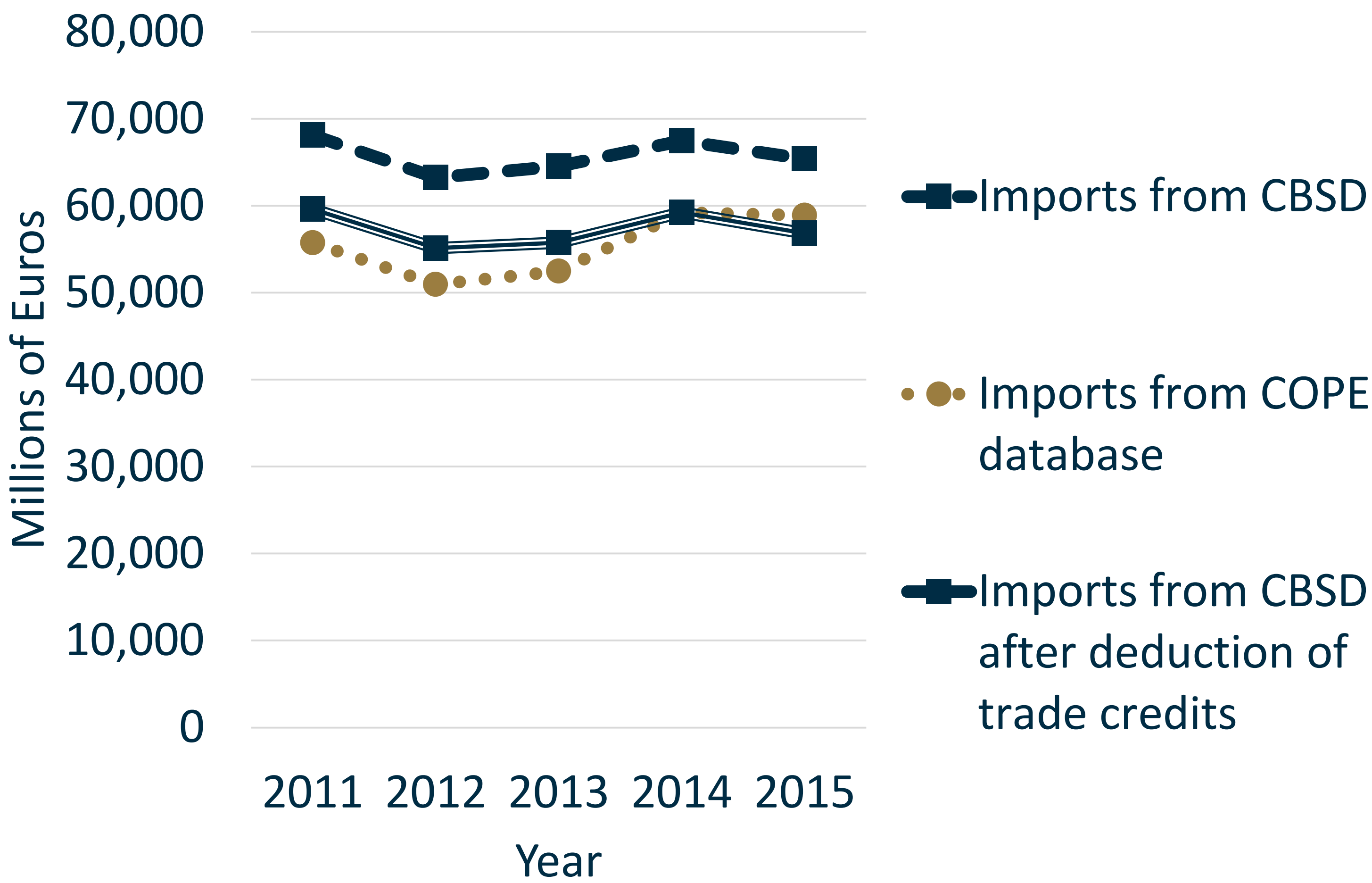
Results: CBSD vs. MIR database



Results: CBSD vs. COPE database



Results: CBSD vs. COPE database



Conclusions

1. **Matching firm-level databases is of crucial importance for the quality of statistics**

2. **Banco de Portugal manages a wide range of internal databases with the information of ones being used as an input for others**

3. **A complete matching is not always possible due to methodological differences between databases**

4. **After the quality control, even in the case of incomplete matching, all the databases show the same trend**

Thank you for your attention!

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IFC-ECCBSO-CBRT Conference on *"Uses of Central Balance Sheet Data Offices' information"*

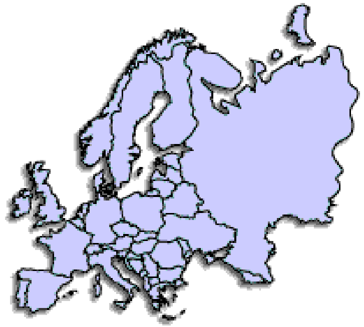
Co-organised by the IFC, the European Committee of Central Balance Sheet Data Offices (ECCBSO) and the Central Bank of the Republic of Turkey (CBRT)

Özdere-İzmir, Turkey, 26 September 2016

Consolidated accounts of non-financial groups: facing the use of ERICA database for economic research; decomposition of ratios technique for cross-country comparison[1]

Saskia Vennix, National Bank of Belgium

[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.



ERICA Working Group
ecbso
European Committee of Central Balance Sheet Data Offices

Consolidated accounts of non-financial groups: facing the use of ERICA database for economic research; decomposition of ratios technique for cross-country comparison

European Committee of Central Balance Sheet Data Offices (ECCBSO)

Özdere-Izmir, 26th September 2016

Saskia Vennix

Vice-chair of the ERICA WG of the ECCBSO

Content

- ERICA WG and ERICA database
- Annual ERICA publication
- Decomposition of ratios

ERICA WG

- **Targets** of ERICA WG:
  - Monitor IFRS new projects
  - Update IFRS standard formats (extended / reduced)
  - Creation of ERICA database (European Records of IFRS Consolidated Accounts):
    - To know better the uses and limits of consolidated accounts
    - To analyze the results of non-financial listed groups
  - XBRL and CBSO
  - Integrated reporting
- Participants of ERICA WG: Austria, Belgium, France, Germany, Greece, Italy, Portugal, Spain, Turkey (observer), ECB (observer) and IASB (observer)

ERICA database: why we created it

- In 2002, knowing the IFRS introduction project in Europe, we created a WG to:
  - Understand better IFRS: "translating" the bound volume into an extended format
  - Check possible impacts of IFRS on CBSOs

- We decided to create a database for:
  - Testing process of reduced standard format
  - Assess real use of IFRS by European groups
  - Financial analysis, amongst others:
    - Fair value / IFRS alternatives used
    - Financial structure / Profitability
    - Sectoral diversification / Restated data
    - Dividends / Cash flows

ERICA database: contents

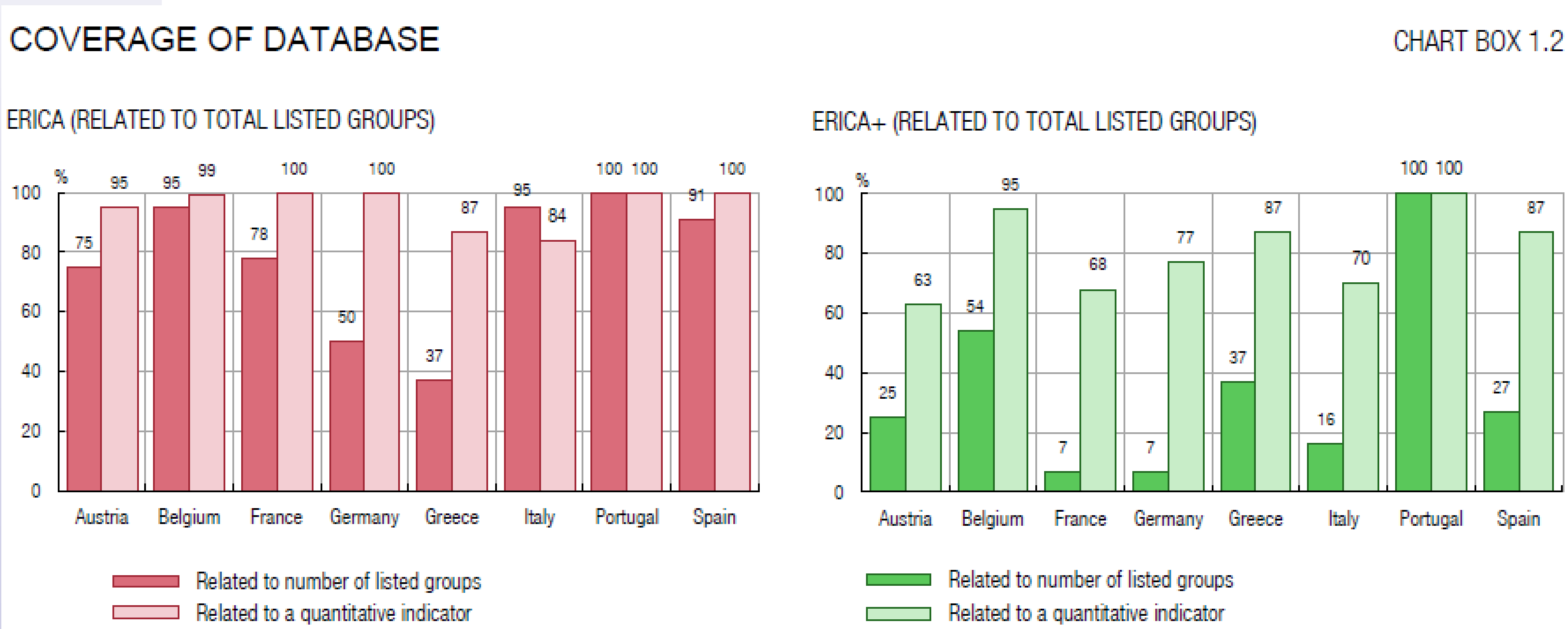
IFRS data of non-financial listed groups (2005-2014)

Country	2009	2010	2011	2012	2013	2014
Austria	53	24	46	45	45	42
Belgium	30	30	80	76	77	77
France	471	454	447	347	348	343
Germany	231	288	315	314	305	219
Greece	30	60	60	60	49	50
Italy	189	193	190	160	163	179
Portugal	43	41	40	39	39	38
Spain	30	30	113	113	111	103

ERICA database: contents

- General characteristics
- Options IFRS
- Employment
- Statement of financial position (78 items)
- Statement of profit or loss by function (39 items)
- Statement of profit or loss by nature (35 items)
- Other comprehensive income (23 items)
- Cash-flow statement (25 items)
- Some additional information on parent entity, breakdown of revenue by sector, market capitalization, fair value gains/losses, reasons of variation of revenue, enz. (ERICA+)

ERICA DB: good coverage of listed groups



Content

- ERICA WG and ERICA database
- Annual ERICA publication
- Decomposition of ratios

ERICA Working Group eccbso European Committee of Central Balance Sheet Data Offices

ERICA analysis publicly diffused (Dec 2015)

TITLE:

"European non-financial listed groups: analysis of 2014 data"

CONTENT

- Profitability
- Financial structure
- Fair value impact
- Box 1 - ERICA database: main characteristics & coverage
- Statistical annexes

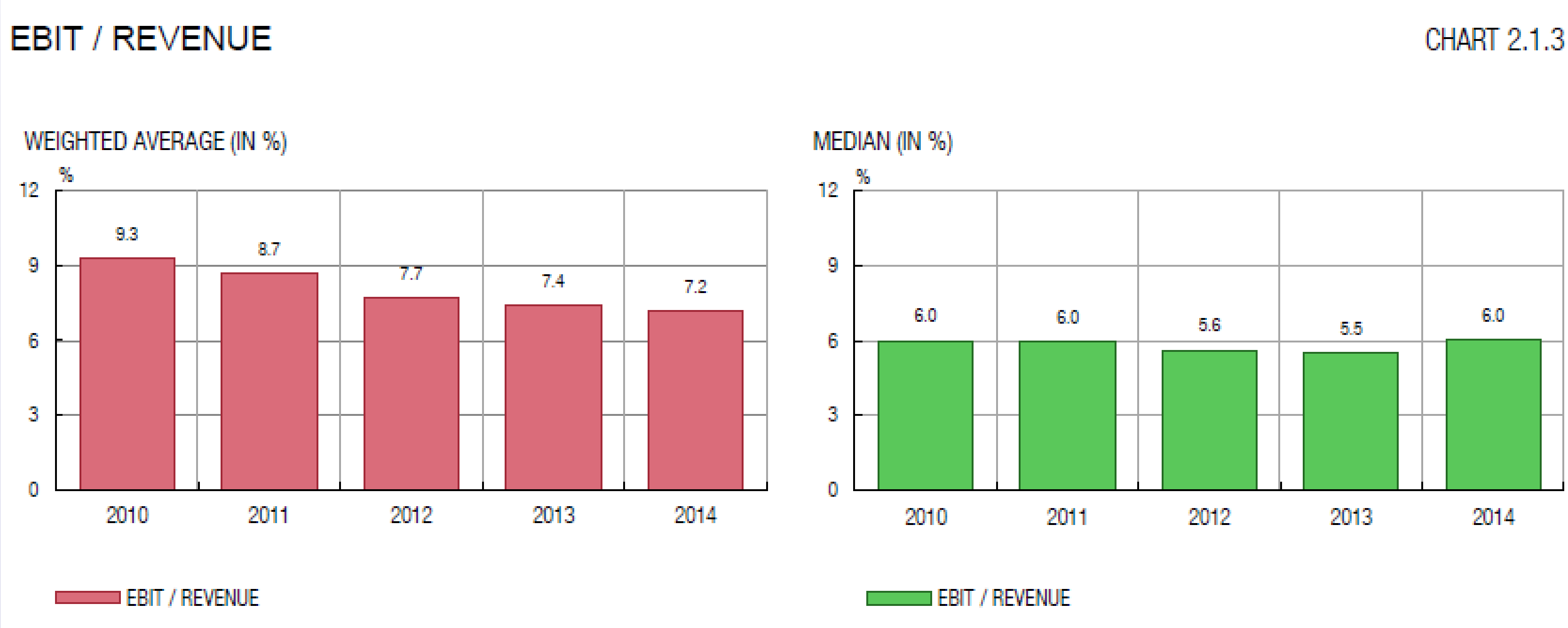
Caution: trends with consolidated data, no distinction between

- External growth (new subsidiaries added in the scope)
- Organic growth (internal increase)

For this reason, we try to work with ratios

ERICA analysis: Profitability

- After three years of poor performance, 2014 shows a picture of slight recovery in results and profitability

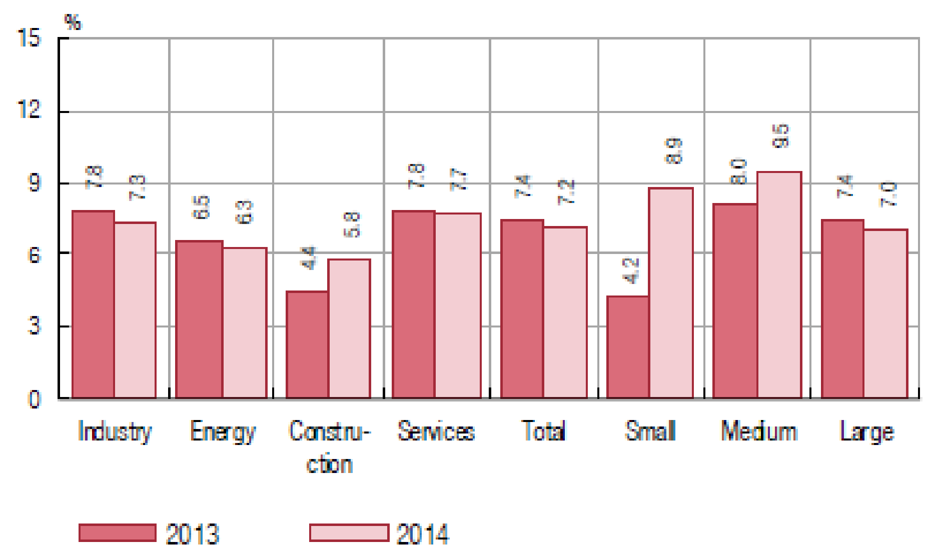


ERICA analysis: Profitability

- After three years of poor performance, 2014 shows a picture of slight recovery in results and profitability

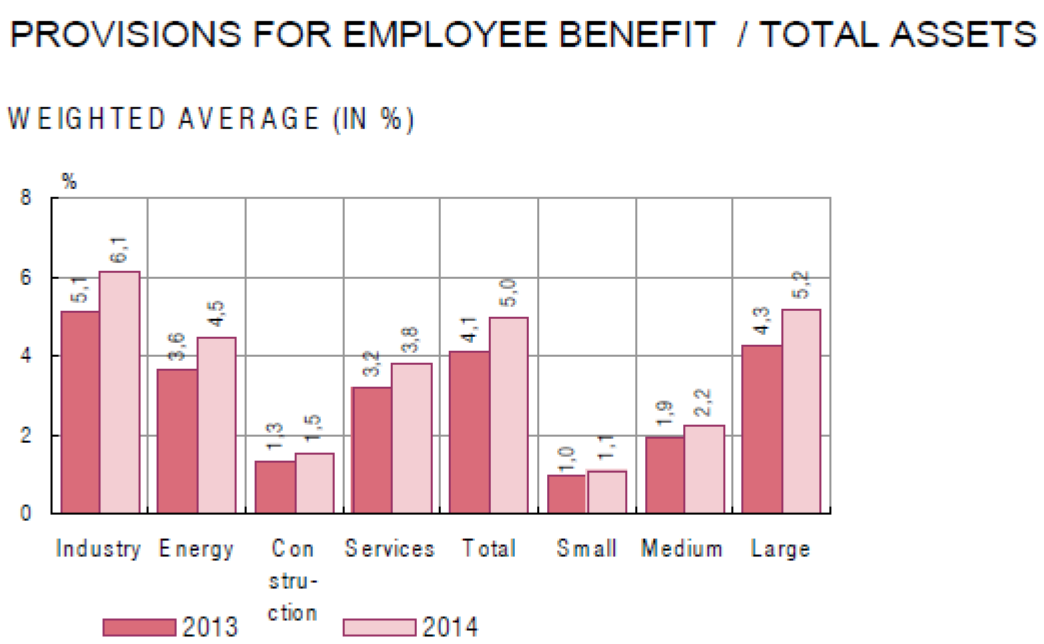
EBIT / REVENUE

WEIGHTED AVERAGE (IN %)



ERICA analysis: Financial structure

- Equity ratio remains largely stable in 2014 due to financial debt expansion and increase in provisions for employee benefits



ERICA analysis: Financial structure

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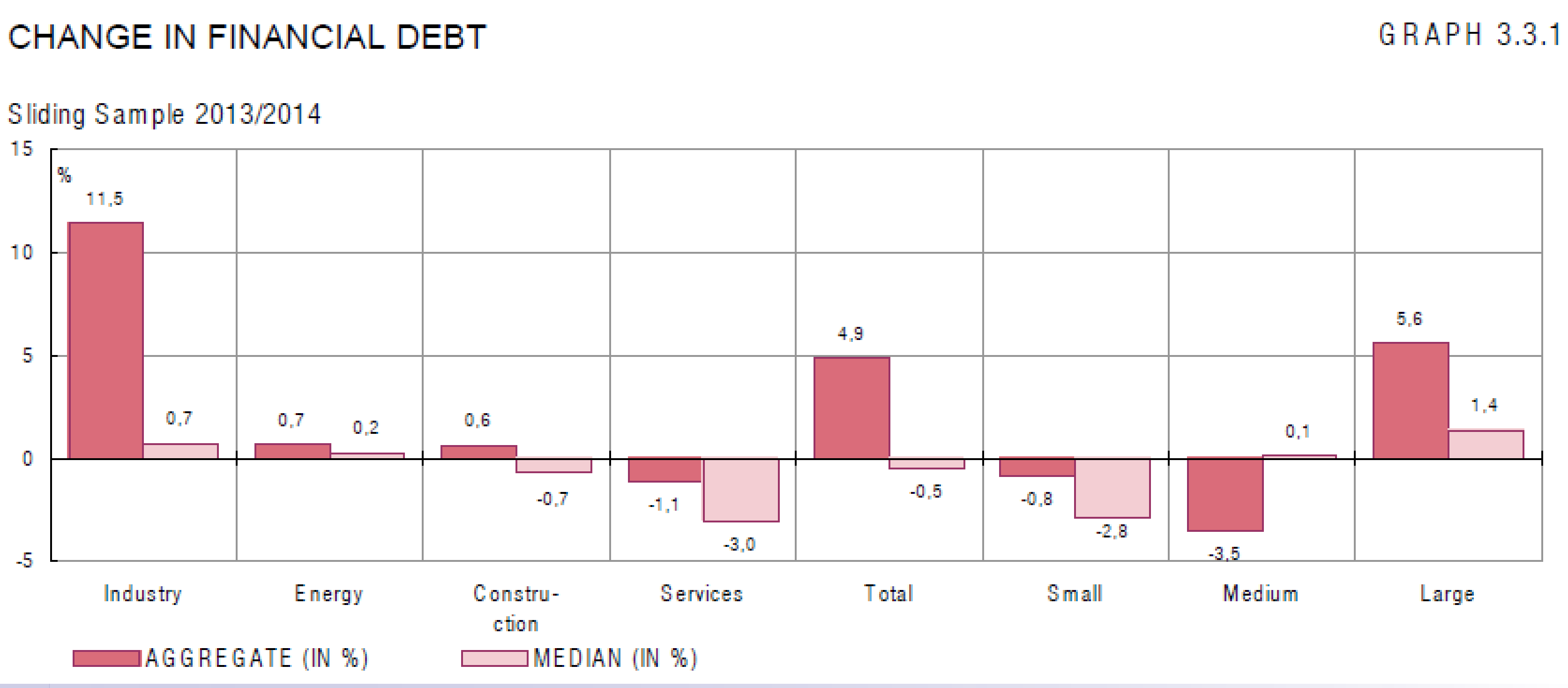
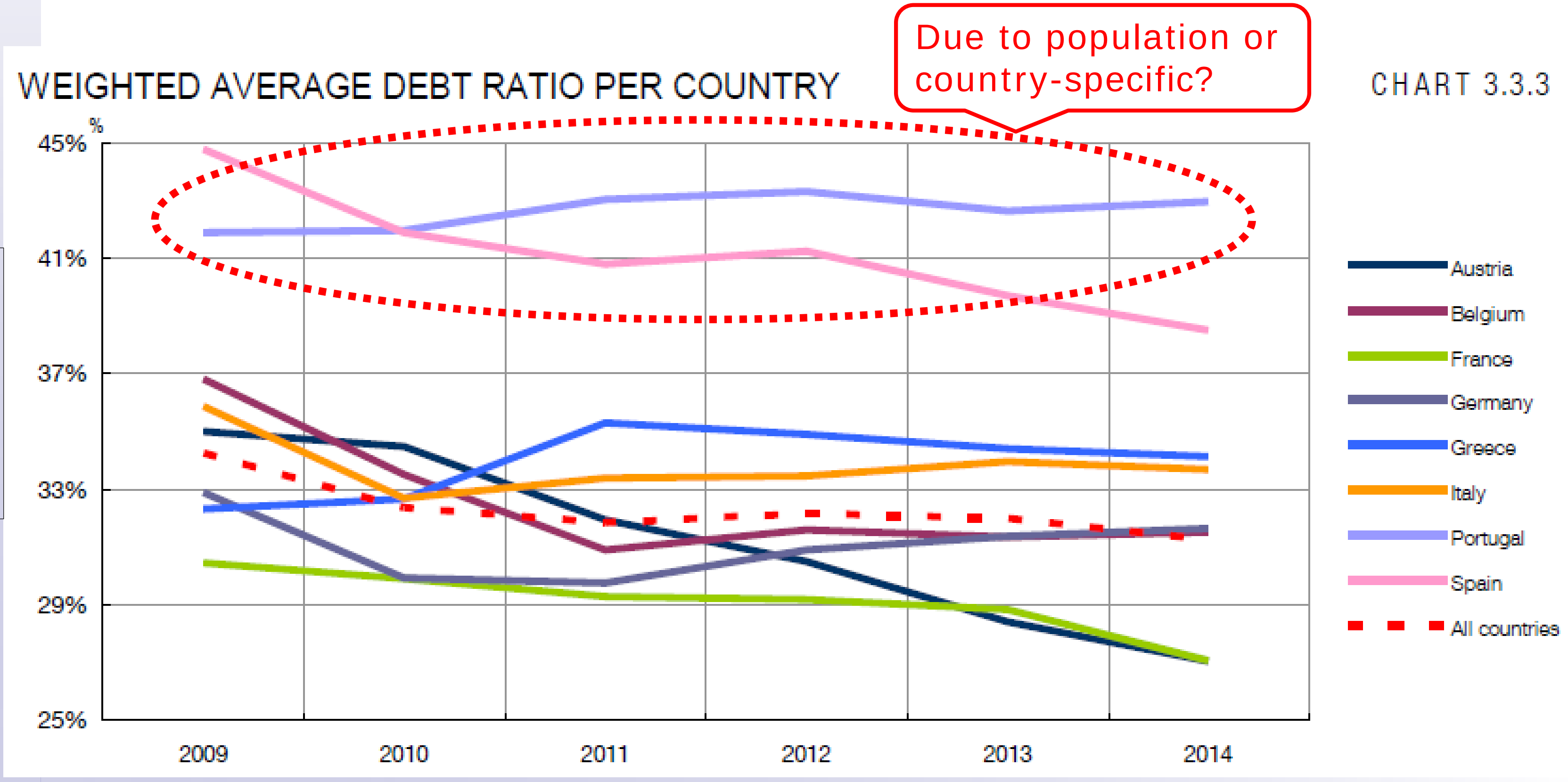


ERICA analysis: Financial debt ratio

- Downward trend in financial debt ratio during 2009-2014



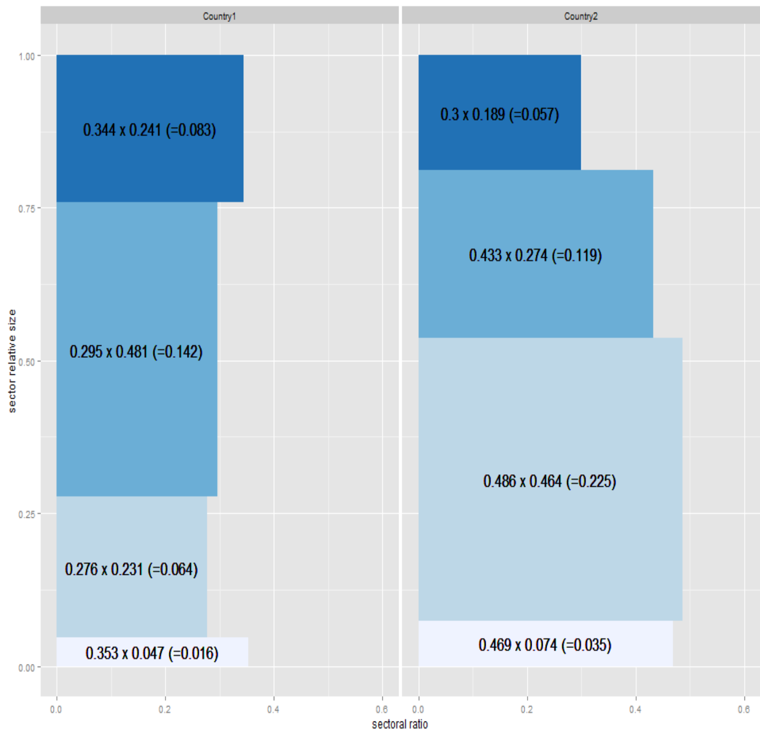
☝ Listed groups are not necessarily representative for national economies ☝

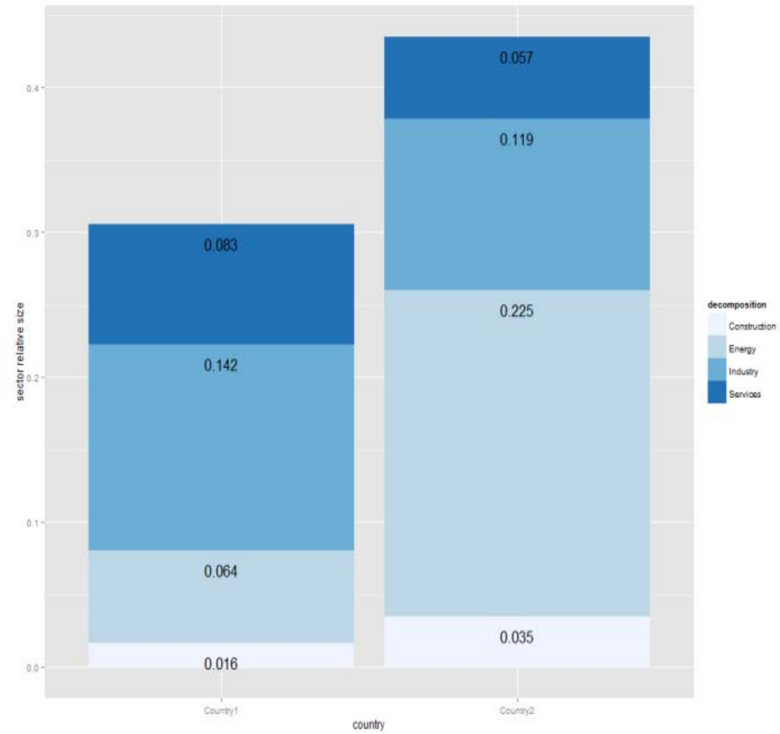
Content

- ERICA WG and ERICA database
- Annual ERICA publication
- Decomposition of ratios

Decomposition of ratios: methodology

Example of sectoral decomposition of a ratio





Decomposition of ratios: methodology

Marshall-Edgeworth cross-country

$$r_i - r_0 = \sum_{j=1}^{n} \left[\underbrace{\frac{r_{ij} + r_{0j}}{2} \left(\sigma_{ij/i} - \sigma_{0j/0}\right)}_{structural\ sector\ j} + \underbrace{\frac{\sigma_{ij/i} + \sigma_{0j/0}}{2} \left(r_{ij} - r_{0j}\right)}_{intrinsic\ sector\ j} \right]$$

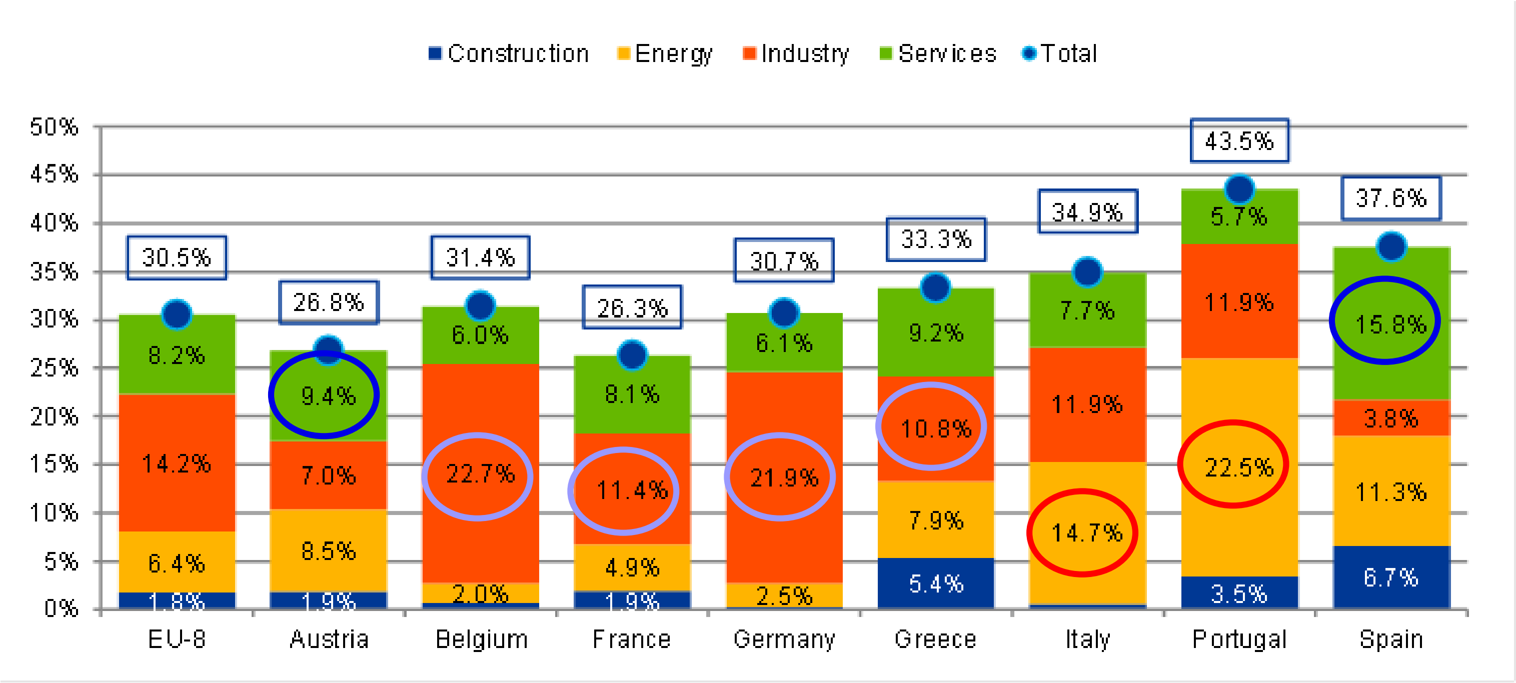
Decomposition of ratios: methodology

Marshall-Edgeworth over time

$$r_i(t_1) - r_i(t_0) = \sum_{j=1}^{n} \left[\underbrace{\frac{r_{ij}(t_1) + r_{ij}(t_0)}{2} \left(\sigma_{ij/i}(t_1) - \sigma_{ij/i}(t_0) \right)}_{\text{structural } for\ sector\ j} \right.$$

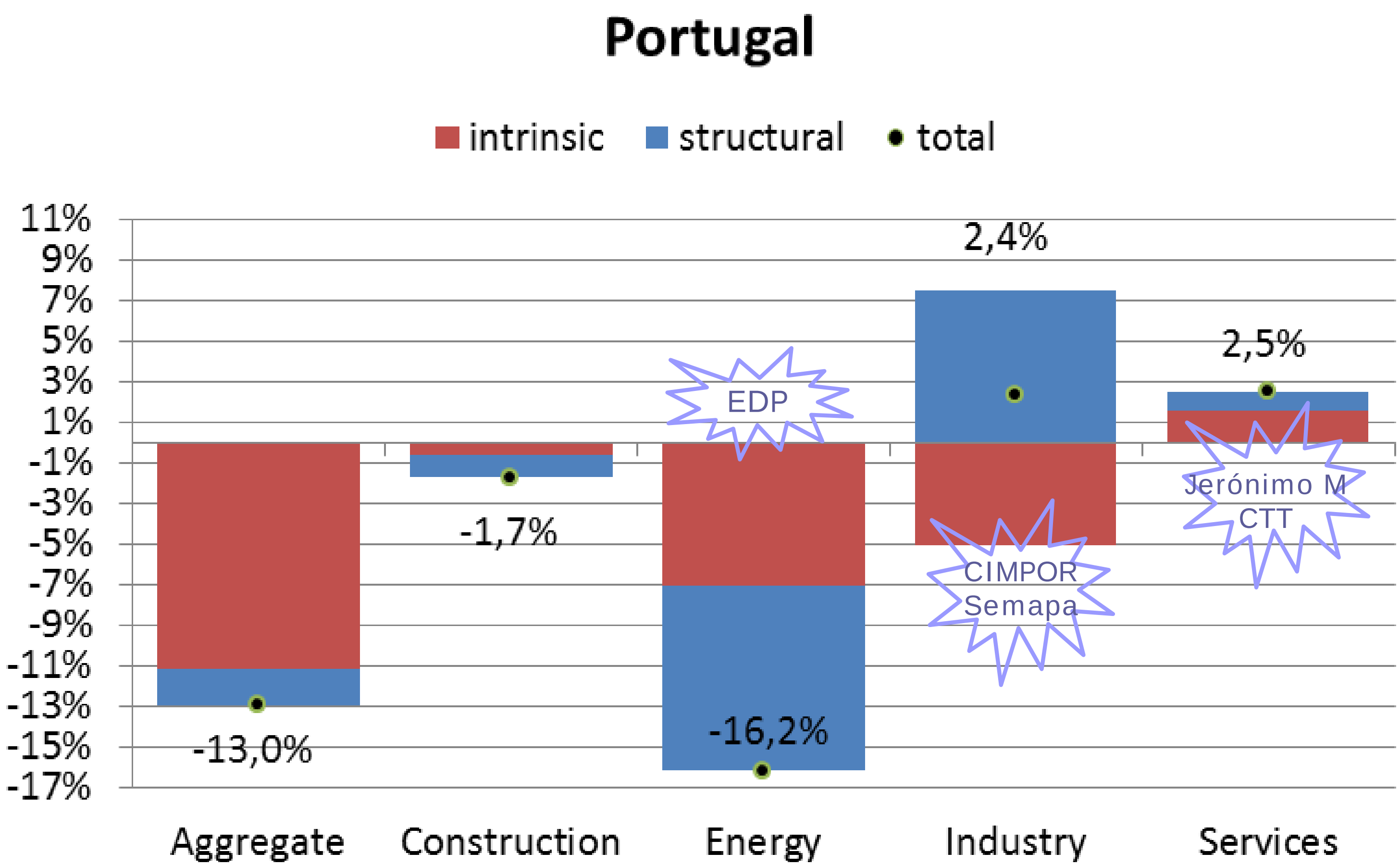
Cross-country analysis: debt ratio

Absolute contribution of the different sectors to the globalised debt ratios in 2014



☝ Listed groups are not necessarily representative for national economies ☝

Cross-country analysis: debt ratio



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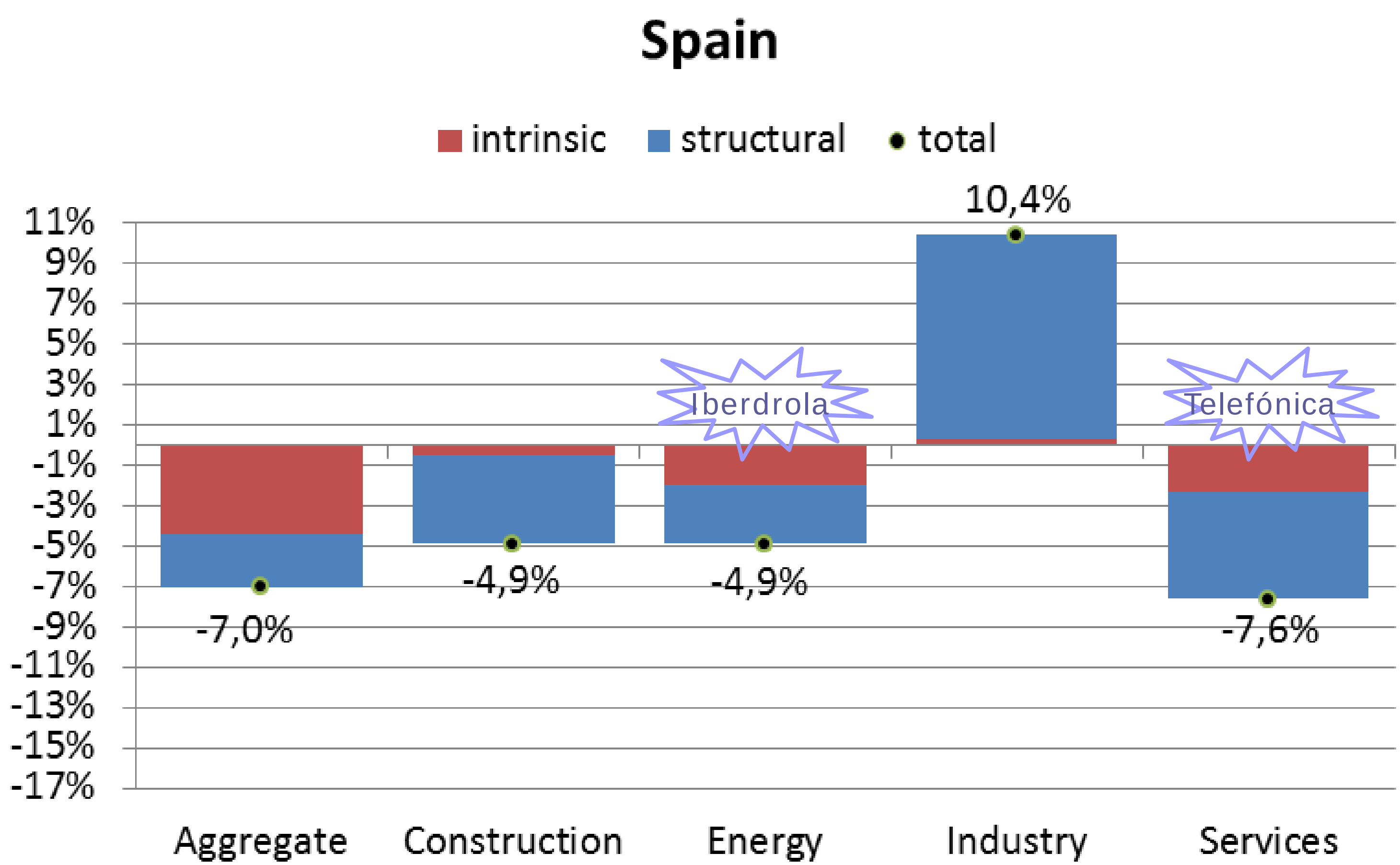
Cross-country analysis: debt ratio



☝ Listed groups are not necessarily representative for national economies ☝

Decomposition of ratios: conclusions

1. Importance of decomposition techniques to distinguish, within the evolution of a country compared to others, the intrinsic impact (ratio behaviour) from the structural component (population sectoral weight).
2. Having this information, analysis should focus on intrinsic effects.
3. Offsetting effects among sectors of activity: the technique has to be applied by sector of activity and by country (not only the total).
4. Impact has to be assessed ratio by ratio: structural effects vary according to the ratio (relative weight of a sector of activity for a precise denominator)

ERICA database, a tool of the ECCBSO

- Know more in:

http://www.eccbso.org/

Thank you!

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A conceptual design of "what and how should a proper macro-prudential policy framework be?" A globalistic approach to systemic risk and procuring the data needed[1]

Murat Cakir, CBRT

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

A Conceptual Design of "What and How Should a Proper Macro-Prudential Policy Framework Be?" A Globalistic Approach to Systemic Risk and Procuring the Data Needed[1]

Murat Cakir[2]

Abstract

During the last half-decade, the 2007 global crisis has kept all interested parties busy and urged them to focus on the causes of this crisis, to find solutions for recovery, and to contrive to be capable of projecting potential ones that may happen in the future. As one of the precautionary tool-sets devised for the authorities among others the classical macro-prudential and systemic risk models focused on banks and sought for the systemically important ones (SIFIs). It had been argued by a handful of interest groups that this sort of approach to risk embedded in a network structure was both unbalanced condoning potential plausible sources of risk to monitor passively as well as take policy actions pro-actively and further was undue in remedying possible causes if, when and where seen indispensable. Therefore, a more macro stance towards the conventional macro-prudential paradigms considering micro elements of the system was seen as vital.

This work attempts to draw an extended framework that would span all potential incumbents forming part of the Circular Flow of Income (CFI), which is treated as a network or a bijective counter-party mapping of incumbent groups of different sources that each have claims against the funds granted to other groups or to members of the same group.

Availability of data would be a focal point for the operability of a model as such. Though the significance of data availability being a central question is inarguable and the necessary data is really scarce, that doesn't abstain one from devising usable designs, nor does it from standing in a proper position in such design efforts for public welfare. In reality, the data is available for a different variety of incumbent groups at different levels of congruity, but unfortunately sparsely distributed among different collectors and users[3]. Still, there is data that can be used for empirical analysis purposes but needs a considerable extent of effort to collect and make use of.

1 I am grateful to Dr. Eray Yucel for his very valuable thoughts and comments on the preparation and format and the conceptual framework of this work, and sharing his precious scarce time in discussing with me about all these matters. Dr Yucel is now teaching at Kadir Has University.

2 Murat Cakir is a Specialist in the Central Bank of the Republic of Turkey. The original ideas and views expressed herein belong to the author only and do not represent those of the Central Bank of the Republic of Turkey or its staff.

3 The problem with data usually is with the last element of the previous statement: congruity. This can be solved to a great extent by a centralisation effort of all the different datasets and letting users feed in and source out from this centre thereby maximising efficiencies at blazing fast speeds and at lowest costs per use at highest possible security levels. This is the subject of another work. For an elaborate analysis consult Cakir (2014).

We propose a simple methodology on how to use the data on the extended framework, -tipping on another study- a data procural system shortly, and provide an in-exhaustive list of potential features that can be used for an extended model at the end. There will be no issue of identification neither of risks from a particular source, nor of policy recommendations since they are a subject of another work and out of the scope of the current one[4]. Still, one should bear in mind that though this other stream of work of ours employs any kind of analytical methodology that'd fit a particular context a general balance sheet, and the valuation of sub-portfolios at risk are the main architectural frame that shapes our analytical basis[5].

Keywords: Systemic Risk, Macro Prudential Policy, Circular Flow of Income

JEL classification: E58, G28

Contents

4 The particulars of this endeavour should be revealed before you read it through. Firstly, this is a direct result of readings of theory of risk in finance, risk of failure literature in particular, combined with empirical work and lessons from experience of hands-on practice involving a huge data set of company financials, individual loan positions vis a vis banks, and bank financials. It has no claim to devise a policy tool or a tool-set, nor does it produce a scheme over which one can build a full-fledged platform. One should be aware if one still will proceed. Particular self-contained specimens are referred to in the remaining of the text; therefore, no specific literature review part is an issue of this work.

5 Take for example, a credit portfolio of a given bank that is unbalanced with/ biased towards a number of housing credits granted to relatively medium and high risk customers. Any house price bubble burst would directly seriously damage the balance sheet structure of the bank given the declining market value of these credits due mainly to non-collectible instalments. A stylized balance sheet of bank after a shock can be consulted with Haldane and May (2011) as well as Amini and Minca (2014).

Prologue: What's with the Traditional Systemic Risk Models and Macro-Prudential Policy Frameworks?

Banks fail[6], non-bank firms fail[7], households fail too, even the individuals fail[8]! In a Schumpeterian world, firm level entries and exits in a healthy economy, though not wished, are normal as long as the number of firms or banks or households that fail doesn't constitute a large and an important part of the given economy or economies in terms of employment, volume of sales, asset sizes and number and complexities in and of describable relationships between and among the economic agents. Most of the bank failures are rooted from the firm failures, in general, or firms' failing to pay back loans to the lender (bank), one way or another.

A further and mostly overlooked wave of failures and being in a lead-lag relationship that result in bank distress emanate from the households either because of a general macroeconomic distress or a lack of discipline in consumption at an atomic level spread throughout the households space, a set of repetitive small or a one shot big size mistake(s)/failure(s) taken with non-rational expectations -some of them being conscious almost as dependent on chance as gambling!- in financing or investment decisions of households and/or individuals either due to financial illiteracy, ignorance about and negligence of risk and/or in the worst case malfeasance[9].

The failures of companies including banks have been subject of a huge literature resulting from failure studies since late 1930s. A lot has been said about the failures of single entities, but only a few were able to make a fully explanatory statement about the whole picture relating them to the environment they are operating in[10], so they started to fade out, though valuable individually in a given framework in and of themselves. Another stream of work that tried to combine the individual risks in a more complex web structure emerged as systemic risk studies, in their stead.

Systemic risk studies, although they date back to as early as 1960s, got more attention in the past two decades and more so after the last crisis breakout in 2007/2008, by the authorities, practitioners and the academia. Failures of big financial institutions during and in its aftermath further intensified the need to focus on the financial sector players that pose

6 Consult Guvenir, and Cakir (2009) for a bibliography of bank failure studies.

7 Consult Cakir (2005) for a bibliography of firm failure studies (In Turkish).

8 Individuals and households also fail as they are not very sophisticated financially, their financial data is almost immeasurable and/or mostly unavailable, and they are not as well covered as the corporates by legislation, hence they are practically defenceless in case of failure compared to corporate entities and enterprises. In mass failures, social and economic costs are heavier which are not perfectly fully measurable.

9 Such as overdue and/or abuse of credit cards and low cost personal credits taken mostly due to lack of sufficient funds to lead a decent life, to be more open rolled over in overlapping periods, which can be defined as moral hazard at an individual level resulting in a Ponzi scheme.

10 Most failure studies, including mine, have made then sufficient but in fact now naïve and distorted assumption of finance theory that in a perfect world given the rationality of managers, all operational acts internally and externally are almost perfectly and instantly reflected in the financial results and reports of the independent entity, further disregarding non-measurable factors including the network relationships between and among the entrepreneurial circles. Making such assumptions simplifies things considerably, however, poses risks to ignore potential relevant factors in so doing.

considerable risk to the whole financial system[11] . Though only a few of this strand of work define the systemic risk not only related to this specific sector, much unfortunately, is either limited mostly solely to it or no other non-financial agent gets ever or just seldom mentioned as systemically important[12]. However, by definition and at least theoretically, anything that has to do with monetary and financial transactions is sure a part of this very risk, therefore, should be included in this stream of work for them to be fully explanatory. Therefore, this focus had been an incomplete one in that it missed out a large and important part of the economy which itself, as mentioned above, is a critical source of distress[13] to the financial sector; namely, the real sector enterprises and households are just two among the many.

Some argued this focus only on banks is an undue one due to the very same reason: coverage. Still, it's not totally undue. The economy is a whole, and any focus on any of these individual parts is due, but this focus should be fair and as much inclusive as possible; not one of the particular risks can be singled out. Hence, all the atomic parts and their features should/must be considered all together, with a little bit more weight[14] to non-financials to tune for the current imbalance towards the financial sector. As said "it's better for the banks too, as it's not about only protecting the value of the banks' assets for a given period of time, but also about guaranteeing the circular flow of money and income" (Knibbe 2013)[15].

Traditional Framework for Systemic Risk Reconsidered: A Conceptual Counterparty-Based Financial Distress Approach

An economic system comprises subsystems, which are the households, financial sector, and real sector firms, and others interconnected with a set of complex relations, which hence even when distinctly defined, are not totally independent from one another; in fact,

11 Though the risk is a tail event, when happened the cost to the whole system is mostly devastating. Some argue that some sort of insurance pool with premia for individual failures would suffice. I would doubt that; cascading propagation demands more insurance payments in total than calculated in the event of realized failures, as past experiences reveal. Still, this does not mean that insurance premia should not be charged, nor buffers be set aside. But the amounts of premia should be more realistic and be computed more conservatively which implies a higher amount than in a usual traditional insurance system thereby increasing the cost of financing in turn.

12 A quick research on abstracts and introductions of most of the work at the links below reveal this very fact
http://www.systemic-risk-hub.org/reference_list.php
http://www.riskresearch.org/
http://www.risk.net/
http://www.risklibrary.net/
http://www.systemicrisk.ac.uk/

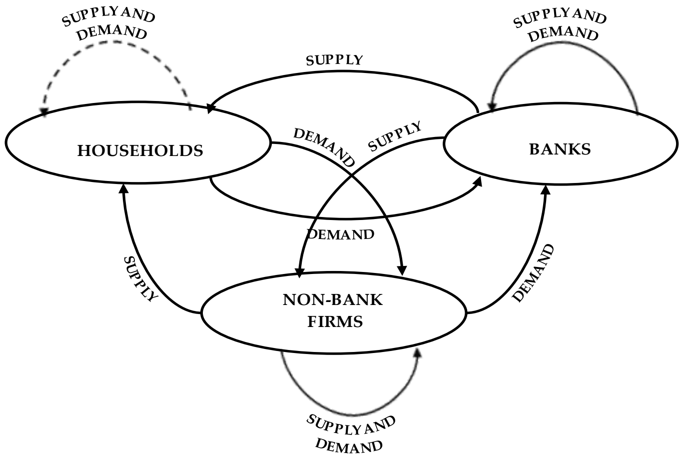
13 We are not after the process of formation of this distress. For a simple yet informative explanation of a chronology of distress build-up consult Adrian and Brunnermeier (2011).

14 Traditional macro stress testing implicates application of risk weights on particular items defined by regulators for banks. These are not a question for the non-banks in such a testing procedure. Some like Acharya, Engle, and Pierret (2013) argue that even the use of regulatory risk weight itself is risky. If one is to use weights, they should be determined differently for each agent and for each source of risk for the item

15 Good news is household debt is now becoming a point of interest by the academia and practitioners, but we need to disclose the fact that the household debt at individual and aggregated levels had always been a hot focal point for the financial sector that were after their funds granted to non-financial and non-corporate sector, namely individuals and households that can be assumed as part of an umbrella group households. Check one particular example by Mian, Sufi, and Verner (2015).

horizontally and vertically as well as cross-integrated. This integration can be depicted with an intertwined relationship network, the workings of which, simply, can be summarised as the supply of and the demand for "the funds" between and among these subsystems, borrowing simply from the systematic structure of the circular flow of income. A simple smaller version of this network is depicted as below (Figure 1)[16].

Figure.1 Graphical Representation of a Simple 3-Agent Funds Flows Network[17]



A set of direct and indirect flows relationship exists between these subsystems imposed by the aforementioned supply of and demand for funds' framework:

1. Households[18] can take out loans to close their funds shortage, to finance their spending and purchases, and to make investments like buying a residential house. They may otherwise want to invest their excess funds from their savings and other incomes into financial and/or investment vehicles, or they simply deposit money in the banks or bank equivalents.

2. Real sector firms, (i.e. non-financial business entities) may enter into credit relationships with banks to invest in physical capital (capital goods) or to finance their routine operations (working capital) as well as to invest in other instruments, mostly in other operations as independent business entities. Besides, they may set up credit and fund transfer relationship(s) between and among each other (e.g. trade credits (notes, bonds, bills as well as trade accounts payables and receivables), inter/intra-group fund transfers etc. (payables to and receivables from shareholders, participations, and affiliated enterprises)).

3. Financial sector firms (banks etc.) may have mutual and/or simultaneous debit and credit relationships with one another. Banks may also enter into syndicated loans contracts with non-domestic banks which in turn themselves define a loan agreement for the bank(s) and pose a risk - if/when an essential amount of it is not paid back or settled mostly due to

[16] A further smaller two-agent (bank-firm) model is devised by Tedeschi, Mazloumian, Gallegati, and Helbing (2012). For a depiction of a 2-agent (bank-firm) network with empirical data consult the appendix.

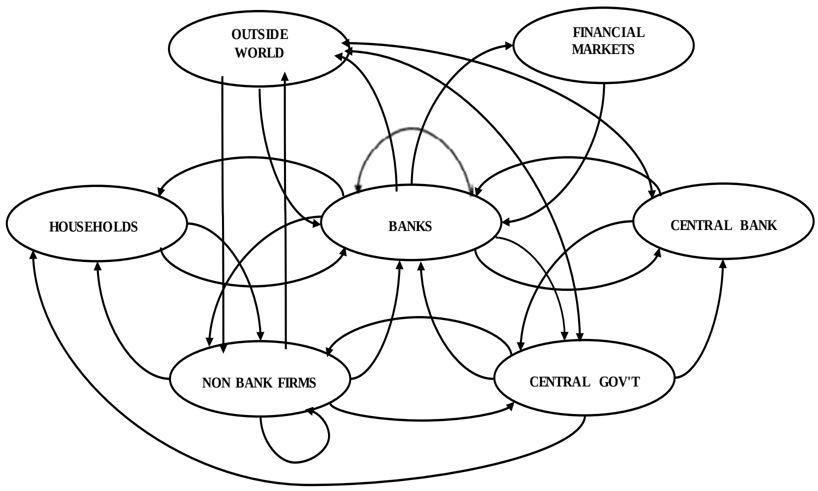
[17] Internode arrows might refer to any type of flows in and/or from the individual nodes (incumbents or incumbent groups), that may include payments of loans, deposits, reciprocal payments on those flows, etc. This can be further complicated by adding multiple agents to each subgroup and depicting network relationships explained below.

[18] Individuals are assumed as part of the households.

non-performing loans (loan losses) - of a cascaded/avalanche-like propagation from non-financial sector firms to other financial and non-financial sector firms.

Both financial sector and real sector firms, if they are a subordinate of a holding company, and if allowed by legislation, there would [definitely] be a funds flow between the group companies and/or holding subordinates as well as the holding company in line with laws and regulations. These happen mostly in unconventional ways. In one particular example, we had observed that a corporation had incurred debt at a specific amount from the bank, and had lent out the same amount to its subordinate[19]. A more complicated depiction of such a network should be as follows.

Figure.2. Graphical Representation of a Conceptual Almost Fully-Exhaustive n-Agent Funds Flow Network[20]



An exhaustive and alternative representation of this flow network is a counter-party matrix where each fund user and source is bijective (two way) matched if/when appropriate or available; that is to say a mapping is possible for the contracted debit-credit (i.e. funds flow) relations between and/or among the agents. This complicated multi-dependency network briefly describes the [very] network model upon which a fully exhaustive systemic risk model can be established.

19 This was a very specific example of a financially stronger incumbent incurring debt at favourable terms and using this debt for financing its operations other than its own legally defined activities, a case which must be closely monitored for tax evasion purposes.

20 Though our original design of Circular Flow of Income is not based upon it there are similarities in our approach to risk and the way it was handled in a macro-framework with the one in Haldane, Hall and Pezzini (2007), which employed a balance sheet approach.

Counterparty Relationship Matrix[21]

Table 1

	USERS						
SOURCES	HOUSEHOLDS	NON BANK FIRMS	BANKS	FINANCIAL MARKETS	CENTRAL GOV'T	CENTRAL BANK	OUTSIDE WORLD
HOUSEHOLDS	?	√	√	?	√		
NON BANK FIRMS	√	√	√	?			√
BANKS	√	√	√	√	√	√	√
FINANCIAL MARKETS	?	?	√		?	?	?
CENTRAL GOV'T	√	√	√	?		√	√
CENTRAL BANK			√	?	√		
OUTSIDE WORLD		√	√	?	√	√	

To exemplify the relationships on this source and form a mapping, using the counter-party relationship matrix, take loans from households to banks (housing, consumer credits and credit cards) and fund flows to banks from households into personal accounts (term deposits, investment, etc.), payments from/to the government to/by the households such as taxes, receivables/payables of firms from/to other firms' accounts (trade bills, bonds and accounts of residents and non-residents). These examples can be extended to almost any number of flow relationships that can be imagined.

A Globalistic Macro-Prudential Framework

The significance of the facts and implications of the late crisis had made policy-makers to feel urged to take a stronger and proactive stance towards a more *prudent* role, and they had either deliberately or by force started to shift their focus towards a more *inclusive* set of rules that would depict a down-to-earth and more *realistic* framework *usable by* all policy-makers working in *cooperation* with signals/messages *understandable* by all incumbents. In an effort to decipher this statement a set of necessary attributes of a policy-making structure upon which new pillars could be laid down as such:

1. Prudence, in the sense that, it can predict possible/potential risks and help taking proper measures before the event [and as early as possible],

2. Inclusion or exhaustiveness, in the sense that, a policy making structure should embrace as many individual stakeholders as possible that are believed to be in and/or to have a more complicated in-between relationship,

3. Realism, i.e. being realistic, with a more plausible set of inputs, of it being able to produce more doable outputs, ideally policy proposals,

[21] Check marks refer to plausible mutual fund flows and question marks to not easily definable / identifiable or somewhat indirect ones.

4. Understandability by all incumbents/stakeholders,

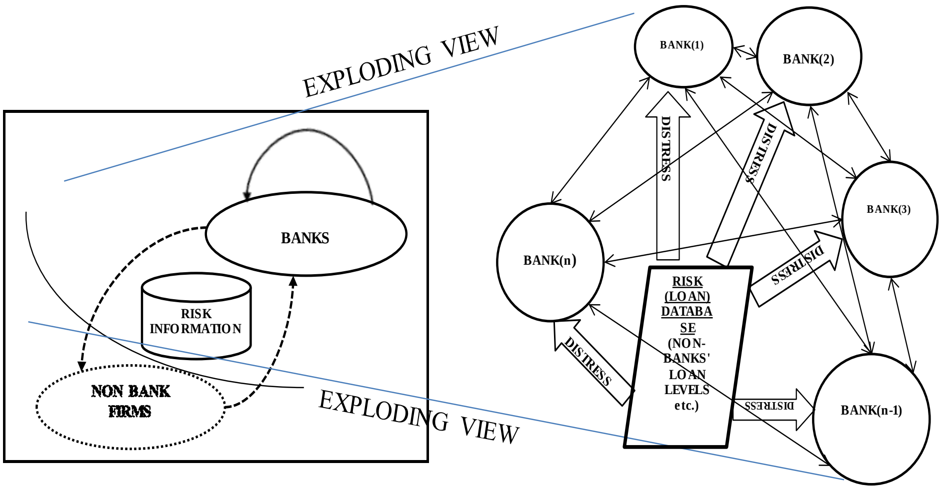
5. Robustness enough to be capable of working with large groups of datasets, requiring a proper algorithm and hardware and software, and

6. Complementarity to other policy frameworks, in the sense that, it can enhance as well as accompany other economic policies already effective and administered in concert.

The traditional approach to the matter would bespeak the good old macro-prudential framework, which in contrast to micro-prudential framework, and aiming at filling the gap between micro-prudential regulations and macroeconomic policy, by mitigating the risk of financial system as a whole, is said to involve therefrom a systemic and an endogenous component by assumption that all individual entities operate in a close network of relations and the risk arises from within due to this complex network structure.

By definition, the traditional cure, namely the macro-prudential framework looks and sounds perfectly totally enveloping, as is. By practice however, it doesn't fulfil the inclusiveness and/or exhaustiveness property. This is claimed by the very fact that the typical traditional systemic risk model condones the unfair treatment of solely the financial sector as mentioned in the prologue, concentrating on the risk levied on individual banks[22] (potential distress) as well as their financials and interbank network relationship. This can be pictured/demonstrated like so (Figure.3).

Figure.3. Graphical Depiction of the Current Traditional Macro-Prudential Frameworks



This is a typical design of the traditional framework from which a SIFI or SIFIs supposedly whose distress or disorderly failure due to its/their size(s), complexity(ies) and interconnectedness with other financial institutions would cause significant disruption to the wider system and economic activity, can be identified. In this design, one or several of these this n-bank system is/are/may be identified as SIFI or SIFIs.

With a mighty and assertive claim of entirety (full exhaustiveness), this macro-prudential framework, overlooks the existence of non-bank (non-financial) agents of the whole structure. In this sense, the macro-prudential framework is unbalanced and biased towards the banking sector.

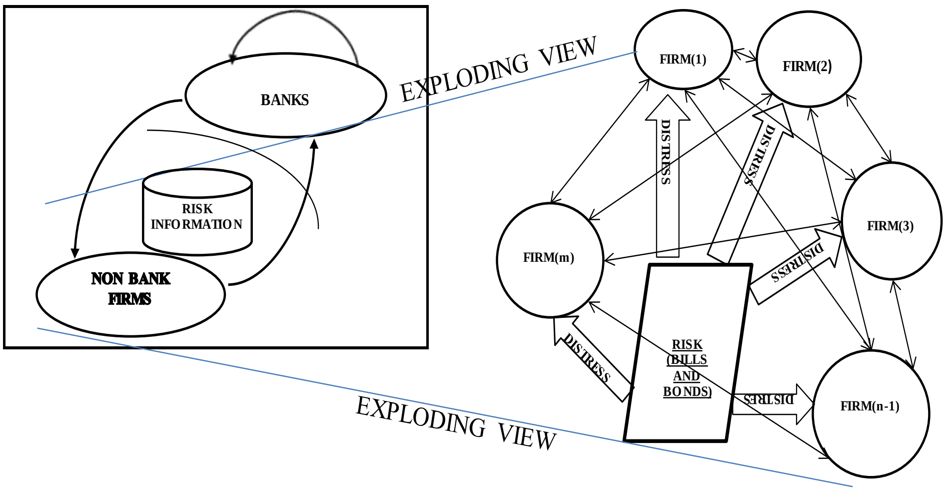
[22] Individual node in a network setting.

A bank goes into distress due to myriad reasons one of which, and the one related to its operations, is the probability of one or a couple of its large debtors[23], or a large number of a group of small entities operating in a particular sector (e.g. contractors in a construction sector operating domestically, earning in domestic currency, but having taken out loans in non-domestic currency and hit by an FX shock) fail/s to honour its/their debt payments, due to multitude of reasons.

The Vicious Risk/Distress Cycle

Think of a risk/distress cycle where a particular bank, identified as a SIFI, is normally at the heart of a traditional macro-prudential policy set-up. In this particular instance, the first impulse is due to a sole non-financial entity that abruptly exerts distress failing to pay back its financial duties on loans. Therefore, the first step to modify the traditional/conventional framework is to include the plausible sources (here the big firm with a huge balance of debt vis à vis the SIFI) that would exert an initial distress to the SIFI in case of an extreme event the examples of which are plenty[24]. This modification procedure of inclusion of a step to the framework yields a process called the determination/identification of a non-financial agent with high potential of failure or with high level of debt to the financial system, shortly the identification of the Systemically Important Non-Financial Institution (or agent) (SINFI).

Figure.4. Proposed Set to Modify the Unbalanced Macro-Prudential Frameworks



Take another example; a group, which may be due to the same or similar reasons, is the cause of an exogenous shock to the financial system. This may be a group of income, a sector as a whole, a specific geographical region of the country, or a group of individual independent entities that act simultaneously in very similar way for no specific reason (e.g where resides a

[23] High debtors are high bettors; crowding out small ones from a limited source of fund base, and posing higher distress at higher default risk in case of the worst case scenario transpires. This assertion belongs to me but me, nor is there an empirical basis I would present, but I hypothesize based on my experience and observations.

[24] The case of multiple simultaneous distresses of different agents is a more extreme (tail-risk) event which we will not cover here but found worth mentioning. In such a major event the split asset bases of individual agents might behave in more complicated ways.

number of subcontractors of a production network that are vertically, horizontally and cross integrated[25]), etc. In this case, the identification of this group is more complex, still, vital and the procedure can be dubbed [loosely] as the identification of the Systemically Important Economic Agents (SIEA); an umbrella term, more formally, an enveloping scheme that subsumes [almost] all the individual subgroups of the circular flow of income that have a potentially very high risk of detriment to the whole of the system if failed[26].

This adds a micro-prudential perspective in that an exogenous shock might cause an imbalance in the financial system which would propagate due to its within-system (systemic) properties. This, in the second round, may be, in case of a SIFI or a group of SIFIs, the cause of an endogenous crisis (Figure.5)[27]. Possible cascading failures propagating from the first corporate failure down to individuals (or households) are as well depicted on this figure[28].

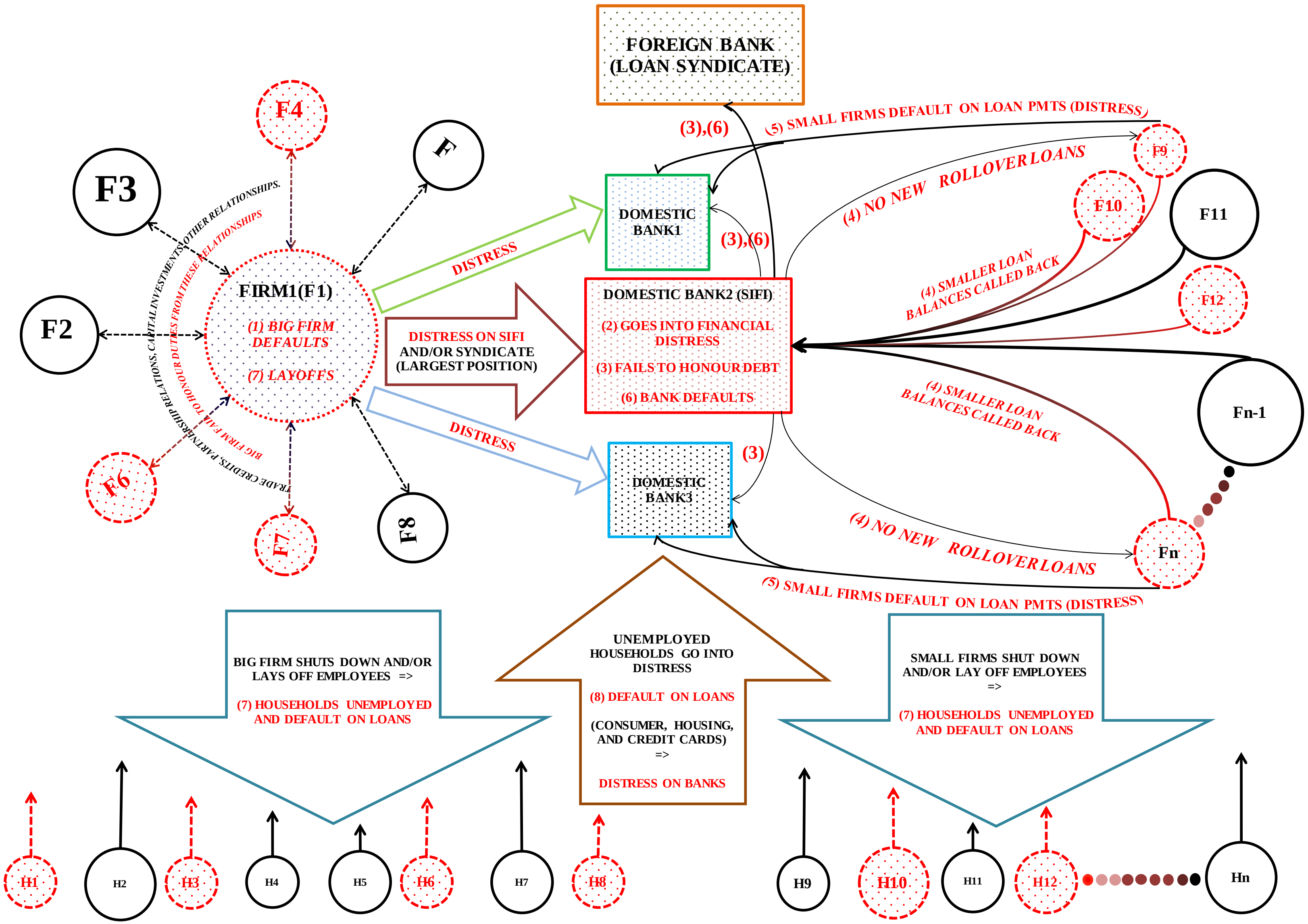
[25] LikeFirms are the firms that operate within the same or similar sectors, within the same or close geographical area(s), of the same/similar size in terms of assets, capital, net sales, of the same/similar structure in terms of assets, liability and capital etc. UnlikeFirms on the other hand are those that operate in different and/or dissimilar sectors, in different and/or farther geographical regions (should not be too far for them to be integrable), dissimilar in size (asset, capital, net sales, etc.) and/or have different financial structures. Integrable firms are those that can be vertically/horizontally or cross integrated. Both LikeFirms and UnlikeFirms can be integrated within a project framework according to various criteria (Cakir, 2012-2015).

[26] A generalised agent (systemically important agent) approach, meaning an economic agent implies any kind of incumbent generally rather than banks specifically, is employed by Acemoglu, Ozdaglar, Tahbaz-Salehi (2015). Systemically important agents' concept looks very similar to our systemically important economic agents which is explained later in this text.

[27] Dr. Mahir Binici and I had very fruitful discussions on the distress propagation, and some of the design attributes are derived from these discussions. He is an affiliated researcher at CBRT and ECB.

[28] Please consult Adrian, Covitz, and Liang (2014) for a more concise treatment of systemic risk as it relates to the non-financial sector.

Figure.5. Risk Cycle in a Simple 3-Agent Network[29]



[29] The firm F1 can be a representative entity which comprises a group of large debtors, firms operating in a particular sector, in a particular geographical region, with an asymmetric revenue-expense (or cash inflow outflow) structure (e.g. those with FX loans but without FX earnings). Risk sources were treated in a similar and detailed set of shock and impact transmission mechanisms framework by Haldane, Hall and Pezzini (2007).

Provision and Procural of the Data Requirements – Model-Driven Feature Selection and Model Deployment Process

Data provision and/or procural is a more complex procedure than it first appears. Conceptually, a fully exhaustive systemic risk model should/must embrace by definition all available and potential data that relate to risk[30], particularly to those in relation of significant loss in value in an incumbent's net worth. Such a model should be fed by the most granular data with minute details at the shortest time possible, which means the availability of data at massive scales is a must[31], and the data should be processed the best way there is and as fast as possible[32].

Another conceptual property of risk assessment and management is the ability to model the risk with the real data and to manage it in the field. This might imply the flexibility in building the model (either empirical or theoretical) through feature identification and employment and the deployment in a recursive manner. As regards the flexibility, rather than enforcing a straightforward and empirically proven set of attributes/features (variables) that can be employed in macro-prudential modelling, a conceptual schema of selecting classes of features, and a two-way model driven self-feeding feature identification process can be adopted for a more global type of modelling. This is both by observation that, though most studies employ a particular group of variables in their models, there still isn't a consensus which set fits best, and by conjecture that each proprietary model might produce a different list of a set of variables (attributes/features) that are relevant solely in a particular study albeit with some similar variables for distinct studies. In a two dimensional layout for a smaller network the process flow can be simply simulated as in Figure 6.

Systemic risk model building thus, based on a recursive feature employment and model deployment process should target the discovery of the potential features that can be employed for macro-modelling with no particular type of pre-imposed model (either proprietary or previously employed) for target risk groups to be specified.

30 A basic predictive model should employ an objective, measurable and a possibly full data set. Though risk (particularly operational) identification and prediction are not solely limited to quantitative determinants, they are the necessary, and most of the time, the best affordable and sufficient inputs to feed a basic model. Data features are out of the scope of this work. Consult for the basic features of data with other sources. Still, availability, measurability, consistency and the quality of the data should be mentioned as necessary conditions/features. Acharya and Bisin (2014) pointed to the fact, under less than perfect information, that agents take on excessive Pareto inefficient (excessive) risk positions, which emphasises the necessity of trading on a centralised clearing system fed with data and supposed to supply it to the public in a transparent set up.

31 This appears to be *sufficient* not necessarily the *necessary condition*. Still, each proprietary system itself would reveal the specific data needs for the particular model and/or paradigm. Although, the claim made by Alter, Craig, and Raupach (2014) might seem highly assertive in that the use of a large credit database is a plus when dealing with contagion, there seems to be a consensus that the greater the relevant data set the better the information content the analytical models produce, as the empirical results as well support by many data mining learning schemes.

32 This means software and hardware capabilities of such [an analysis] platform is an important concern. This amount of data is not easy in turn to be provided by a single provider or a handful of providers. At least an inter-organisational data sharing consensus should be reached; ideally all such data should be centralised (consult Cakir (2014)). Without delving into specifics, necessary legislative process should as well be on the agenda for this centralisation effort to be realised.

More specifically the rules for the model driven feature identification process can be formulated as such:

1. Whatever the type of model used (theoretical or empirical, and proprietary or previously employed traditional) features deemed relevant should be included in the final model deployment process. The deployed final model is to involve all the features that relate to potential net loss in net worth,

2. There is no constraint in the employment of models, but we suggest that the groups of sources of risk (financial firms, non-financial firms, households etc.) should be differentiated in selecting the models (independent of the other group or groups of risk),

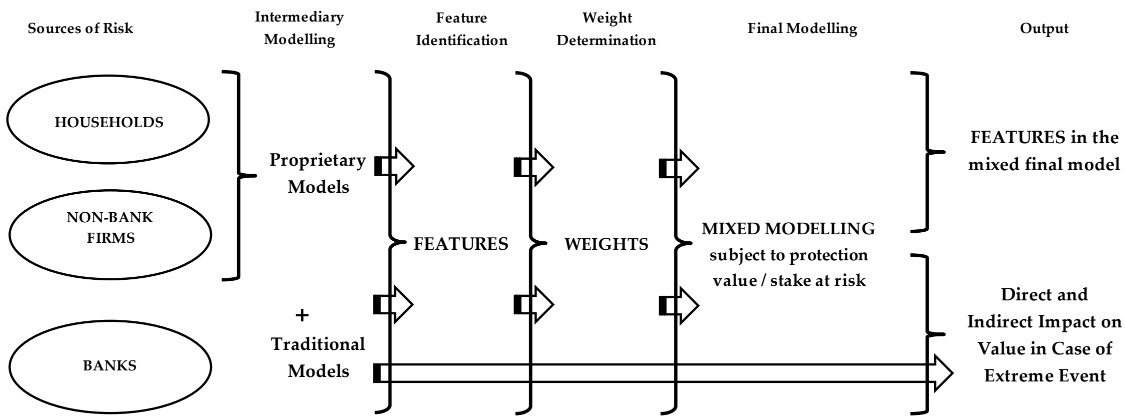
3. Weighting of the features rests upon the particular model as well as the risk groups. It might prove to be complicated but it must be done no matter what and has to consider the stake at the bank's assets (loss given default perhaps!),

4. Final model shall be static for a shorter and dynamic for a longer period of time, and

5. Each individual model with a set of features found relevant for the static periods will be proprietary for the given period and the given particular economy.

In summary, such a model deployment process can be defined as being an amalgam of a top down approach whereby relevant features identified conceptually are blended with a bottom up approach where the largest set of features adopted from literature in concordance with this particular conceptual design.

Figure.6. Flow Chart of Feature Identification and Model Building Process



Unquestionably, among these groups, individuals and households are the hardest ones for any type of modelling endeavour, as a model as such would have to deal with behavioural issues along with many economic, financial and accounting variables most of which are unavailable for most incumbents belonging to these groups. It's even harder to find a larger set of features over a global scale relevant for all countries [which should be empirically tested]

By intuition and experience the data are categorised under four main groups[33] (Table.2). Some potential data types belonging to these pairs may be enumerated like, data about banks' financials, corporate financials, markets, loans (individual and total), credit cards, securities and stake-holding, funds transfers all in ratio and notional sizes or fair values wherever they may apply. Operational and connectedness features are hard to find and complicated and impossible in households' case[34].

Potential Features Categories that Can Be Included in the Proposed Framework for the Groups of Incumbents

Table 2

		FEATURE TYPE			
		FINANCIAL	RISK (LOAN CREDIT)	OPERATIONAL	CONNECTEDNESS (NETWORK)
NODE TYPE	HOUSEHOLDS	√	√	?	√
	NON BANK FIRMS	√	√	√	√
	BANKS	√	√	√	√

As the punchline of this work, the practical and down to earth issue of procuring the relevant, and in fact necessary data to complete the whole design should be mentioned for one last time. The conceptual facet of the procurement surely is maybe the most difficult part of the design, and most certainly is of the implementation. The cure for difficulties in data procurement is decidedly the most special, proprietary and context-specific experience of the designer, and in most situations depend on the legislative structures of the individual data providing frameworks residing in distinct sovereign bodies. Therefore, it shouldn't be surprising to come across models from different legislative structures albeit with same or similar variables but mostly with totally different ones overall, across the board.

33 An alternative categorisation devised for modelling the vulnerabilities of U.S. financial system can be consulted in Aikman, et.al. (2015).

34 For a tentative inexhaustive set of lists of features based on this categorisation please consult the appendix. Note that not all pairs could have been studied to produce such feature lists.

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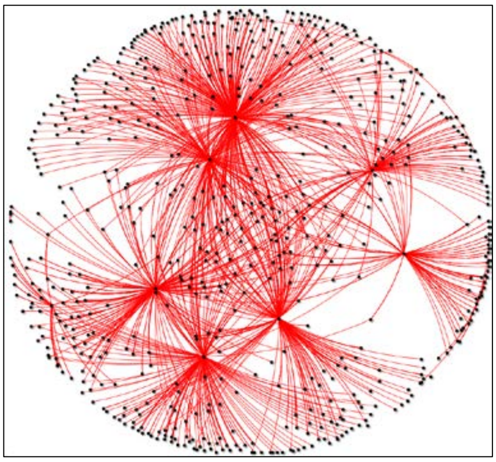
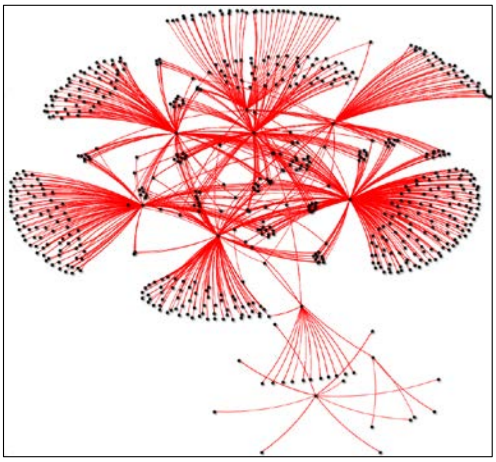
Appendix

A. Representation of a Bank-Firm (2-Agent) Loan Relationship Network with Empirical Data

Panel – A



Panel – B



Nodes refer to both banks as well as the firms that borrow from those banks. This network diagram was constructed by using real data to exemplify how such a relationship can be portrayed using data about debtee / obligee, debtor / obligor and risk balance (loan/credit balances).

Panel A is drawn à la Fruchterman-Reingold Algorithm while Panel B Harel-Koren à la Fast Multiscale Algorithm. The relationship does not change however visualisation may improve to convey the same information about a sample of about 1700 data points depicting a loan relationship between 631 individual firms with 11 individual banks. Weights (size of loan balance) and identification data are concealed due to confidentiality reasons. Networks were produced by using NodeXL.

B. List of Potential Features for Risk Groups

Note that we do not claim that these lists are fully exhaustive and they are just meant to be provided as a basis for any systemic risk study to employ, if one would like to opt to.

Financial Ratio Features for Banks

Assets Quality	
	Financial Assets (Net) / Total Assets
	Total Loans / Total Assets
	Total Loans / Total Deposits
	Loans Under Follow-Up (Gross) / Total Loans
	Loans Under Follow-Up (Net) / Total Loans
	Specific Provisions / Loans Under Follow-Up
	Permanent Assets / Total Assets
	Consumer Loans / Total Loans
Assets Quality Index	
	Past Due Loans (Net) / Average Total Assets
	Subsidiaries and Associated Companies (Net) + Fixed Assets (Net) / Average Total Assets
	Past Due Loans (Net) / Total Loans
	Provisions For Past Due Loans / Average Total Loans
Balance-Sheet Structure	
	Domestic Currency Assets / Total Assets
	Domestic Currency Liabilities / Total Liabilities
	Foreign Currency Assets / Foreign Currency Liabilities
	Domestic Currency Deposits / Total Deposits
	Domestic Currency Loans / Total Loans
	Total Deposits / Total Assets
	Funds Borrowed / Total Assets
Capital Adequacy	
	Shareholders’ Equity / (Amount Subject To Credit + Market + Operational Risk)
	Shareholders' Equity / Total Assets
	(Shareholders' Equity - Permanent Assets) / Total Assets
	Net On Balance Sheet Position / Total Shareholders' Equity
	Net On and Off Balance Sheet Position / Total Shareholders' Equity
Capital	
	Shareholders' Equity / Average Total Assets
	Liabilities / Shareholders' Equity
	Paid Up Capital / Shareholders' Equity
	Free Capital / Shareholders' Equity
	Loans Under Follow-Up (Net) / Shareholders' Equity
	Total Loans (Net) / Shareholders' Equity
	Subsidiaries and Associated Companies (Net) / Shareholders' Equity
Income-Expenditure structure	
	Net Interest Income After Specific Provisions / Total Assets
	Net Interest Income After Specific Provisions / Total Operating Income
	Non-Interest Income (Net) / Total Assets
	Other Operating Expenses / Total Assets
	Personnel Expenses / Other Operating Expenses
	Non-Interest Income (Net) / Other Operating Expenses
Liability Structure	
	Total Loans / Deposits
	Deposits / Liabilities

Financial Ratio Features for Banks (Continued)

Liquidity	
	Liquid Assets / Total Assets
	Liquid Assets / Short-Term Liabilities
	Domestic Currency Liquid Assets / Total Assets
	Cash and Dues From Central Bank, Other Banks and Money Market / Demand + Term Deposits
	Liquid and Quasi-Liquid Assets / Average Total Assets
Profitability	
	Net Profit/Losses / Total Assets
	Net Profit/Losses / Total Shareholders' Equity
	Income Before Taxes / Total Assets
	Total Income / Average Total Assets
	Total Expenses / Average Total Assets
	Net Of Interest Income / Average Total Assets
	Net Of Interest Expense / Average Total Assets
	Non-Interest Expenses / Average Total Assets
	Profit (Loss) For The Period / Average Shareholders' Equity
	Interest Income On Loans - Interest Paid For Deposits / Net Of Interest Income
	Total Income / Total Expenses
	Total Interest Income / Total Interest Expenses
	Non-Interest Income / Non-Interest Expenses
	Interest Income / Total Income
	Interest Expenses / Total Expenses

Financial Level Indicator Features for Banks

Size			
	Derivatives		
	Securities Financing Transactions (SFTs)		
	Other Assets		
	Gross Notional Amount of Off-Balance Sheet Items		
Substitutability/Financial Institution Infrastructure			
	Payments Made in the Reporting Year (Excluding Intragroup Payments)		
	Assets under Custody		
	Underwritten Transactions in Debt and Equity Markets		
		Equity Underwriting Activity	
		Debt Underwriting Activity	
Complexity			
	Notional Amount of Over-The-Counter (OTC) Derivatives		
		OTC Derivatives Cleared Through a Central Counterparty	
		OTC Derivatives Settled Bilaterally	
	Trading and Available-For-Sale Securities		
		Held-For-Trading Securities (HFT)	
		Available-For-Sale Securities (AFS)	
		Trading and AFS Securities That Meet the Definition of Level 1 Assets	
		Trading and AFS Securities That Meet the Definition of Level 2 Assets, with Haircuts	
	Level 3 Assets		
Cross-Jurisdictional Activity			
	Cross-Jurisdictional Claims		
	Cross-Jurisdictional Liabilities		
		Foreign Liabilities (Excluding Derivatives and Local Liabilities in Local Currency)	
			(Any Foreign Liabilities to Related Offices Included)
		Local Liabilities in Local Currency (Excluding Derivatives Activity)	

Financial Ratio Features for Firms

Liquidity	
	Current Ratio
	Acid-Test Ratio (Quick Ratio)
	Cash Ratio
	Days Sales Outstanding
Solvency Ratios	
	Total Liabilities / Total Assets [Debt to Assets = Total Debt / Total Assets]
	Shareholders Equity / Total Assets
	Debt to Equity [Total Debt / Total Equity]
	Shareholders Equity / Total Liabilities [Equity to Debt = Total Equity / Total Debt]
	Long Term Debt / (Long Term Debt + Equity)
	Interest Coverage Ratio
	Debt-Service Coverage Ratio
	Net Profit and Interest Expenses / Fixed Interest Charges
	Net Profit / Fixed Interest Charges
Financial Structure	
	Short Term Liabilities to Total Liabilities
	Long Term Liabilities to Total Liabilities
	Long Term Liabilities to Long Term Liabilities and Equity
	Current Assets to Total Assets
	Tangible Fixed Assets to Total Assets
	Tangible Fixed Assets (Net) to Equity
	Tangible Fixed Assets (Net) to Long-Term Liabilities
	Fixed Assets (Net) to Short-Term Liabilities and Long-Term Liabilities
	Fixed Assets (Net) to Equity
	Fixed Assets (Net) to Long-Term Liabilities and Equity
	Short-Term Liabilities to Short-Term Liabilities and Long-Term Liabilities
	Bank Loans to Total Assets
	Short-Term Bank Loans to Total Assets
	Bank Loans to Short-Term Liabilities and Long-Term Liabilities
Turnover Ratios	
	Receivables Turnover
	Working Capital Turnover
	Net Working Capital Turnover
	Tangible Fixed Assets Turnover
	Fixed Assets Turnover
	Equity Turnover
	Total Assets Turnover

Network Features for Banks

Interconnectedness
Intra-Financial System Assets
Funds Deposited with or Lent to Other Financial Institutions
Unused Portion of Committed Lines Extended to Other Financial Institutions
Holdings of Securities Issued by Other Financial Institutions:
Net Positive Current Exposure of Securities Financing Transactions with Other Financial Institutions
Over-The-Counter Derivatives with Other Financial Institutions That Have a Net Positive Fair Value
Intra-Financial System Liabilities
Funds Deposited by or Borrowed from Other Financial Institutions:
Unused Portion of Committed Lines Obtained from Other Financial Institutions
Net Negative Current Exposure of Securities Financing Transactions with Other Financial Institutions
Over-The-Counter Derivatives with Other Financial Institutions That Have a Net Negative Fair Value
Securities Outstanding
Secured Debt Securities
Senior Unsecured Debt Securities
Subordinated Debt Securities
Commercial Paper
Certificates of Deposit
Common Equity
Preferred Shares and Any Other Forms of Subordinated Funding Not Captured

Network Features for Firms

Interconnectedness
Loans and Credits
Short Term Bank Loans
Long Term Bank Loans
Trade Notes Receivable
Trade Notes Payable
Trade Bonds and Bills Receivable
Trade Bonds and Bills Payable
Stake and Share Holdings
Payables to Shareholders
Payables to Participations
Payables to Affiliated Enterprises
Receivables from Shareholders
Receivables from Participations
Receivables from Affiliated Enterprises

Risk Features for Households

Risk Positions and Balances
Credits and Loans
Individual Balances on Credit Cards
Individual Balances on Housing Loans
Individual Balances on Consumer Loans
Individual Balances on Car Loans (through banks and/or finance companies)
Investments and Insurance Policies
Balances in Deposits (Term, miscallenous)
Balances in Shares
Balances in Bonds
Balances in Miscallenous Instruments
Notional and Fair Market Values of Collaterals for Housing and Car Loans
Coverage of Insurances on Collaterals and Individuals that Take on Loans and Credits

Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

IFC-ECCBSO-CBRT Conference on *"Uses of Central Balance Sheet Data Offices' information"*

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Özdere-İzmir, Turkey, 26 September 2016

A conceptual design of "what and how should a proper macro-prudential policy framework be?"
A globalistic approach to systemic risk and procuring the data needed[1]

Murat Cakir, CBRT

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

TÜRKİYE CUMHURİYET MERKEZ BANKASI

"What and How Should a Proper Macro-Prudential Policy Framework Be?"

Murat Çakır

Central Bank of the Republic of Turkey

Izmir, 26 September 2016

PRESENTATION PLAN

Motivation behind a proper (!?) macro-prudential policy framework

Description of the current / traditional and proposed frameworks

Description of the data needed and tips for model building

MOTIVATION BEHIND A PROPER MACRO-PRUDENTIAL POLICY FRAMEWORK

MOTIVATION BEHIND A PROPER MACRO-PRUDENTIAL POLICY FRAMEWORK

Crisis Outbreak 2007-2008 STARTLED and URGED authorities!

PROGNOSIS: Banking system is responsible for the **materialisation** of the **CRISIS**!

Understand the causes

Find solutions for recovery

Take precautionary actions

DECISION: Banking system must be closely **MONITORED** and **FOCUSED UPON (?)** and those RISKY should be **IDENTIFIED** as **IMPORTANT** for the whole **SYSTEM**!

Systemically Important Financial Institutions!

ACTION: MORE PROACTIVE and **PROPER POLICY MAKING** with outputs relating to below processes

Mental: Focus extension and shift towards, Research oriented searching for causes given the impact,

Behavioural: Regulatory, Supervisory, Rule Enforcing, Retributive and Punitive,

A 'PROPER' POLICY ACTION?

is one that is said to be

A more inclusive -possibly fully exhaustive (!), more realistic, understandable and a complimentary to other policies

FRAMEWORK that would impose policy-makers

To take a stronger and proactive stance, and

To assume a more prudent role

WHAT'S BEHIND THE NEED FOR SUCH A PARADIGM SHIFT?

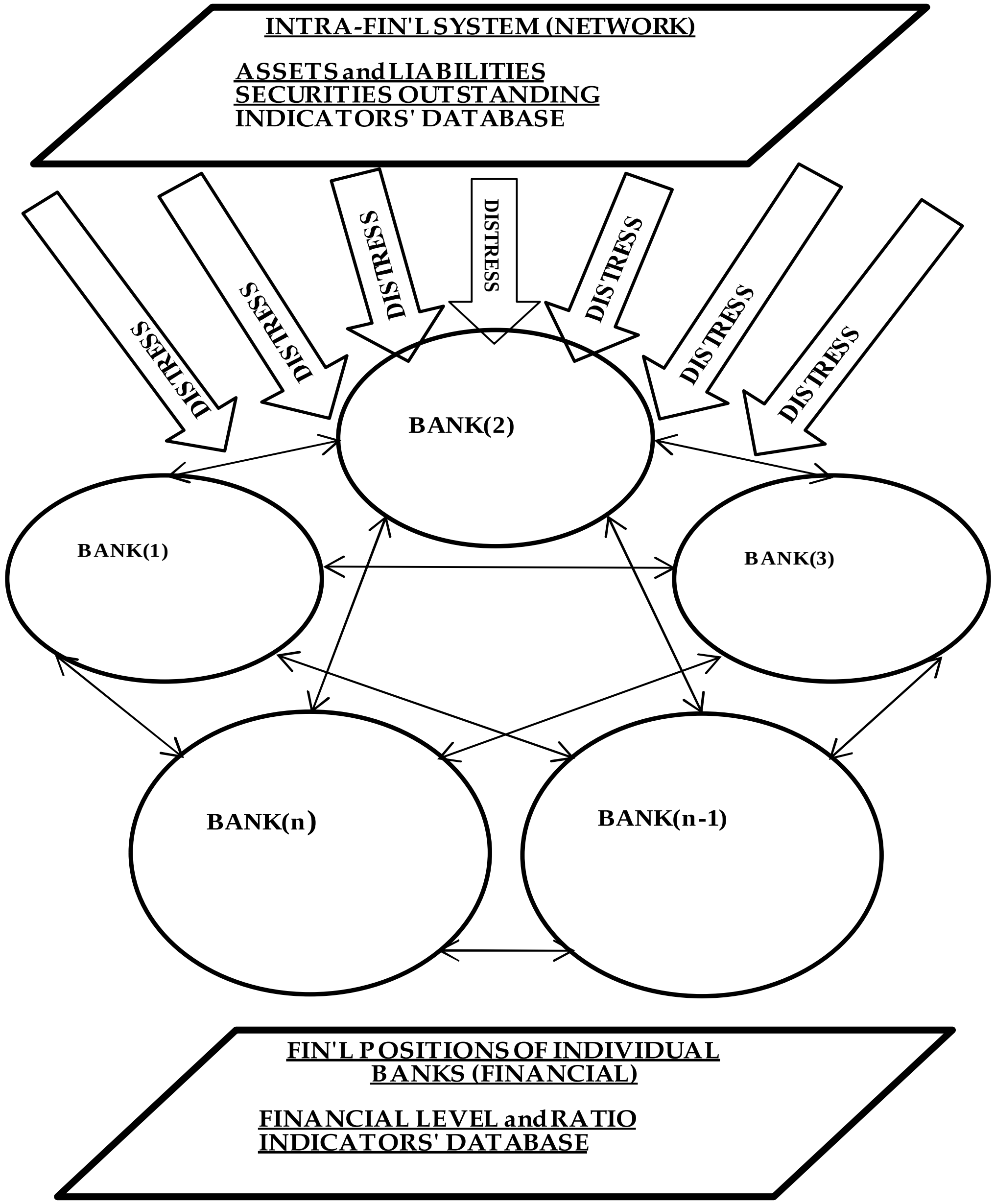
We Did Need This Paradigm Shift!

As something **MUST HAVE GONE WRONG** with the old one as 'the crisis materialised even when there was a set of rules in **EFFECT**!'

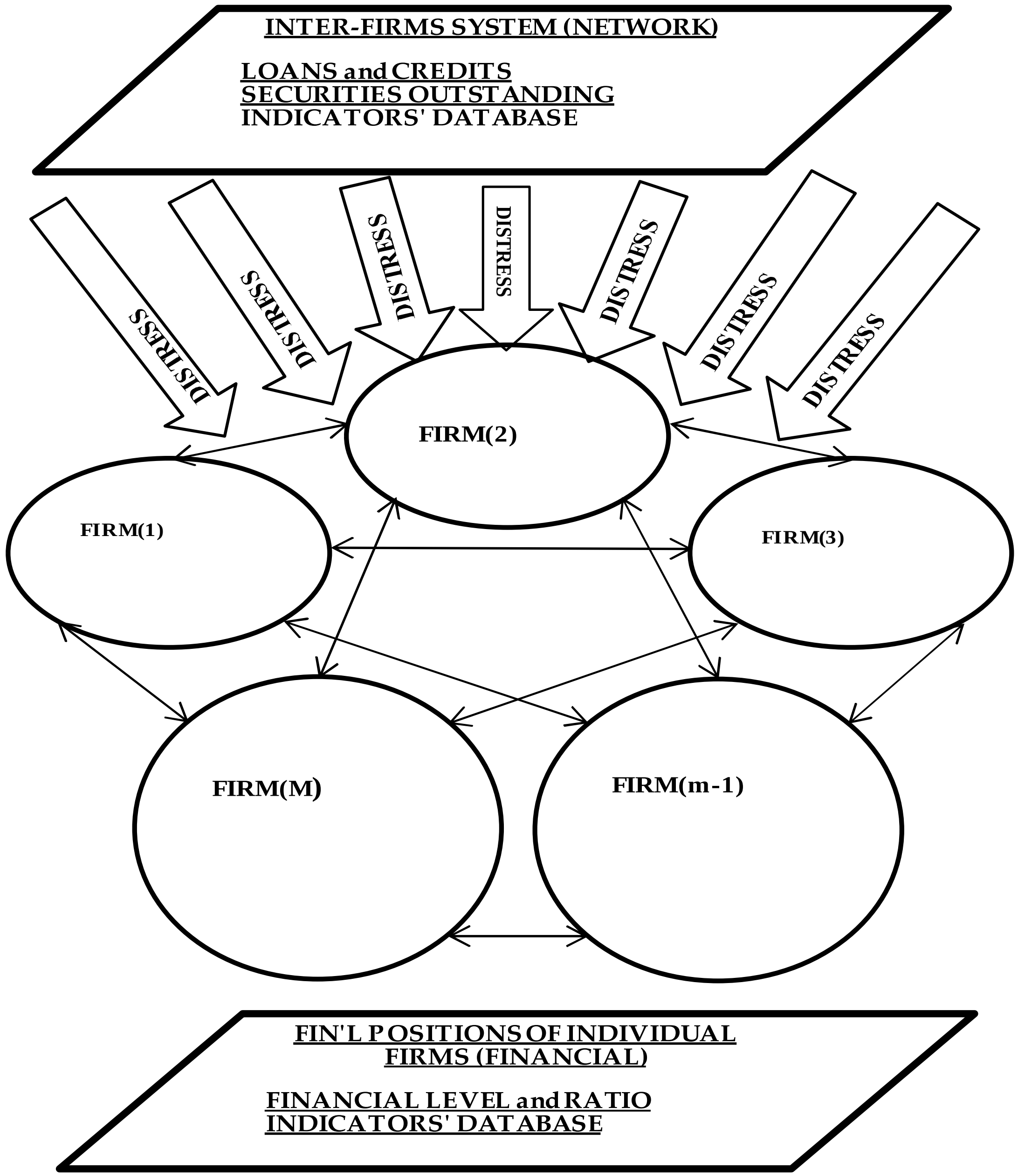
What we had before had to be **RECONSIDERED**

DESCRIPTION OF THE TRADITIONAL AND PROPOSED FRAMEWORKS

SIMPLE 1-AGENT (BANK TO BANK) NETWORK

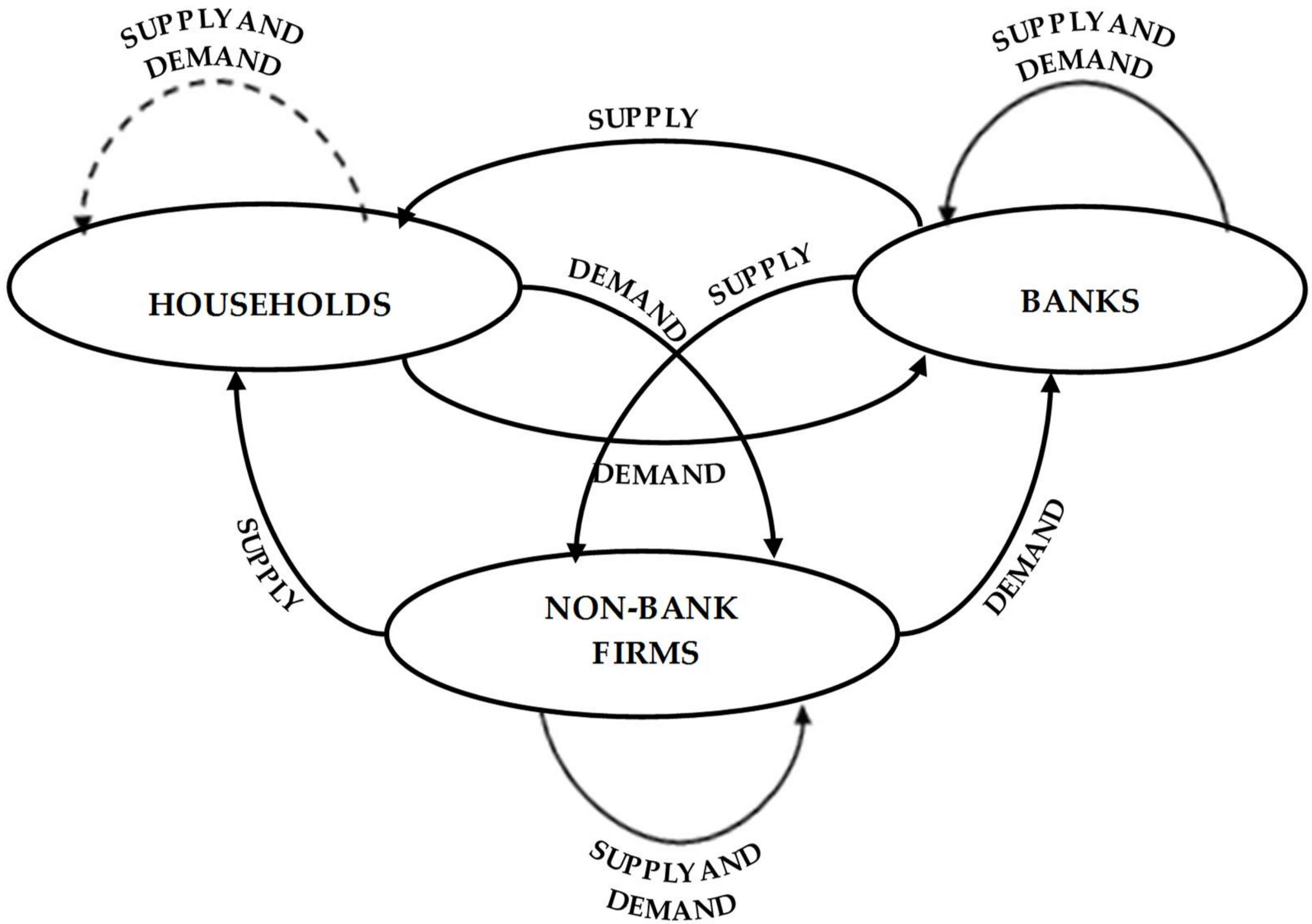


SIMPLE 1-AGENT (FIRM TO FIRM) NETWORK (PROPOSED SET TO ADD)

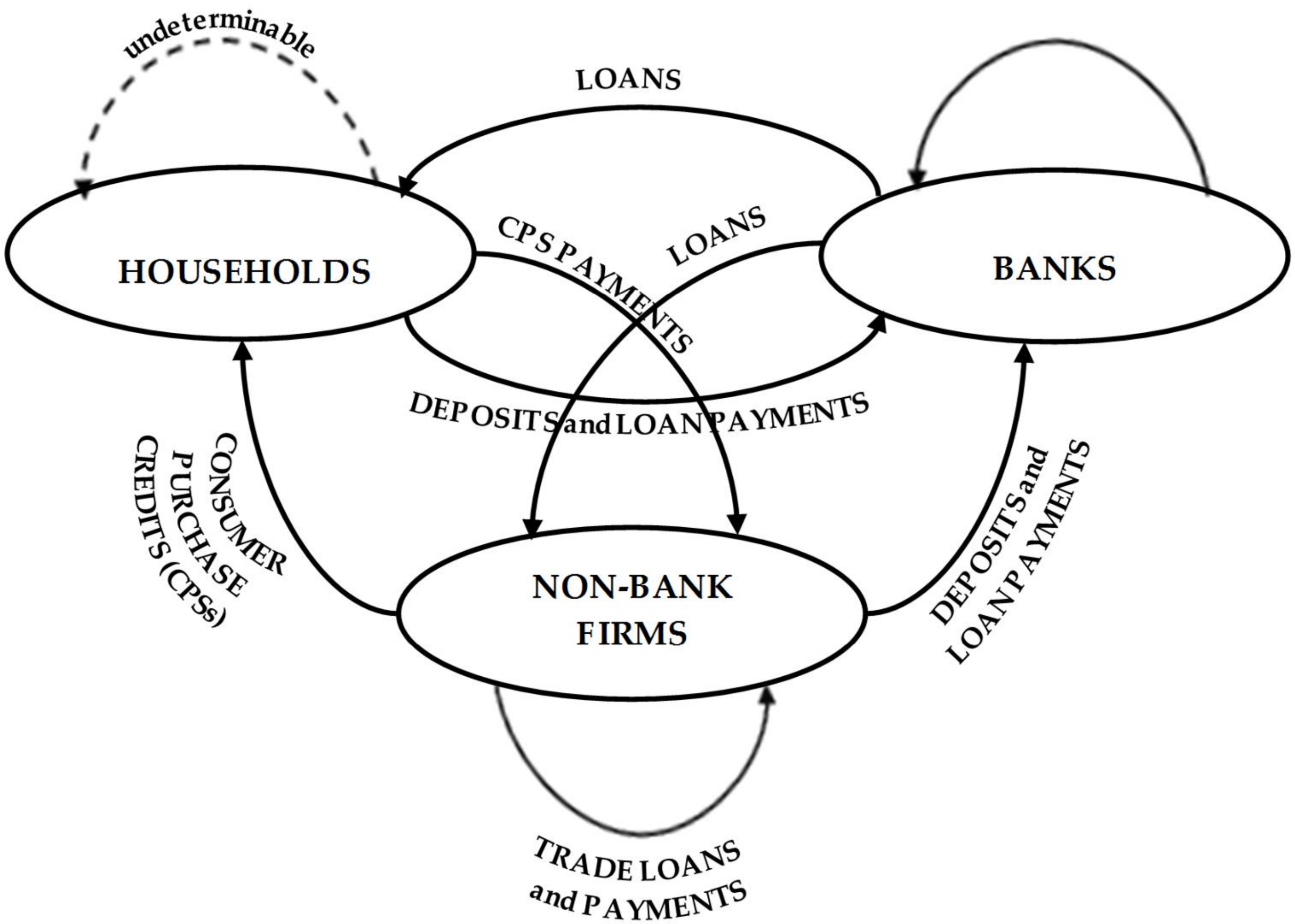


TÜRKİYE CUMHURİYET MERKEZ BANKASI

SIMPLE 3-AGENT FUNDS FLOWS NETWORK

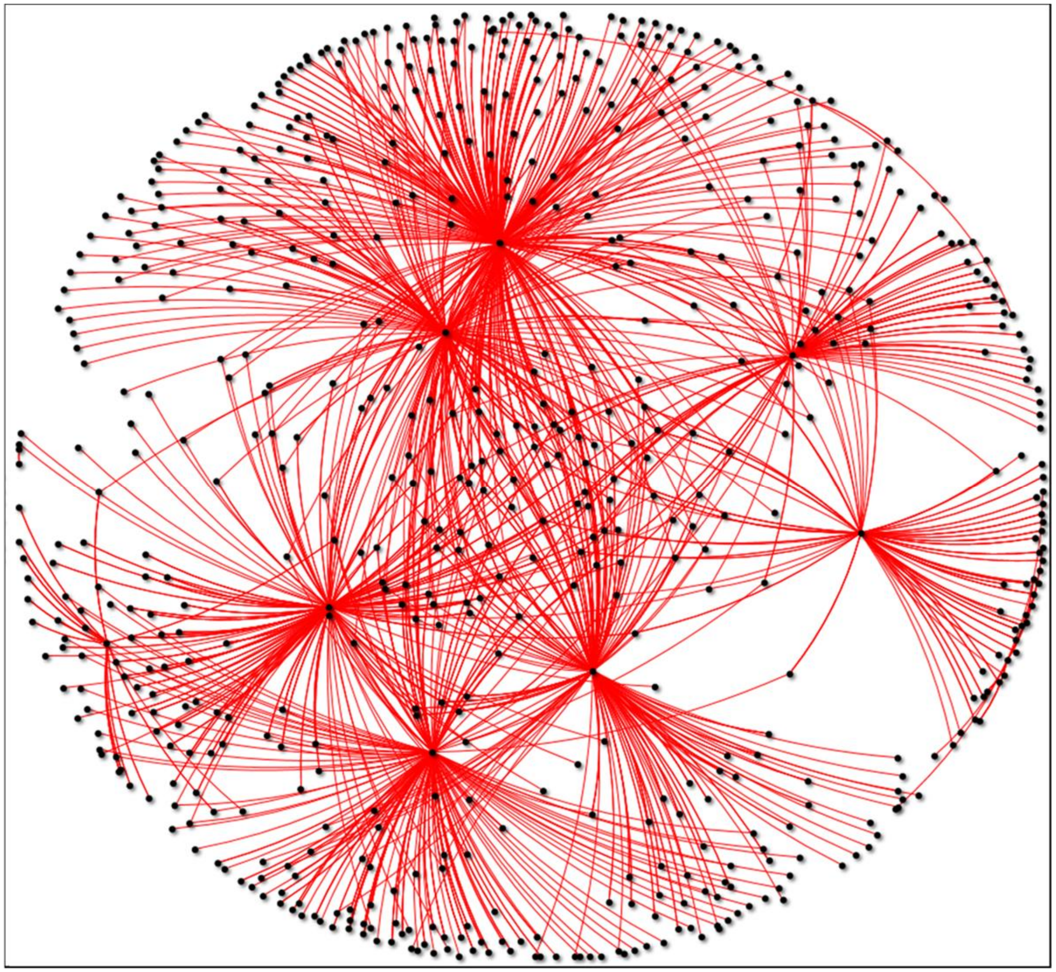


A SAMPLE SIMPLE 3-AGENT FUNDS FLOWS NETWORK



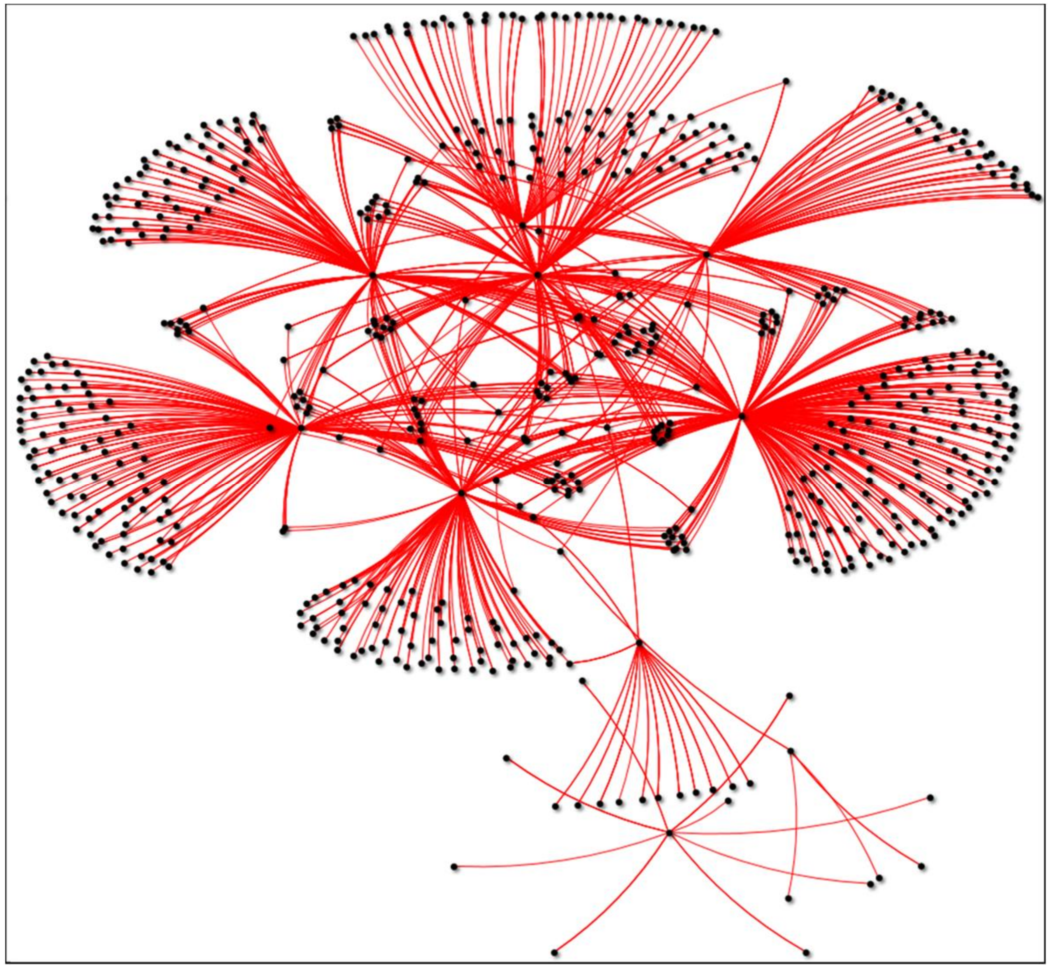
TÜRKİYE CUMHURİYET MERKEZ BANKASI

REPRESENTATION OF A BANK-FIRM (2-AGENT) LOAN RELATIONSHIP NETWORK WITH EMPIRICAL DATA



Fruchterman-Reingold Algorithm (Node-XL)

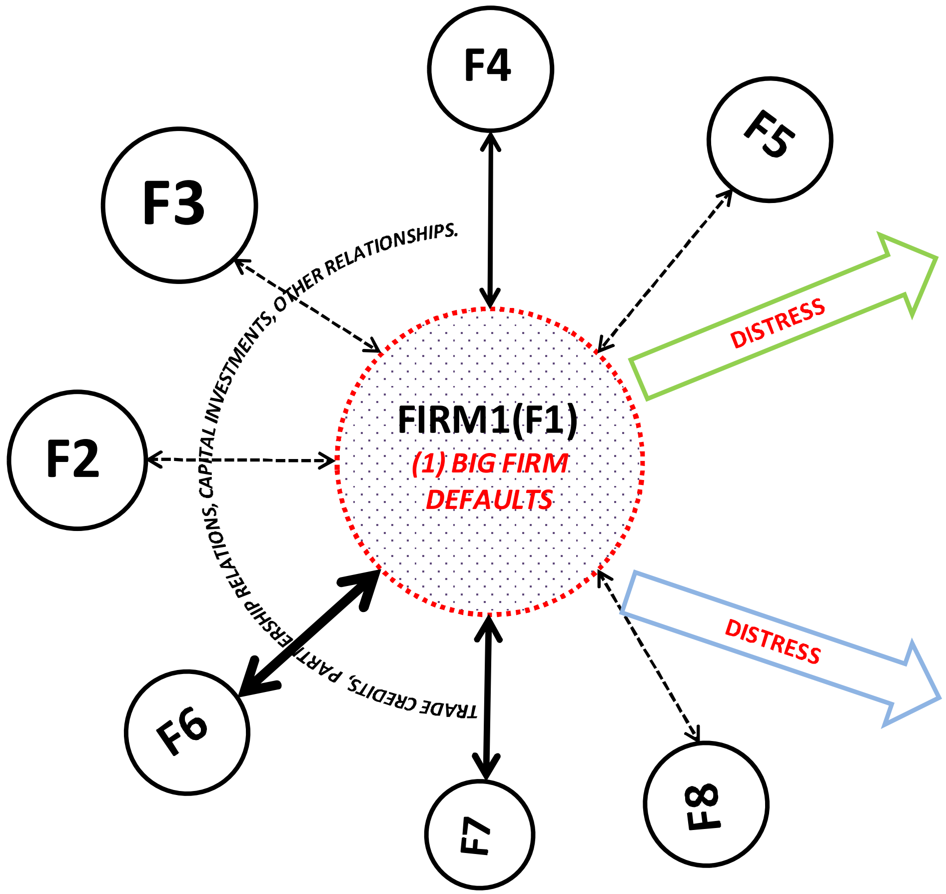
REPRESENTATION OF A BANK-FIRM (2-AGENT) LOAN RELATIONSHIP NETWORK WITH EMPIRICAL DATA



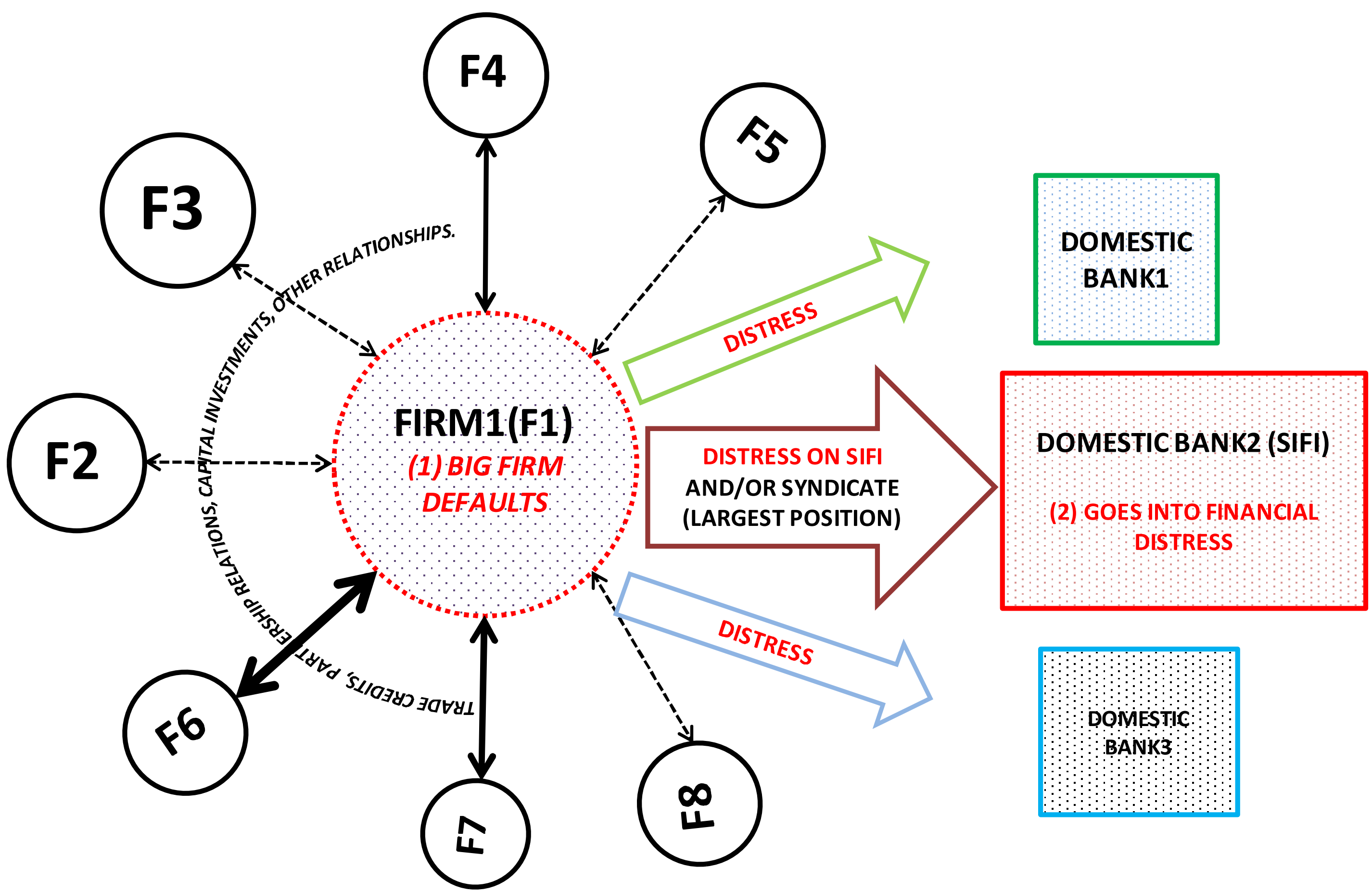
Harel-Koren Fast Multiscale Algorithm (Node-XL)

RISK CYCLE ILLUSTRATED IN A SIMPLE 3 AGENT NETWORK

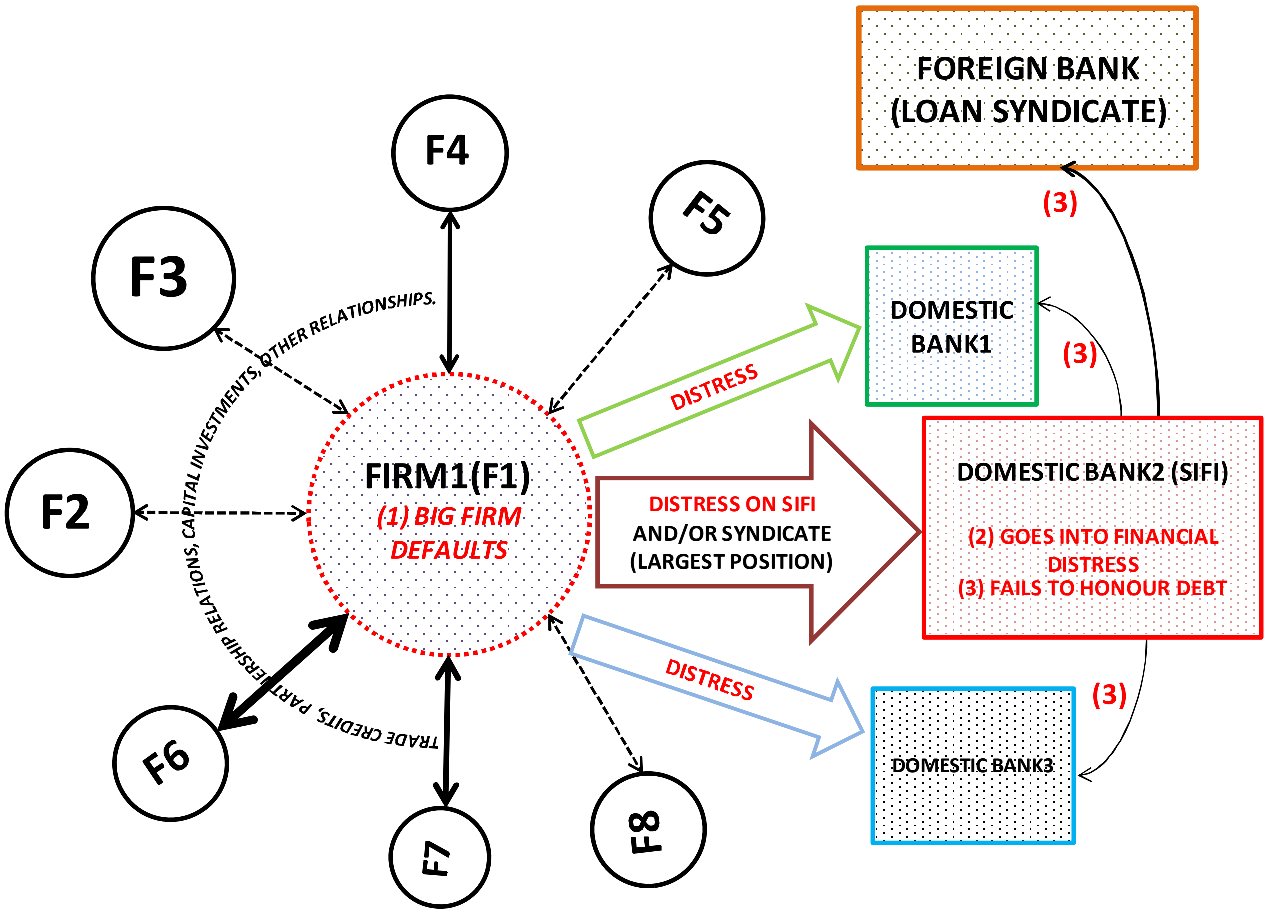
BIG FIRM DEFAULTS!



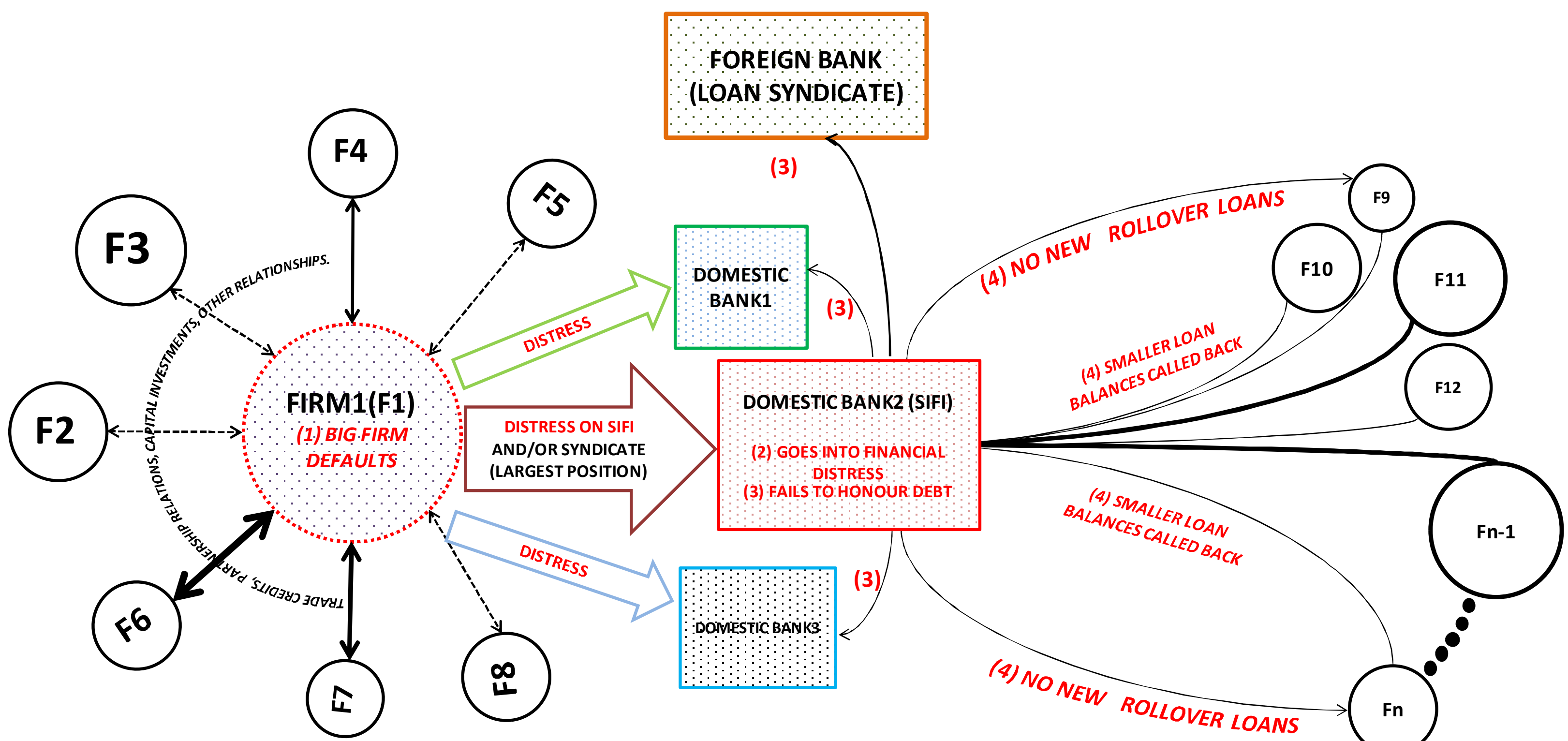
BANK GOES INTO FINANCIAL DISTRESS!



BANK FAILS TO HONOUR ITS DEBT!



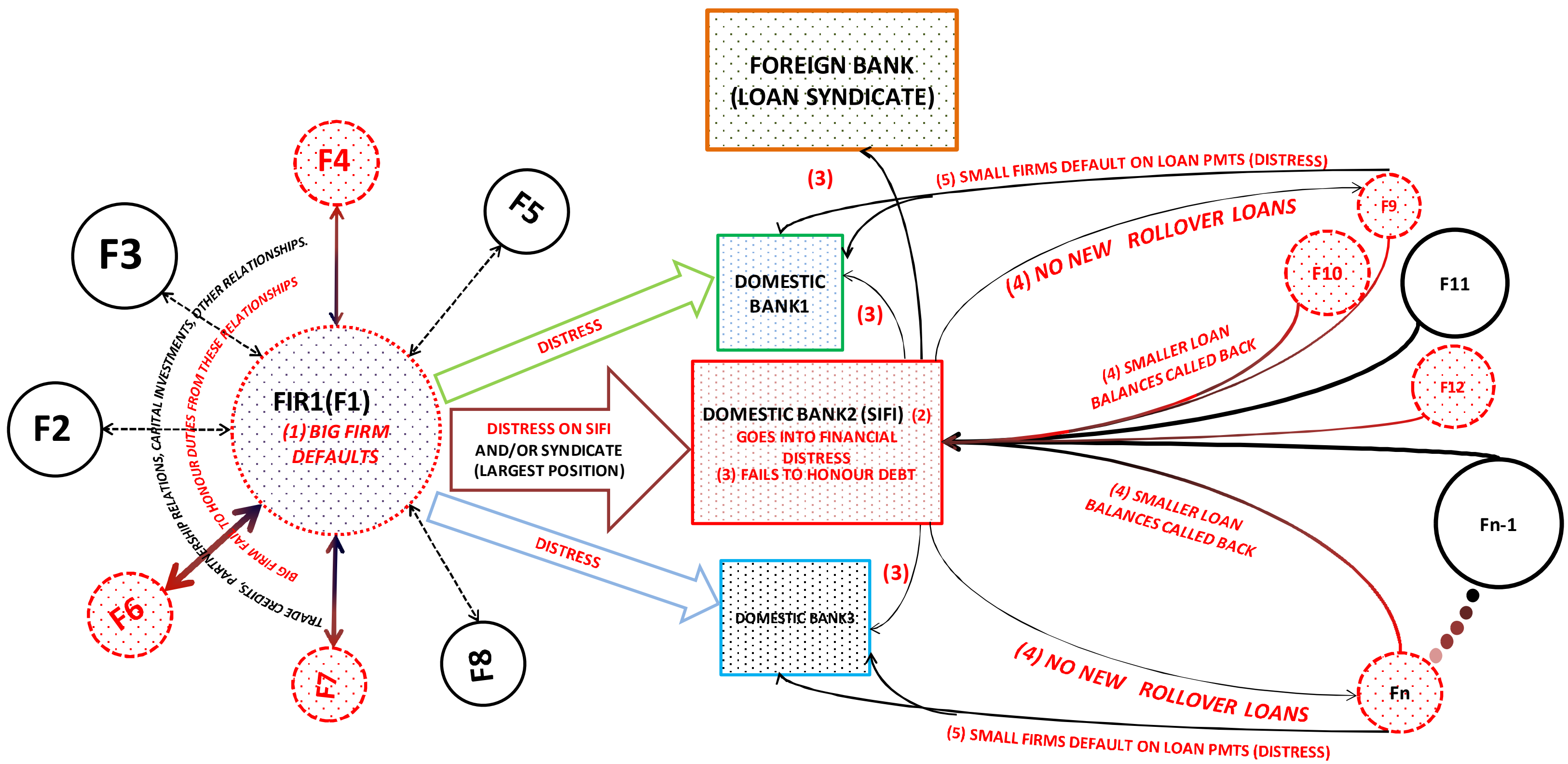
BANK RECALLS SMALLER CREDIT BALANCES! (DOES NOT RENEW OLD BALANCES - NO ROLLOVER FUNDS)



TÜRKİYE CUMHURİYET MERKEZ BANKASI

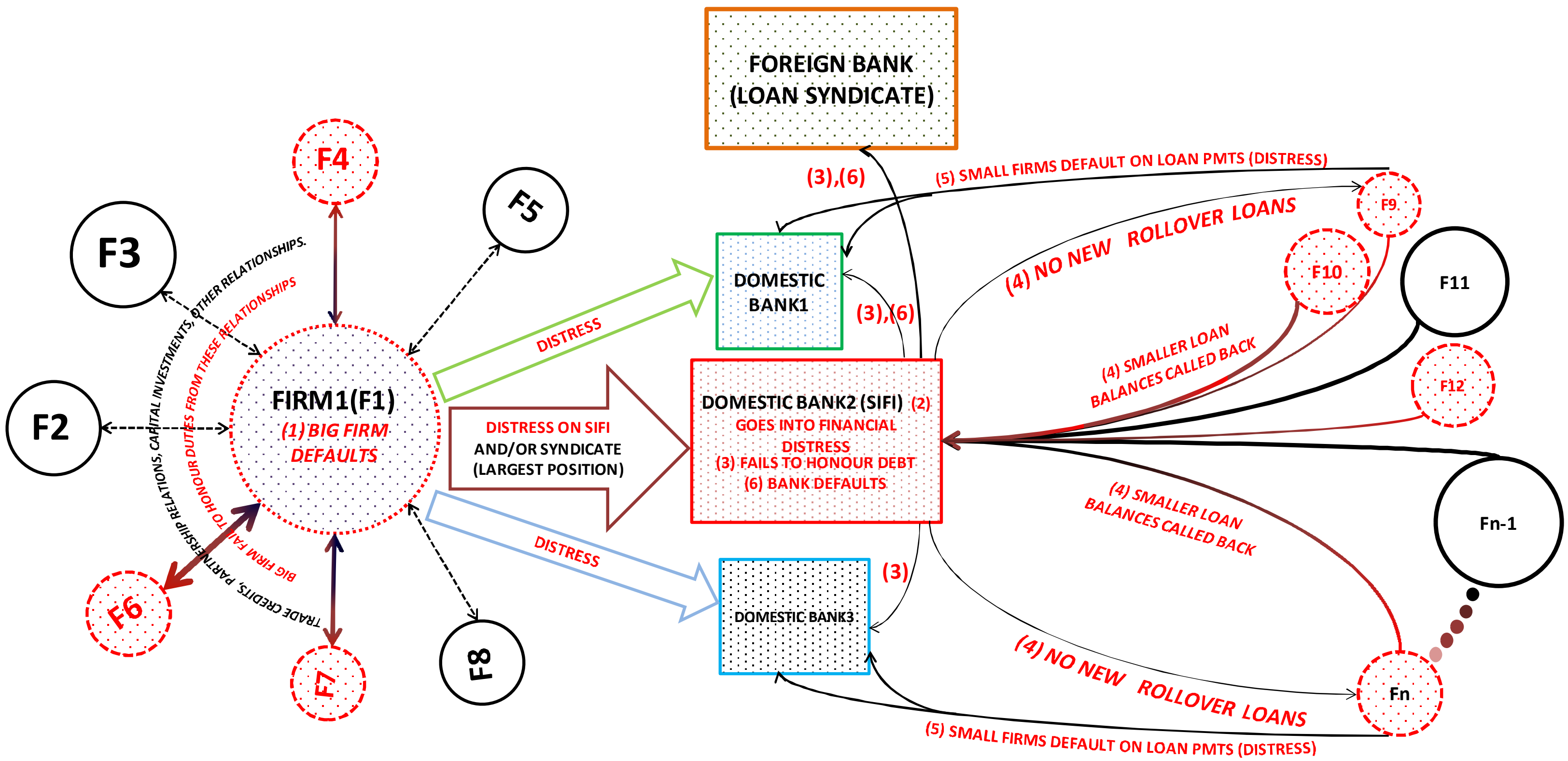
RISK CYCLE ILLUSTRATED IN A SIMPLE 3 AGENT NETWORK

SMALL FIRM(S) DEFAULT(S)!



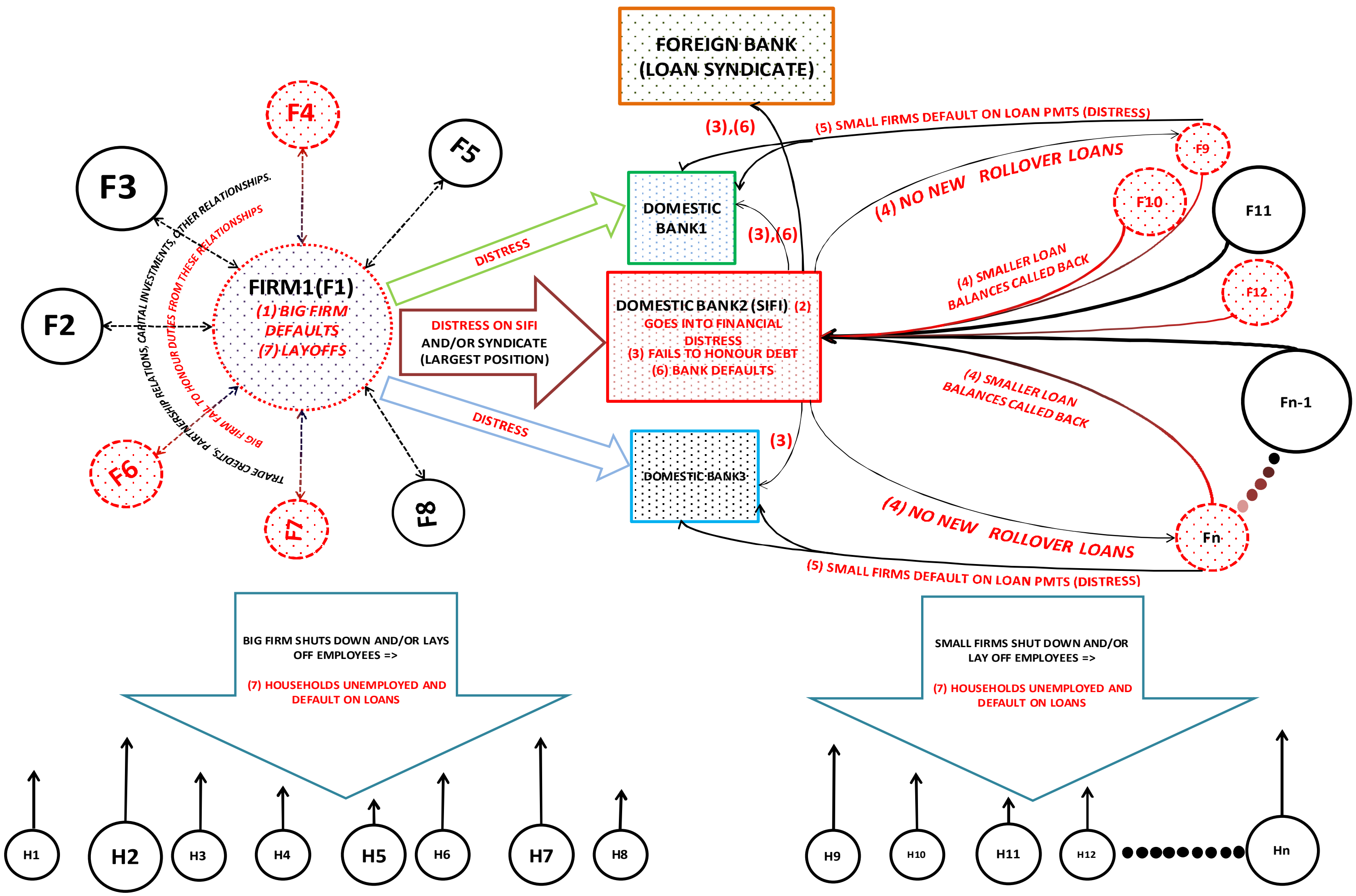
RISK CYCLE ILLUSTRATED IN A SIMPLE 3 AGENT NETWORK

BANK DEFAULTS!

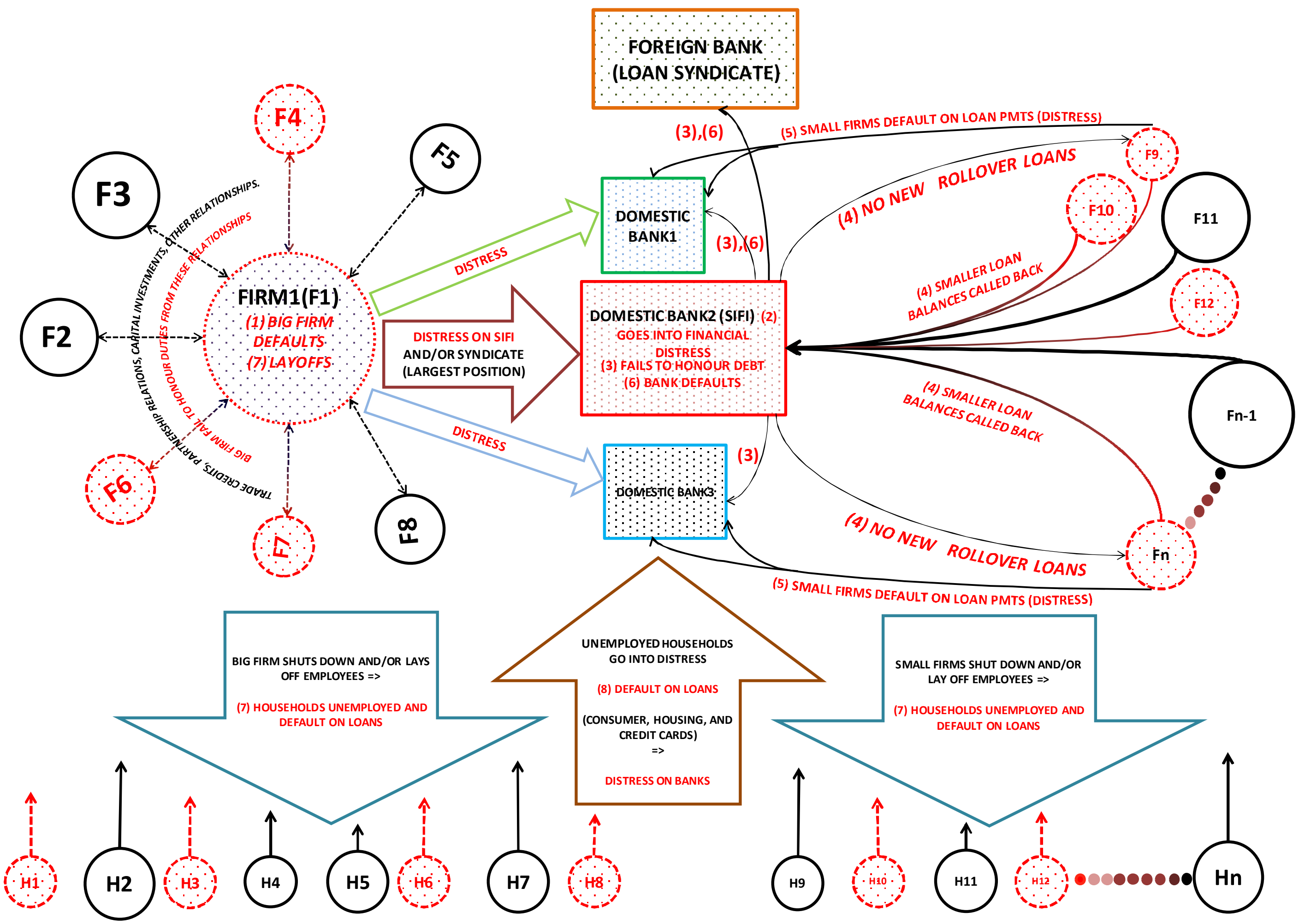


RISK CYCLE ILLUSTRATED IN A SIMPLE 3 AGENT NETWORK

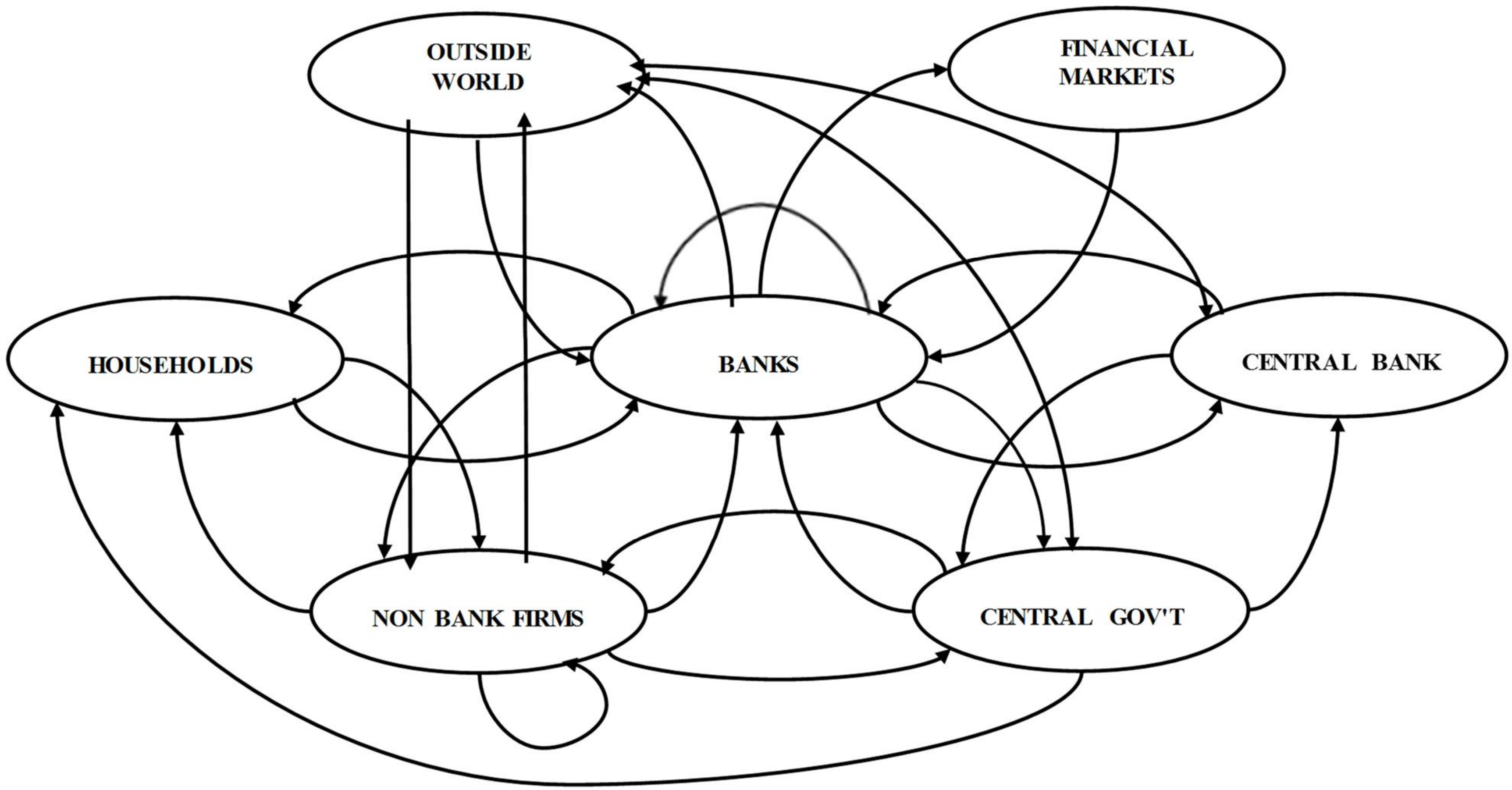
HOUSEHOLDS UNEMPLOYED!



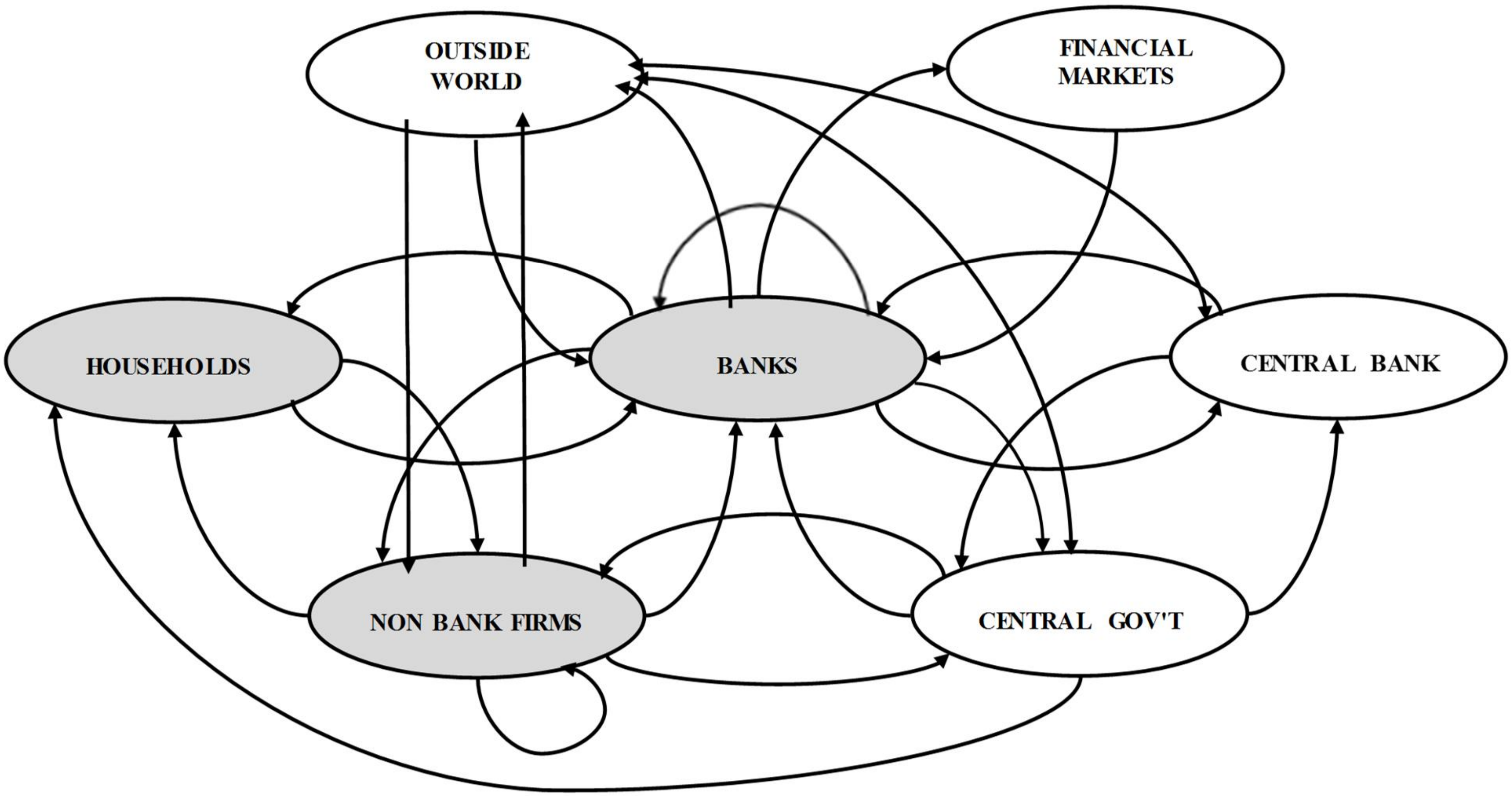
HOUSEHOLDS DEFAULT ON LOANS!



ALMOST FULLY EXHAUSTIVE
n-AGENT FUNDS FLOWS NETWORK



HOUSEHOLDS-BANKS-NONBANK FIRMS SUB-NETWORK



TÜRKİYE CUMHURİYET MERKEZ BANKASI

FULLY EXHAUSTIVE n-AGENT COUNTERPARTY RELATIONSHIP MATRIX

USERS

SOURCES

	HOUSEHOLDS	NON BANK FIRMS	BANKS	FINANCIAL MARKETS	CENTRAL GOV'T	CENTRAL BANK	OUTSIDE WORLD
HOUSEHOLDS	?	✓	✓	?	✓		
NON BANK FIRMS	✓	✓	✓	?			✓
BANKS	✓	✓	✓	✓	✓	✓	✓
FINANCIAL MARKETS	?	?	✓		?	?	?
CENTRAL GOV'T	✓	✓	✓	?		✓	✓
CENTRAL BANK			✓	?	✓		
OUTSIDE WORLD		✓	✓	?	✓	✓	

DESCRIPTION OF THE DATA NEEDED (AND TIPS FOR MODEL BUILDING)

FEATURE IDENTIFICATION RULES

Full coverage of the relevant features significant from the individual models

Free employment of individual models for independent incumbent groups

Weighting constrained by the potential loss impact in Bank’s or Banks’ assets, and equity

Static short-term, dynamic long-term modelling

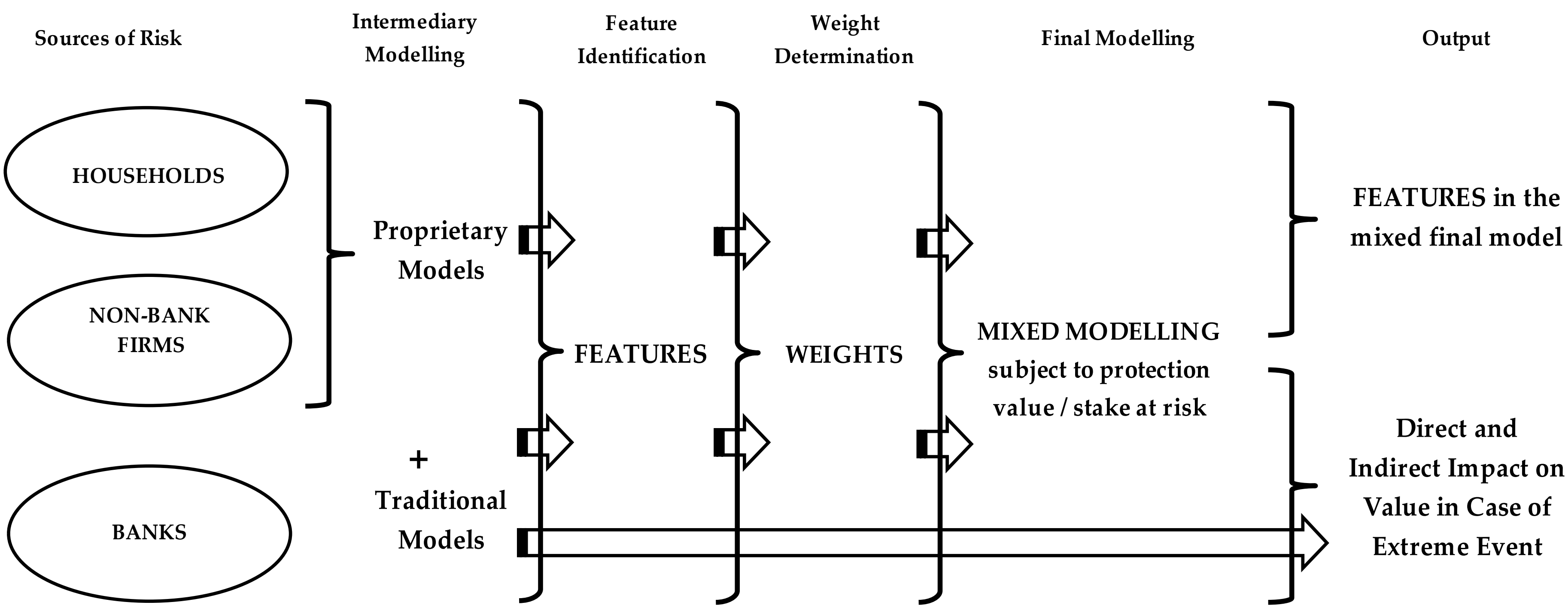
FEATURE CATEGORIES FOR THE PROPOSED FRAMEWORK

FEATURE TYPE

NODE TYPE (SYSTEM INCUMBENTS)

	FINANCIAL	RISK (LOAN CREDIT)	OPERATIONAL	CONNECTEDNESS (NETWORK)
HOUSEHOLDS	✓	✓	?	✓
NON BANK FIRMS	✓	✓	✓	✓
BANKS	✓	✓	✓	✓

FEATURE IDENTIFICATION AND MODEL BUILDING PROCESS



Thank you for your attention…

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Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

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Özdere-İzmir, Turkey, 26 September 2016

Sectoral risk in the Italian Banking System[1]

Matteo Accornero, Giuseppe Cascarino, Roberto Felici,
Fabio Parlapiano and Alberto Maria Sorrentino,
Bank of Italy

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

Sectoral Risk in the Italian Banking System[1]

by Matteo Accornero*, Giuseppe Cascarino*, Roberto Felici*, Fabio Parlapiano**, Alberto Maria Sorrentino*
* *Bank of Italy - Financial Stability Directorate, DG Economics and Statistics*
** *Bank of Italy - Financial Risk Management Directorate, DG Markets and Payment Systems*

Abstract

We apply a structural multi-factor credit risk model to assess the importance of sectoral risk for the Italian banking system. Using a unique and detailed supervisory dataset, we estimate the credit risk stemming from exposure of Italian banks to different sectors of the economy. We provide estimates of standard credit risk measures, such as expected and unexpected losses, and we investigate the contribution of each sector to credit risk as a whole. We identify the sectors which could pose a threat to the stability of the banking system, highlighting the macro-prudential actions that could be envisaged.

Keywords: Sectoral risk, Systemic risk, Structural Multi-Factor Model.

JEL classification: G21, G32.

Contents

[1] This article is based on the results of a working paper of the same authors circulated as "Credit Risk in the Banking System: an Application to Sectoral Risk in Italian Banks".

Introduction[2]

In a large and diversified economy, business conditions tend to be different in different sectors. Profitability, investment opportunities and risks might follow different paths across sectors, leading to a diversified level of default risk for borrowers belonging to different sectors. Accordingly, the dynamic of defaults for the entire economy is better described when accounting for multiple sectoral risk factors (De Servigny and Renault, 2002; Das et al., 2007; Saldías, 2013).

In credit risk modelling, the contribution of these latent sectoral risk factors, influencing the correlation of defaults among firms, is defined "sectoral risk". As such, sectoral risk represents an additional risk component in credit portfolios, arising when there is a concentration of borrowers in a sector; however currently no specific capital requirement is prescribed.[3] Sectoral risk might represent a threat for the stability of the banking system when capital requirements for exposures to a particular sector are significantly misaligned with respect to those that take into account sectoral risk.

In this paper we outline a methodological framework for the analysis of sectoral risk for macroprudential purposes. We analyse the corporate exposure of the Italian banking system and we estimate for each sector a set of credit risk measures, including: expected and unexpected losses. Moreover, we estimate the marginal contribution to total losses of each sector and we suggest this measure as an indicator that approximates the systemic relevance of economic sectors.

Assessing the impact of sectoral risk in macroprudential analysis is a relevant and relatively new perspective in financial stability monitoring. The European Systemic Risk Board identified, among others, the risk of excessive credit growth and sectoral risk as intermediate macro-prudential objectives relevant to the banking sector (see ESRB, 2014). The current regulatory framework for banking supervision in Europe provides to macroprudential authorities a differentiated set of tools to monitor and contain systemic risk arising from different sources.[4] Among these tools sectoral risk weights are aimed at offsetting the risk that credit institutions may be excessively exposed to risk sources linked to a specific sector or to sectors highly correlated. A few European countries have taken macro-prudential measures in this regard, and existing measures have targeted only the real estate sector via increased risk weights (see ESRB, 2015).

Sectoral risk analysis can benefit from the availability of micro data on credit portfolios. In particular, the capacity of supervisors to use promptly macroprudential

2 We thank all the participants to the ECCBSO/IFC/CBRT conference "Uses of Central Balance Sheet Data Offices' Information" held in CBRT Premises, Özdere-İzmir, September 26 th 2016 for useful comments and suggestions. We also thank Giorgio Gobbi and the members of the Financial Stability Directorate. All errors are our own. The views expressed in this paper are solely of the authors and do not necessarily reflect those of the Bank of Italy or of the Eurosystem.

3 The current Basel framework for credit risk is based on an Asymptotic Single-Factor (ASRF) model (see BCBS 2005).

4 The main regulatory references are the following: Directive 2013/36/EU on access to the activity of credit institutions and the prudential supervision of credit institutions and investment firms; (CRD IV); Regulation (EU) No 575/2013 on prudential requirements for credit institutions and investment firms (CRR); Regulation (EU) No 1024/2013 conferring specific tasks to the European Central Bank concerning policies relating to the prudential supervision of credit institutions.

tools depends also on the quality, granularity and timeliness of the information, and on the availability of models to use this information wisely.

In this paper we identify those sectors that account for most of the credit risk exposure for the Italian banking system, including those relatively more risky due to their cyclicality and default risk vulnerability. In terms of systemic relevance, *Industrial Goods and Services*, *Construction*, *Trade* and *Real Estate* are the most relevant sectors for the Italian banking system. This ranking is mainly determined by the size of the credit exposure of each sector. In some cases though, such as *Construction,* the contribution to risk is greater than that to total exposure because of relatively high default risk profile and positive correlation with other sectors.

Our contribution to the literature is twofold. First, our work overcomes the typical microdata limitations found in previous studies, i.e. lack of PD and LGD for individual firms. To the best of our knowledge, previous works assumed homogeneous PD within each sector and fixed LGD for every exposure. We use a unique supervisory dataset and we show that significant differences exist within and between sectors. Second, this work contributes to identify the build-up of sectoral risks by means of credit risk indicators, such as a sector's marginal contribution to the expected shortfall of the banking system, providing a useful warning signal of potential threats to the stability of the banking system.

The rest of the paper is organized as follows: Section 2 outlines the model, risk indicators and the dataset; Section 3 discusses results; and Section 4 concludes.

Methodology and data

The model

We use a structural multi-factor model as in Duellman and Masschelein (2006), and in Duellman and Puzanova (2013), prompted by the seminal work in Merton (1974). Composite latent risk factors $\boldsymbol{Y}$, affecting the standardized asset return X of a firm i belonging to a sector s drive default dependencies:

$$X_{i,s} = \sqrt{r_i}\, Y_s + \sqrt{1-r_i}\, \varepsilon_{i,s}\ , \quad \varepsilon_{i,s} \sim^{iid} N(0,1) \tag{1}$$

$$Y_s = \sum_{k=1}^{K} \alpha_{s,k} Z_k\ , \quad \text{with} \ \sum_{k=1}^{K} \alpha_{s,k}^2 = 1\ , \quad Z_k \sim^{iid} N(0,1)$$

where: $r_i \in (0,1)$ is the factor loading which relates a firm assets return to the dynamic of a latent sectoral factor, $\varepsilon_i \sim iid$ is an idiosyncratic risk component. The composite risk factors $\boldsymbol{Y}$, one for each sector, are expressed as linear combinations of K iid standard normal factors $\boldsymbol{Z}$, which represent as many elementary risk factors as the number of sectors ($K = S$). The coefficients $\alpha_{s,k}$ are obtained by the Cholesky decomposition of the correlation matrix of the sectoral risk factors; the correlation between asset returns of two firms i and j is then $\rho_{i,j} = \sqrt{r_i r_j} \cdot \sum_{k=1}^{K} \alpha_{i,k}\alpha_{j,k}$, and depends on the strength with which a sector is correlated with the others.

Defaults are triggered when a firm standardized asset return is below the threshold implied by the PD for that firm:

$$X_i \leq \Phi^{-1}(PD_i)$$

The distribution of the loss L is estimated via Monte Carlo simulations of systematic and idiosyncratic factors, and comparing the simulated standardized return with the threshold $\Phi^{-1}(PD_i)$ to identify the individual defaults in each scenario.

$$\mathrm{L} = \sum_{\mathrm{s}=1}^{\mathrm{S}} \sum_{\mathrm{i}=1}^{\mathrm{I_s}} \mathrm{D}_{\{\mathrm{X_{i,s}} \leq \Phi^{-1}(\mathrm{PD_i})\}} \cdot \mathrm{EXP_{i,s}} \cdot \mathrm{LGD_{i,s}} \tag{2}$$

where: i is the number of borrowers in sector s and EXP is the credit exposure. The implementation of the model requires a large set of data, including: PD at borrower level, exposures and LGD at loan level, the correlations matrix of sectoral risk factors and the factor loadings on the sectoral risk factors $\sqrt{r_i}$. Moreover, we assume an homogeneous factor loading equal to 0.5 for all sectors, as in Duellman and Masschelein (2006) .

Risk measures

For a portfolio of loans the estimation of credit risk measures is based on the distribution of potential losses L for that portfolio. The loss resulting from the default of a single borrower i at a given time is a random variable that can be decomposed as the product of three elements:

$$L_i = D_i \cdot EXP_i \cdot LGD_i$$

where $D_i \sim Ber(PD_i)$ is a binomial variable that assumes value 1 with probability PD_i. At the portfolio level, total losses $L = \sum_i L_i$, are analysed using the expected and the unexpected losses, i.e. a level of losses that can exceed the expected value. The latter is generally calculated as the difference between a measure of tail risk, typically the expected shortfall (ES), and the expected loss:

$$EL \equiv \mathrm{E}[L] = \Sigma_i \mathrm{E}[L_i] = \Sigma_i \; PD_i \cdot EXP_i \cdot LGD_i$$

$$UL \equiv ES \text{ - } EL$$

Estimating expected losses is a straightforward task, once PD and LGD are available. On the contrary, the calculation other risk measures from the loss distribution involves the consideration of dependences between individual losses. In our set-up, the default event is the only uncertain component, while credit exposures and LGD are considered as non-stochastic. By doing so, we relax prior assumptions on the homogeneity of PD and LGD (see Duellman and Masschelein, 2006 and Tola 2010).

The definition of ES for confidence level q and the potential loss L_s of the sub-portfolio s is the following:

$$ES_q(L_s) = \mathrm{E}\big[L_s \mid L_s \geq VaR_q(L_s)\big]$$

ES for the total loss can be decomposed into marginal contributions (MC) of each sector (Duellman and Puzanova, 2011). Marginal contribution measures have a desirable full allocation property, i.e. they sum up to the overall ES so that for each sector they can be interpreted as the share of ES attributable to a sector, approximating the systemic relevance of a sector. Indicating with $\mathrm{w_s}$ the relative weight of the exposures in sector s, the marginal contribution is as follows:

$$\mathrm{MC_s}= \mathrm{w_s}\frac{\partial}{\partial \mathrm{w_s}}\mathrm{ES_q}(\mathrm{L_{tot}})=\mathrm{E}[\mathrm{L_s}|\ \mathrm{L_{tot}}\geq \mathrm{VaR_q}(\mathrm{L_{tot}})].$$

Credit exposures, PD, LGD and correlations

Our dataset consists of a panel of firm-bank level data on credit exposures, PD and LGD for the years 2010-2015. Credit exposures of Italian banks towards non-financial firms based in Italy were gathered from different sources: i) the Italian National Credit Register (NCR), provided detailed information on individual exposures; ii) supervisory reports provided us with corporate debt securities holdings by banks. Banks' exposure towards economic sectors and concentration indices are reported in Table 1.[5] At the banking system level, the distribution of banks' credit to non-financial firms is not even, with a few economic sectors accounting for a large part of the exposure. For the year 2015, *Industrial Goods and Services* (20%), *Trade* (14%), *Construction* (12%) and *Real Estate* (11%) account for about half of banks credit exposure toward the corporate sector. The shares of remaining sectors range from 1% to 9% with *Media* (0.4%), *Telecommunications* (0.9%), and *Oil and Gas* (1.5%) representing the smallest exposures.

We use firm-level PD retrieved from the Bank of Italy In-house Credit Assessment System (BI-ICAS). These are 1-Year point-in-time probabilities of default of Italian non-financial firms available on a monthly basis.[6] We use LGD estimated from the Archive of historically registered losses on defaulted positions' available at the Bank of Italy (BI-AoL).[7]

In structural credit risk modelling it is common practice to approximate risk factors correlations by using equity correlations. According to the literature, we use equity indices correlations based on GARCH-DCC model as prompted in Engle (2002) and recommended in Puzanova and Duellmann, (2013) when dealing with portfolio credit risk models.

5 Stock market indices and Italian firms follow different industry classification systems, the ICB and NACE respectively. We mapped NACE taxonomy into ICB codes in order to consistently assign a firm to its sector. When a direct association was not possible, firms were assigned to Others Sectors. We assume that all borrowers, including diversified firms, can be uniquely assigned to individual business sectors.

6 The statistical model underlying BI-ICAS is a reduced form logit model which combines two credit scores obtained from a set of financial and credit variables at the level of individual firms.

7 The statistical model underlying LGD estimates is presented in a previous working paper by the same authors circulated as "Credit Risk in the Banking System: an Application to Sectoral Risk in Italian banks".

Results

Figure 1 reports EL rate for each sector, this is the product between firm-level PD and exposure-level LGD and represents a measure of loss per unit of capital which ought to be priced in interest rates. For the year 2016, at the level of the banking system, EL accounts for about 2.1% of total exposure, however there is substantial difference across sectors. *Construction* and *Real Estate*, which represent a large part of banks' credit exposure, exhibit EL above the average; in contrast, *Industrial Goods and Services* and *Trade* present EL below the average. The least risky sectors are *Oil and Gas* and *Telecommunications* where low levels of PD are associated with high LGD. Turning to elementary components of EL rate, it is interesting to notice that the EL is strongly correlated with the average PD, but much less with the LGD, which actually appears to be high in sectors with very low expected losses. A possible explanation is that lenders try to minimize potential losses by asking for more and better quality collateral for borrowers with high default risk. Our LGD estimate averages around 54%, a value that is close to the parameter used in previous studies (Duellmann and Masschelein, 2006; Tola, 2010). However, our estimate show that there is significant variance in average LGD values across sectors, enriching the insight that can be gained by using microdata.

In Figure 2 the ES for the banking system, expressed as a percentage of the total exposure, is decomposed into its elementary components. The ES is calculated under the multi-factor approach (ES_{95}_multi) using Monte-Carlo simulations. Besides this estimate, a single-factor estimate is provided with at the same confidence interval (ES_{95}_single). Total losses identified by ES_{95}_multi can therefore been split into (i) EL (expected losses), (ii) the risk identified by the ES95_single and (iii) the additional risk arising from the consideration of the sectoral risk, namely a sectoral component. Figure 2 suggests that sectoral risk represents a limited portion of total credit risk faced by the Italian banking system. Most of risk derives from the ES_{95}_single component, i.e. derives from the aggregate level of PD and LGD. Moreover, after several years of increase, sectoral risk has decreased in 2016.

Figure 3 decomposes the UL rate into its elementary components. The UL for the banking system is traced back to the contributing sectors and to the contributing risk component. The single-factor component is chiefly responsible for the increase in overall risk from 2011 to 2013 in the four most important sectors defined above, while the contribution of the sectoral component is stable over time. The sectoral component has a negative influence on total risk for several sectors in particular, among the most important sectors, *Trade* and *Real Estate*. This means that the economic capital for these sectors decreases when taking into account sectoral risk. This might be due both to a portfolio effect, a correlation effect or an interplay between the two effects.

Figure 4 compares MC risk measures obtained from the two approaches, the single and the multi-factor model. The multi-factor model estimates show greater risk contribution with respect to the single-factor counterpart for those sectors that are highly correlated with the rest of the economy. To the extent to which the dependence structure between defaults is described more accurately by the multi-factor model, our comparison shows that economic capital could be misallocated when using a single factor model of credit risk, leading to over(under) estimation of capital requirements for some exposures with respect to their contribution to the overall risk.

Over time the four main sectors maintained a relevant role. Though, while *Industrial Goods and Services* is the sector having the largest share of credit, up to 2015 the largest part of risk has been concentrated in *Construction*. Moreover, while for all periods in *Industrial Goods and Services* and *Construction* MC based on the multi factor approach has been greater than the corresponding MC based on the single risk factor, the opposite has been true for the other two main sectors, *Trade* and *Real Estate*.

Conclusion

This paper outlines a framework for the estimation of potential losses on banks' corporate portfolios.

We apply a multi-factor credit risk model to a detailed dataset, consisting of exposures by Italian banks to Italian non-financial firms. We present credit risk measures at the sectoral level and assess the contribution of different sectors to the overall level of risk. Aggregated risk measures are analysed in their elementary components and their temporal dynamics.

Our analysis shows that the use of available data sources and credit risk models allows for the identification of those sectors which might become relevant for the stability of the banking system.

The analysis is also motivated by the macroprudential policy tools included in the Basel framework, which offer the possibility for supervisors to address vulnerabilities arising from specific classes of exposures.

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Table 1: Banks' exposure (a) to non-financial firms by sector

	2010	2011	2012	2013	2014	2015
Other sectors	2.7	2.7	2.9	2.9	3.1	3.5
Oil and gas	2.0	1.9	1.5	1.4	1.4	1.5
Chemicals and basic resources	6.8	6.7	6.6	6.8	6.7	6.7
Construction	17.2	16.4	15.6	14.7	12.9	11.8
Industrial goods and services	18.8	19.2	19.4	19.1	19.7	20.2
Automobiles and parts	2.6	2.6	2.6	2.5	2.7	3.1
Agricolture, food and beverages	6.9	7.3	7.7	8.2	8.5	8.7
Personal and household goods	4.3	4.3	4.2	4.3	4.4	4.5
Health care	1.5	1.5	1.6	1.7	1.7	1.8
Trade	12.7	12.8	13.1	13.8	14.3	14.4
Media	0.6	0.6	0.5	0.5	0.4	0.4
Travel and leisure	4.1	3.9	3.9	4.0	3.9	4.0
Telecommunications	1.0	1.0	0.8	0.8	0.8	0.9
Utilities	4.8	5.4	5.9	5.6	6.0	5.7
Real estate	12.8	12.5	12.5	12.2	11.7	11.2
Tehnology	1.4	1.4	1.4	1.4	1.5	1.6
Total	100.0	100.0	100.0	100.0	100.0	100.0
Total[(b)]	870.1	870.0	800.2	706.2	681.7	664.4

(a) Percentage values; (b) Billions of euros.

Table 1 reports banks' exposure to non-financial firms by sector, as sourced from the NCR. Stock market indices and the NCR follow different industry classification systems, the ICB and NACE respectively. We mapped NACE taxonomy into ICB codes in order to consistently assign a firm to its sector. When a direct association was not possible, firms were assigned to Other Sectors. We assume that all borrowers, including diversified firms, can be uniquely assigned to individual business sectors.

Figure 1: Sectoral risk measures: EL and its components

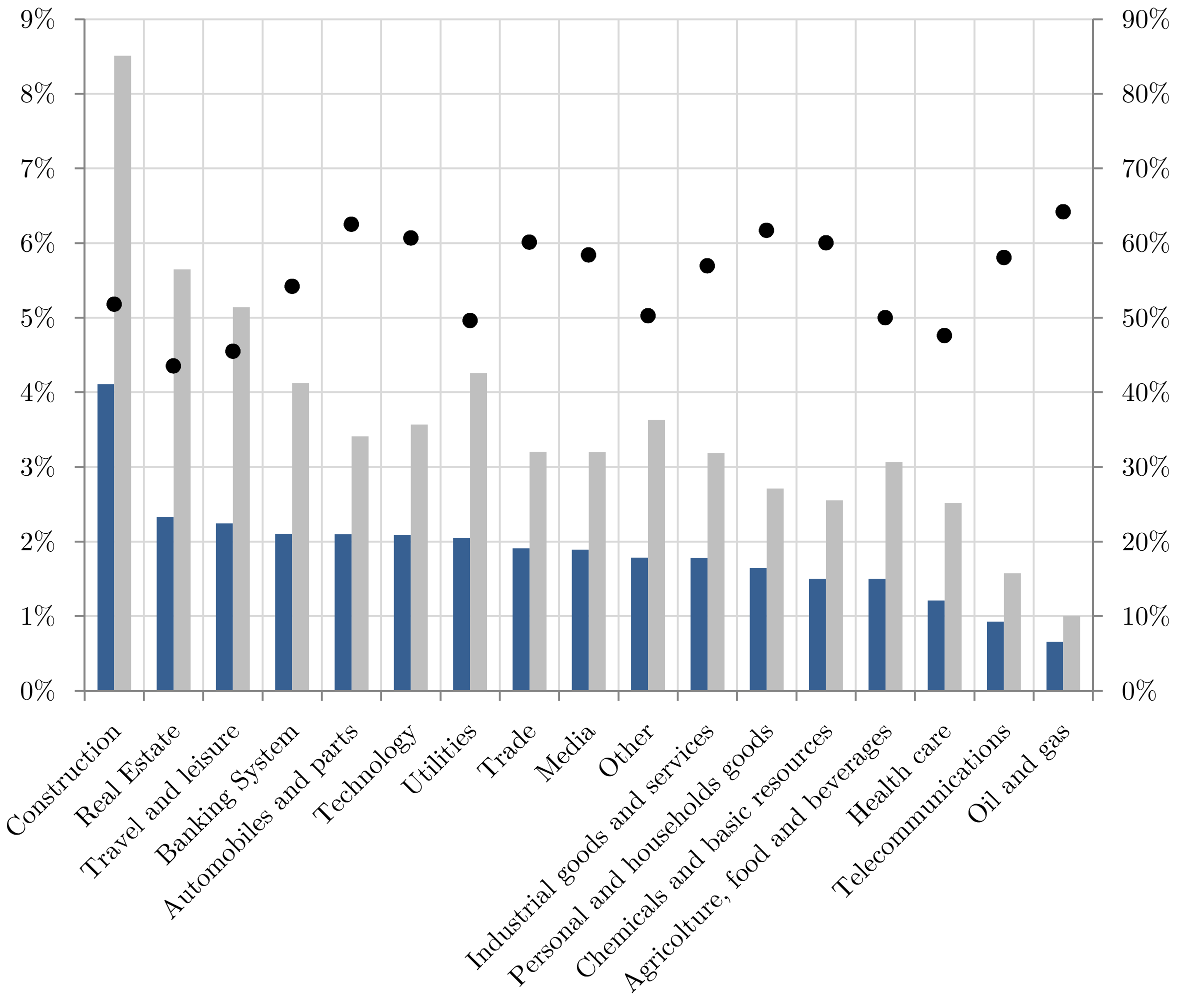


Figure 1 reports average EL rate (dark blue bars, left axis), PD (light grey bars, left axis) and LGD (black dots, right axis) by sector. Sectors are sorted by decreasing level of EL rate. EL rate were computed as the product between firm-level PD and exposure-level LGD at December 2015; PD were sourced from the In-House Credit Assessment System of the Bank of Italy, while LGD estimates were based on Archive of historically registered losses on defaulted positions' available at the Bank of Italy (BI-AoL).

Figure 2. ES and its components

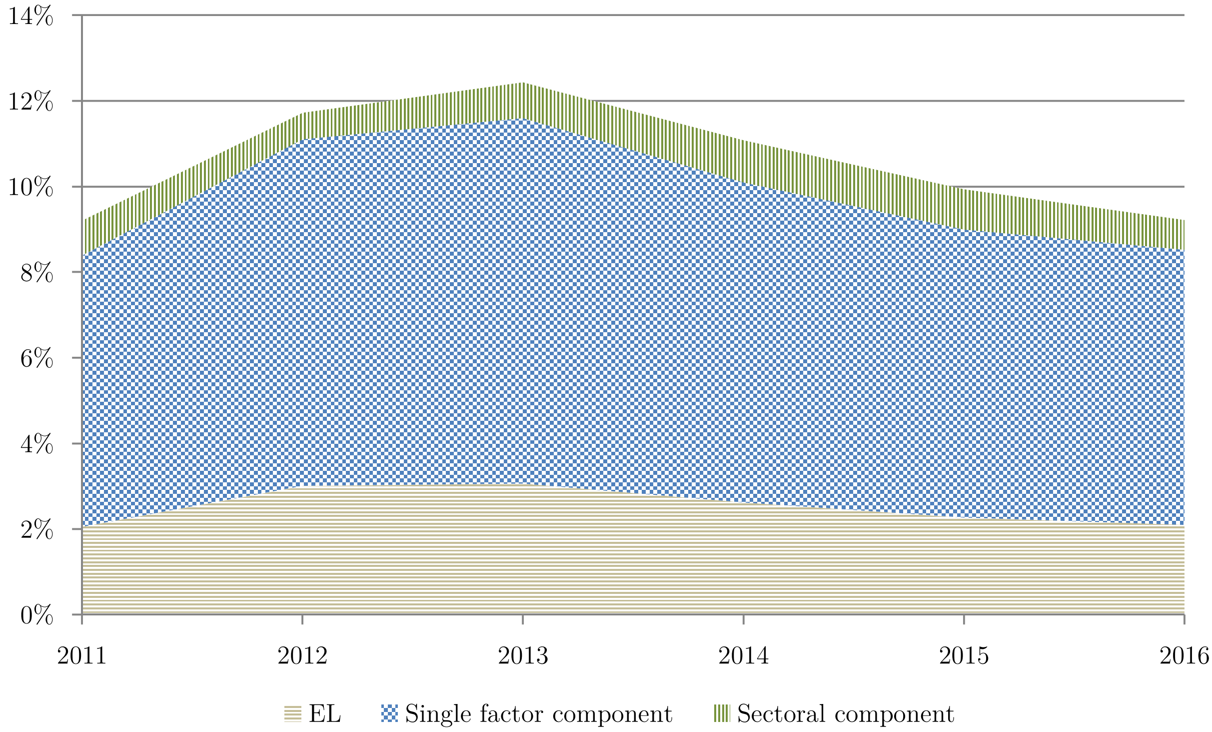
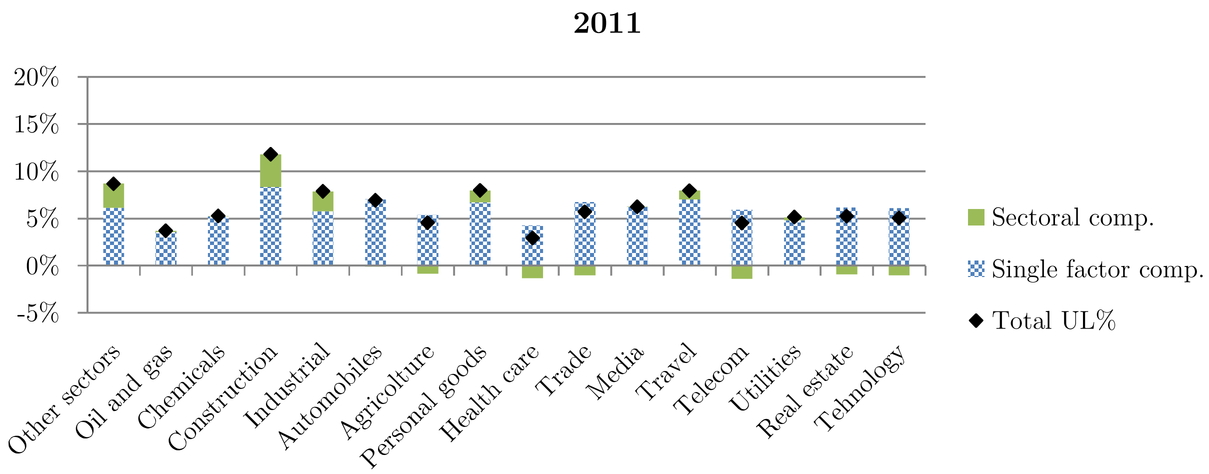
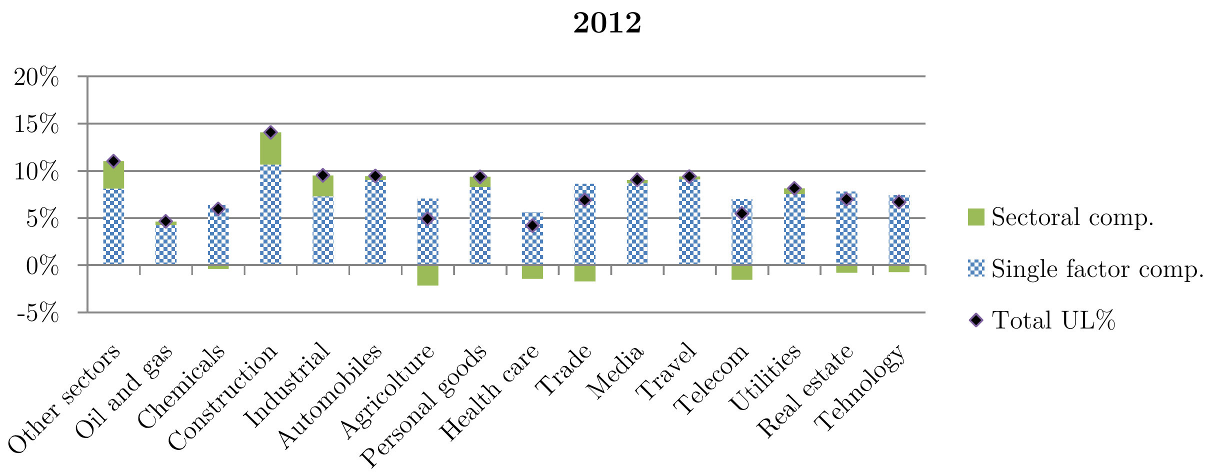
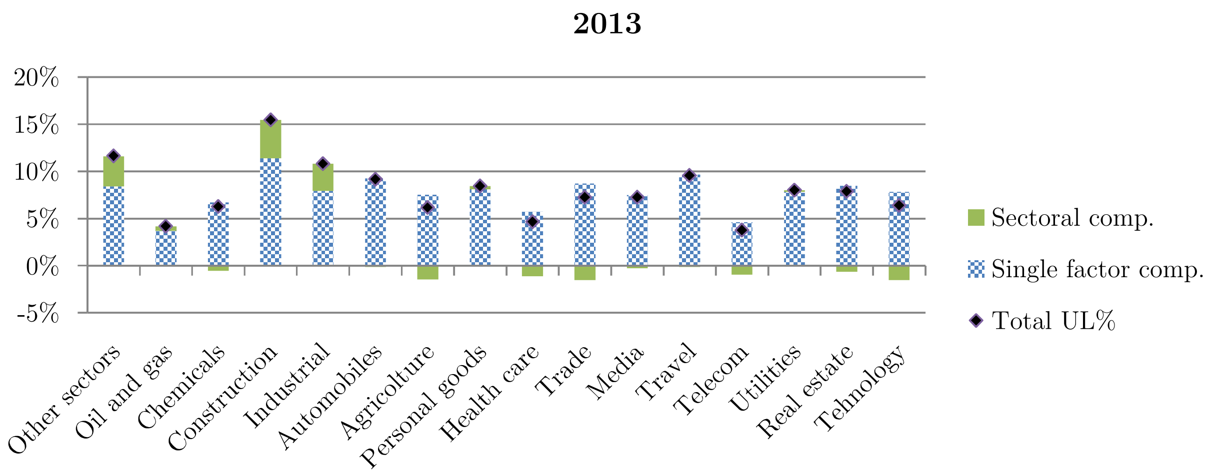


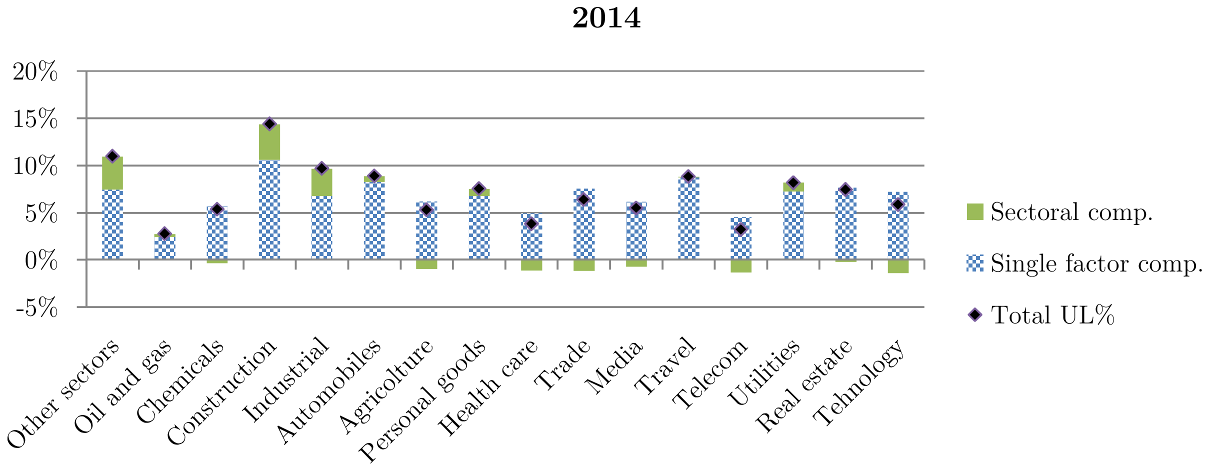
Figure 2 shows ES estimates under multi-factor model using Monte Carlo simulations. The overall ES is decomposed into its elementary components, i.e. EL, the product between firm-level PD and exposure-level LGD; the component obtained under the single-factor model; the sectoral component.

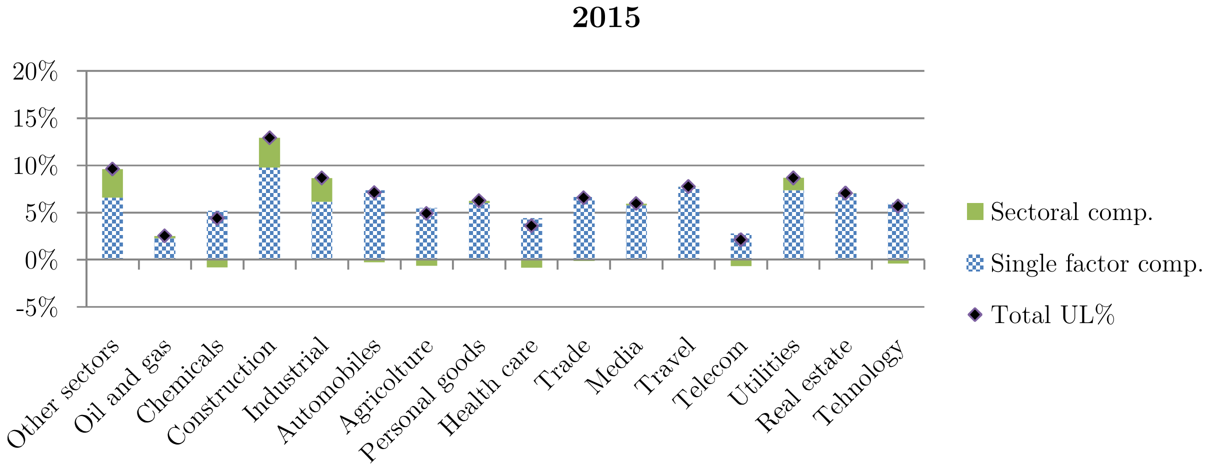
Figure 3. Sectoral UL% and its components











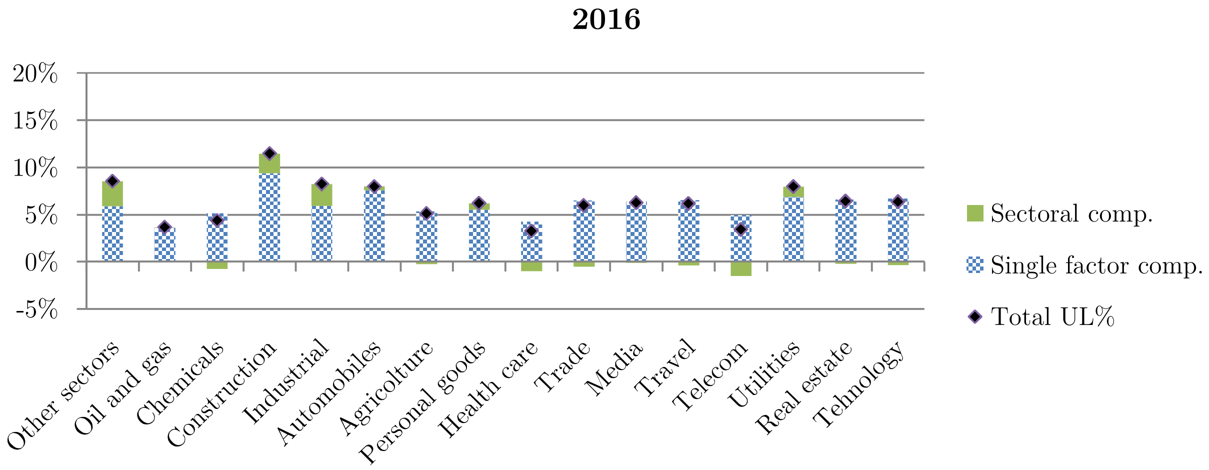
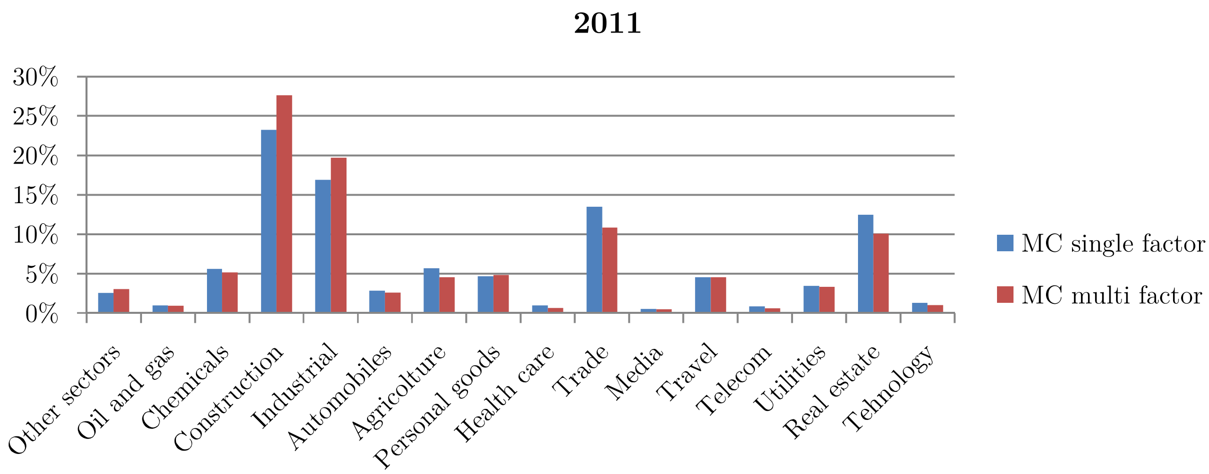
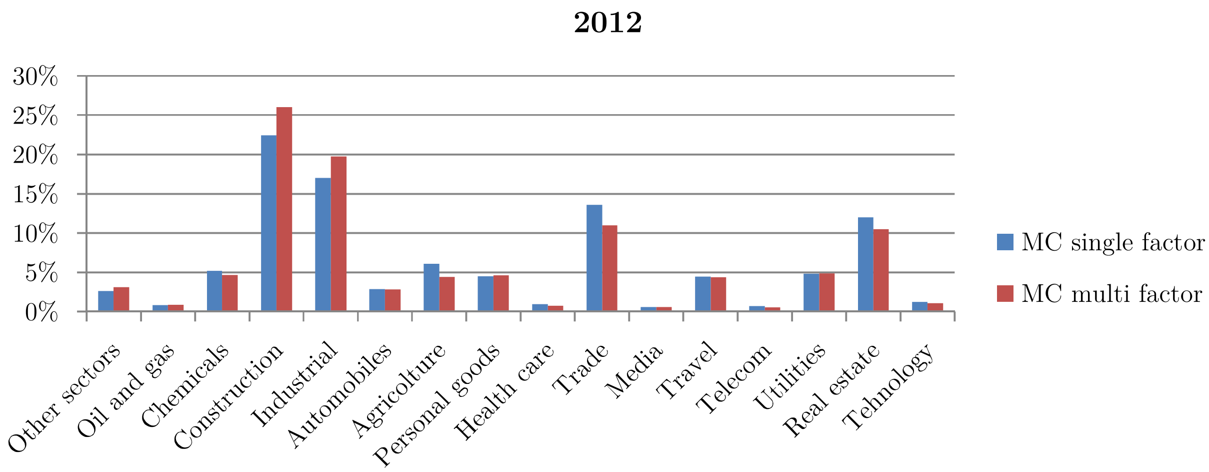
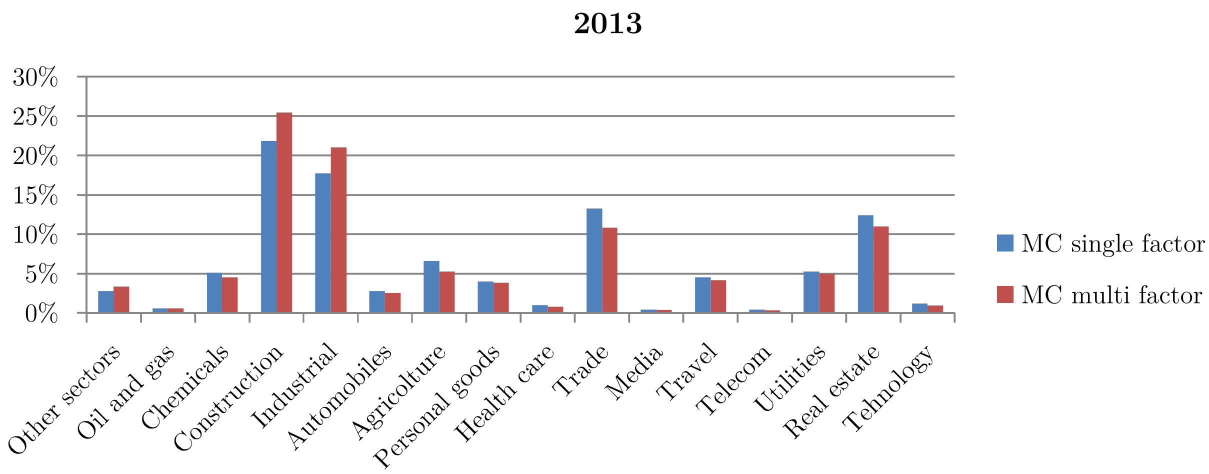


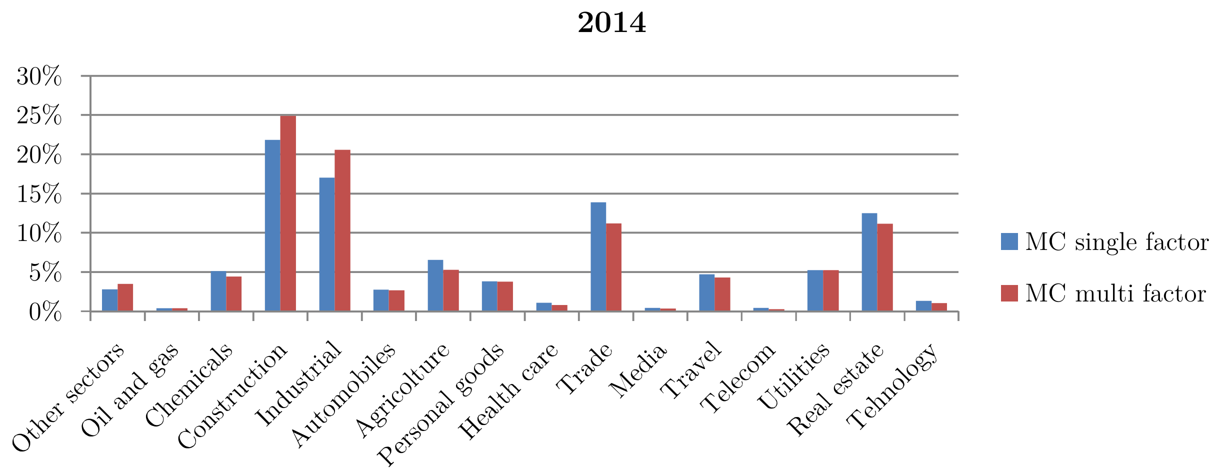
Figure 3 shows UL estimates sector by sector under multi-factor model using Monte Carlo simulations. The overall UL is decomposed into its elementary components, i.e. the component obtained under the single-factor model and the sectoral component.

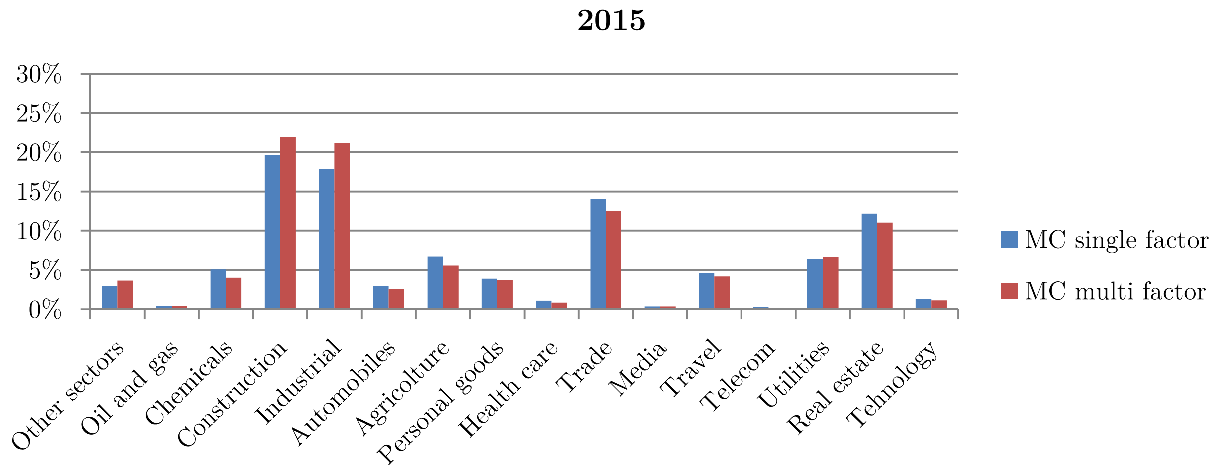
Figure 4. Sectoral MC under single and multi-factor model











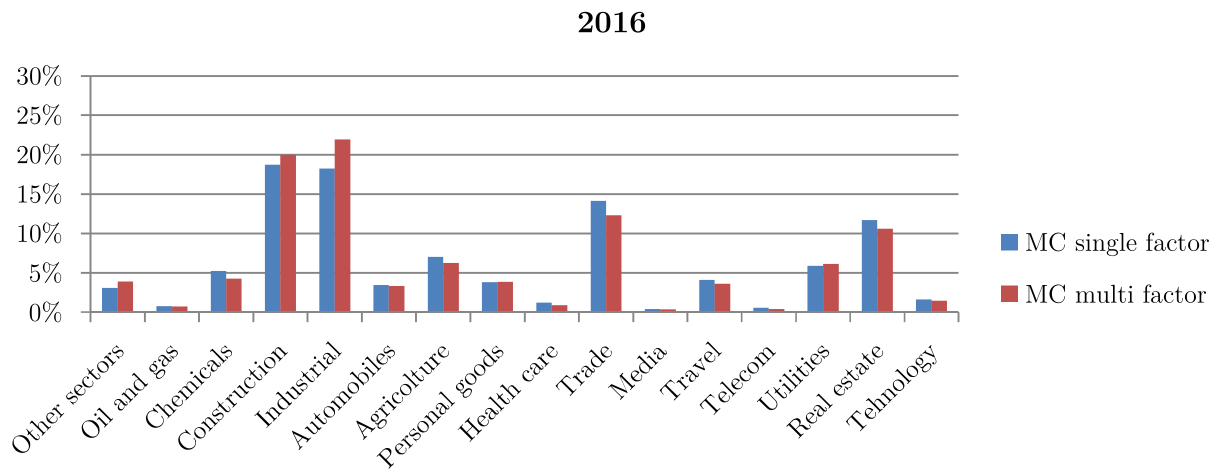


Figure 4 shows the marginal contribution (MC) of each sector to the total ES95 under single multi-factor models.

Irving Fisher Committee on
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BANK FOR INTERNATIONAL SETTLEMENTS

IFC-ECCBSO-CBRT Conference on *"Uses of Central Balance Sheet Data Offices' information"*

Co-organised by the IFC, the European Committee of Central Balance Sheet Data Offices (ECCBSO) and the Central Bank of the Republic of Turkey (CBRT)

Özdere-İzmir, Turkey, 26 September 2016

Sectoral risk in the Italian Banking System[1]

Matteo Accornero, Giuseppe Cascarino, Roberto Felici, Fabio Parlapiano and Alberto Maria Sorrentino,
Bank of Italy

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

BANCA D'ITALIA
EUROSISTEMA

SECTORAL RISK
IN ITALIAN BANKING SYSTEM

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TÜRKIYE CUMHURIYET MERKEZ BANKASI

eccbso
European Committee of Central Balance Sheet Data Offices

Irving Fisher Committee on Central Bank Statistics
BANK FOR INTERNATIONAL SETTLEMENTS

SECTORAL RISK AND BANKS' DISTRESS

Past episodes of bank distress have shown that excessive credit growth and concentration of credit risk may pose a threat to the stability of a single institution and for the banking system (**BIS, 2006**).

SECTORAL RISK AND DEFAULT CORRELATION

Default of non-financial firms display positive correlations within and across industries and sectoral (systematic) risk factors might drive their dependence structure (**De Servigny and Renault, 2002; Das et al., 2007; Saldías M., 2013**)

SECTORAL RISK AND THE BASEL FRAMEWORK

The IRB approach uses the Asymptotic Single-Risk Factor model whose consistency requires two key assumptions:

- Borrowers-idiosyncratic risk is diversified away in banks' portfolios;
- Macro-economy apart, there are no additional sources of credit risk at sectoral or geographical level (**Gordy, 2003**);

As a result, IRB risk-weights are portfolio invariant.

THIS WORK

To the best of our knowledge, previous works assumed homogeneous *PD* within each sector and fixed *LGD* for every exposure. We use a unique supervisory dataset and we show that significant differences exist within and between sectors.

BANKING SYSTEM LEVEL

This paper analyzes the exposure of the Italian banking system to credit risk arising from different sectors of the economy.

SECTORAL LEVEL

We investigate whether credit exposure towards some economic sectors is particularly vulnerable to credit risk, providing estimates of expected and unexpected losses on credit portfolios.

We obtain a measure of contribution to systemic risk stemming from credit exposures in different economic sectors.

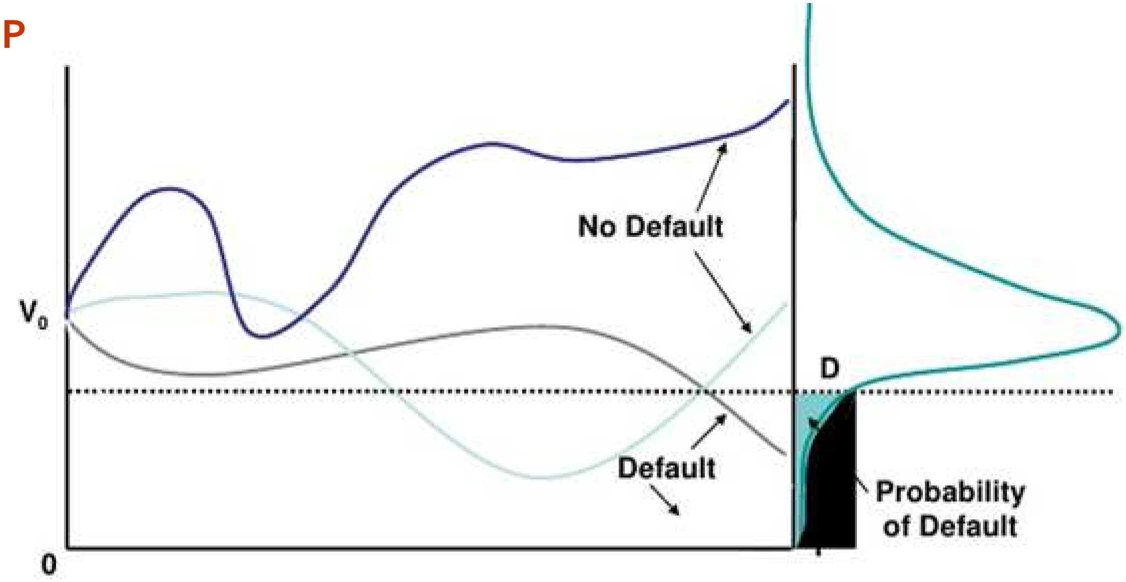
RESULTS

We find that **at the level of the banking system**, credit exposure is concentrated in a few sectors, including those sectors which are more vulnerable to credit risk due to their high cyclicality.

We show that measures of portfolio risk are positively correlated with the concentration structure of economic sectors, and this may represent a problem if banks are excessively exposed toward concentrated sectors.

In terms of systemic relevance, *Industrial Goods and Services*, *Construction*, *Trade* and *Real Estate* are the most relevant sectors for the Italian banking system. This ranking is mainly determined by the size of the credit exposure of each sector. In some cases though, such as *Construction*, the contribution to risk is greater than that to total exposure because of relatively high default risk profile and positive correlation with other sectors.

THE MODEL SET-UP



We use a structural multi-risk factor model where a default is triggered when a firm standardized asset return falls below the default threshold implied by the PD for that firm:

$$X_i \leq F^{-1}(PD_i)$$

Where: **X** represent firm *i* standardized asset return; and PD is the Probability of Default.

THE MODEL SET-UP

Default dependencies are driven by composite latent risk factors **Y**, affecting the standardized asset return **X** of a firm *i* belonging to a sector **s**:

$$X_{s,i} = \sqrt{r_i}\, Y_s + \sqrt{1-r_i}\, \varepsilon_{s,i} \ , \quad \varepsilon_{s,i} \overset{iid}{\sim} N(0,1)$$

Where: r ∈ (0,1) is the factor loading; ε is an idiosyncratic risk component.

The composite risk factors **Y,** one for each sector, are expressed as linear combinations of *iid* standard normal factors **Z** and **α{s,k}** are obtained by the Cholesky decomposition of the correlation matrix of the sectoral risk factors **ρ{s,k}**.

$$Y_s = \sum_{k=1}^{S} \alpha_{s,k} Z_k \ , \quad \text{with} \ \sum_{k=1}^{S} \alpha_{s,k}^2 = 1 \quad , \quad Z_k \overset{iid}{\sim} N(0,1)$$

THE MODEL SET-UP

The Loss Distribution is estimated via Monte Carlo simulations of systematic and idiosyncratic factors, and by comparing the simulated standardized return with the threshold to identify the individual defaults in each scenario.

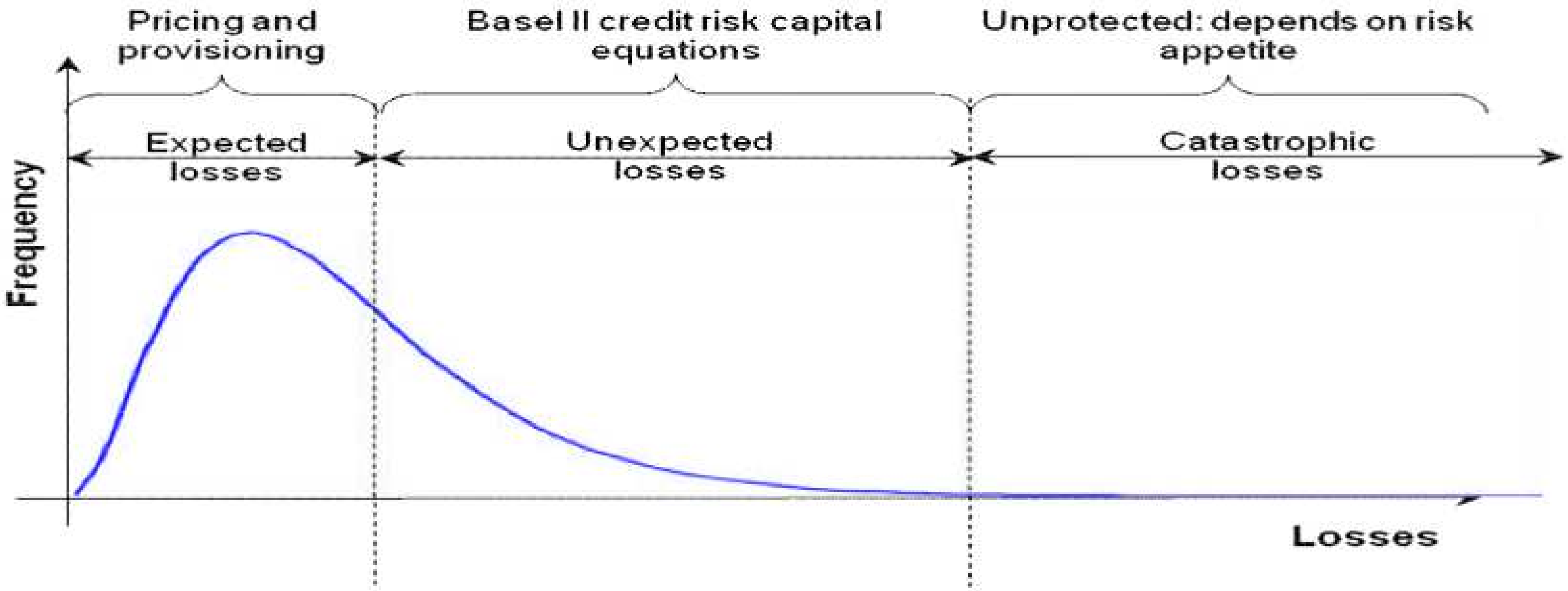
$$L = \sum_{s=1}^{S} \sum_{i=1}^{I_s} D_{\{X_{s,i} \leq \Phi^{-1}(PD_i)\}} \cdot EXP_{s,i} \cdot LGD_{s,i}$$

Where: **D** = 1, when a firm defaults; **EXP** is Exposure at Default; **LGD** is Loss Given Default.

CREDIT RISK MEASURES: EL - UL - ES

$$EL \equiv \mathbb{E}[L] = \Sigma_i \mathbb{E}[L_i] = \Sigma_i \; PD_i \cdot EXP_i \cdot LGD_i,$$

$$UL \equiv ES - EL$$



CONTRIBUTION TO SYSTEMIC RISK: MC

The Expected Shortfall for the banking system can be decomposed into marginal contributions of each sector (Tasche, 2008; Dullman and Puzanova, 2011).

$$MC_s = w_s \frac{\partial}{\partial w_s} ES_q(L_{tot}) = \mathbb{E}[L_s | \; L_{tot} \geq VaR_q(L_{tot})]$$

Marginal contribution measures have a desirable full allocation property, i.e. they sum up to the overall ES so that for each sector it can be interpreted as the share of ES attributable to a sector, approximating the systemic relevance of a sector.

DATA AND SOURCES

Credit Data

- Exposures At Default (EXP)
  - National Credit Register;
  - Supervisory Reports on security holdings;

- Probabilities of Default (PD)
  - BI-ICAS (Bank of Italy In-House Credit Assessment System)

- Loss Given Default (LGD)
  - Supervisory Reports on loans workout ;

Market Data

- Sectoral risk factors correlations
  - FTSE sectoral indices (via Datastream).

PD, Probability of Default

- Bank of Italy In-House Probability of Default of individual borrowers;
- > 500.000 borrowers;
- 12 - month PD estimated via a reduced form credit scoring model based on:
  - Financial statements;
  - Credit data;
  - Geo – Sectorial data;

LGD, Loss Given Default

- Model-based estimations for LGD of individual exposures
- A regression model was estimated using data from Loan Workout procedures;

$$LGD = \beta_0 + \beta_1 Log(EXP) + \beta_2 Size + \beta_3 Guarantee\_coverage\_ratio + \beta_4 Guarantee\_type + \varepsilon,$$

SECTORAL EQUITY CORRELATIONS

Based on:

- 16 indices FTSE-Italy Supersectors indices sourced from DATASTREAM;
- 5 Years daily observations;

Lowly correlated sectors: Chemicals, Agriculture, Heath Care and Trade.

Highly correlated sectors: Industrial G., Oil and Gas, Construction and Utilities.

	Chemicals	Automobiles	Agriculture	Technology	Health Care	Personal G.	Industrial G.	Media	Oil and G.	Travel	Real Estate	Trade	Construction	Telecom.	Utilities	Others
Chemicals	1.00															
Automobiles	0.49	1.00														
Agriculture	0.41	0.46	1.00													
Technology	0.46	0.53	0.39	1.00												
Health Care	0.38	0.48	0.42	0.45	1.00											
Personal G.	0.51	0.57	0.53	0.54	0.54	1.00										
Industrial G.	0.59	0.67	0.54	0.62	0.55	0.68	1.00									
Media	0.47	0.57	0.43	0.51	0.47	0.54	0.65	1.00								
Oil and G.	0.62	0.58	0.50	0.54	0.47	0.59	0.71	0.58	1.00							
Travel	0.46	0.56	0.46	0.49	0.49	0.60	0.64	0.56	0.57	1.00						
Real Estate	0.39	0.49	0.38	0.46	0.45	0.46	0.58	0.53	0.51	0.48	1.00					
Trade	0.38	0.46	0.38	0.41	0.40	0.51	0.52	0.44	0.45	0.44	0.42	1.00				
Construction	0.54	0.65	0.50	0.59	0.54	0.62	0.75	0.65	0.65	0.63	0.57	0.49	1.00			
Telcom.	0.37	0.41	0.36	0.37	0.40	0.42	0.55	0.49	0.51	0.48	0.40	0.29	0.50	1.00		
Utilities	0.52	0.55	0.51	0.51	0.52	0.57	0.71	0.59	0.69	0.61	0.54	0.40	0.65	0.58	1.00	
Others	0.63	0.70	0.57	0.64	0.59	0.68	0.85	0.72	0.84	0.70	0.63	0.51	0.80	0.66	0.86	1.00

TABLE 1. CREDIT EXPOSURE

	2010	2011	2012	2013	2014	2015
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Trade	12.7	12.8	13.1	13.8	14.3	14.4
Media	0.6	0.6	0.5	0.5	0.4	0.4
Travel and leisure	4.1	3.9	3.9	4.0	3.9	4.0
Telecommunications	1.0	1.0	0.8	0.8	0.8	0.9
Utilities	4.8	5.4	5.9	5.6	6.0	5.7
Real estate	12.8	12.5	12.5	12.2	11.7	11.2
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FIG 1. CREDIT RISK MEASURES: EL AND ITS COMPONENTS

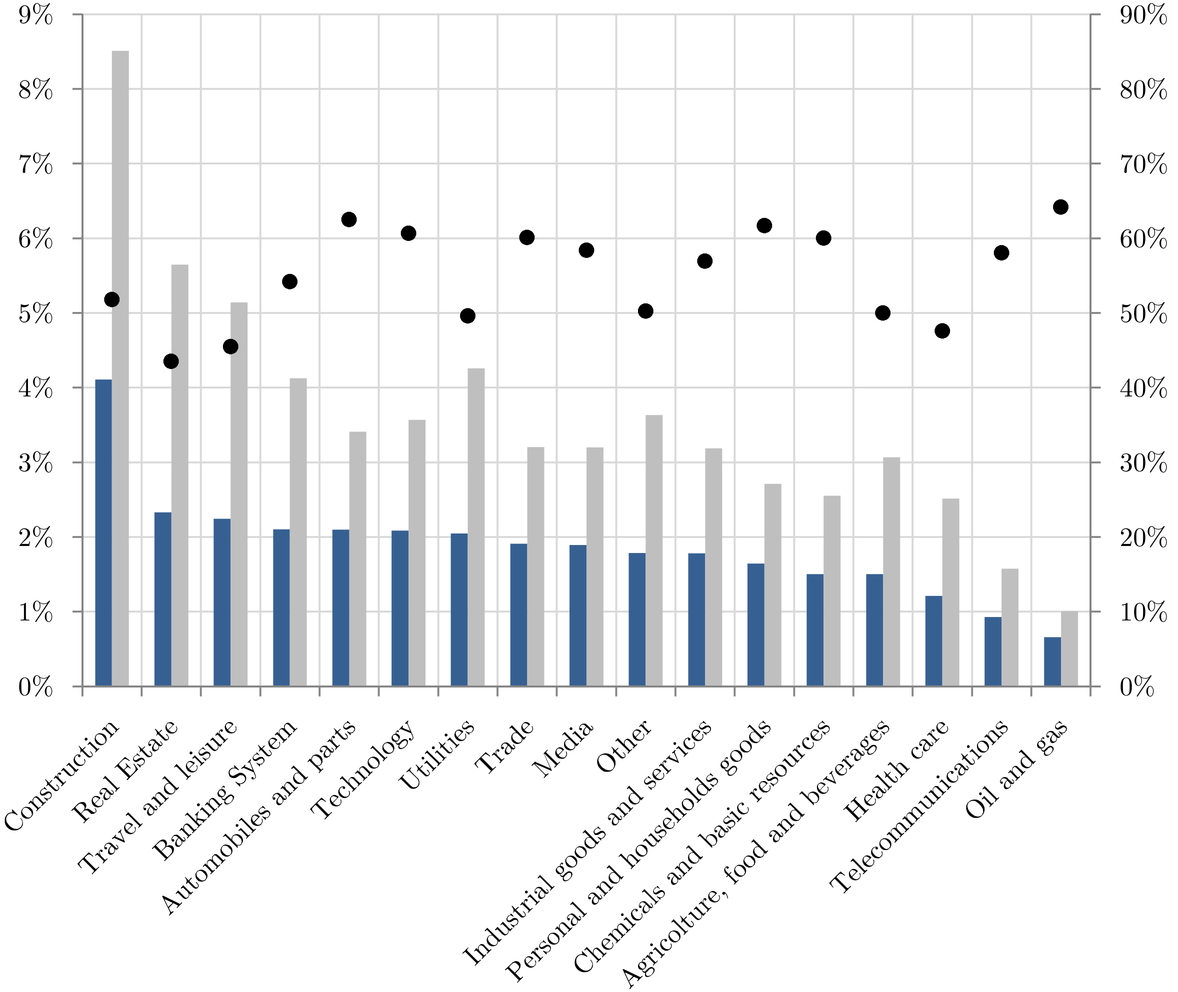


Figure 1 reports average EL rate (dark blue bars, left axis), PD (light grey bars, left axis) and LGD (black dots, right axis) by sector. Sectors are sorted by decreasing level of EL rate. EL rate were computed as the product between firm-level PD and exposure-level LGD at Dec. 2015.

FIG 2. CREDIT RISK MEASURES: ES AND ITS COMPONENTS

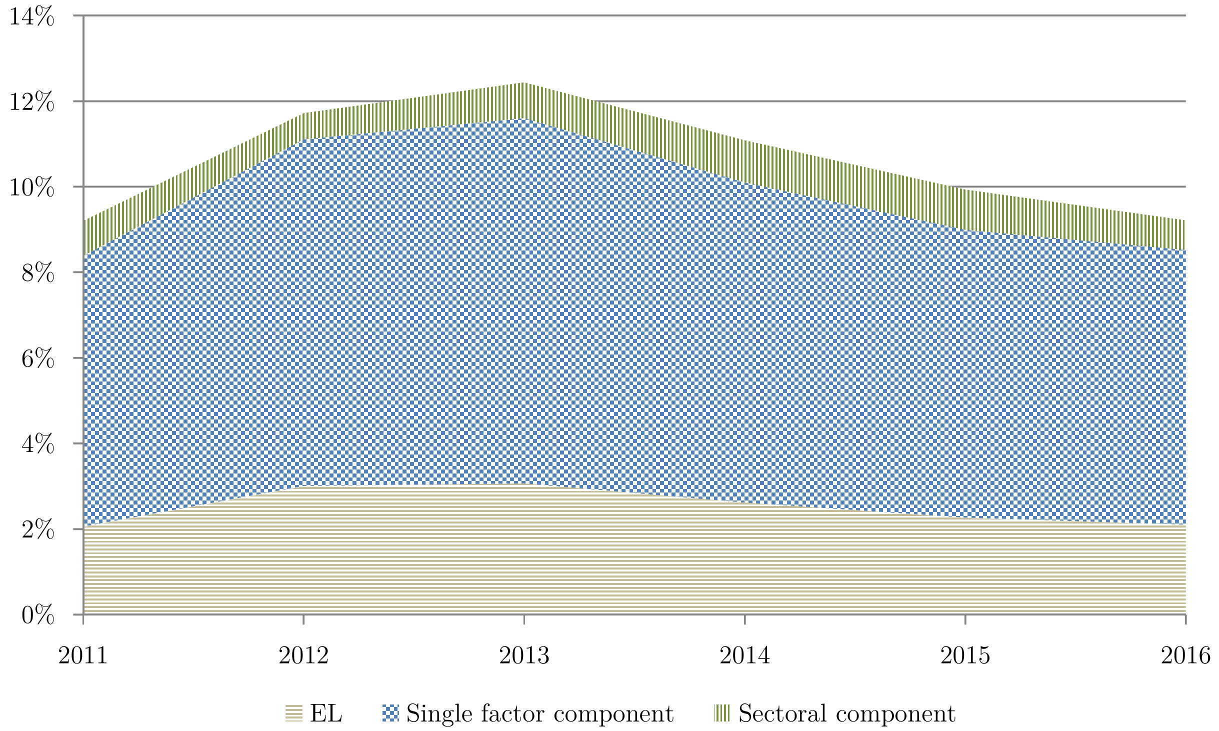
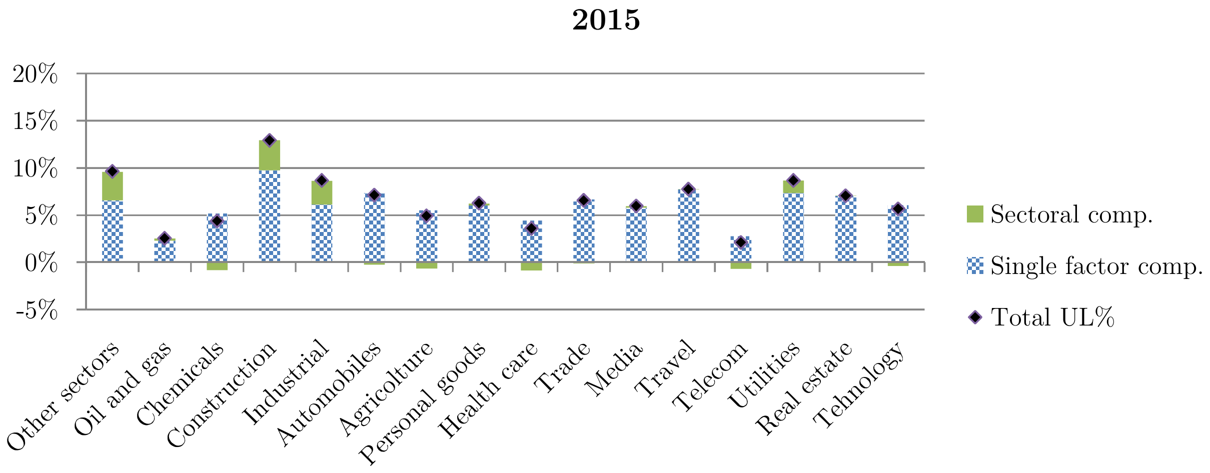


Figure 2 shows ES estimates under multi-factor model using Monte Carlo simulations. The overall ES is decomposed into its elementary components, i.e. EL, the product between firm-level PD and exposure-level LGD; the component obtained under the single-factor model; the sectoral component.

FIG. 3 SECTORAL UL% AND ITS COMPONENTS



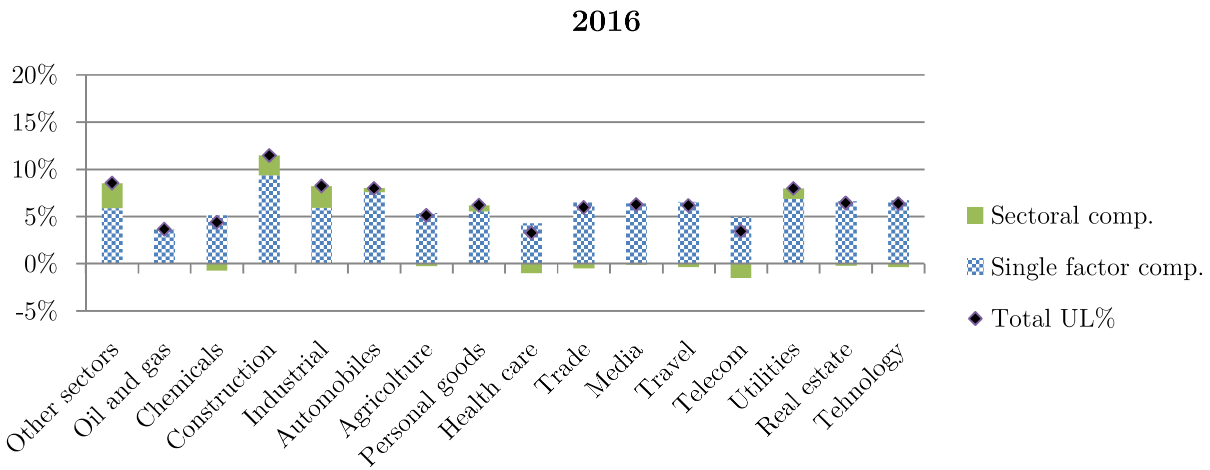
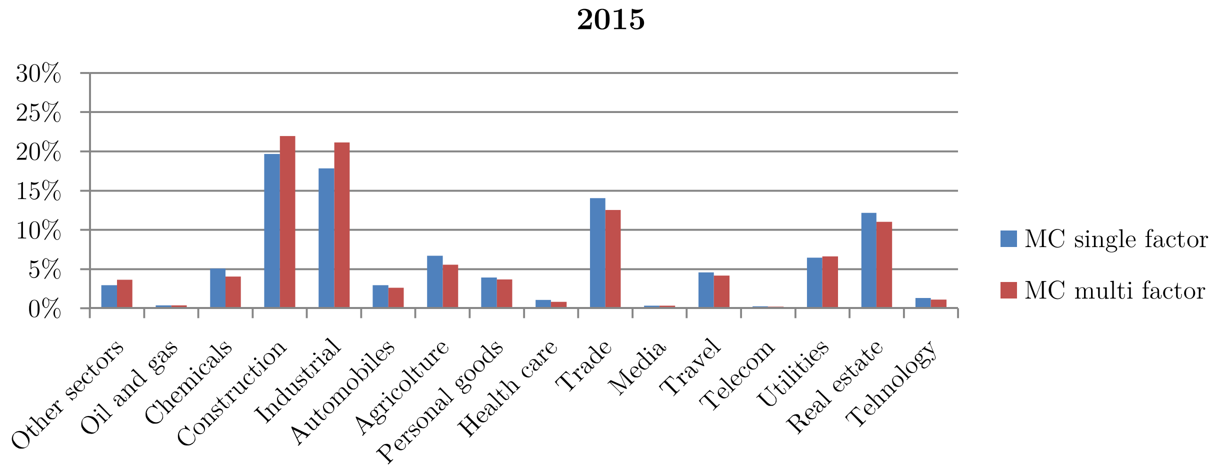


Figure 3 shows UL estimates sector by sector under multi-factor model using Monte Carlo simulations. The overall UL is decomposed into its elementary components, i.e. the component obtained under the single-factor model and the sectoral component.

FIG. 4 SECTORAL MC UNDER SINGLE AND MULTI-FACTOR MODEL



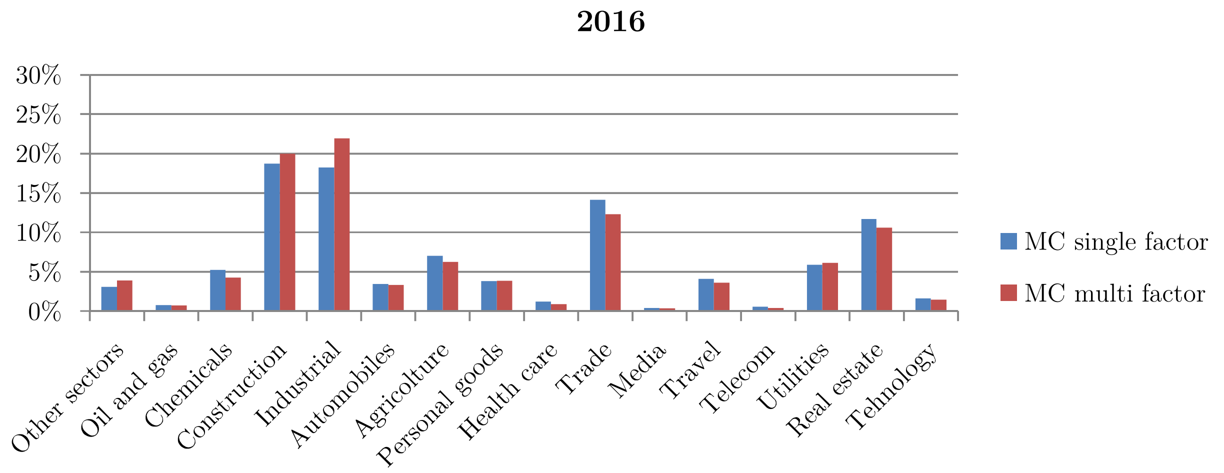


Figure 4 shows the marginal contribution (MC) of each sector to the total ES under single and multi-factor models.

FINAL REMARKS

Measuring concentration and sectoral risk can help to spot and prevent excessive credit growth and concentration of credit risk that are a threat to the stability of a single institution and for the banking system

With micro data at hand, sectoral risk analysis can adopt standard risk-management techniques used by banks risk management desks, such as VaR or ES, that enable us to consider credit risk at the bank portfolio level, to aggregate the individual bank risk measures at system level and to drill down to marginal measures of sectoral risk

Computing sectoral risk with micro data requires granular information on credit, but also balance sheet data and market data. In particular balance sheet data can be used for the estimation of individual PD and LGD.

Thank you for your attention!

For any question or suggestion you can contact me at:

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Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

IFC-ECCBSO-CBRT Conference on *"Uses of Central Balance Sheet Data Offices' information"*

Co-organised by the IFC, the European Committee of Central Balance Sheet Data Offices (ECCBSO) and the Central Bank of the Republic of Turkey (CBRT)

Özdere-İzmir, Turkey, 26 September 2016

Bank quality, judicial efficiency and borrower runs: loan repayment delays in Italy[1]

Fabio Schiantarelli, Boston College and IZA, Massimiliano Stacchini, Bank of Italy
and Philip E. Strahan, Boston College and NBER

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

Bank Quality, Judicial Efficiency and Borrower Runs: Loan Repayment Delays in Italy

Fabio Schiantarelli, Boston College & IZA

Massimiliano Stacchini, Bank of Italy

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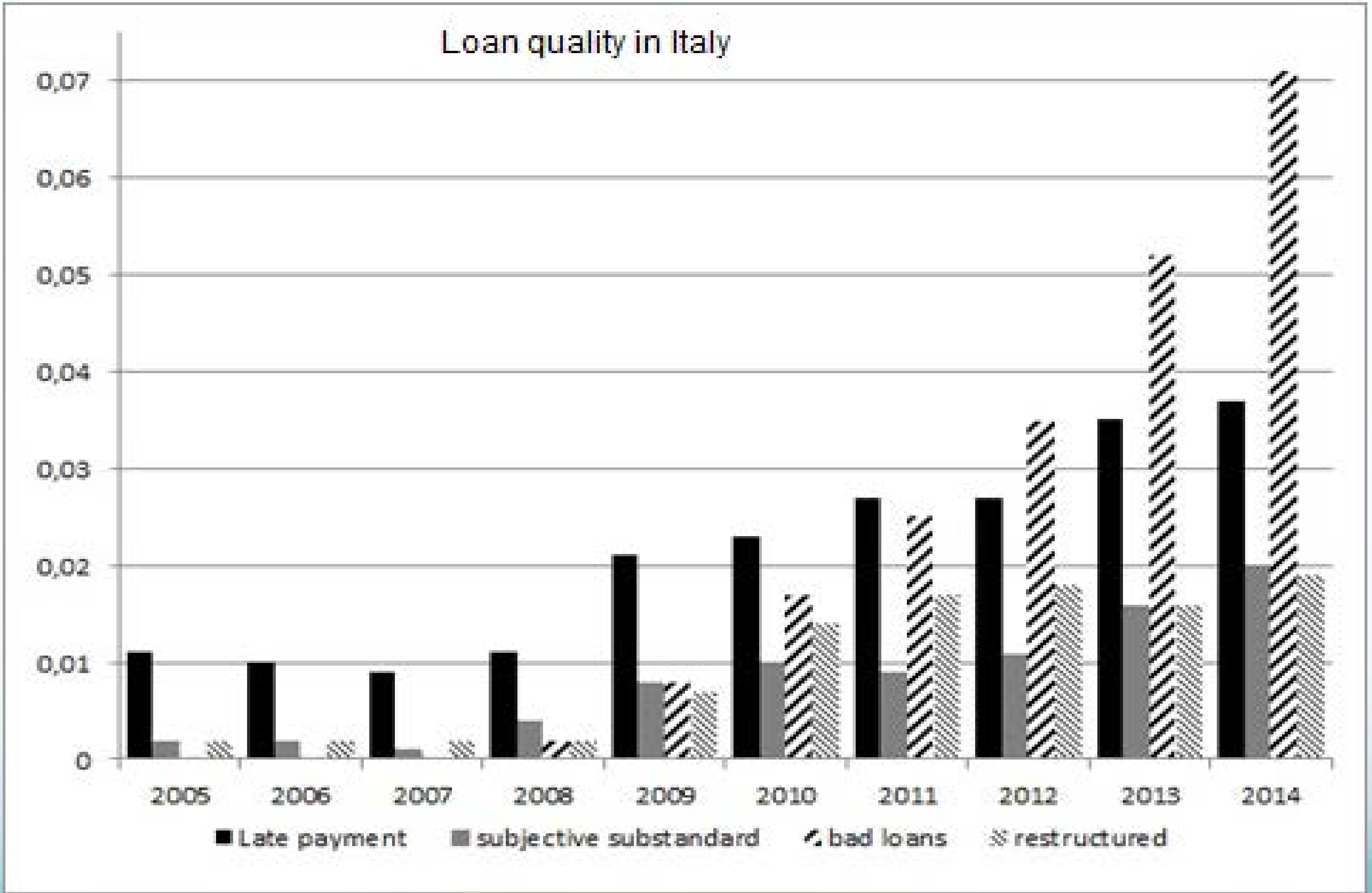
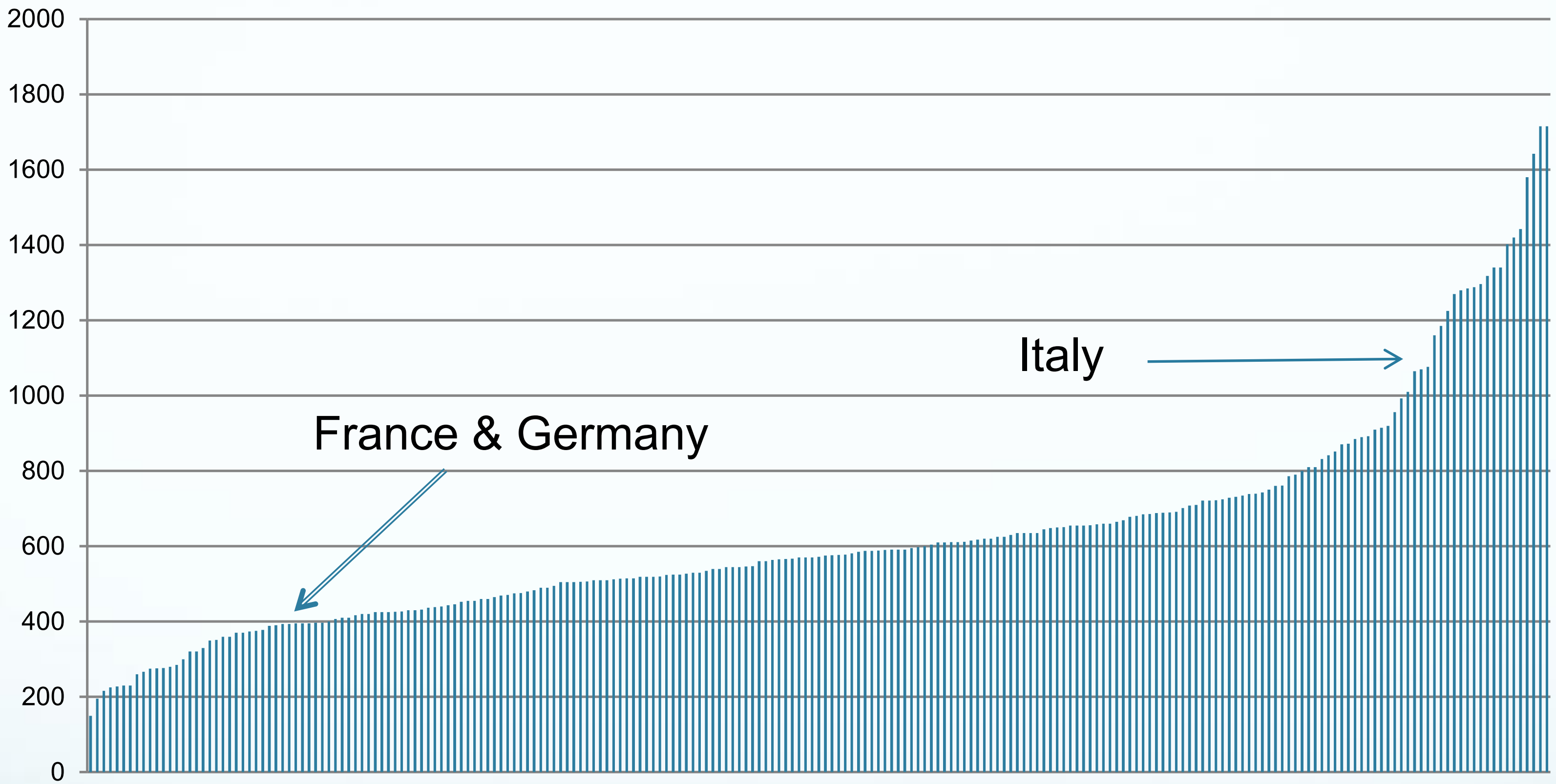


The recession has left a legacy of non-performing loans on Italian banks’ balance sheets.

World Bank Development Indicator: Time to Enforce a Contract



“The snail’s pace of Italy’s courts throws sand into the wheels of the economy in myriad ways. Banks struggle to resolve bad loans because bringing deadbeat debtors to court takes far the longest in Europe (WSJ, 2014).”

Legislative reforms in 2015 and 2016

“One factor that until now has played a role in the growth of the stock of non-performing loans has been the slowness of insolvency and recovery procedures.

The legislative reforms introduced last summer and those approved at the beginning of this month serve to speed them up.

With the out-of-court assignment of property pledged by firms as collateral, recovery times could shrink to a matter of months from the previous estimate of more than three years, already reduced by last summer’s reforms.”

I. Visco (The Governor’s Concluding Remarks, 2016)

What makes Banks Fragile?

- Standard story: Liquidity Risk

- Depositor runs a la Diamond and Dybvig (1983)
- Interbank market "freeze" (Iyer et al, 2013)
- Lines of credit (Kashyap, Rajan and Stein, 2001; Gatev and Strahan, 2006)

Liquidity risk in the financial Crises

- Gorton & Metrick (2010)
- Ivashina & Scharfstein (2011)
- Ippolito, Peydro, Paolo and Sette (2014)

Our question: Can Bank Fragility Stem from Provision of <u>Credit</u>?

Theory says 'yes';

Borrower may fail to repay lender if

- lender is perceived to be weak, i.e. unlikely to lend in the future
- lender's enforcement capacity is limited.

Bond and Rai (JDE, 2009)

Trautmann and Vlahu (JBF, 2013)

Carrasco and Salgado (JFE, 2014)

Little empirical support for this idea

Main Results

- New channel through which credit risk might enhance bank fragility.
- Borrowers <u>delay their loan repayments (default) selectively</u>: probability increases in banks weakened by past bad loans.
  - Effect is stronger for large borrowers
- Selective default is evident only where <u>legal enforcement is weak</u>.
  - We exploit local variation in enforcement across Italy
- Effect reflect <u>borrower</u> choice NOT <u>lender</u> choice

Why Italy?

- Massive increases in <u>borrower distress</u> during the "Seven years' War".

  - Manufacturing lost 17 percent of its productive capacity.

  - Net job destruction reached almost one million

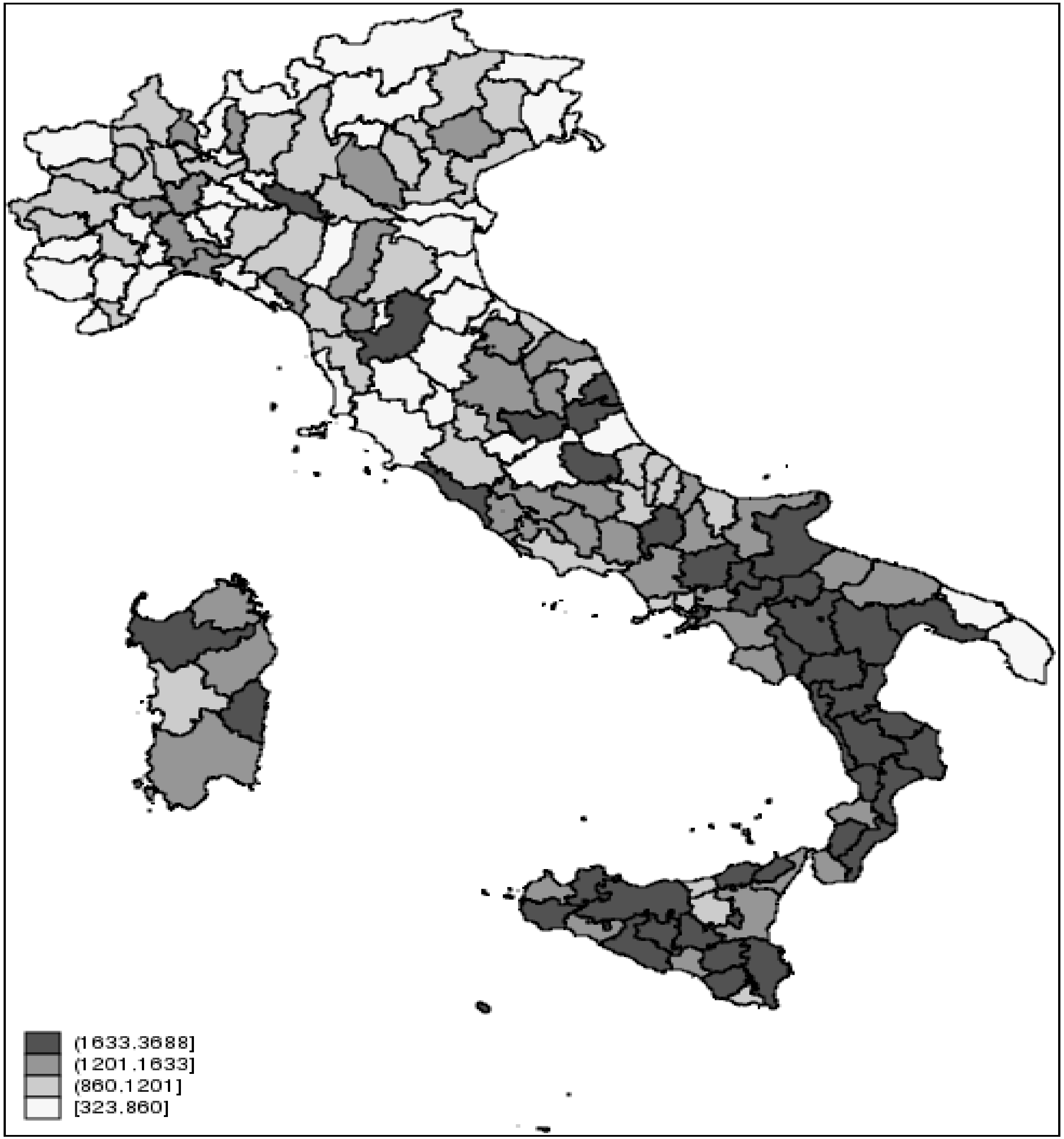
- <u>Data</u>: Detailed information on outcomes at the loan-level

- <u>Multiple lending</u>: Firms very often borrow from more than one bank in Italy

- <u>Enforcement</u>

  Varies widely across Italy

Length of Property Execution Proceedings (# of days)



Identification: two challenges

- Weak borrowers may be matched to weak banks
  - Firm-time (multiplicative) effects fully remove any variation in borrower health
- Want to focus on borrower’s choice to default
  - Dependent variable leaves out bank decision on loan classification

Identification (Empirical Model)

- We want to focus on selective default, so we look within borrower-quarter

$$y_{i,b,t} = \sum_{k=1}^{K} \alpha_k x_{b,t-1} + \theta_{i,t} + \delta_b + \varepsilon_{i,b,t}$$

- $y_{i,b,t}$ = 1 if loan payment is late or overdrawn with the bank;
  = 0 if performing

Identification (Model, cont'd)

- Control for borrower fundamental with firm-time fixed effects (a la Khwaja and Mian, 2008)
- Control for bank effects
- Focus on the effect of time-varying measure of bank health ($X_{b,t-1}$)
  - With firm-year effects, regression driven by firm choice as to which bank not to pay.
- And, we introduce interactions to look at firm characteristics, relationships, and legal enforcement

Identification: Where is variation coming from?

- Firm pays all its banks

  No, removed by firm*time effect

- Firm defaults on all banks

  No, removed by firm*time effect

- Firm that defaults on one bank but pays the other

  Yes, fixed effect will not perfectly explain these observations

Variation driven by differences in bank characteristics

This is what we mean by '<u>Selective Default</u>'

Data

Sample: About 32,000 firms, from 2008 to 2013.

Source: Balance Sheet Register,

99% unlisted; firms account for more than 75% of total net revenues of Italian incorporated firms

Median firm has 50 employees

Match to:

- loan level data from Credit Register, Bank of Italy
- bank level data from Supervisory Reports, Bank of Italy

Solvency: Capital/assets, Bad loans/assets, Loss on sovereign bonds/assets,

Profitability: Profits/Equity

Liquidity: (Retail deposits and bonds with households)/assets;

(Cash and bonds)/assets

Size: Log Assets

Baseline Regression

DepVar: Delay

	Without Profits	With Profits
Capital/assets	0.021	0.037
Bad loans/assets	0.114**	0.099**
Sovereign losses/assets	0.002*	0.003
Profits	-	0.001
Deposits/assets	0.002	0.002
(Cash+bonds)/assets	-0.006	-0.012
Log of Assets	-0.001	-0.001
Share from Bank	0.012***	0.014***
Bank Effects	Y	Y
Firm-Time Effects	Y	Y
Observations	2,656,566	1,066,184
Cluster	By Bank	By Bank

Economic Impact

- Increase of bad loans/assets from 25th to 75th Percentile = 0.05
- Estimated effect on default = 0.05 x 0.114 = <u>0.5%</u>
- <u>Large</u> relative to mean default rate of 3% (~16 percent increase from the mean)

Bank weakness matters more for large firms

Dep.var.: Delay

	Smallest	Medium	Large	Largest
Capital/assets	0.034	0.017	0.037	0.056
Bad loans/assets	0.076*	0.041	0.108***	0.138**
Sovereign losses/assets	0.002	0.004	0.003	0.004
Profits/assets	-0.003	0.009	-0.006	0.002
Deposits/assets	0.003	0.005	0.001	0.002
(Cash+bonds)/assets	-0.012	-0.022**	-0.007	-0.010
Log of Assets	-0.002	-0.002	-0.001	-0.001
Share from Bank	0.007***	0.008***	0.013***	0.025***
Bank-Firm/Type Effects	Y			
Firm-Time Effects	Y			
Observations	1,065,889			
Cluster	Bank			
P-value for F-test of Coefficient Equality	0.020			

Do results reflect legal inefficiency?

- Interact <u>Bank characteristics</u> with <u>Log of Days to Execute Property Disputes</u>
  - How long to repossess collateral?
  - Large variation across Italy
- Match by location of lender's head office

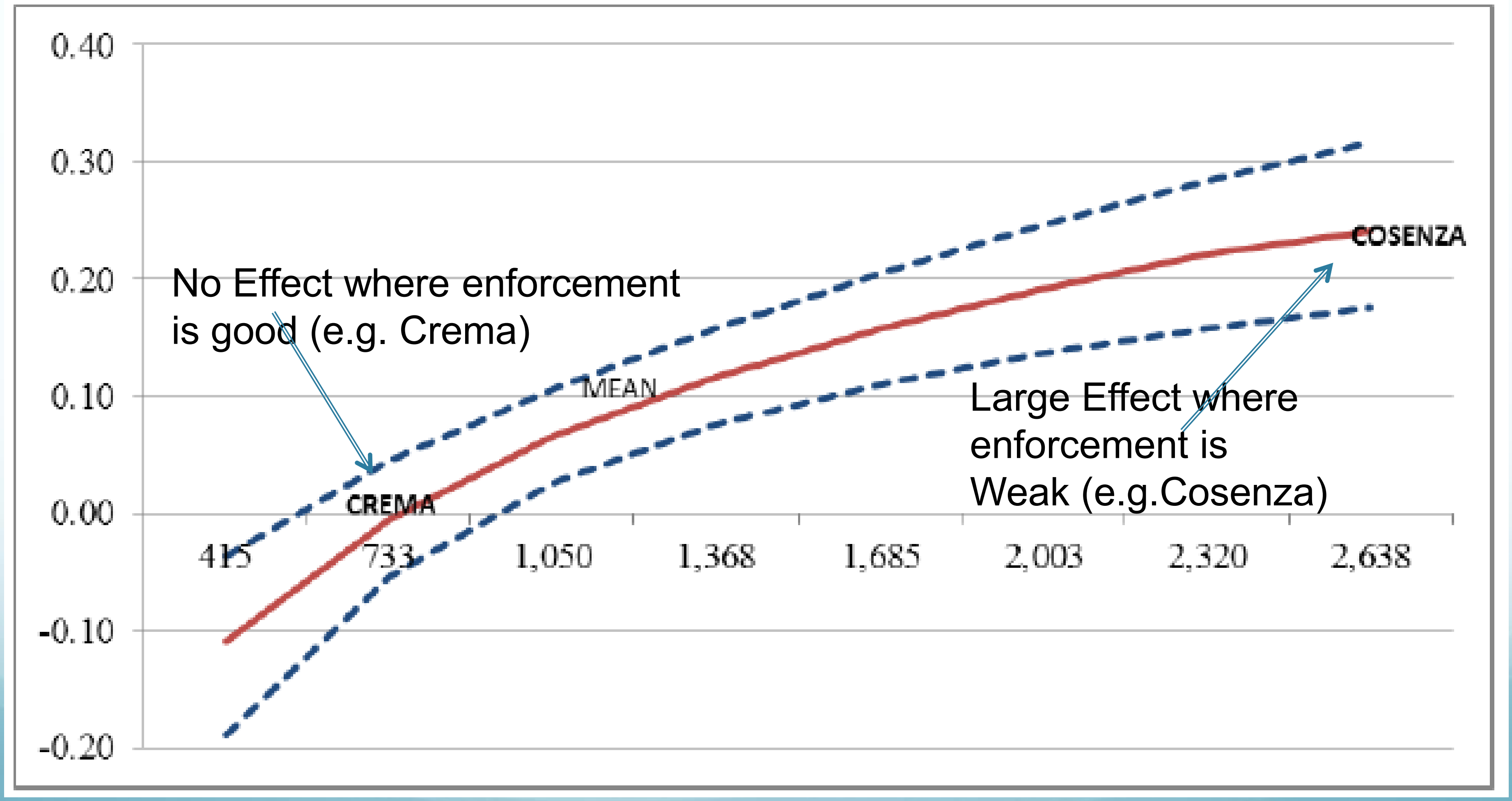
  ➔ Direct effect taken out by bank fixed effects
- Use 2007 data on legal efficiency (pre-determined)

  ➔ no mechanical relationship with losses in our sample

YES: Interaction with 2007 Legal Efficiency

	Without Profits	With Profits
Capital/assets	-0.398	-0.533
Capital/assets * Log Efficiency	0.060	0.082
Bad loans/assets	-1.301***	-1.063***
Bad loan * Log Efficiency	0.196***	0.162***
Sovereign losses/assets	0.004	-0.001
Sovereign Loss * Log Efficiency	-0.001	0.001
Profits/assets	-	0.017
Profit * Log Efficiency	-	-0.001
Deposits/assets	-0.057	-0.075*
Deposits * Log Efficiency	0.010	0.012*
(Cash+bonds)/assets	0.172*	0.069
Cash+bonds * Log Efficiency	-0.025*	-0.011
Log of Assets (Billions €)	-0.011	-0.013
Log assets * Log Efficiency	0.002	0.002
Share from Bank	-0.002	-0.005
Share * Log Efficiency	0.002	0.003
Bank Effects	Y	Y
Firm-Time Effects	Y	Y
Observations	2,656,566	1,066,184
Cluster	Bank	Bank

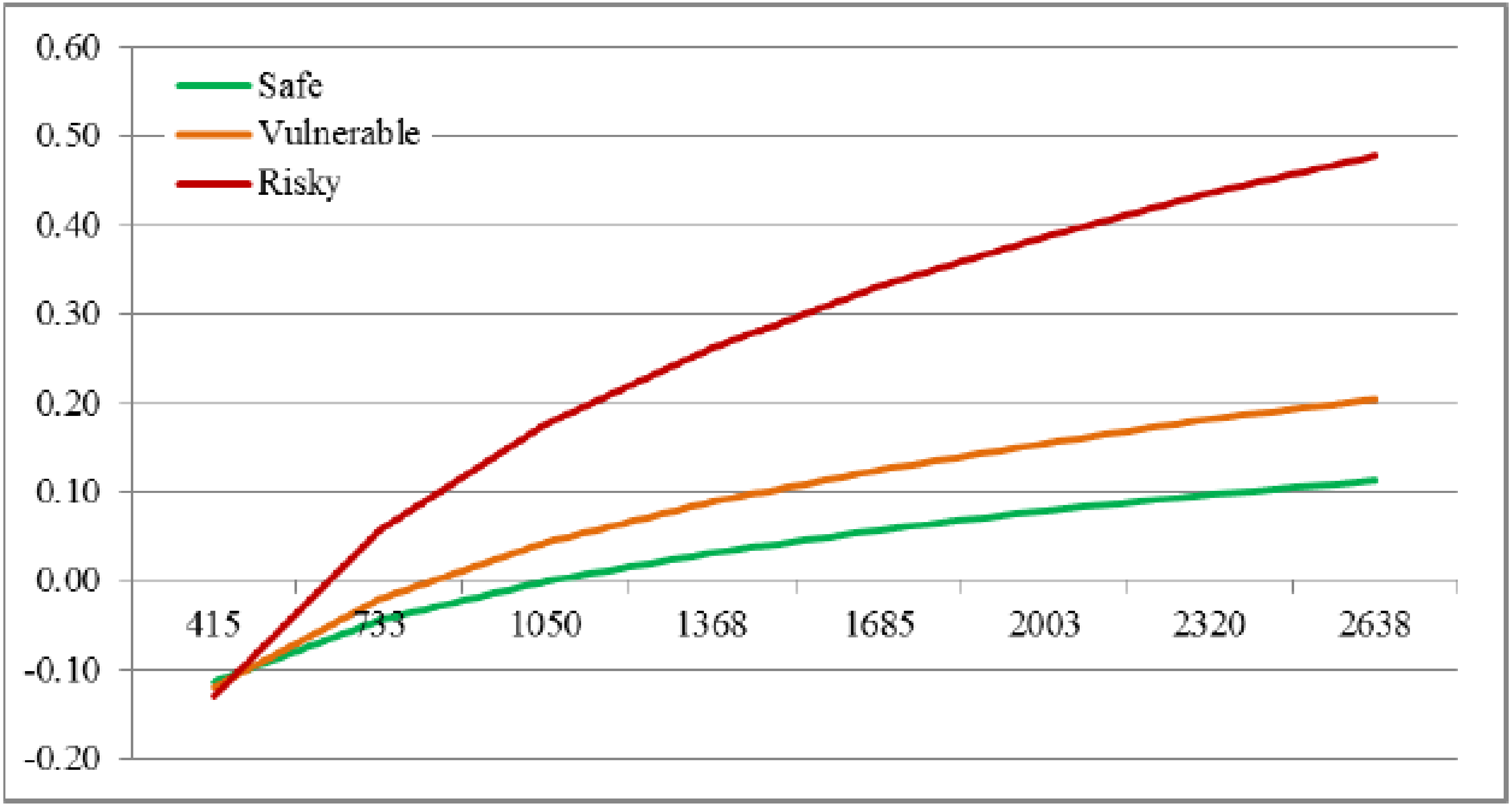
Magnitude of Bad Loans on Late Payment, by Legal Efficiency



Selective v. Strategic Default

	Without Profits	With Profits
Safe Firms (Strategic)		
Bad loans/assets	-0.873***	-0.576***
Bad loan * Log Efficiency	0.124***	0.082***
N	502,356	202,475
Vulnerable Firms (Selective)		
Bad loans/assets	-1.177***	-1.062***
Bad loan * Log Efficiency	0.177***	0.159***
N	1,597,259	641,802
Risky Firms (Selective)		
Bad loans/assets	-2.089***	-1.521***
Bad loan * Log Efficiency	0.322***	0.244***
N	556,951	221,907
Bank Characteristics X Inefficiency	Y	Y
Bank Effects	Y	Y
Firm-Time Effects	Y	Y
Cluster	Bank	Bank

Magnitude of Bad loans on Late Payment, by Legal Efficiency & Borrower Risk Type (Z- score)



Robustness Checks

- Use First Late Payment only
  - Because distressed banks may be slower to write off bad loans
  - (Once a loan goes into arrears, we drop all subsequent observations)
- Use Term Loans only
  - Because distressed banks might cut lines more aggressively, leading to defaults
- Control for other Loan Terms
  - maturity, price, real collateral, receivables
- Results are robust to region (North v. South)
- Results similar with bank * firm fixed effect

Final remarks

- Banks can face ‘borrower runs’
  - Another dimension of bank fragility, related to credit provision rather than to liquidity provision
- Borrowers selectively default against weak banks
- This only emerges where Legal Enforcement is weak

- Our results point to Legal Enforcement as an additional component required to reduce fragility stemming from credit risk.

- Better enforcement might limit the use of mechanisms (i.e., lender of last resort facilities, deposit insurance) that might generate moral hazard costs.

- Controversial possibility: can too much transparency can be destructive?

Thanks !

Summary Statistics

	2008	2009	2010	2011	2012	2013
Loan Defaults						
Late Payments, all	1.90	3.00	3.10	3.20	4.20	5.90
Late Payments, term loans	1.30	2.10	2.20	2.30	3.10	4.20

	Mean	Q25	Q75
Bank Characterstics			
Capital/assets (solvency)	0.14	0.08	0.17
Bad loans/assets (solvency)	0.03	0.01	0.06
Sovereign losses/assets (solvency)	-0.08	-0.20	0.03
Profits/assets	0.02	0.01	0.04
Deposits/assets (funding liquidity)	0.60	0.41	0.86
(Cash+bonds)/assets (asset market liquidity)	0.16	0.06	0.25
Assets (Billions €)	36.00	0.14	2.60

Firm characteristics

	mean	p25	p50	p75
leverage	52	28	57	77
age	25	13	23	33
total assets	62,298	7,905	14,720	32,556
empl	153	24	49	106

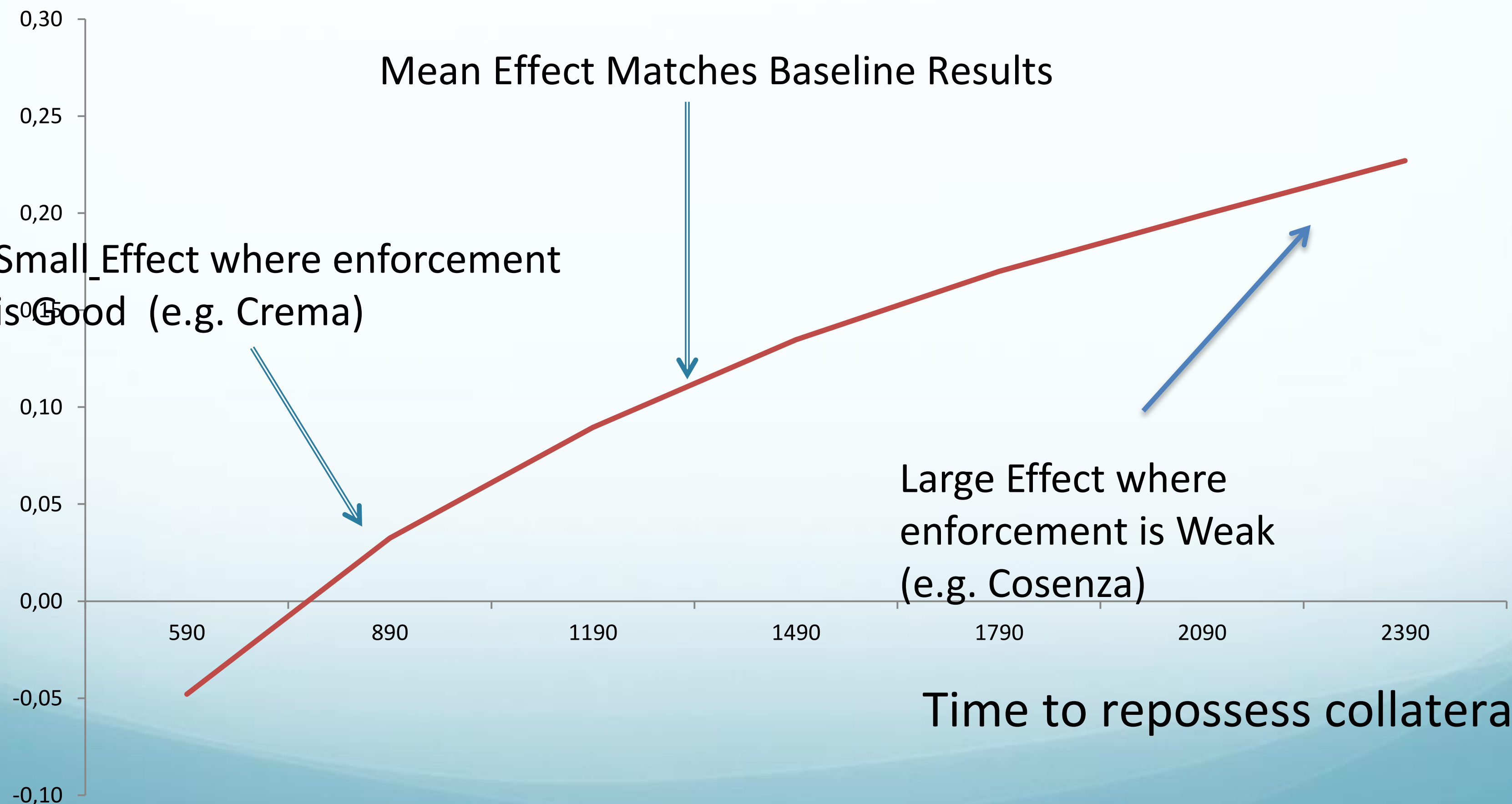
And for risky firms (split by z-score)

	Safe	Vulnerable	Risky
Capital/assets	-0.012	-0.008	0.134**
Bad loans/assets	0.021	0.096**	0.227***
Sovereign losses/assets	0.001	0.003**	0.003
Deposits/assets	-0.001	0.004	-0.001
(Cash+bonds)/assets	-0.004	-0.001	0.006
Log of Assets (Billions €)	-0.001	-0.001*	-0.001
Share from Bank	0.005***	0.012***	0.032***
Bank-Firm/Type Effects	Y	Y	Y
Firm-Time Effects	Y	Y	Y
Observations	502,356	1,597,259	556,934
Cluster	Bank	Bank	Bank

Main results
Selective Default Stronger where Legal Enforcement is Weak

∂ Prob (borrower delays loan repayment)

∂ Bank's accumulated bad loans



Bank Relationships in Italy

- Most firms have at least 2 relationships (our data)
- Typical number of banks in Italy is highest in EU (Ongena & Smith, 2000)
- But not correlated with Legal Enforcement variation within Italy

Do relationships mitigate selective default?

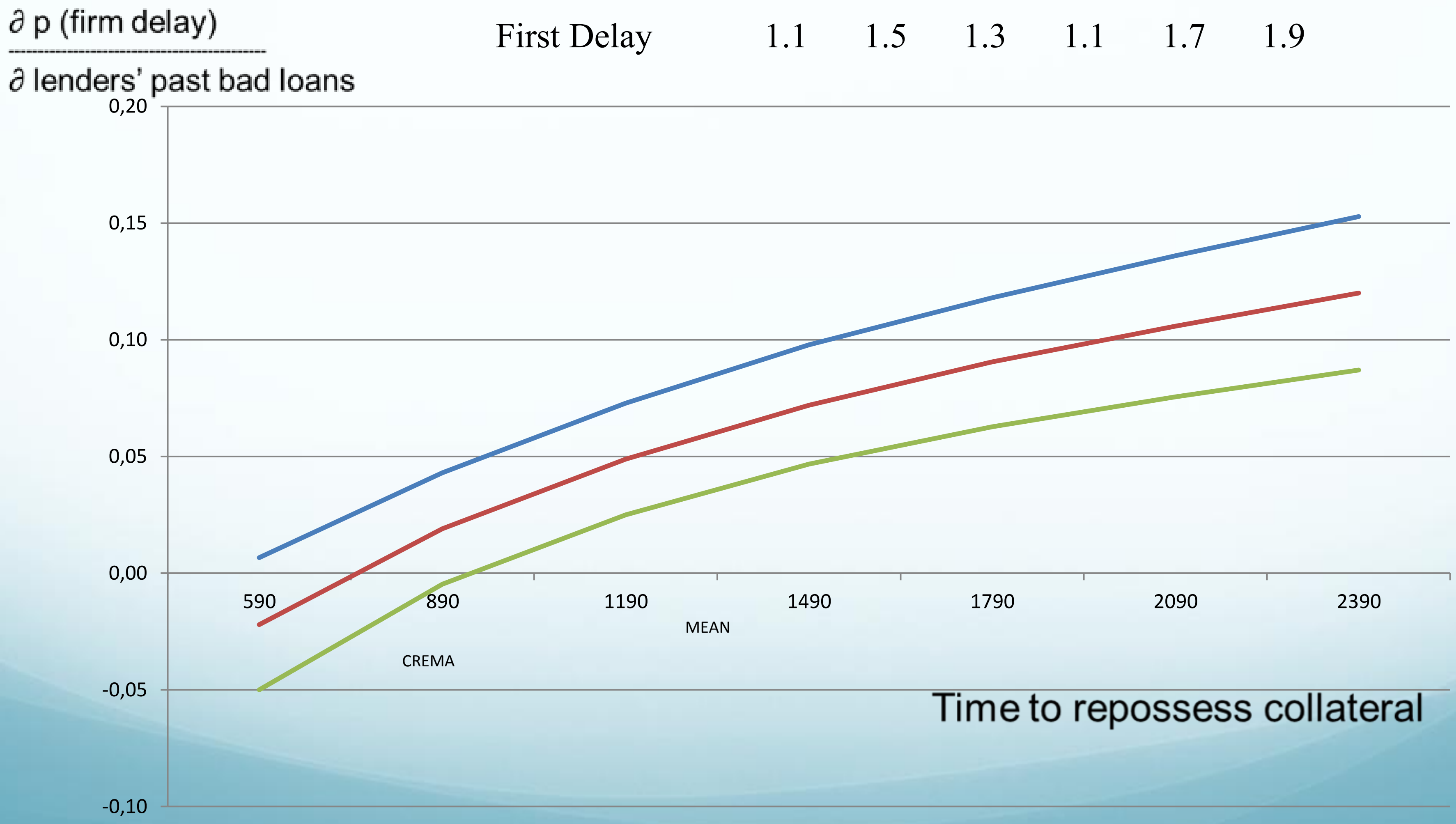
- Introduce interactions between bank’s share with bank-level characteristics

NO: Interaction with share

	Without Profits	With Profits
Capital/assets	0.034	0.050
Capital/assets * Share	-0.094	-0.095
Bad loans/assets	0.114***	0.102***
Bad loan * Share	-0.002	-0.020
Sovereign losses/assets	0.002	0.003
Sovereign Loss * Share	0.002	0.002
Profits/assets	-	0.006
Profit * Share		-0.039
Deposits/assets	0.004	0.005
Deposits * Share	-0.015	-0.016
(Cash+bonds)/assets	-0.008	-0.014
(Cash+bonds) * Share	0.020	0.021
Log of Assets (Billions €)	-0.001	-0.001
Log assets * Share	-0.001*	-0.002**
Share from Bank	0.038***	0.047***
Bank Effects	Y	Y
Firm-Time Effects	Y	Y
Observations	2,656,566	1,066,184
Cluster	Bank	Bank

First Delayed Repayment

	2008	2009	2010	2011	2012	2013
First Delay	1.1	1.5	1.3	1.1	1.7	1.9

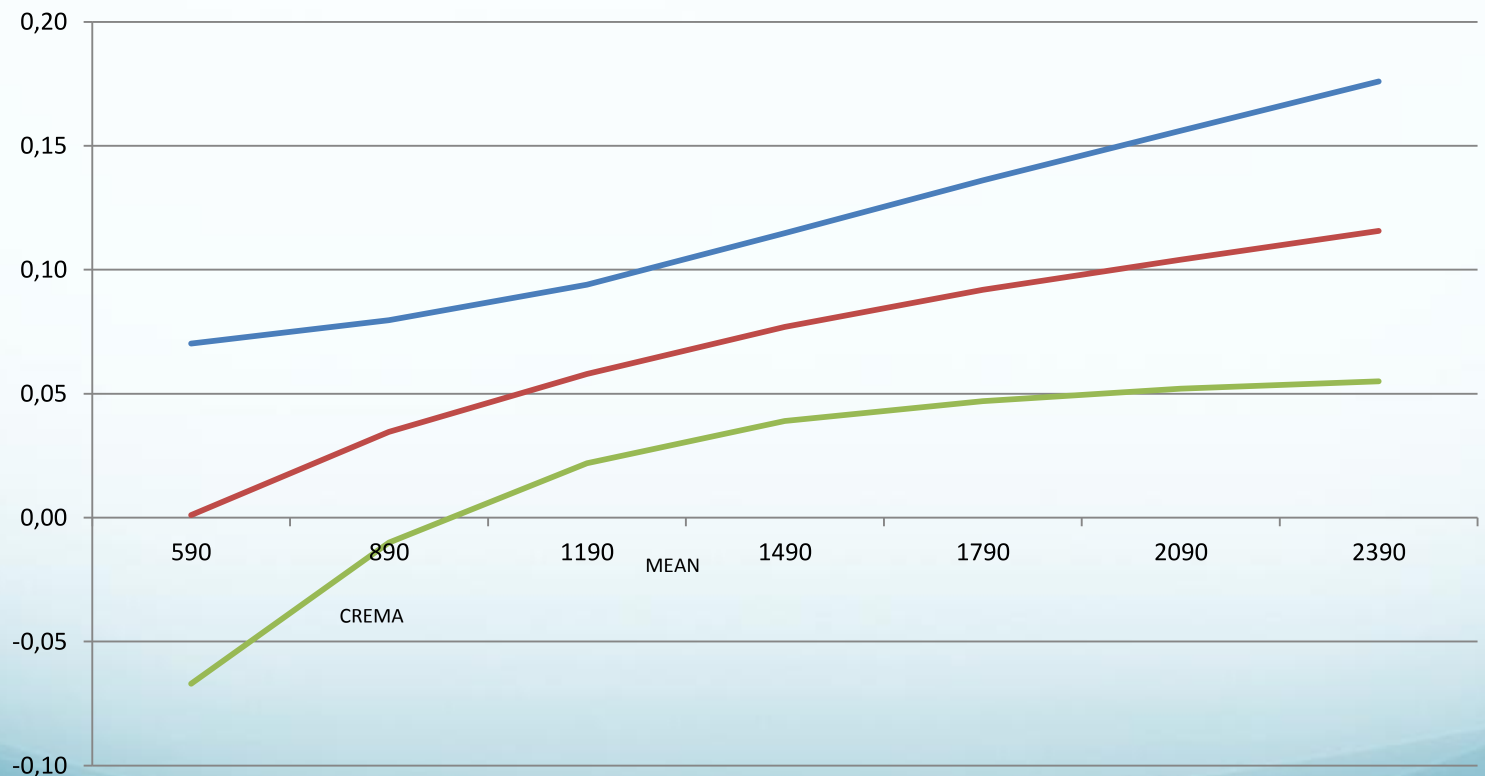


Term Loans Only

	2008	2009	2010	2011	2012	2013
Delay Term loans	1.3	2.1	2.2	2.3	3.1	4.2

∂ p (firm delay)

∂ lenders' past bad loans



Time to repossess collateral

Loan Transition Matrix

		Loan State at time 12/2014			
		Perf- orming	Past Due / overdrawn	Substandard / Restructured	Bad Loans
Loan State at 12/2013	Performing	92.39%	1.04%	5.67%	0.90%
	Past Due / overdrawn	**27.49%**	**13.70%**	**46.91%**	**11.90%**
	Substandard / Restructured	3.97%	0.22%	71.86%	23.94%
	Bad Loans	0.10%	0.01%	0.27%	99.62%

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Assessment of SMEs by credit institutions using CBSO (Central Balance Sheet Data Office) data[1]

Manuel Ortega, Bank of Spain

[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.

Assessment of SMEs by credit institutions using CBSO (Central Balance Sheet Data Office) data

A use case developed by the Banco de España

Manuel Ortega. Head of CBSO. Banco de España 2017.09.15

Abstract

Since 2016, Spanish credit institutions are obliged to use a harmonised risk assessment methodology established under a binding regulation approved by the Banco de España. The "SME-Financial Information" report that credit institutions must provide to SMEs that are to have their credit facilities reduced must meet certain requirements. Among other things, it must include the relative position of the company within its sector of activity. This note presents the full project developed by Banco de España and the content of the above report, more specifically, the part developed by the Banco de España CBSO using the BACH database methodology of the European Committee of Central Balance Sheet Data Offices (ECCBSO).

Keywords: CBSO (Central Balance Sheet Data Offices), financial statements, statistics, non-financial corporations, risk assessment, benchmark information, accounting data, XBRL files, BACH database

JEL classification: D80, G21

Contents

Promoting SME financing in Spain: legal precedent

Presentation of the project: legal precedent (Law 5/2015)

As a consequence of the financial crisis and the deterioration of the financial conditions facing non-financial corporations, the Spanish Government passed, in April 2015, Law 5/2015 on the promotion of financing to SMEs, aimed at easing access to financing for SMEs and increasing the alternative methods of financing. Among a vast variety of measures set out, some centred on the creation of legal support for new financing channels (asset securitisation, participating loans, crowdfunding, etc.). Other measures sought to reduce the information asymmetry gap, a problem specifically affecting SMEs, especially when small companies wishing to establish new financing relationships with commercial banks have to provide full financial information on their behaviour.

To that end, Law 5/2015 obliges credit institutions to provide a financial report on the financial situation and payment track record to SMEs that are to have their credit facilities reduced. More precisely, when commercial banks decide to reduce credit facilities, they must give 3 months' notice to the non-financial corporation and, at the same time, provide a document entitled "SME-Financial Information" ("Información financiera PYME", in Spanish). The law establishes an obligation for the Banco de España to standardise this document and to create a standardised methodology for the assessment of the credit quality of an SME (also including sole proprietors).

Banco de España banking regulation (Circular 6/2016): SME report and risk assessment methodology

In December 2015, the Banco de España, in fulfilment of the above obligation, published a draft regulation setting out the harmonised content of the report and of the risk assessment methodology, both developed by the Directorate General Banking Supervision with the participation of other departments of the Bank. After receiving the input and feedback of the different stakeholders from the private sector, the regulation was passed and published in the Official Gazette as Circular 6/2016, of 30 June 2016.

The content of the "SME-Financial Information" report must principally include the records available at the credit institution about the credit history of the company, such as:

- **Reporting to the Central Credit Register-CCR** (the information submitted monthly by all commercial banks to Banco de España's CCR, on loans and all types of credit provided to non-financial corporations, sole proprietors and households) about the particular SME concerned.
- **Information provided by the commercial bank to private data compilers** about the solvency history of the company.
- **Credit history, with all kinds of details** about the records for the last 5 years', including, for example: a) a list of all credit products arranged by the company, past and current, b) a list of unpaid loans, c) refinancing agreements, d) insurance contracts connected to financial flows, ….

- **Detailed movements over the last year** in all the financial contracts arranged by the company with the bank.
- **Credit rating** given, according to the harmonised methodology defined in the regulation.
- **Relative position of the company within its sector of activity**. The content of this part of the report will be detailed in the next section of this article.

The aforementioned report is highly confidential and can only be provided to companies that request it or that are to have their credit facilities reduced at this commercial bank. In the first case, when the report is prepared at the request of a company (that is, when the non-financial corporation asks for it), the commercial bank can apply a charge. Otherwise (when the commercial bank is obliged to prepare the report due to a reduction in credit), the report has to be prepared and provided free of charge to the SME.

As mentioned earlier, Law 5/2015 established an obligation for the Banco de España to develop a harmonised method of risk assessment to be applied by commercial banks when assessing loans to SMEs and sole propietors. In a nutshell, the method aims to assess, in a standardised manner, the credit quality of an SME.

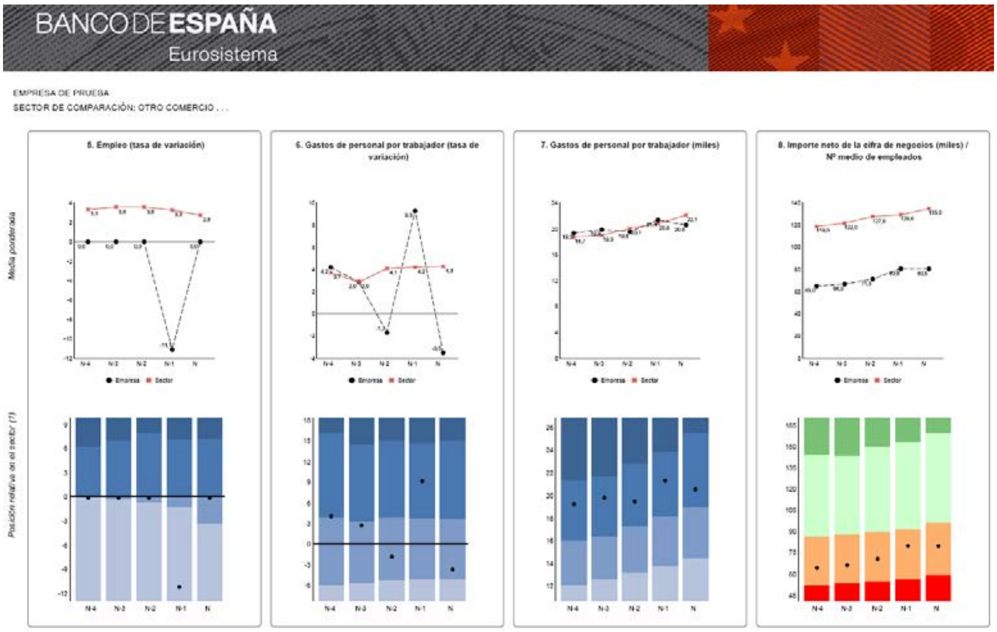
According to the method developed by Banco de España, which financial institutions are obliged to apply since 2016, three variables have to be taken into account:

- **Financial situation of the debtor**. For that purpose, financial corporations should use the financial statements officially filed by companies in the Mercantile Registers in Spain.
- **Qualitative variables**, such as years of relationship with the debtor, sector of activity where it operates, experience and track record with the shareholders of the company....
- **Behavioural variables**, like the existence of previous default and/or payment delays, overdrafts, other....
- Additionally, and as an objective measure of the financial situation, the commercial bank has to take into account the **relative position of the debtor in relation to companies of the same size and sector of activity**.

The result of the analysis must then be classified under one of the following levels or headings: "low risk", "medium-low risk", "medium-high risk", "high risk" and finally, "not available" (the latter applies when there is not enough information to deliver an opinion). The system introduces a degree of flexibility: each credit institution has to declare to the regulator (Banco de España) the relationship in respect of these levels and the 3 groups of variables defined in the method. Those interested in learning about the full details of the method applied can find them (only in Spanish) in Circular 6/2016, http://app.bde.es/clf_www/leyes.jsp?id=155613&tipoEnt=0).

Position of the debtor within its sector of activity. Available past experience: BACH database and XBRL data

As part of the “SME-Financial Information” report, the information about the position of the company in relation to its sector of activity and size has become an important part of the method, due to its intrinsic homogeneity, if it were defined properly. More precisely, financial and risk analysts, in addition to their opinion derived from qualitative and behavioural information, can base part of their assessment on unquestionable statistical data: the position of a company inside a population distribution. In April 2015, the Banco de España´s CBSO participated in the interdepartmental working group created by the Bank to define the content of the risk assessment methodology. The CBSO contributed its experience, since 1984, in the preparation of benchmark studies provided to the companies contributing to its surveys and databases. Annually, these companies receive, in return for their collaboration on the CBSO survey, an individual study showing their behaviour in relation to companies of the same sector and size, in weighted average terms and in relation to the statistical distribution. For a set of selected economic and financial ratios, the company can observe graphically whether it belongs to the best-positioned (those above the third quartile of the statistical distribution) or the worst-positioned companies (those below the first quartile).



The participation of the CBSO in the aforementioned working group was based on the following:

- **Graphic benchmark analysis.** Preparation of a visual technical solution similar to the individual study provided to the Spanish non-financial corporations (the benchmark study previously mentioned).

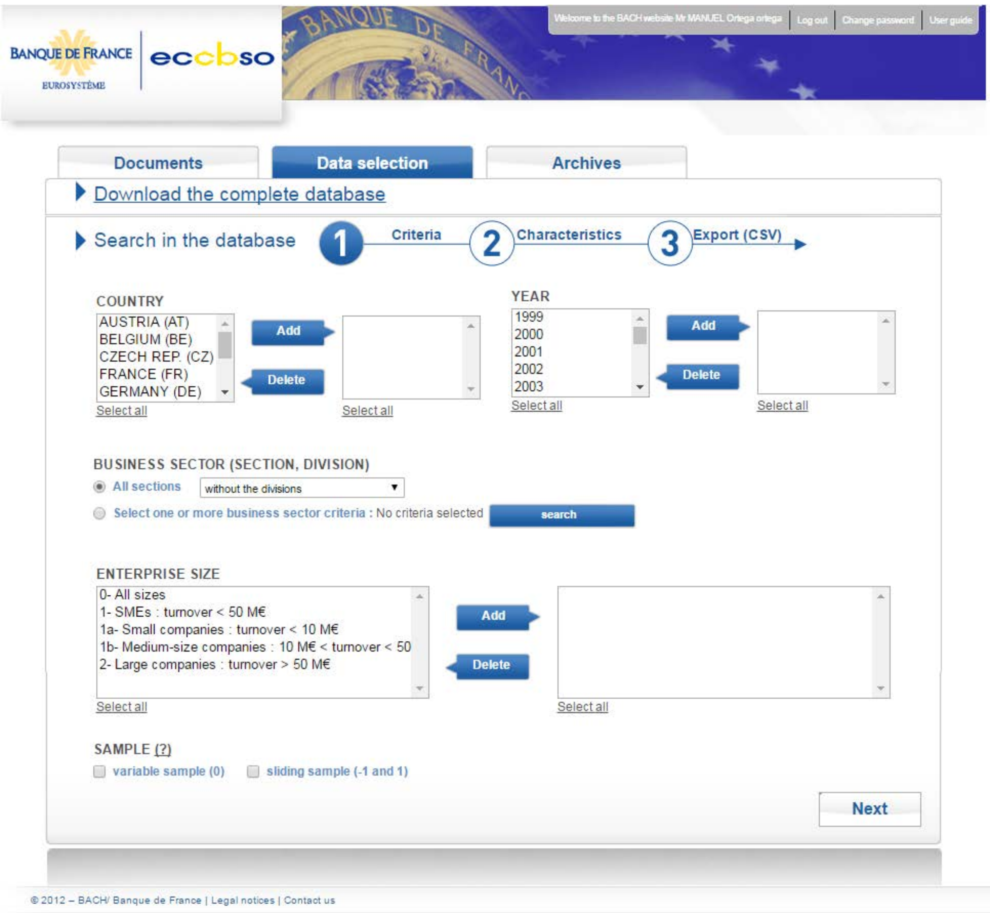
- **Homogeneous ratios definitions.** Selection of economic and financial ratios from a European database and well-tested methodology: BACH database of the European Committee of Central Balance Sheet Data Offices, to which Banco de España's CBSO has contributed since its inception, in 1987.
- **Use of available information.** Definition of the ratios in a simplified version, in order to use the official information available: the statutory deposit of the annual accounts in the Mercantile Registers, in electronic format (XBRL)
- **Tool free of charge, using electronic standards.** Development of a user-friendly tool (Excel) to facilitate its immediate use by credit institutions that prefer not to develop their own internal IT solution, and to use the XBRL files available in the Mercantile Registers for that purpose.

Homogeneity ratios definition: use of BACH database methodology

From April 2015 to October 2015 several meetings were organised internally with different areas of the Banco de España and with credit institutions, in order to define the risk assessment methodology. With respect to the study of the position of the debtor in relation to its sector of activity, it was decided to define several areas of analysis and to select commonly used ratios for each. The areas selected were (those interested in the list of ratios and definitions can find them in "Circular 6/2016, anejo 3", and on the Banco de España website, http://www.bde.es/bde/en/areas/cenbal/, under the heading "Template of report on borrower position"): activity, margins, profitability, liquidity, working capital, indebtedness, solvency and interest repayment capacity. Finally, 9 ratios were defined.

Once the areas had been selected, the precise definition was established according to the BACH methodology. According to the website of the ECCBSO (www.eccbso.org), BACH (Bank for the Accounts of Companies Harmonized) "is a database containing harmonised annual accounts statistics of European non-financial enterprises. Hence, the database was conceived as a useful tool both for country comparisons and to analyse the structure and performances of the non-financial companies in Europe". The database includes aggregated values from the income statement, balance sheet and financial ratios, in absolute values, weighted averages and quartiles, from 10 European countries (Austria, Belgium, Czech Republic, France, Germany, Italy, Poland, Portugal, Slovakia and Spain). The period covered is from 2000 onwards, providing details for breakdowns by four size classes (Small, Medium, SMEs, Large) and business sectors (NACE sections and divisions).

The below image captures the homepage of the BACH database, hosted by Banque de France on its website, freely available for all users. The same information, but only relating to the Spanish figures, can be found and accessed free of charge on the Banco de España website, under the heading "Sectorial ratios of non-financial corporations (RSE database); the main difference between the two databases is that the version available on the Banco de España website offers more details according to the sector of activity (3 digits NACE, instead 2 digits BACH). **The RSE database is the result of collaborative work between by Banco de España's CBSO and the Spanish Mercantile Registers.**



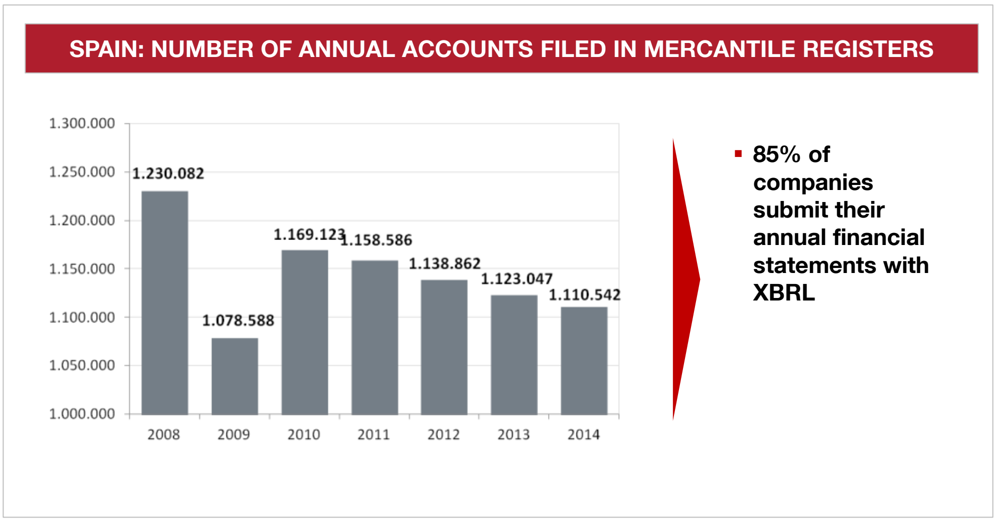
Use of the information available about companies: official data deposited in Mercantile Registers (XBRL files)

Since 1991 Spanish companies are obliged to deposit their annual financial statements (balance sheet, income statement, cash flow and annex) in the Mercantile Registers. The Banco de España´s CBSO, in collaboration with them and with the national accounting standards setter (ICAC, Instituto de Contabilidad y Auditoría de Cuentas), under the legal umbrella of the Ministry of Justice, maintains the official formats for such depositing that are used by all companies in Spain. SMEs have to use an abridged version of the format, which since 2008 is also available in electronic format, under the XBRL standard[1]. For that purpose, all the aforementioned institutions collaborate with the XBRL Spanish association, preparing annually the XBRL taxonomy that "translates" into digital language the prescriptions established in the accounting regulations and annual changes thereto.

Finally, every year over 800,000 companies deposit their annual accounts in XBRL files with the Mercantile Registers. The definitions of the ratios selected in the project,

[1] Those interested in learning more about XBRL can obtain information on the websites of the non profit international organization XBRL Int (https://www.xbrl.org/), or of the Spanish XBRL association (http://www.xbrl.es/es/)

taking into account the BACH methodology, have been adapted to use the information available in the XBRL files. Finally, **the 9 ratios selected can be calculated using 15 variables of the balance sheet and 11 variables of the income statement that all Spanish SMEs have to submit in the statutory deposit**: no extra work is necessary from the companies and/or the credit institutions to obtain the ratios of the new risk assessment method.



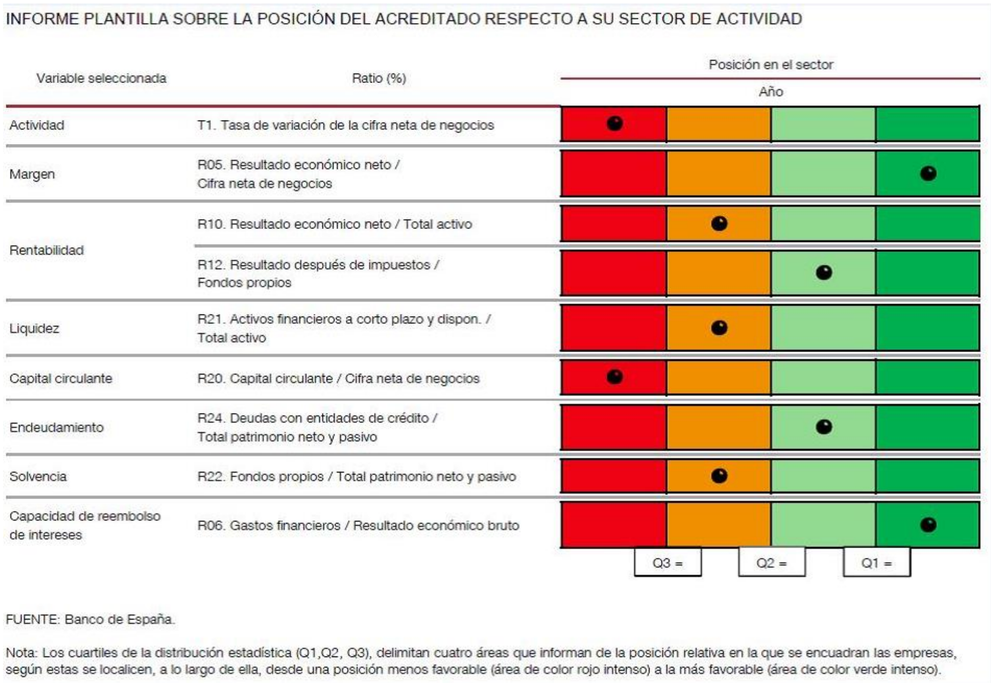
Technical solution for financial institutions and non-financial corporations: Excel/XBRL tool freely available on the web

In order to introduce the new regulation with the least possible impact on the risk assessment process of financial institutions, the Banco de España introduced the system with a long period of preparation and distributed a self-developed tool to ease the introduction of the new system. The first internal meetings among the Banco de España departments involved took place in April 2015. Afterwards, from June 2015 to October 2015 several meetings and exchanges of opinion with the credit institutions made it possible to take into account the opinion of their experts. Finally, in December 2015 the draft regulation was published for public comment; in June 2016 the regulation was approved.

The second measure taken in order to ease the introduction of the new methodology was to create a freely available tool, developed using an Excel file with XBRL embedded solution (the tool is available at http://www.bde.es/bde/en/areas/cenbal/). The tool allows:

- **Automatic uploading of non-financial corporation data.** Introduction of non-financial corporation data (15 items of the balance sheet and 11 of the income statement) can be done manually or automatically, using the XBRL file deposited by the company in the Mercantile.

- **Calculation of the 9 ratios for non-financial corporations**. The embedded formulae (using the BACH methodology) of the 9 ratios included in the tool allow their calculation for each corporation under scrutiny.
- **Uploading of the ratios of the sector of activity**. Once the corporation's sector of activity and size have been selected and downloaded from the RSE database, the user of the tool can automatically upload them to the Excel file. This process is necessary in order to obtain the benchmark data that will serve as reference to allocate the SME in the statistical distribution; doing it means that one can easily check in which part of the population the company is situated (among the best or worst performing companies). This process, that has to be done individually, case by case, has also been eased for credit institutions interested in developing their own internal tool: those interested have received the full dataset with the Spanish data to integrate it into their own risk assessment processes
- **Display of the data of the company on a comparative basis with its sector of activity and size.** As result, the position of the company can be known. The next image shows an example of this product.



Final remarks

Historically, access in Spain to finance by small non-financial firms depended more on the existence of sufficient collateral and/or guarantors than on the use of professional analysis of the past and foreseeable future performance of the company. In a new environment, where the suitability of a company to receive funding will be based on a profound knowledge of the company, the availability of information, qualitative and quantitative is the cornerstone of any risk assessment procedure. The development of harmonised but flexible methods, together with the availability of benchmark data for comparisons (between a company and its peers), becomes a crucial tool for credit institutions. The one developed by the Banco de España using European methodology and the data available in its Central Balance Sheet Data Office is intended to serve this purpose.

Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

IFC-ECCBSO-CBRT Conference on *"Uses of Central Balance Sheet Data Offices' information"*

Co-organised by the IFC, the European Committee of Central Balance Sheet Data Offices (ECCBSO) and the Central Bank of the Republic of Turkey (CBRT)

Özdere-İzmir, Turkey, 26 September 2016

Assessment of SMEs by credit institutions using CBSO data: a user´s case developed by the Banco de España[1]

Manuel Ortega, Bank of Spain

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[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.

BANCO DE ESPAÑA
Eurosistema

Assessment of SMEs by credit institutions using CBSO data:

a user´s case developed by the Banco de España

Conference "Uses of Central Balance Sheet Data Offices´ Information"

IFC / ECCBSO / CBRT
Özdere-Izmir, September 26th, 2016

Manuel Ortega
Head of Central Balance Sheet Data Office Division. Banco de España
Chairman of ERICA (European Records of IFRS Consolidated Accounts) WG, of ECCBSO
Representative of Banco de España in XBRL Spain

DIRECTORATE GENERAL ECONOMICS STATISTICS AND RESEARCH
STATISTICS DEPARTMENT

CONTENT

1. Presentation of the project
   - Legal precedent
   - Report "SME financial information"
   - Risk assessment methodology
2. Experience previously available (BACH database and XBRL)
3. Technical solution for financial institutions
4. Challenges for CBSOs: representativeness and new ratios

1. Presentation of the project: legal precedent

- **Law 5/2015 promoting SME financing**
    - *How to promote financing to SMEs: easing access, increasing the alternative methods of financing*
    - ***Easing access: reducing the information asymmetry gap***
    - *To that end, the law obliges financial institutions to provide a financial report on the financial situation and payment track record to SMEs that are to see their credit facilities reduced. This is the "SME financial information" report **("Información Financiera-PYME")***

- The **Banco de España** was obliged by this law to:
    - ***Standardise this document***
    - *Create a **standardised methodology for the assessment** of the credit quality of an SME (also including sole proprietorships)*

1. Presentation of the project: "SME financial information" report

- In December 2015 the Banco de España published a Draft Regulation with the harmonised content of the report and of the risk assessment methodology, developed by the Directorate General Banking Supervision. **In June 2016 the Regulation was published** in the Official Gazette "Circular 6/2016, 30 June 2016")

- **Content of the "SME financial information" report.** Mainly, records available at the credit institution with the credit history of the company:
  - *Declarations to the Central Credit Register*
  - *Information provided to private data compilers about solvency history*
  - *Credit history*
  - *Movements over the last year in financial contracts*
  - *Credit rating*

- The report also has to provide the relative position of the Company within its sector of activity

- The report is confidential and can only be provided to the company

1. Presentation of the project: a single harmonised method for credit assessment

- **Target of the method**: to assess, in a standardised and comparable manner, the credit quality of the SME

- **Harmonised risk assessment method**. Taking into account three variables:
  - ***Financial situation of the debtor***. *To that aim: use of financial statements officially filed with the Mercantile Registers*
  - ***Qualitative variables*** *(years of relationship, sector of activity, shareholder experience...)*
  - ***Behavioral variables*** *(default, payment delays, overdrafts...)*
  - *Additionally, relative position of the debtor in relation to the companies of the same sector of activity and size*

- **Result:** qualify each creditor under one of these levels or headings: “Low risk” “Medium-Low risk”, “Medium-High risk”, “High risk”, “Not available”

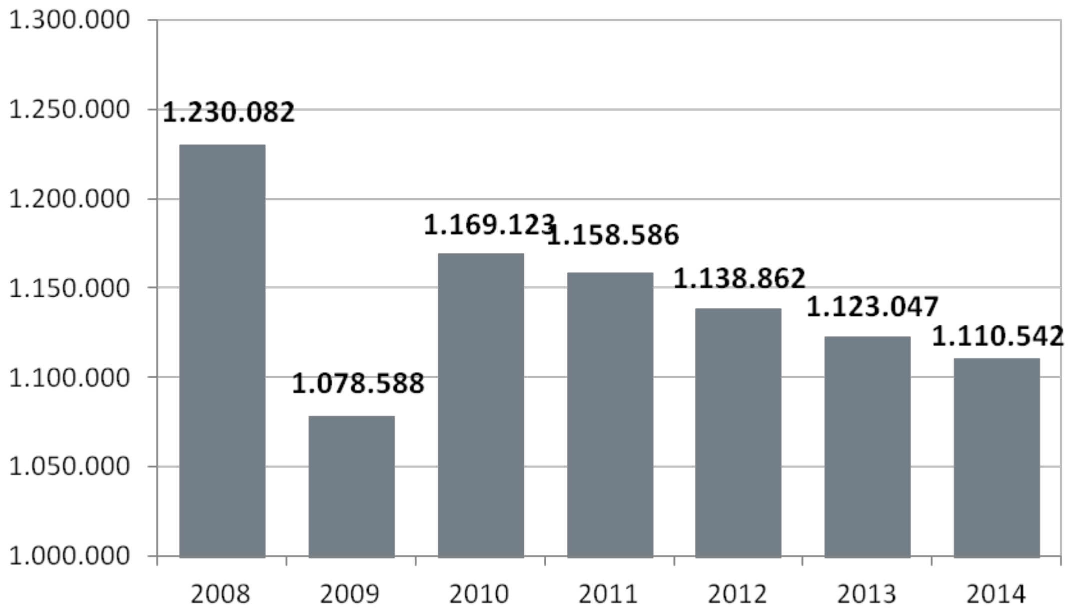
- **Flexibility:** each credit institution declares the relationship in respect of these levels and the 3 groups of variables defined in the method

CONTENT

2. Experience in Spain: XBRL files available

Mercantile Registers receive thousands of annual accounts (XBRL instance documents) every year

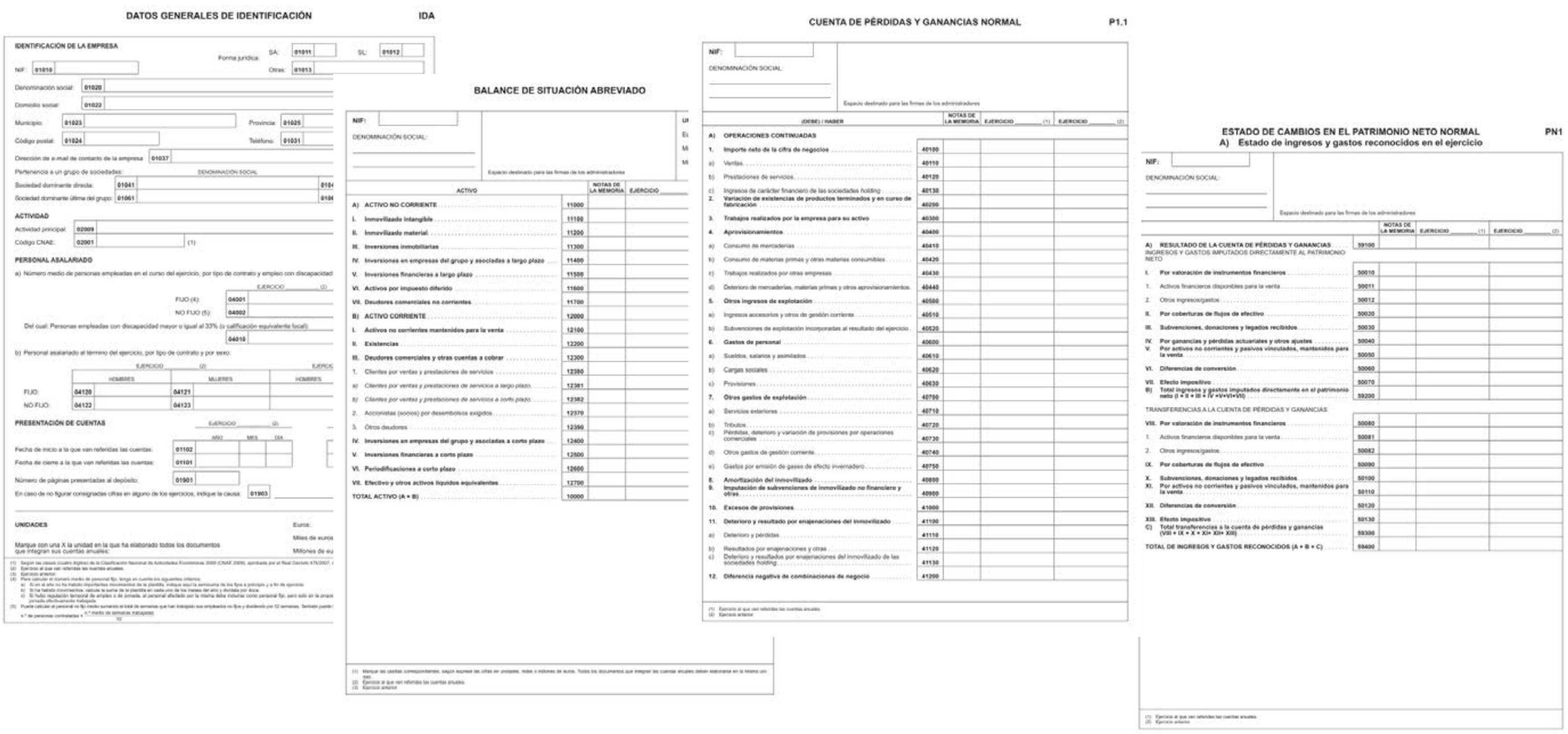
NUMBER OF ANNUAL ACCOUNTS FILED



- **85% of companies submit their annual financial statements with XBRL**

2. Experience in Spain: XBRL files available

XBRL Instances filed with Mercantile Registers include: Balance Sheet, Profit and Loss Account, Statement of Changes in Equity and identification data, among others



2. Experience in Spain: individual study for CBSO collaborators (non-financial corporations)

BANCO DE ESPAÑA
Eurosistema

Example of comparative study provided to Non-Financial corporations by CBSO

HOJA RESUMEN. DATOS D

EMPRESA DE PRUEBA
SECTOR DE COMPARACIÓN: OTRO COMERCIO ..

COMPARACIÓN SERIE HISTÓRICA, EMPRESA-SECTOR (1)

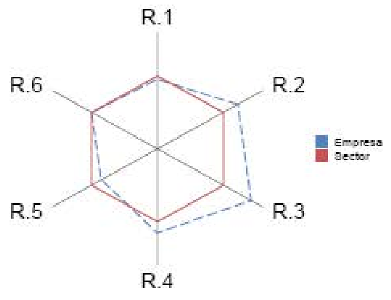
	N-4		N-3		N-2		N-1		N	
	Empresa	Sector	Empresa	Sector	Empresa	Sector	Empresa	Sector	Empresa	Sector
Cifra neta de negocios (Tasa de variación)	3,2	5,6	2,9	5,1	6,6	5,2	0,5	5,6	-0,2	5,3
Gastos de personal por trabajador (Tasa de variación)	4,2	3,7	2,9	2,9	-1,7	4,1	9,3	4,2	-3,5	4,3
Resultado ordinario neto (Tasa de variación)	-12,5	17,2	14,3	13,6	68,8	6,1	88,9	0,2	29,4	10,3
Rentabilidad ordinaria del activo (Porcentaje)	2,8	8,2	3,1	8,3	5,1	8,0	9,2	7,3	11,7	8,5
Coste medio de la financiación (Ratio)	0,0	6,4	0,0	5,8	0,0	5,8	0,0	5,5	n.s	6,8
Endeudamiento (Ratio. Saldos medios)	0,0	47,4	0,0	47,3	0,0	46,4	0,0	46,8	0,0	47,4

(1) Información del sector en media ponderada

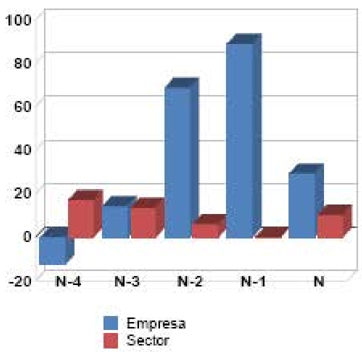
n.d. = dato no disponible   n.s. = dato no significativo   n.c. = no calculable

SITUACIÓN COMPETITIVA
EMPRESA-SECTOR AÑO N (2)

R.1 Crecimiento Cifra neta de negocios
R.2 Crecimiento Resultado ordinario neto
R.3 VAB cf / Cifra neta de negocios
R.4 Margen bruto de explotación
R.5 Cifra neta de negocios / Empleados
R.6 Rentabilidad ordinaria de los recursos propios



RESULTADO ORDINARIO NETO
(Tasa de variación)



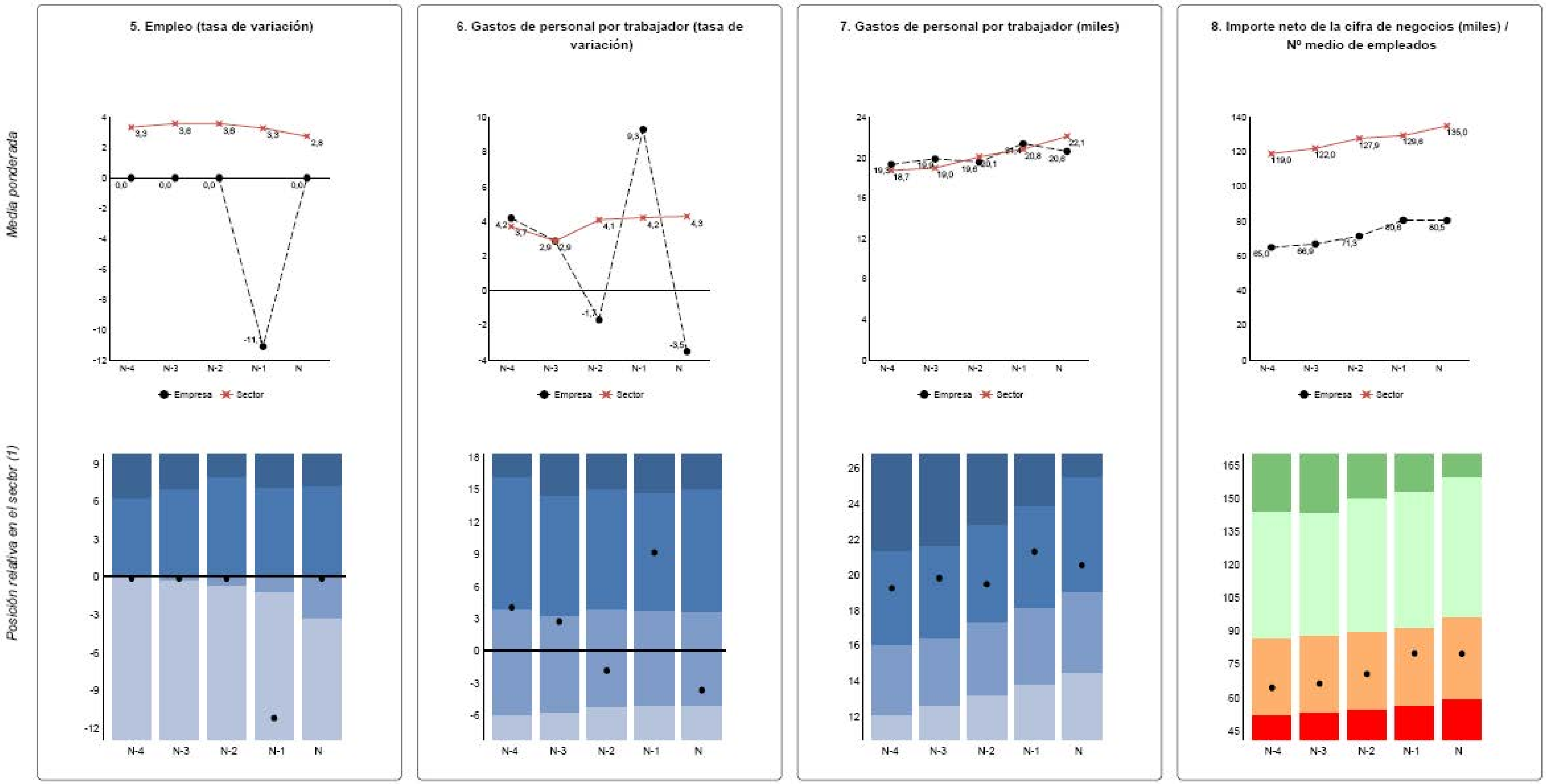
ESTRUCTURA DE GASTOS AÑO N

2. Experience in Spain: individual study for CBSO collaborators (non-financial corporations)

BANCO DE ESPAÑA
Eurosistema

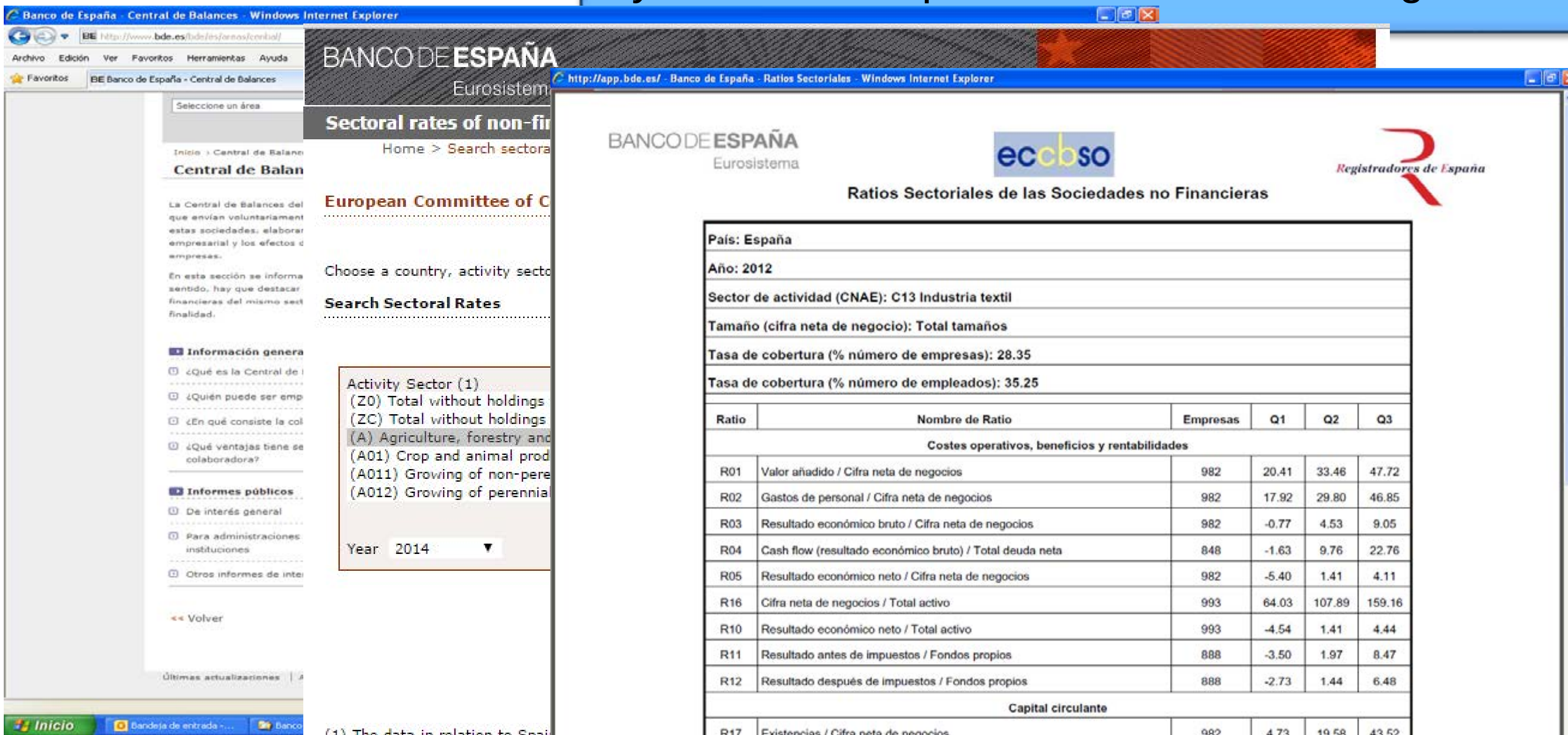
Example of comparative study provided to Non-Financial corporations by CBSO

EMPRESA DE PRUEBA
SECTOR DE COMPARACIÓN: OTRO COMERCIO . . .



2. Experience available: BACH database, the Spanish version

RSE (statistical distributions) database, created by Banco de España and Mercantile Registers



Ratio	Nombre de Ratio	Empresas	Q1	Q2	Q3
	Costes operativos, beneficios y rentabilidades				
R01	Valor añadido / Cifra neta de negocios	982	20.41	33.46	47.72
R02	Gastos de personal / Cifra neta de negocios	982	17.92	29.80	46.85
R03	Resultado económico bruto / Cifra neta de negocios	982	-0.77	4.53	9.05
R04	Cash flow (resultado económico bruto) / Total deuda neta	848	-1.63	9.76	22.76
R05	Resultado económico neto / Cifra neta de negocios	982	-5.40	1.41	4.11
R16	Cifra neta de negocios / Total activo	993	64.03	107.89	159.16
R10	Resultado económico neto / Total activo	993	-4.54	1.41	4.44
R11	Resultado antes de impuestos / Fondos propios	888	-3.50	1.97	8.47
R12	Resultado después de impuestos / Fondos propios	888	-2.73	1.44	6.48
	Capital circulante				
R17	Existencias / Cifra neta de negocios	982	4.73	19.58	43.52

This database, derived from BACH, provides information for the comparative analysis of individual corporations with aggregates of non-financial corporations, using 29 ratios, with details by size (turnover), economic activity (3 digits) and country

CONTENT

3. Technical solution for financial institutions: Excel report comparing company to its sector of activity

Excel file with XBRL api (developed by XBRL Spain and the Banco de España): a harmonised automated solution

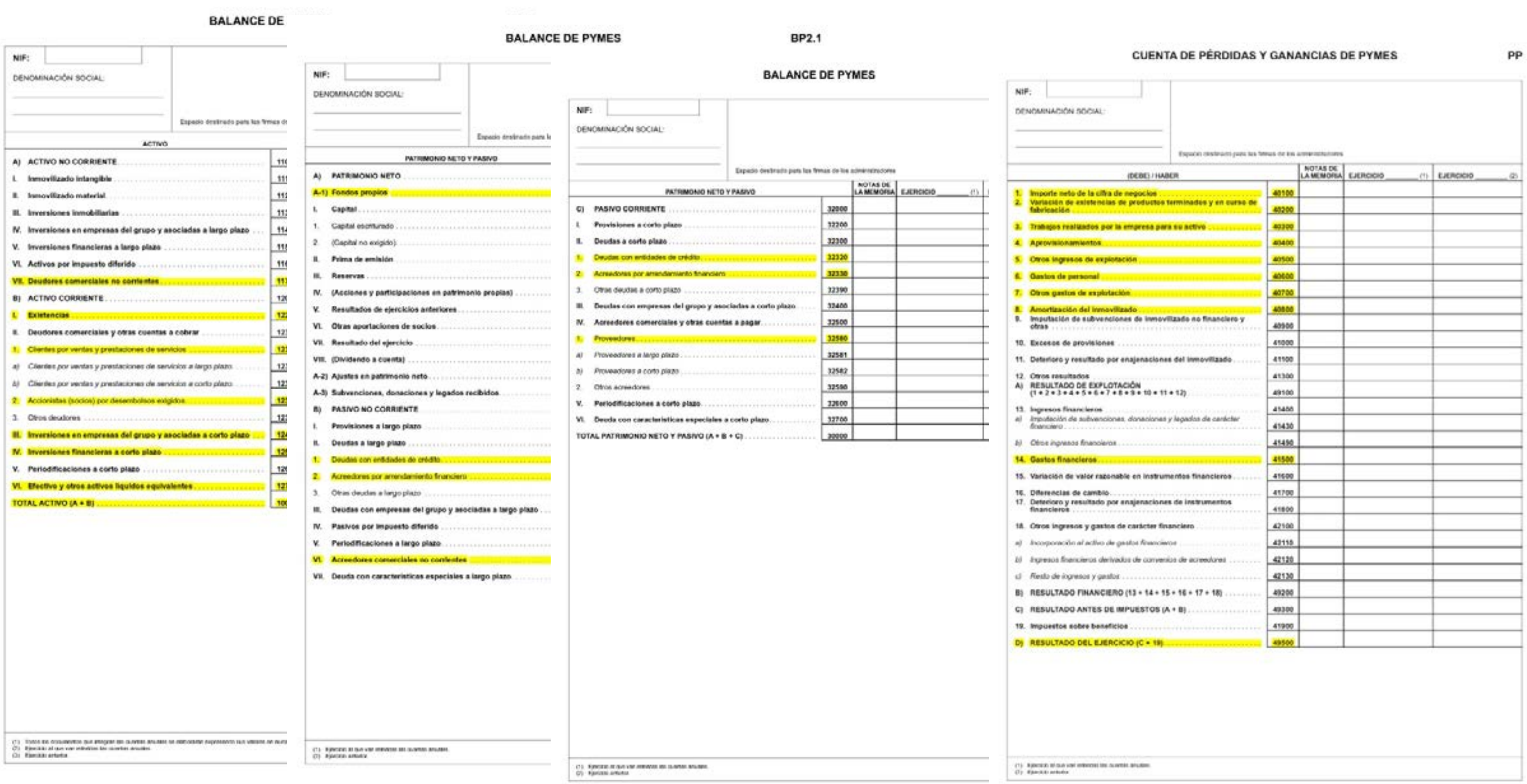
1. Company data, two options:
    1. *Manual typing on the Excel*
    2. *Import of XBRL file officially filed with the Mercantile Register*

2. Sector of activity data:
    1. *Download an xls file from RSE database*
    2. *Use the Excel file to print the report*

3. Technical solution for financial institutions: Excel report comparing company to its sector of activity

Company data:

- *Annual accounts officially filed with Mercantile Registers*
- *15 variables from Balance Sheet, 11 from profit and loss account*



RCH

3. Technical solution for financial institutions: Excel report comparing company to its sector of activity

Sector of activity and size of the Company: data available in RSE database (i.e. BACH methodology)

Only using 9 ratios (8 BACH ratios + **Rate of change of Net Turnover**)

Ratios Sectoriales de las Sociedades no Financieras

País: España
Año: 2014
Sector de actividad (CNAE): N829 Actividades de apoyo a las empresas n.c.o.p.
Tamaño (cifra neta de negocio): Total tamaños
Tasa de cobertura (% número de empresas): 4,64
Tasa de cobertura (% número de empleados): 34,4

Ratio	Nombre de Ratio	Empresa	Q1	Q2	Q3
Costes operativos, beneficios y rentabilidades					
R01	Valor añadido / Cifra neta de negocios	1874	35,26	59,33	79,86
R02	Gastos de personal / Cifra neta de negocios	1874	27,65	49,09	74,72
R03	Resultado económico bruto / Cifra neta de negocios	1874	-0,48	5,30	17,82
R04	Cash flow (resultado económico bruto) / Total deuda neta	1280	-2,18	8,30	31,59
R05	Resultado económico neto / Cifra neta de negocios	1874	-3,81	2,79	12,85
R16	Cifra neta de negocios / Total activo	1956	23,17	101,13	209,20
R10	Resultado económico neto / Total activo	1956	-1,53	2,39	9,98
R11	Resultado antes de impuestos / Fondos propios	1707	0,00	6,40	24,80
R12	Resultado después de impuestos / Fondos propios	1707	-0,10	4,88	19,38
Capital circulante					
R17	Existencias / Cifra neta de negocios	1874	0,00	0,00	0,04
R18	Deudores comerciales / Cifra neta de negocios	1874	3,21	13,98	29,35
R19	Acreedores comerciales / Cifra neta de negocios	1874	0,00	0,00	2,88
R20	Capital circulante / Cifra neta de negocios	1874	-0,17	10,53	26,48
Gastos e ingresos financieros					
R07	Gastos financieros y asimilados / Cifra neta de negocios	1874	0,00	0,18	1,47
R06	Gastos financieros y asimilados / Resultado económico bruto	1408	0,00	2,57	16,80
R09	Resultado financiero / Cifra neta de negocios	1874	-1,01	-0,04	0,01
R08	Resultado financiero / Resultado económico bruto	1408	-12,64	-0,94	0,03
Estructura del activo					
R13	Inmovilizado financiero / Total activo	1956	0,00	0,37	9,24
R14	Inmovilizado material / Total activo	1956	0,39	7,67	34,60
R15	Activo circulante / Total activo	1956	28,26	68,05	93,37
R21	Activos financieros a corto plazo y dispon. / Total activo	1956	5,19	21,81	52,70
Estructura del pasivo					
R22	Fondos propios / Total patrimonio neto y pasivo	1956	16,37	47,99	78,53
R23	Provisiones para riesgos y gastos / Total patrimonio neto y pasivo	1956	0,00	0,00	0,00
R24	Deudas con entidades de crédito / Total patrimonio neto y pasivo	1956	0,00	0,00	13,62
R25	Deudas con entidades de crédito, medio y largo plazo / Total patrimonio neto y pasivo	1956	0,00	0,00	6,04
R26	Deudas con entidades de crédito, corto plazo / Total patrimonio neto y pasivo	1956	0,00	0,00	0,33
R27	Deudas a medio y largo plazo / Total patrimonio neto y pasivo	1956	0,00	0,00	19,37
R28	Deudas a corto plazo / Total patrimonio neto y pasivo	1956	9,32	30,28	62,50
Actividad					
T1	Tasa de variación de la cifra neta de negocios	1847	-12,32	1,62	23,19

Fuente: Base de datos RSE (ratios sectoriales de sociedades no financieras). Banco de España (Central de Balances) / Registros de España (Registros Mercantiles - CPE).- Comité Europeo de Centrales de Balances.

3. Technical solution for financial institutions: Excel report comparing company to its sector of activity

Informe-plantilla sobre la posición del acreditado respecto a su sector de actividad

Imprimir informe

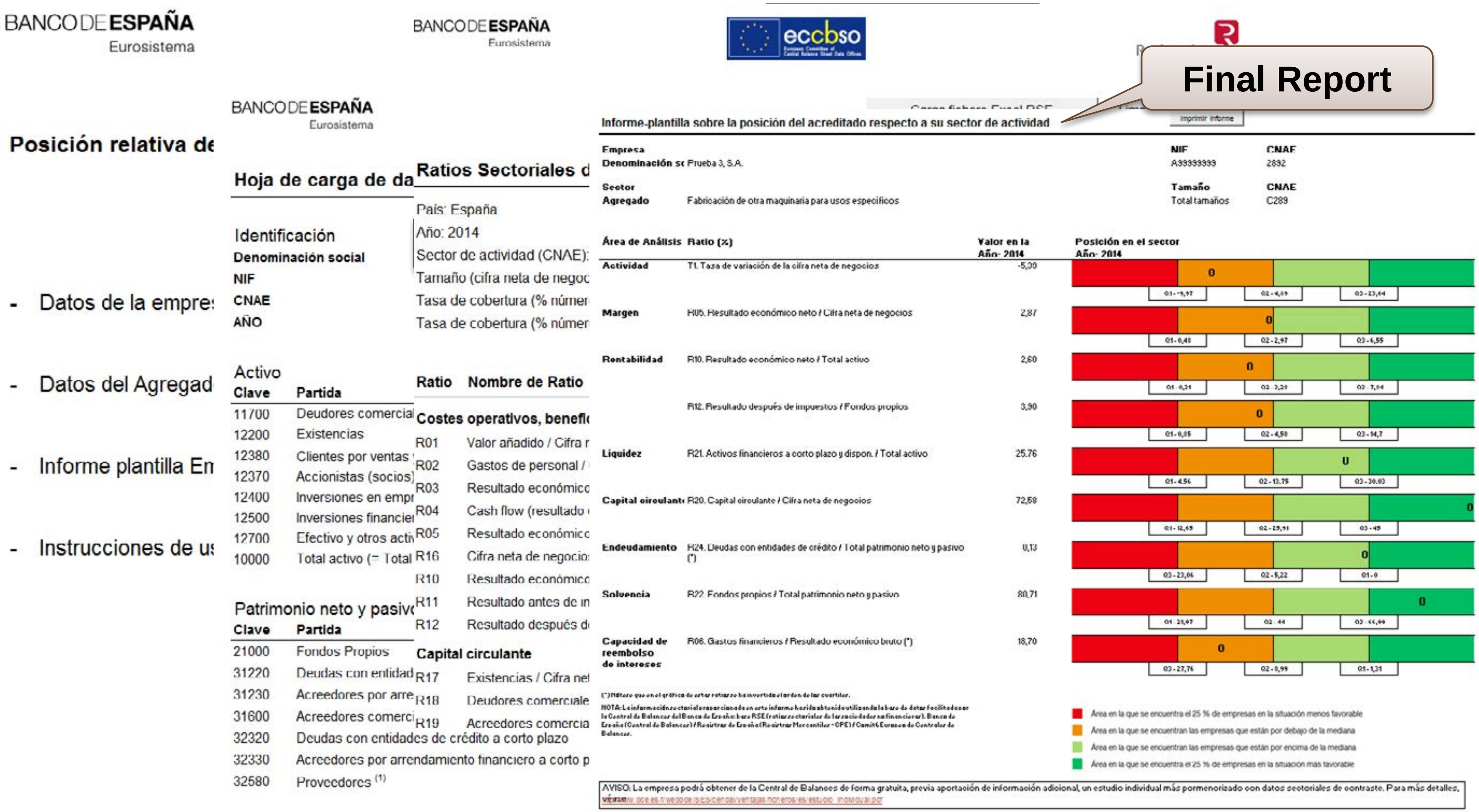
Empresa		**NIF**	**CNAE**
Denominación sc	Prueba 3, S.A.	A99999999	2892
Sector		**Tamaño**	**CNAE**
Agregado	Fabricación de otra maquinaria para usos específicos	Total tamaños	C289

Área de Análisis	Ratio (%)	Valor en la Año: 2014	Posición en el sector Año: 2014			
			Marker			
Actividad	T1. Tasa de variación de la cifra neta de negocios	-5,39	0	Q1 - -9,97	Q2 - 4,89	Q3 - 23,64
Margen	R05. Resultado económico neto / Cifra neta de negocios	2,87	0	Q1 - 0,48	Q2 - 2,97	Q3 - 6,55
Rentabilidad	R10. Resultado económico neto / Total activo	2,60	0	Q1 - 0,31	Q2 - 3,28	Q3 - 7,84
	R12. Resultado después de impuestos / Fondos propios	3,90	0	Q1 - 0,85	Q2 - 4,58	Q3 - 14,7
Liquidez	R21. Activos financieros a corto plazo y dispon. / Total activo	25,76	0	Q1 - 4,56	Q2 - 13,75	Q3 - 30,03
Capital circulant	R20. Capital circulante / Cifra neta de negocios	72,58	0	Q1 - 12,65	Q2 - 25,91	Q3 - 45
Endeudamiento	R24. Deudas con entidades de crédito / Total patrimonio neto y pasivo (*)	0,13	0	Q3 - 23,06	Q2 - 5,22	Q1 - 0
Solvencia	R22. Fondos propios / Total patrimonio neto y pasivo	80,71	0	Q1 - 21,97	Q2 - 44	Q3 - 66,99
Capacidad de reembolso de intereses	R06. Gastos financieros / Resultado económico bruto (*)	18,70	0	Q3 - 27,76	Q2 - 8,99	Q1 - 1,31

(*) Nótese que en el gráfico de estos ratios se ha invertido el orden de los cuartiles.

Using 26 accounting concepts and 9 sectorial ratios, we see in a nutshell the financial situation of a company within its sector of activity

3. Technical solution for financial institutions: Excel report comparing company to its sector of activity



CONTENT

1. **Presentation of the project**
   - ❑ **Legal precedent**
   - ❑ **Report “SME financial information”**
   - ❑ **Risk assessment methodology**

2. **Experience previously available (BACH database and XBRL)**

3. **Technical solution for financial institutions**

4. **Challenges for CBSOs: representativeness and new ratios**

4. Challenges. Representativeness: new quality controls

New fears: statistics directly applied to risk assessment decision / Need for stability

1) Exclusion of anomalous microdata (**“outliers”)**

2) Confidentiality criteria **(confidentiality)**

3) Revision of Banque de France Requirements **(Banque de France Requirements)**

4) Additional controls to censor nodes with anomalous values **(Box plot controls)**

5) Representativeness of the provisional sample (December of t+1) compared to the definitive one (June of t+2) **(homogeneity of provisional sample)**

6) Concentration of the observations near the quartiles **(density of the sample)**

NEW

7) The coverage of the sample: Saving nodes with a high coverage despite their data **(Coverage)**

4. Challenges: need of new ratios (rate of growth / more NACE details)

SME Financial information

R21

R25

R05

R12

R10

R20

R22

R24

ADDITIONAL REQUIREMENTS OF INFORMATION NOT PROVIDED BY BACH:

Turnover annual variation rate:

This ratio doesn´t exist in BACH database. It would be very useful to include this ratio in BACH Database

OTHER NEW REQUIREMENTS? NEW CHALLENGES FOR BACH?

- More accurate ratios to measure Liquidity (Cash and banks/Total Assets)?
- New ratios to measure the cost of financing?
- Greater breakdowns by sector? by size?

THANKS. QUESTIONS?

Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

IFC-ECCBSO-CBRT Conference on *"Uses of Central Balance Sheet Data Offices' information"*

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Özdere-İzmir, Turkey, 26 September 2016

CoCAS and the usage of CBSO Data for In-house-Credit Assessment[1]

Felix Rieger, Deutsche Bundesbank,

and Gerhard Winkler, Central Bank of the Republic of Austria

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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.

CoCAS and the usage of CBSO data for In-house Credit Assessment

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In-house Credit Assessment in the Eurosystem Collateral Framework

- Eurosystem liquidity-providing operations must be based on **adequate collateral** *(Article 18.1 of the Statute of the ESCB)*
- Types of **eligible assets**:
  ✓ marketable assets (bonds)
  ✓ non-marketable assets: mostly **credit claims**
- European Credit Assessment Framework (ECAF) → maintaining high **credit quality standards**
- Four credit quality assessment sources: External Credit Assessment Institutions (ECAI), **NCB's In-house Credit Assessment Systems (ICAS)**, Internal Rating-Based (IRB) Systems of Banks, Rating Tools
- **ICAS**
  ✓ developed and operated by (currently eight) NCBs
  ✓ to assess credit risk of non-financial companies
  ✓ subject to Eurosystem acceptance and validation procedure

CoCAS within ICAS OeNB and Bundesbank: The need for balance sheet data

- **CoCAS** (Common Credit Assessment System)
  - ✓ jointly developed by OeNB and BBk
  - ✓ used for assessment of NGAAP accounts and IFRS consolidated accounts
- **ICAS** have a two stage rating system:

- **Statistical model** on balance sheet ratios (1st stage) for **IFRS consolidated accounts** is common for all NCBs participating in CoCAS. Generates a rating proposal
- OeNB and Bbk use common sector-specific models also for their **NGAAP financial statements**
- **Human expert analysis** (2nd stage) comprises additional qualitative and quantitative criteria which may change the rating proposal from the 1st stage
  - ➢ one of the categories being relative position of a corporation in the sector/size category
- **Need for balance sheet data in both stages**

CoCAS and CBSO data: IFRS format

CoCAS format for IFRS consolidated accounts is based on standard format developed by the ERICA Working Group

Start of CoCAS: 2 out of 8 NCBs, participating in ERICA WG, use CoCAS (ICAS implemented in 4)

At present: 5 out of 8 NCBs, participating in ERICA WG, use CoCAS (ICAS implemented in 7)

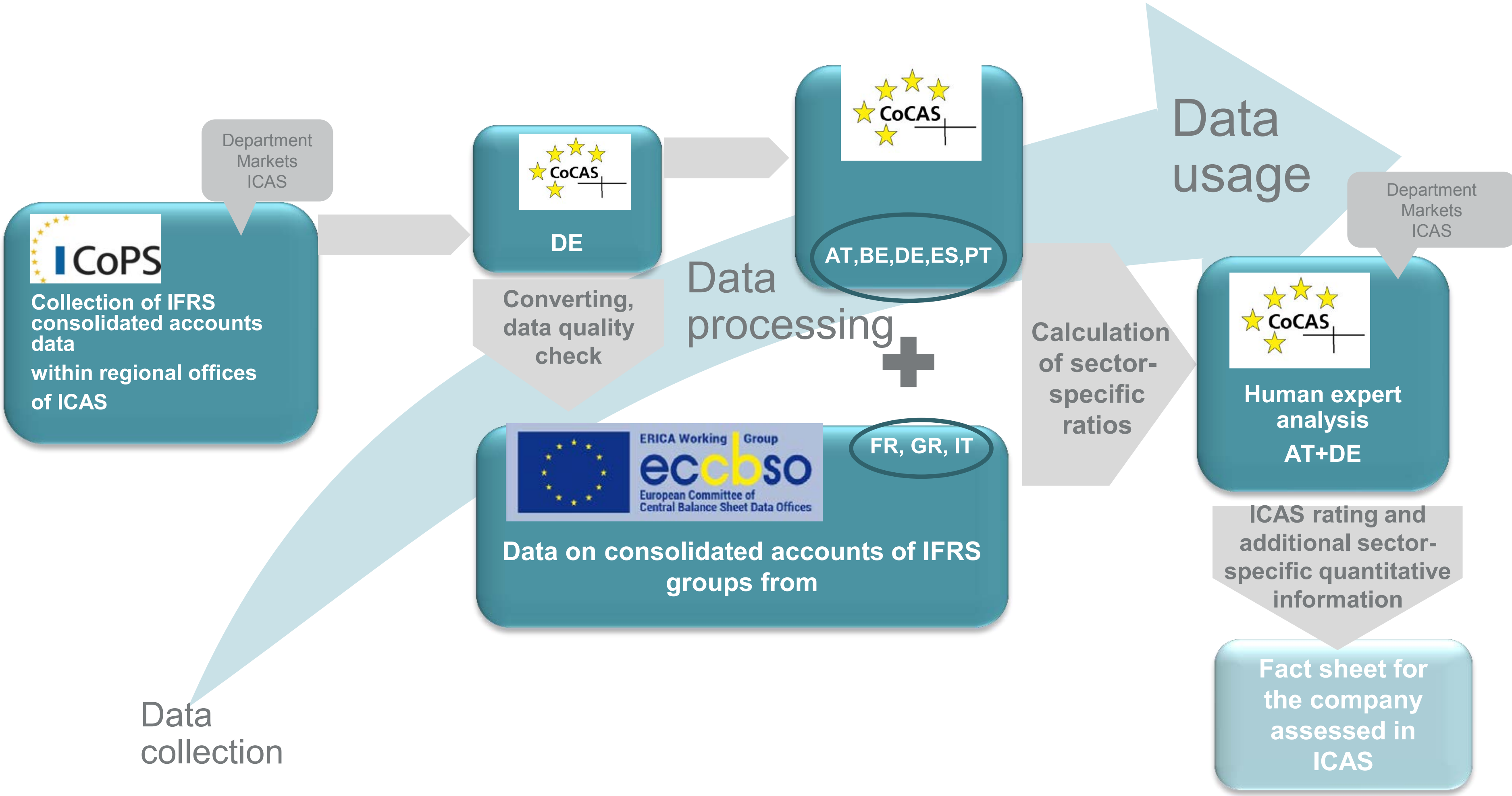
- OeNB
- Bbk
- BdE
- NBB
- BdP

- ERICA WG and CoCAS basically use the same harmonised format

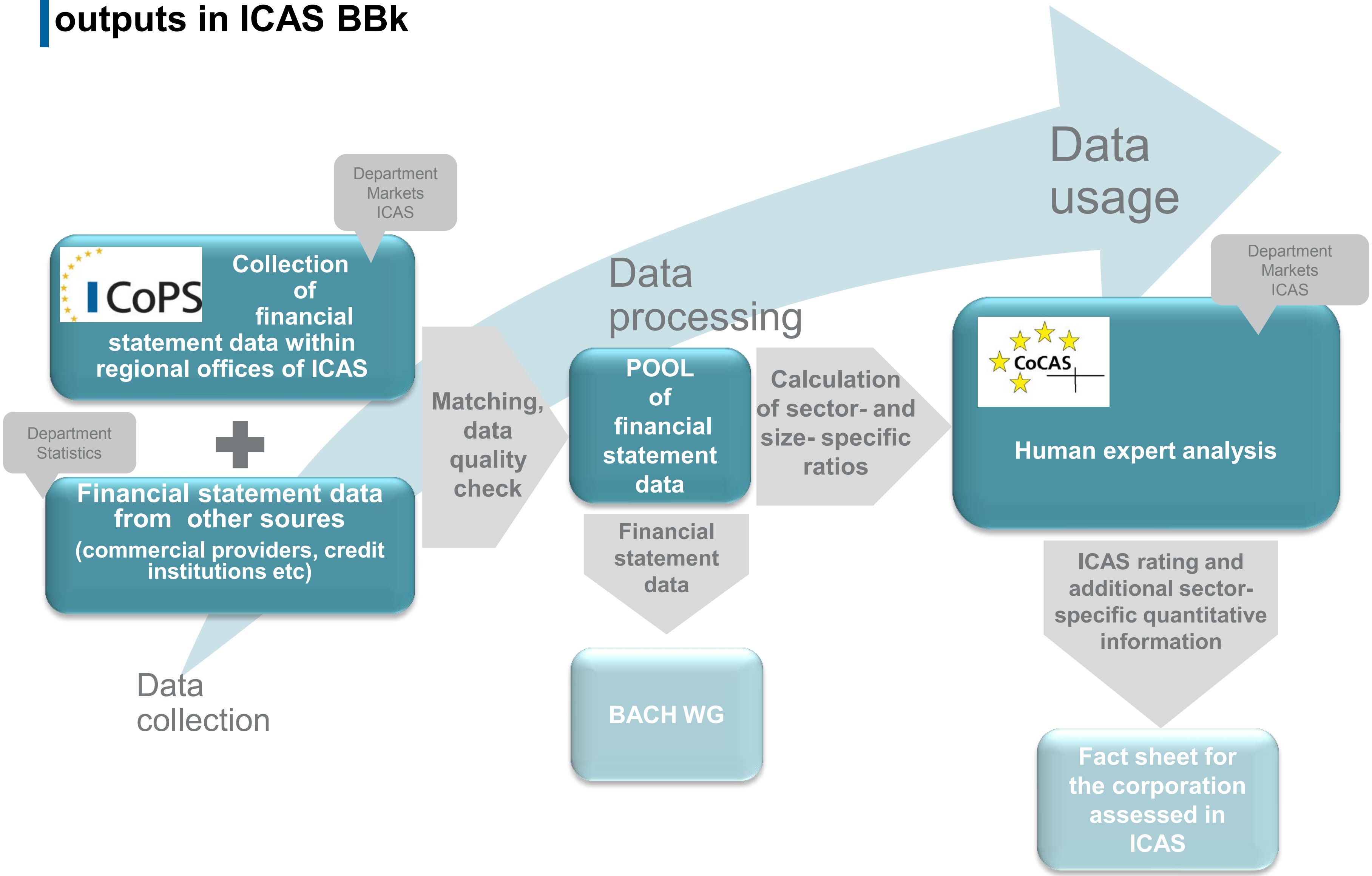
Cooperation between CoCAS and ERICA

- CoCAS related issues and the work of ERICA WG are influenced by each other:
  - ✓ regular work on **harmonisation of formats**
  - ✓ ICAS relevant items included in ERICA format, ERICA relevant items implemented in CoCAS
  - ✓ **study of "real cases"** in ERICA WG allows a broader view on IFRS groups which are internationally interconnected
  - ✓ ICAS related issues (analysis of financial statements) may offer interesting topics for a **deeper cross-country research in ERICA WG**
    - ✓ Thus learning from each other…

The German example: IFRS consolidated accounts data – inputs & outputs in ICAS Bundesbank



The German example: NGAAP financial statements data – inputs & outputs in ICAS BBk



Conclusion

- **In-house credit assessment of corporations important part of Eurosystem credit assessment framework**

- **In-house credit assessment of corporations needs balance sheet data as most important input**

- **Balance sheet data needed for**
  - ✓Statistical models
  - ✓As part of human expert assessment stage: Peer group analysis
  - ✓Peer group analysis as service to analysed corporations (in Bundesbank)

- **The right format of the data: ERICA and CoCAS**

- **In-house credit assessment is user of CBSO data, but can also be an important source of CBSO data (Bundesbank case)**

IFC-ECCBSO-CBRT Conference on *"Uses of Central Balance Sheet Data Offices' information"*

Co-organised by the IFC, the European Committee of Central Balance Sheet Data Offices (ECCBSO) and the Central Bank of the Republic of Turkey (CBRT)

Özdere-İzmir, Turkey, 26 September 2016

Firm default probabilities revisited[1]

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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.

Firm default probabilities revisited

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Abstract
This article describes a tool to assess the creditworthiness of the Portuguese non-financial firms. In its design, the main goal is to find factors explaining the probability that any given firm will have a significant default episode vis-à-vis the banking system during the following year. Using information from the central credit register for period 2002–2015 and a comprehensive balance sheet data set for period 2005–2014, we develop a method to select explanatory variables and then estimate binary response models for ten strata of firms, defined in terms of size and sector of activity. We use this methodology for the classification of firms in terms of one-year probability of default consistent with typical values of existing credit rating systems, in particular the one used within the Eurosystem. We provide a brief characterisation of the Portuguese non-financial sector in terms of probabilities of default and transition between credit rating classes. (JEL: C25, G24, G32)

Introduction

This article describes a tool to assess the creditworthiness of the Portuguese non-financial firms. The main goal is to find factors explaining the probability that any given firm will have a significant default episode vis-à-vis the banking system during the following year. The output of this tool is a probability of default in banking debt with a one-year horizon. This value is then mapped into a masterscale where companies are grouped into homogeneous risk classes. The fact that credit quality is assessed only in terms of banking debt is essentially not limiting our analysis for two reasons. First, most credit in Portugal is granted by banks. Only a few large firms typically issue market debt. Second, defaults in issued debt should be highly correlated with defaults in bank loans.

Acknowledgements: We thank Lucena Vieira for skilfully supplying the data, Manuel Lingo and Florian Resch (Oesterreichische Nationalbank) for sharing with us their expertise in the design of credit rating systems, and our colleagues at the Statistics Department and Economics and Research Department who helped us in this project.

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Credit Quality Step	Upper default probability limit
1 & 2	0.1
3	0.4
4	1.0
5	1.5
6	3.0
7	5.0
8	100

TABLE 1. Credit Quality Steps within the Eurosystem. All values in percentage.
Source: ECB.

Each risk class will be labeled by a "credit rating" and in the rest of this article we will refer to a risk class using its label. A credit rating is then a synthetic indicator reflecting several features (e.g. solvency, liquidity, profitability) that measure the firm's ability to fulfill its financial commitments.

In the current exercise the Eurosystem's taxonomy will be used, where a credit rating is designated by "Credit Quality Step". Table 1 presents the different risk classes and the associated upper limits of the probability of default. See ECB (2015) for additional details.

This article is partly based on previous efforts made in Martinho and Antunes (2012), but there is a vast policy and scholarly literature on the topic (see, for example, Coppens *et al.* 2007; Lingo and Winkler 2008; Figlewski *et al.* 2012), as well as a variety of documents produced by public and private institutions, including the European Central Bank (ECB), the European Banking Authority (EBA), Fitch Ratings, Moody's and Standard & Poors.

Credit ratings are used in a variety of situations. The most obvious one relates to the banks' credit allocation process. Ratings are indeed an important tool for lenders to select the borrowers according to their predefined risk appetite and to determine the terms of a loan. A higher credit ranking usually means better financing terms, including lower costs and access to more diversified instruments such as, for instance, securities markets.

Periods of broader materialisation of credit risk, like the one recently experienced in Portugal, put even more emphasis on the relevance of the firms' credit assessment process. Data for 2015 show that the total debt of non-financial corporations in Portugal represents 115% of GDP, one of the highest values in the euro area. A considerable share of this debt is in banks' balance sheets, where non-financial corporations were responsible for close to 28% of the total bank credit (bank loans and debt securities). The quality of these credits has been deteriorating substantially over the last years, putting pressure on the banks' results and capital requirements. Between December 2008 and December 2015 the non-performing loans ratio of non-financial corporations increased from 2.2% to 15.9%. In the same period the share of companies with overdue loans rose 10 percentage points to 29% in December 2015.

Early warning systems that can help predict future defaults are therefore of utmost relevance to support, at the banks' individual level, the credit allocation process and, at the aggregated level, the analysis of the financial stability of the overall banking system. Credit ratings are useful because they allow regulators and other agents in the market to identify potential problems that may be forthcoming in particular strata of firms—for example, defined in terms of activity sector or size. This is particularly important in an environment where banks' incentives in terms of reporting accurately and consistently probabilities of defaults of firms have been challenged. For example, Plosser and Santos (2014) show that banks with less regulatory capital systematically assign lower probabilities of default to firms than banks with more regulatory capital. This underreporting then implies that, for a loan with the same firm, different banks will constitute different levels of capital.

Credit ratings can also be useful as input for stress tests in order to evaluate the impact that changes in the economic environment may have on the financial sector performance. These measures can be used to estimate expected losses within a given time frame and are therefore key instruments for the risk management of financial institutions as well as for supervisory purposes. For this last purpose, it is important as well to have a benchmark tool to validate the capital requirements of each financial institution.

The existence of independent credit assessment systems also supports investment. As investment opportunities become more global and diverse, it is increasingly difficult to decide not only on which countries but also on which companies resources should be allocated. Measuring the ability and willingness of an entity to fulfil its financial commitments is key for helping make important investment decisions. Oftentimes, investors base part of their decisions on the credit rating of the company. For lenders it is difficult to have access and to analyse detailed data about each individual company presenting an investment opportunity. These grades are used as well to design structured financial products and as requirements for inclusion of securities portfolios eligible for collateral in various operations of the financial institutions.

The existence of this kind of indicator is also important for the borrower as it can provide better access to funding. Moreover, management and company owners can also use credit ratings to get a quick idea of the overall health of a company and for a direct benchmark with competitors.

Under the Eurosystem's decentralised monetary policy framework, national central banks grant credit to resident credit institutions. In order to protect the Eurosystem from financial risk, eligible assets[1] must be posted

1. Eligible collateral for refinancing operations includes not only securities but also credit claims against non-financial corporations.

as collateral for all lending operations. The Eurosystem Credit Assessment Framework (ECAF) defines the procedures, rules and techniques which ensure that the Eurosystem requirement of high credit standards for all eligible assets is met. Credit assessment systems can be used to estimate non-financial corporations' default risk. On the one hand, this credit assessment dictates whether credit institutions can pledge a certain asset against these enterprises as collateral for monetary policy operations with the national central bank. On the other hand, in the case of eligible assets, the size of the haircut is also based on the credit rating.[2]

For economic analysis, credit ratings are particularly relevant to evaluate the monetary policy transmission mechanism and to gauge the health of quality of credit flowing to the economy through the financial system. For instance, this tool can be used to evaluate if companies with the same level of intrinsic risk are charged the same cost by the banks or if there are additional variables determining the pricing of loans. There are a number of theories explaining these differences, typically in terms of asymmetries of information or the level of bank capital (see, for example, Santos and Winton 2015, and also Plosser and Santos 2014). It is also particularly interesting to compare firms from different countries of the euro area and quantify the component of the interest rate that can be attributed to the company risk, and the part stemming from other reasons, namely problems in the monetary policy transmission mechanism or country-specific risk. The data used by credit assessment systems is also valuable to identify sustainable companies that are facing problems because of lack of finance. This information can be used to help design policy measures to support companies that have viable businesses but whose activity is constrained by a weak financial system.

For statistical purposes the use of credit ratings is straightforward. Indeed, any statistic based on individual company data can be broken down into risk classes. For example, it can be valuable to compile interest rate statistics by risk class of the companies or to simply split the total bank credit by risk classes.

In order to describe a rating system suitable for the uses described above, this article is structured as follows. First, the data are presented and the default event is defined based on the available data and appropriate conventions. Second, the methodology underpinning the rating system is described. Then a calibration exercise is performed to fine-tune the model to the credit assessment system used within the Eurosystem. Fourth, some results are presented in terms of model-estimated and observed default rates and transitions among credit risk classes. Finally, a conclusion is provided.

2. To assess the credit quality of collateral, the Eurosystem takes into account information from credit assessment systems belonging to one of four sources: (i) external credit assessment institutions (ECAI); (ii) national central banks' in-house credit assessment systems (ICAS); (iii) counterparties' internal ratings-based systems (IRB); and (iv) third-party providers' rating tools (RT).

Data

The analysis in this article uses Banco de Portugal's annual *Central de Balanços* (CB) database—which is based on *Informação Empresarial Simplificada* (IES), an almost universal database with detailed balance sheet information of Portuguese firms—and the *Central de Responsabilidades de Crédito* (CRC), the Portuguese central credit register. CB contains yearly balance sheet and financial statements from virtually all Portuguese corporate firms, both private and state owned, since 2005 until 2014, which is the most recent year available. One of the main benefits of using CB is the ability to perform the analysis at the micro level. CRC records all credit institutions' exposures to Portuguese firms and households at monthly frequency, providing firm- and individual-level information on all types of credit and credit lines. For the purpose of this analysis, the time span ranges from 2002 until 2015.

In this article only private non-financial firms with at least one relationship vis-à-vis the financial sector were considered, which for the sake of simplicity will only be referred to as firms. The main reason for the exclusion of firms with no bank borrowing is that the aim is to estimate default probabilities. In addition, on the CB side observations regarding self-employed individuals and firms that reported incomplete or incoherent data, such as observations with negative total assets or negative business turnover, were excluded. As for the CRC, only information regarding performing and non-performing loans was considered, and credit lines, write-offs and renegotiated credit were disregarded. Moreover, all firm-bank relationships below €50 and firms that had an exposure to the financial system as a whole (aggregated over all the firm-bank relationships) below €10,000 were excluded.

Default definition

A firm is considered to be "in default" towards the financial system if it has 2.5 per cent or more of its total outstanding loans overdue. The "default event" occurs when the firm completes its third consecutive month in default. A firm is said to have defaulted in a given year if a default event occurred during that year. It is possible for a single firm to record more than one default event during the period of analysis but, in order to make sure we are not biasing the sample towards firms with recurrent defaults, we exclude all observations of the firm after the first default event.

We only include firms that either are new to the financial system during the sample period (that is, firms which did not have banking relationships before 2005, possibly because they did not even exist) or have a history of three years with a clean credit record. We exclude firms that enter the CRC database immediately in default.

#	Size
1	Micro
2	Small, medium and large

#	Industry
1	Manufacturing, mining and quarrying
2	Construction and real estate activities
3	Wholesale and retail trade and the primary sector
4	Utilities, transports and storage
5	Services

TABLE 2. Size and industry groups of firms.

Source: Banco de Portugal.

Data treatment and definitions of variables

In order to increase group homogeneity, we split the sample into micro firms and all other firms (i.e., small, medium and large firms). These two groups were further divided based on the firms' classification into thirteen industry NACE groups. Some industries were bundled according to their affinity, as was for instance the case of the real estate sector and the construction sector. We ended up with five groups of industries (manufacturing, mining and quarrying; construction and real estate activities; wholesale and retail trade and the primary sector; utilities, transports and storage; services) and two groups for size (micro firms; all other firms), in a total of ten groups of firms to be used in the econometric estimations. See Table 2.

The CB database contains detailed balance sheet data of Portuguese non-financial firms. For the purpose of this analysis, only a subset of CB's variables were used. The large pool of variables can be categorised into specific groups such as leverage, profitability, liquidity, capital structure, dimension, and a residual group which corresponds to variables related with the balance sheet ratios that do not fit in any of the groups previously defined. All the level variables are scaled by dividing them by either the firm's total assets, current liabilities or total liabilities, depending on the case. We never use denominators that can have negative values as that would create significant discontinuities when the denominator is close to zero. To account for the possible influence of the economy as a whole on a specific firm, we consider a small set of macro factors: nominal and real GDP growth, total credit growth and the aggregate corporate default rate. This choice was motivated by previous literature on the topic; for example, Figlewski *et al.* (2012) have found that real GDP growth and the corporate default rate help explain transitions across rating classes. Table 3 summarises the subset of CB variables and the macro factors used in this analysis.

Measures of:	Variables
Leverage	Financial debt; Bank debt; Interest paid
Profitability	Value-added per worker; Profit / Loss; EBIT; Cash flow; EBITDA
Liquidity	Cash; Current liabilities
Capital structure	Equity; Current assets; Tangible assets
Dimension	Total assets; Age; Turnover; Employees
Other idiosyncratic	Wages; Trade debt
Macroeconomy	Aggregate default rate; Credit growth; Nominal GDP growth; Real GDP growth

TABLE 3. Summary of variables used in the regressions.

Source: Banco de Portugal. Precise definition of variables available upon request.

As previously mentioned, firms that had negative total assets, liabilities or turnover were removed from the analysis. Additionally, firms with total assets, turnover or the number of employees equal to zero were excluded. In order to cope with values for skewness and kurtosis far from what would be expected under the Normal distribution, strictly positive variables were transformed into their logarithms in order to reduce skewness. Because this transformation is not applicable to variables that can be negative, the set of variables was expanded with the ranks of all variables normalised between 0 and 1. The rank transformation was applied within each year-size-industry group to increase homogeneity. A final group of well-behaved variables was kept unchanged. This included variables expressed in shares and macro variables.

Methodology

In this study, we develop an approach based on a multi-criteria system of variable selection out of a large pool of potential variables. We build upon the methodology used by Imbens and Rubin (2015) of explanatory variables selection through maximum likelihood estimation. This methodology selects variables in an iterative process based on the explanatory prediction power that each variable is able to provide. A variable under scrutiny will be included if the increase in explanatory power is above a certain threshold. We adapt this approach for our own purposes.

Selection of explanatory variables

More specifically, we start by estimating a base model with fixed effects for size (only for non micro-sized firms) and for activity sector (at a disaggregation level of a few sectors per industry). For each variable of the initial pool of N variables, we estimate a model with the fixed effects plus that variable. These regressions will then be compared to the base model by using a likelihood ratio (LR) test. The algorithm then picks the variable associated to the model with the highest likelihood statistic under the condition that it is above the initial likelihood at a 5% significance level; this corresponds to an LR ratio of at least 3.84.

The process is then repeated but the base model is now the model with the fixed effects plus the variable picked in the previous step. The next variable is to be chosen among the remaining pool of $N - 1$ variables, but from this second step on we add criteria other than the requirement in terms of the LR. These criteria address potential problems stemming from a completely agnostic inclusion of variables. More specifically, the following conditions are added in order for the candidate variable to be included in the model:

1. It must have linear and non-linear correlation coefficients with any of the variables already present in the model lower than 0.5. This condition aims at avoiding potential problems of multicollinearity.
2. It has to be statistically significant at the 5% level in the new regression, while all of the previously included variables must remain statistically significant. This is to avoid that non significant variables survive in the final model specification.
3. It has to be such that the new model estimate improves the AUROC criterion[3] relative to its previous value. In addition, the new model estimate also has to improve the AIC information criterion. This condition addresses the potential problem of over-fitting the model, as this criterion penalises the inclusion of parameters.

The process ends when none of the remaining variables in the set of potential variables fulfills all the conditions 1–3 or, to avoid the proliferation of parameters, a maximum of ten variables has been reached. In order to maintain the approach as replicable and as simple as possible, a Logit specification was chosen.

All ten models (one for each combination between two size categories and five industries) were estimated by pooling the existing observations together, spanning the period from 2005 to 2014 in terms of the balance sheet information. All explanatory variables pertain to the end of the current year t. The dependent variable is defined as an indicator of the default event during year $t + 1$. Note that when the restriction on the maximum number of variables is removed none of the ten models includes more than 13 variables. Moreover, when analysing the evolution of the AUROC with each variable added it

3. AUROC stands for “area under the Receiver Operator Characteristic”. See Lingo and Winkler (2008) and Wu (2008) for the definition and the stochastic properties of this synthetic measure.

is possible to see that this benchmark tends to flatten out before the tenth variable; see Figure 1.

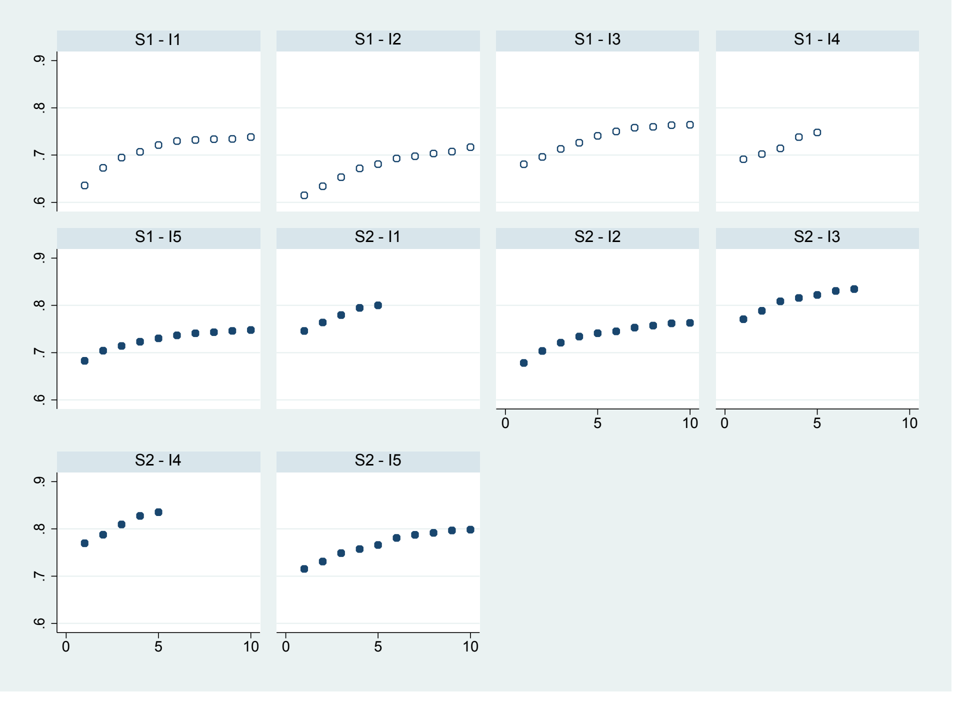

FIGURE 1: The AUROC as a function of the number of variables selected according to the methodology defined in the text. S# means size group # and I# means industry #; see Table 2 for details.

Source: Banco de Portugal and authors' calculations.

A summary of the results

After applying the proposed methodology to our data set, we obtained ten estimated Logit models; Table 4 displays some information characterising them.[4] A first observation is the overall consistent goodness-of-fit, which can be gauged by the AUROC.[5] These values lie in the range 0.72–0.84 and reject comfortably the hypothesis that the models are not distinguishable from

4. In practice we did not use the original variables, except in cases where they represented shares or growth rates, because the algorithm always chose the transformed variables (logarithm or rank).

5. For a critique of the AUROC as a measure of discriminatory power in the context of model validation, see Lingo and Winkler (2008).

Group	Obs.	Defaults	Def. ratio	# variables	AUROC	Brier Score
S1 - I1	58063	3000	5.17%	**10**	0.738	0.047
S1 - I2	53543	2965	5.54%	10	0.717	0.050
S1 - I3	178178	7696	4.32%	**10**	0.764	0.039
S1 - I4	2681	121	4.51%	5	0.748	0.041
S1 - I5	123048	5336	4.34%	**10**	0.748	0.040
S2 - I1	98065	3887	3.96%	5	0.800	0.035
S2 - I2	58325	3861	6.62%	10	0.763	0.057
S2 - I3	96738	3062	3.17%	7	0.835	0.028
S2 - I4	3903	128	3.28%	5	0.836	0.030
S2 - I5	73782	2476	3.36%	10	0.798	0.031
Overall	746326	32532	4.36%	n.a.	0.777	0.0393

TABLE 4. A summary of the Logit estimations for ten strata of firms. Values in bold mean that the procedure was stopped due to the limit on explanatory variables. S# means size group # and I# means industry #; see Table 2 for details.

Source: Banco de Portugal and authors' calculations.

a random classifier. Also, in each model the Brier score, a measure of the goodness of fit, is considerably small. The Spiegelhalter (1986) test applied to each model (not reported) also indicates that the level predicted for the probability of default is consistent with the observed defaults.

Although the methodology includes ten separate models there are several similarities among them. Table 5 presents a summary of the variables more often chosen using the procedure described above. Most importantly, the different models seem to have a core group of variables, even if they enter different models in slightly different variants: for instance, cash to total assets or cash to current assets as a measure of liquidity are always chosen, although they are never chosen together for the same model.

All ten models include a measure for profitability, alternating between cash-flow to total assets or earnings to total assets, and a measure for liquidity. Nine out of the ten models include the cost of credit as well as short-term liabilities, measured by current liabilities to total assets. Eight models include a measure for leverage and seven models include the weight of the employees' wage bill to total assets. Seven models select one macro factor among nominal GDP growth, total credit growth and the aggregate default rate. Finally, six models include the age of the firm and five models include a proxy for the firm's productivity as measured by value-added per worker.

Curiously, the weight of trade debt to total liabilities is also selected for five different models, all of them pertaining to micro-sized firms. This indicates that for this group of firms the behaviour of suppliers is particularly important.

Variable	# times selected	Avg. rank	Sign in regs.
r(Cash flow / Total assets)	6	1.0	-
r(Earnings / Total assets)	4	1.0	-
r(Interest paid / Financial debt)	9	3.1	+
r(Current liabilities / Total assets)	5	3.4	+
r(Age)	5	4.4	-
r(Wages / Total assets)	5	4.6	-
r(Cash / Current assets)	6	6.0	-
r(Financial debt / Total assets)	5	5.6	-
log(Current liabilities / Total assets)	4	4.5	+
r(Cash / Total assets)	4	5.8	-
r(Trade debt / Current liabilities)	5	7.2	+
log(Financial debt / Total assets)	2	3.0	+
r(Value-added per worker)	5	7.8	-
Nominal GDP growth	3	6.3	-
Credit growth	2	5.0	+
Agg. Default Rate	2	5.0	+
log(Equity / Total assets)	1	3.0	-
r(Bank debt / Total assets)	1	4.0	+
r(Employees)	2	8.5	+
log(Wages / Total assets)	2	9.0	-
log(Turnover)	2	9.5	-
log(Age)	1	7.0	-
r(Current assets / Total assets)	1	10.0	-

TABLE 5. Qualitative results of the variable selection procedure. r(·) denotes the rank of the variable within the size-industry group in the current year; log(·) denotes the natural logarithm of the variable. The second column contains the number models for which the variable is chosen by the variable selection algorithm (out of a maximum of ten models). The third column contains the average rank (1 is first, 10 is tenth) with which the variable was chosen. The fourth column contains the sign of variable's coefficient in the Logit estimation of the default event. Variables are ordered by the product of the inverse of number of times chosen by the average rank, in ascending order. S# means size group # and I# means industry #; see Table 2 for details.

Source: Banco de Portugal and authors' calculations.

Another significant result is that the variables that are more often chosen by the algorithm are also among the first variables to be selected, which indicates that these variables have the largest contribution to the explanatory power of the model. In particular, the variables measuring profitability are the first to be picked by the algorithm in the ten different models.

Another important observation is that the coefficient of each variable always enters the model with the sign that would be expected, even though the algorithm does not impose any restriction to this effect. Moreover, when a variable is selected for more than one model the variable's coefficient sign is the same across those models.

Rating class calibration

The next step in the setup of a rating tool system is to calibrate the model so that observed default rates of firms at any given credit category are consistent with the typical default rates used to define them (see Table 1). This step is usually needed because, while the average of the conditional model-estimated default probability should match the observed average default rate, this need not be so across different groups of firms, and in particular across rating classes. One basic requirement for the calibration that we want to perform is that overall the observed default rate is consistent with the conditional default rate stemming from the estimated models. While this requirement is generally fulfilled in-sample, one question remains: is the model conditional default probability consistent also across different categories of risk?

To answer this question, let us first define the concept of *z-score* in the context of our analysis. The Logit model used in the methodology described above is framed in terms of an unobserved latent variable which is then transformed into a number between 0 and 1, the probability of default. To keep the analysis simple, it suffices to say that the coefficients β of each one of the Logit models are estimated so that the probability of default is, to the extent possible, accurately given by

$$\Pr\{\text{default}_{t+1} = 1|x_t\} = \frac{1}{1 + e^{-x_t\beta}}$$

where default_{t+1} is an indicator of a default event occurring in year $t + 1$, x_t is a (row) vector of regressors in year t—including a constant and variables characterising the firm and possibly the economy—and β is a (column) vector of coefficients. It is a property of these coefficients that the in-sample average of the predicted default rates (as computed by the equation above) is equal to the observed average default rate. The z-score of each observation is simply defined as the estimated value of the latent variable, that is, $z_t = x_t\beta$.

The answer to the question above is broadly positive. Figure 2 depicts the model-predicted default probabilities (the dash-dotted curve) along with average observed default rates (the dots in the graph). Each point represents the fraction of defaults for groups of firms with relatively similar z-scores. The lower (more negative) the z-score, the lower the estimated probability of default of the firm. We can see that using a Logit specification does a good job explaining the relationship between z-scores and observed default probabilities for groups of firms across the whole z-score distribution.

One way to try to improve the fit is to have a more flexible approach. While this procedure is not consistent with the estimation process, we view that as a fine-tuning exercise rather than something that invalidates the results obtained using regression analysis. The solid line is one such attempt: it is a semiparametric curve interpolating the dots. It is readily seen that the two curves (the Logit and the semiparametric) are really telling the same story, but the semiparametric one lies above the Logit for very negative z-scores. This means that, for that range of z-scores, the semiparametric curve is going to be more conservative in assigning probabilities to firms.

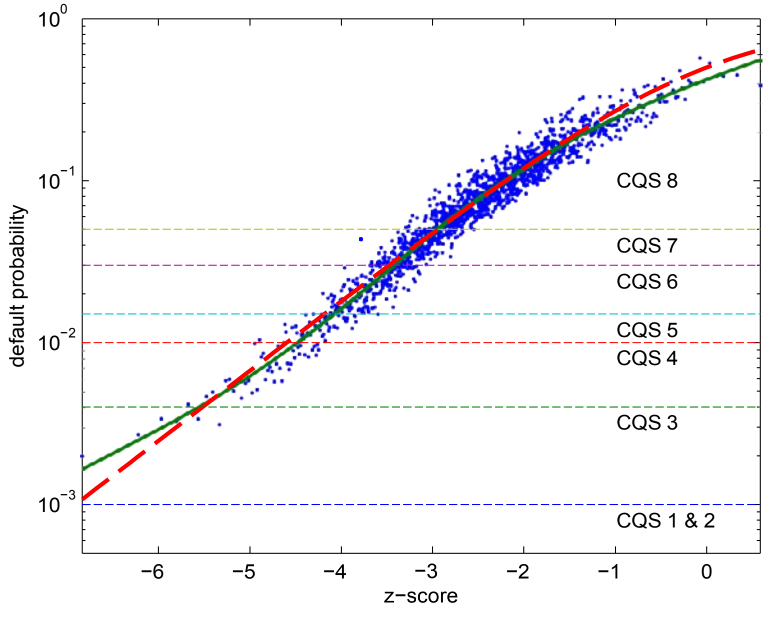

FIGURE 2: Probabilities of default of firms. Each dot represents the observed default rate for groups of firms with similar z-scores. Upper limits for default probabilities of each Credit Quality Step as defined by the Eurosystem also depicted.

Source: Banco de Portugal and authors' calculations.

We now provide additional details on the procedure of fitting the semiparametric curve to the dots, but the reader uninterested in mathematical details can safely skip the following section.

Fitting the dots

The dots in Figure 2 are empirical probabilities of default for groups of observations in the sample. Each dot in the graph represents a pair from the set of points $S^n = \{(\hat{d}_q^n, \hat{z}_q^n)\}_{q=1,\ldots,Q^n}$. These points were obtained as follows. First we sorted in ascending order all the z-scores (which are normalised and can be compared across the different groups of firms) of the sample. We then identified the first n defaults and set r_1^n as the order number of the observation with the n^{th} default. We grouped these observations in set $A_1^n = \{z_1, \ldots, z_{r_1^n}\}$. We then computed the ratio $\hat{d}_1^n = \frac{n}{\#A_1^n}$ and defined $\hat{z}_1^n$ as the median of set A_1^n. We repeated the procedure for the next group of n defaults by finding set $A_2^n = \{z_{r_1^n+1}, \ldots, z_{r_2^n}\}$, default rate $\hat{d}_2^n = \frac{n}{\#A_2^n}$ and median z-score $\hat{z}_2^n$. This process was carried out in a similar fashion until we exhausted all the observations, ending up with a total of Q^n pairs of empirical default rates and z-scores. Notice that, for all q, $\hat{z}_{q-1}^n \leq \hat{z}_q^n \leq \hat{z}_{q+1}^n$, that is, these points are also sorted in ascending order in terms of the z-scores, although not necessarily in terms of default probabilities. Not all points were plotted in Figure 2; only a representative sample was.

One word about the choice of n. If this number is too small then the standard deviation of the estimated empirical probability will be relatively high. To see this, assume that the default event has a Binomial distribution within A_q^n, and take $\hat{d}_q^n$ as an estimator for the default probability. Then, an estimate of the standard deviation of $\hat{d}_q$ would be

$$\sqrt{\frac{\hat{d}_q^n(1-\hat{d}_q^n)}{\#A_q^n - 1}}$$

which decreases with $\#A_q^n$ We picked $n = 23$ in our simulations because, due to the relative scarcity of very negative z-scores (associated to relatively low probabilities of default), we wanted to have meaningful estimates for default rates even in high rating classes. With this choice we ended up with Q^{23} close to 1400. We later address the significance of the estimates obtained with this choice. The robustness of the general results of this analysis with respect to this choice is performed elsewhere. For commodity we will drop n from the notation described above.

In order to keep the analysis as standard and simple as possible, we fitted a smoothing spline to the points in the figure. The smoothing spline is a semiparametric curve that approximates a set of points in a graph while penalising the occurrence of inflexion points along the whole curve. More specifically, we chose the following specification:

$$s(\cdot) = \arg\min p \sum_{q=1}^{Q} (\log(\hat{d}_q) - s(\hat{z}_q))^2 + (1-p) \int_{\hat{z}_1}^{\hat{z}_Q} (s''(z))^2 dz.$$

In this formulation, function $s : [\hat{z}_1, \hat{z}_Q] \to]-\infty, 0]$ is a cubic spline defined over the set of points in S. A cubic spline is a set of cubic polynomials defined in intervals and "glued" together at the unique z-scores contained in S. By construction, $s(\cdot)$ has continuous second derivative $s''(\cdot)$ in all points. Parameter p governs the smoothness of the interpolating curve. If p is close to 1, one gets the so-called natural cubic interpolant, which passes through all the points in S.[6] If p is close to 0, the penalisation of the second derivative

6. Technically, if there are points in S with the same z-score, the natural interpolant passes through the average of the log default rates among all the points with the same z-score.

ensures that the solution will be the linear interpolant, which has zero second derivative.

The curve of the smoothing spline with $p = 0.3$ is depicted in Figure 2 as the solid line.

One thing that is clear from Figure 2 is that the empirical default probability will still be a noisy measure: while each point represents the median z-score for the set of observations leading to a given number of observed defaults (23 defaults), it is possible to have groups of very similar firms—in the sense they have very similar z-scores—and still observe relatively different observed default rates among those groups of firms. That concern is addressed by the models' performance in terms of the AUROC, which has already been presented. In any case, the general shape of the cloud of points tells us that the analytical framework captures well the probability of default across firms: a random model would yield a cloud coalescing along an horizontal line in the graph at the unconditional observed default rate. The figure then underlines that even when large AUROC measures can be obtained, the default event is still a very uncertain event.

Defining credit quality classes

The general approach chosen for the purpose of categorising firms in terms of credit default classes is (i) to obtain reference values for default probabilities from external sources, then (ii) to choose thresholds in terms of z-scores for the different credit classes, and finally (iii) to check *ex post* the observed in-sample default probabilities' consistency with the previously defined credit classes. We also provide a more detailed analysis of the transitions of firms across credit categories and to default.

We now turn to the question of defining credit quality classes. The horizontal dashed lines of Figure 2 represent upper limits of credit classes according to the Eurosystem credit quality system (see Table 1). For example, class 3 corresponds, in the standard framework of monetary policy, to the lowest-rated firms whose loans can still be posted as collateral by financial institutions for monetary refinancing operations with the Eurosystem. Instead of using the Logit curve to compute conditional probabilities—which is depicted as the dash-dot curve in the graph—we adopt a semiparametric approach and fit a smoothing spline to this set of points. Additional robustness exercises were performed but are not reported here in terms of the parameters of smoothing spline.

Comparing the semiparametric curve with the Logit curve in Figure 2, we see that for the lowest estimated default probabilities for which we have data in the sample the smoothing spline is more conservative in terms of credit class classification, while over the mid-range of z-scores the Logit is slightly more conservative. For higher estimated default rates, the two curves are equivalent, and for the highest estimated default probabilities the Logit is again more conservative than the smoothing spline.

The strategy followed here will be to use the intersections of the smoothing spline with the upper limits of the credit classes as classification thresholds in terms of z-scores.[7] These values can be observed in Figure 3, where we also depict the upper value of the probability within the class.

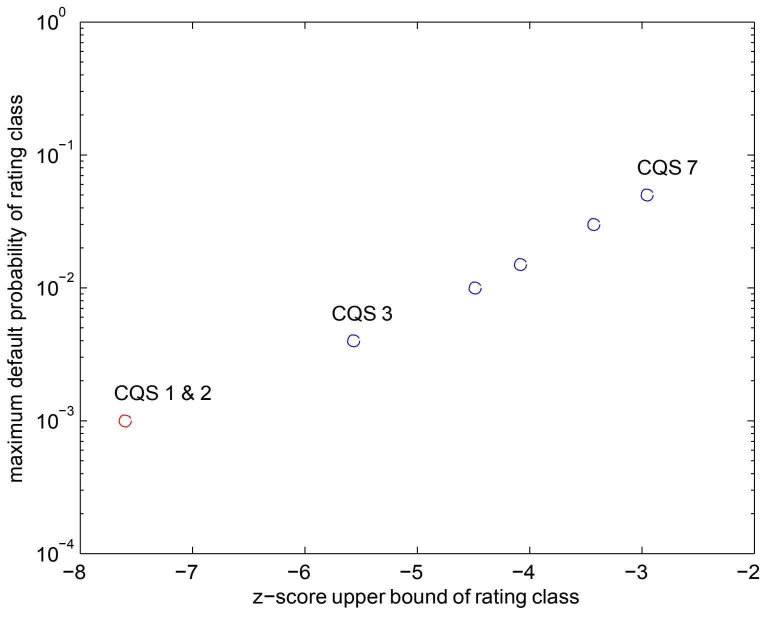

FIGURE 3: Thresholds in terms of z-scores defined according to the text.
Source: ECB, Banco de Portugal and authors' calculations.

Two observations are important at this point. First, it is clear that even with this strategy a post-classification evaluation of the method is warranted. This is because the thresholds define classes in terms of z-scores but if the observed default rates are too noisy they will have no discrimination power relative to adjacent classes. The fact that the dots represent a relatively smooth function of the probability of default with respect to the z-score gives us confidence about the capacity of the classification method to produce reasonable results.

Second, it is not possible to classify firms with credit rating classes with default probabilities below a certain value, that is, above a certain credit rating. The reason for this is the scarcity of observations classified in lower risk classes. For example, the upper limit of the default probability admissible for a

7. For class 1 & 2, the intersection was extrapolated. More on this below.

firm with a Credit Quality Step 1 would be[8] about 0.03% during one year. This means that we need approximately 67 thousand observations classified with that rating to expect observing 20 defaults.[9] If we cannot classify this number of firms with such rating in our sample, we also cannot be sure that those firms really have a probability of default compatible with the step 1 rating. Even if we are willing to lower the number of expected default events to, say, 5, we still need 17 thousand observations. In practice, for our data set we found that thresholds up to class 2 are possible: this is one class above the highest credit class for which it is possible to consistently estimate default rates. This point can made by noting that, using the notation previously introduced, $\hat{d}_1^{23} = \frac{23}{11486} = 0.002$, that is, the first 23 defaults occur for the best 11,486 z-scores. This default rate is significantly lower than the upper limit of credit class 3, and above the upper limit of credit class 2.[10] Using the fitted curve of Figure 2 to extrapolate one class above (in terms of rating) class 3 seems reasonable. For this reason we lumped Credit Quality Steps 1 and 2 into the class labeled "1 & 2". In Figure 4 we have depicted observed default rates for each class using the thresholds shown in Figure 3. Also represented are the upper default probability limits of each credit class. Since we are using a conservative approach in defining the thresholds, we see that, for all classes except class 1 & 2, the observed default rates are lower than the upper limit of each class. Moreover, assuming within-class binomial distribution[11] the lower bound of the 90% confidence interval of the default rate lies above the upper limit of the class immediately to its left (that is, with better credit quality) and the upper bound lies below the upper limit of the class.

Classes with few observations

Class 1 & 2 merits a special reference. Out of a sample of more than 740 thousand firm-year observations spanning the period 2005–2014, the above methodology allows us to classify 1177 observations in class 1 & 2. Out of these observations only two were defaults. This means that the statistical significance of the empirical default rate is low: one more or one less default would change considerably the observed default rate of the class. In Figure 4, this can be seen by the wide 90% confidence interval, whose lower limit is 0 and higher limit is 0.35%, assuming a binomial distribution of defaults within

8. This would be roughly equivalent to ratings of AA- and above (Fitch and Standard & Poors) or Aa3 and above (Moody's).

9. That is, $20 \times \frac{1}{0.0003} \approx 67,000$ observations.

10. Assuming a binomial distribution, the lower and upper limits of the 90% confidence interval of $\hat{d}_1^{23}$ are 0.13% and 0.27%, respectively.

11. Under the binomial distribution, the observed default rate of a given class is the maximum likelihood estimator of the default rate.

the class. This also means that we do not reject the null hypothesis that, under a binomial distribution, the actual probability of default is lower than 0.1%.

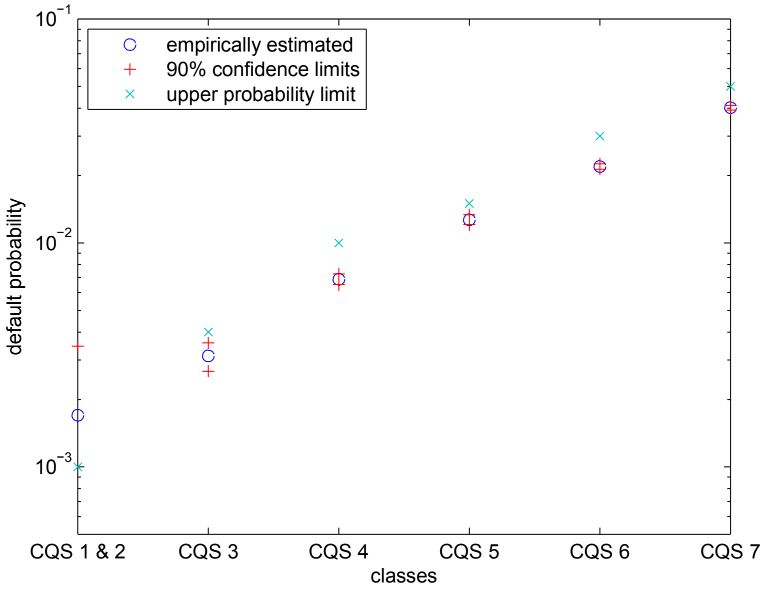

FIGURE 4: Observed default probabilities across classes using the thresholds in terms of z-scores defined according to the text. Confidence intervals are estimated assuming that within each class the default event follows a binomial distribution. Upper limits for default probabilities of each Credit Quality Step as defined by the Eurosystem also depicted as dashed horizontal lines.

Source: ECB, Banco de Portugal and authors' calculations.

All in all, one would assume that the model should be able to reliably distinguish firms in terms of all credit categories, with the best class being a residual class that lumps all high credit quality observations. The discriminating power of the model is limited by the number of observations in each class; we deem it reasonable to classify firms up to class 2. In the next section we perform an analysis of transitions of firms across classes and to default.

Some results

We now present some of the results of the rating system applied to our data. The results are consistent with the observation from Figure 2 that the z-scores seem to be effective in distinguishing firms in terms of their propensity to default.

Credit risk dynamics

Transition tables are a useful way to characterise the dynamics of firms across rating classes and to default. These tables typically contain the probability of moving to a specific credit rating class or to default, conditional on the current rating class. Table 6 contains some general statistics of our sample, including the observed default rates conditional on rating class and also exits from the sample.

Overall, we see that the default rates across classes vary considerably but are close to both their model-predicted values and the upper limit of the respective class, as seen in Figure 4. Class 8 is the most prevalent, while unsurprisingly the least numerous one is class 1 & 2, which accounts for about 0.16% of the sample. Applying the Spiegelhalter (1986) test within each class allows us not to reject (with the exception of class 8) the null that all model-estimated default forecasts match the true but unknown probability of default of the firm.[12]

As for exits without default from the sample, values vary between 11% and 18%, with an overall mean of 13.8%. These transitions are defined as permanent exits from the sample due to any of the following situations, all of them without any registered default: (i) exit from activity by merger, acquisition or formal extinction; (ii) the firm's loans are fully amortised; (iii) at least one of the regressors selected in the Logit model is not reported by the firm. Defaults can always be detected even if the firm ceases to report to CB because banks still have to report any non-performing loans by legally existing firms. These numbers compare favourably with similar measures found in the literature. For example, Figlewski *et al.* (2012) reports that, out of a sample of about 13,000 observations, the withdrawal rate was 33%.

Over time, the model-estimated default probabilities follow reasonably well the observed default rates. A notable exception is 2009, when observed default rates were considerably higher than what the respective credit risk class would suggest. This was a widespread phenomenon. See, for example, Chart 14 in Vazza and Kraemer (2015). In Table 7 this can be assessed by the differences in observed default rates in year t and the predicted default rates in year $t-1$ for year t. We see that most of the variation is due to the highest risk class, where the construction and real estate industry and the micro firms are over-represented (see Table 9 below).

Table 8 reports the overall transition matrix, which contains the share of firms migrating from one risk class to another in the subsequent year, conditional on non default and non exit. The table shows that in 3 out of 7 classes the majority of firms remained in the same risk class. It is also seen that

12. For class 8 we indeed reject the null at 5% significance. The average model-estimated default rate is 10.0% while the observed value is 10.3%. See Table 6.

the large majority of firms either stayed in the same category or moved only one category up or down. In addition, notice that, conditional on non default and non exit, firms were more likely to be downgraded than to be upgraded, except class 8 for obvious reasons.

The Markovian structure of the matrix allows us to compute a long-run distribution across credit classes (called the "ergodic" distribution). This would be the distribution prevailing in a year in the distant future if the rate at which firms entered and left the data set were those observed in the sample. It turns out that such distribution is remarkably similar to the actual shares of firms observed in Table 4. This suggests that the sample is a reasonable representation of the long-run dynamics of firms across credit rating classes.

One thing that is important to note is the relatively low persistence of credit class categories that emerges with this tool. The average persistence of a firm in the same class is much smaller than the persistence observed by ratings from rating agencies. For example, Vazza and Kraemer (2015) document that, out of 7 credit risk categories, the average fraction of firms staying in the same credit category is 87%; the comparable number in our sample is 45%. There are at least two reasons for this.

First, rating agencies typically produce ratings for relatively large corporations that have strong incentives to be rated, while in our case all firms are *ex ante* included in the sample. Moreover, several strategic considerations could bias the persistence values. While typically credit rating agencies follow firms even when they are no longer rated to detect potential defaults, firms that are currently rated might have an incentive to withdraw the rating if they suspect they will be downgraded. The other two possibilities—rating unchanged or upgrade—do not induce such a powerful incentive. This strong selection bias of the static pools of rating agencies, while not affecting the transitions to default—as ratings are conditional on the actual balance sheet of firms—would tend to produce much more persistent ratings than a rating tool that potentially includes all firms.

Second, ratings agencies and also other rating systems (such as Banco de Portugal's ICAS, currently applied to mostly large Portuguese corporations) typically involve dedicated analysts which have some latitude in adjusting the ratings coming from the statistical models underlying the system. This could also be a origin of more persistent ratings as the analyst would be reluctant to change the rating if, for example, the newly computed probability of default were marginally outside the range of the previous rating. No such adjustments are done here and even minor changes in the model-estimated default probabilities could entail changes in credit risk category.

Table 9 presents the model-estimated probabilities of default versus the empirical probabilities of default separately for each industry group and for each size category, as well as the share in terms of observations of each risk class in the group. When compared to the other sectors, the table shows that the construction and real estate sectors (industry 2) have a particularly high average default probability. This result is observed both in the comparison of estimated and empirical default probabilities and in the shares of each class. Class 8 is more than twice as large as any other risk class in this specific industry group.

Relatively risky are also micro-sized firms (size 1), none of which is considered to be in class 1 & 2 while about 74% of them are concentrated in the three worst risk classes. In contrast, about 57% of larger firms (size 2) are in the three worst risk classes.

The table shows that the five industries are generally skewed to riskier classes, particularly classes 6 and 8.

Additional validation

It is outside the scope of this article to present a detailed characterization of the method's performance out-of-sample and validation exercises. For a simple approach to this issue, the interested reader is reported to, for example, Wu (2008). Aussenegg *et al.* (2011) and Coppens *et al.* (2016) and references therein provide more advanced material.

Conclusion

The aim of this article is to present a method to assess the creditworthiness of the Portuguese non-financial firms by estimating the probability that any given firm will have a significant default episode vis-à-vis the banking system during the following year. The outcome of the model is then mapped into a masterscale where companies are grouped into homogeneous risk classes, originating a synthetic indicator of the firm's ability to fulfill its financial commitments.

By merging balance sheet information from 2005 until 2014 with credit register information from 2002 until 2015 we were able to estimate ten different models with good explanatory power in terms of the default risk of a firm. With the exception of class 8, the model-estimated default probabilities are not statistically different from the observed default probabilities.

The results also show how firms are mostly allocated to higher risk classes, with some industries and firm size classifications not represented in the lowest risk class. As expected, micro-sized firms have, on average, estimated and observed default probability higher than larger firms. The same can be seen for the construction and real estate sectors when compared to the rest of the industry sectors.

With respect to the dynamics in the transition tables presented, we can see that, from one year to the next, most firms remain in the same risk class or move to an adjacent class. Moreover, the overall transition table also seems to indicate that our model is a fairly good representation of the long-run risk distribution of the Portuguese non-financial sector.

Finally, it should be stressed that the available data do not allow us to classify firms beyond a certain credit quality. This is due to the scarcity of observations for the lower risk classes. For a finer classification among high ratings it is necessary to include professional analysts in the process and, perhaps, resort to more structural models of default as opposed to statistical approaches like the one followed here.

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CQS	Withdrawn	Default rate			Share of
		Observed	Estimated	*Upper limit*	total sample
1 & 2	16.4	0.17	0.10	*0.10*	0.16
3	11.1	0.31	0.28	*0.40*	5.5
4	11.6	0.69	0.69	*1.00*	16.7
5	11.8	1.27	1.24	*1.50*	11.1
6	12.4	2.20	2.17	*3.00*	21.8
7	13.1	4.02	3.91	*5.00*	16.0
8	17.6	10.3	10.00	*100*	28.8
Full sample	13.8	4.36	4.25	*n.a.*	100

TABLE 6. Observed and model-estimated default rates and rate of exits from the sample without default, by rating class. Model default rates estimated using the semiparametric methodology. All values in percentage. Model-estimated default rate for CQS 1 & 2 set to the upper limit of the class.

Source: Banco de Portugal and authors' calculations.

CQS	Default rate	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	Total
1 & 2	Estimated	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10
	Observed	0.00	1.75	0.00	0.00	0.72	0.00	0.00	0.00	0.00	0.00	0.17
3	Estimated	0.29	0.28	0.29	0.28	0.28	0.28	0.28	0.28	0.28	0.28	0.28
	Observed	0.16	0.30	0.33	0.78	0.17	0.27	0.42	0.22	0.26	0.39	0.31
4	Estimated	0.70	0.70	0.70	0.70	0.69	0.69	0.69	0.69	0.69	0.69	0.69
	Observed	0.48	0.51	0.64	0.87	0.42	0.77	1.13	0.77	0.70	0.46	0.69
5	Estimated	1.24	1.24	1.24	1.24	1.24	1.24	1.24	1.24	1.24	1.24	1.24
	Observed	0.82	1.00	1.46	1.82	1.05	1.59	1.89	1.34	1.02	0.66	1.27
6	Estimated	2.17	2.17	2.18	2.18	2.18	2.17	2.17	2.17	2.16	2.16	2.17
	Observed	1.35	1.84	2.41	3.33	1.70	2.54	3.40	2.21	1.68	1.42	2.20
7	Estimated	3.90	3.90	3.91	3.91	3.91	3.91	3.90	3.92	3.90	3.89	3.91
	Observed	2.61	3.56	4.64	6.09	2.99	4.51	5.86	3.99	3.30	2.35	4.02
8	Estimated	9.06	9.20	9.32	9.52	10.30	10.25	10.62	10.95	10.20	9.78	10.04
	Observed	6.57	7.99	10.43	14.44	8.09	11.00	15.29	11.32	8.59	6.42	10.31
Total	Estimated	3.77	3.91	4.03	4.30	4.64	4.25	4.59	4.82	4.13	3.75	4.25
	Observed	2.63	3.40	4.54	6.53	3.62	4.68	6.74	4.98	3.47	2.43	4.36

TABLE 7. Observed and model-estimated default rates over time, by rating class. Model default rates estimated using the semiparametric methodology. All values in percentage. Model-estimated default rate for CQS 1 & 2 set to the upper limit of the class.

Source: Banco de Portugal and authors' calculations.

CQS in year t	CQS in year t+1						
	1 & 2	3	4	5	6	7	8
1 & 2	36.5	**55.9**	5.9	0.7	0.8		0.1
3	1.5	**56.5**	32.0	4.5	3.6	1.1	0.8
4	0.0	10.7	**51.3**	17.3	13.7	4.1	2.8
5	0.0	2.0	25.8	26.1	**30.6**	9.3	6.2
6	0.0	0.8	9.4	14.4	**40.2**	20.5	14.7
7		0.3	3.5	5.3	24.6	31.8	**34.4**
8		0.1	1.4	2.2	9.1	16.0	**71.2**

TABLE 8. Transition matrix between credit rating classes, conditional on firms being in the sample in two consecutive years and not defaulting. Rows add up to 100 percent. All values in percentage.

Source: Banco de Portugal and authors' calculations.

CQS	Statistic	Industry					Size		Total
		1	2	3	4	5	1	2	
1 & 2	Estimated def. rate	0.10		0.10	0.10	0.10		0.10	0.10
	Observed def. rate	0.00		0.18	0.00	0.00		0.17	0.17
	Share of obs.	*0.02*		*0.40*	*0.70*	*0.00*		*0.36*	*0.16*
3	Estimated def. rate	0.29	0.34	0.27	0.26	0.31	0.33	0.27	0.28
	Observed def. rate	0.40	1.38	0.30	0.00	0.19	0.29	0.32	0.31
	Share of obs.	*5.89*	*0.45*	*8.61*	*12.56*	*3.56*	*1.33*	*10.79*	*5.52*
4	Estimated def. rate	0.69	0.74	0.68	0.68	0.70	0.72	0.67	0.69
	Observed def. rate	0.68	0.94	0.75	0.79	0.56	0.70	0.68	0.69
	Share of obs.	*17.45*	*6.48*	*19.12*	*19.33*	*18.41*	*13.10*	*21.20*	*16.69*
5	Estimated def. rate	1.24	1.25	1.24	1.24	1.24	1.24	1.24	1.24
	Observed def. rate	1.44	1.45	1.25	0.56	1.14	1.24	1.31	1.27
	Share of obs.	*10.81*	*7.72*	*11.44*	*10.75*	*12.72*	*11.24*	*10.88*	*11.08*
6	Estimated def. rate	2.17	2.22	2.16	2.16	2.16	2.18	2.16	2.17
	Observed def. rate	2.24	2.25	2.10	2.22	2.26	2.21	2.17	2.20
	Share of obs.	*21.02*	*21.73*	*21.19*	*18.45*	*23.39*	*24.15*	*18.83*	*21.79*
7	Estimated def. rate	3.91	3.94	3.89	3.91	3.89	3.91	3.90	3.91
	Observed def. rate	3.89	3.76	3.98	5.28	4.32	4.11	3.86	4.02
	Share of obs.	*15.52*	*20.40*	*14.67*	*12.65*	*15.86*	*18.54*	*12.82*	*16.00*
8	Estimated def. rate	10.15	10.47	10.12	9.83	9.45	9.54	10.83	10.00
	Observed def. rate	10.37	10.80	10.47	9.75	9.59	9.71	11.26	10.31
	Share of obs.	*29.29*	*43.22*	*24.56*	*25.55*	*26.06*	*31.64*	*25.12*	*28.75*
Total	Estimated def. rate	4.30	5.96	3.81	3.70	3.88	4.51	3.93	4.24
	Observed def. rate	4.41	6.10	3.91	3.78	3.97	4.60	4.05	4.36
	Share of obs.	*100.00*	*100.00*	*100.00*	*100.00*	*100.00*	*100.00*	*100.00*	*100.00*

TABLE 9. Model-estimated and observed default rate for selected groups of firms. Model default rates estimated using the semiparametric methodology. All values in percentage. Model-estimated default rate for CQS 1 & 2 set to the upper limit of the class.

Source: Banco de Portugal and authors' calculations.

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Özdere-İzmir, Turkey, 26 September 2016

Firm default probabilities revisited[1]

António Antunes, Homero Gonçalves and Pedro Prego,

Bank of Portugal

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

Firm default probabilities revisited

António Antunes (Banco de Portugal and NOVA SBE)

Homero Gonçalves (Banco de Portugal)

Pedro Prego (Banco de Portugal)

July 7th, 2016

BANCO DE PORTUGAL
EUROSYSTEM

Economics and Research Department

Outline

1. Datasets
2. Data treatment
3. Default definition and variables groups
4. Methodology
5. Rating schedule estimation
6. Results

Informação Empresarial Simplificada (IES)

Time span: 2005 – 2014

Individual firm identifier

Firm characteristics:

- Size
- Industry
- Age

Balance Sheet information

Profit & Loss Statement

Cash-flow information

Central Credit Register (CRC)

Time span: 2002 – 2015

Individual firm (borrower) identifier

Firm (borrower) information:

- Performing vs non-performing
- Type of product
- Type of responsibility
- Lender institution

IES dataset treatment

- Dropped observations:
  - Negative total assets
  - Negative liabilities
  - Negative turnover
  - Firms with total assets, number of employees or turnover equal to zero
- Ratios winsorized at the 2nd and 98th percentiles
- Strictly positive variables with very high kurtosis and/or high skewness are used in logs
- All variables are duplicated with one version being used in ranks with a uniform distribution between 0 and 1
  - This process takes place before the winsorizing occurs
  - Ranks are calculated within each year-size-industry group

CRC dataset treatment

- All firm-bank relationships below 50€ are dropped

- Only loans considered in the analysis
  - Credit lines, write-offs and renegotiated credits are excluded

- Only individual and first mutuary credits
  - Other mutuary and/or garantor(s) are excluded

- All firms with total credit vis-à-vis the finantial system below €10.000 are removed

Default definition

- Firms with a non-performing part of total credit of, at least, 2.5% are considered in default

- The default event occurs when the firm completes its third consecutive month in default

- Needs to have a clean record (non default status) for the previous 3 years

- After default event, the firm is removed from the sample

Default definition and variables groups

Variables Groups

Leverage	Profitability	Liquidity	Capital Structure	Dimension	Other	Macro factor
• Finantial debt • Banking debt • Interest paid	• EBIT • EBITDA • Profit/Loss • VAB/worker	• Cash Holdings • Current Liabilities	• Equity • Current Assets • Tangible Assets	• Total Assets • Turnover • Employment • Age	• Trade Debt • Wages	• Agg. Default • Credit Gr. • NGDP Gr. • RGDP Gr.

Size

1. Micro
2. Small, Medium and Large

Industry Sector

1. Manufacturing & Transporting and storage
2. Construction & Real estate activities
3. Wholesale & Retail Trade & Primary sector
4. Utilities & Mining and quarrying
5. Service Sector

Imbens & Rubin's (2015) stepwise approach

➢ Iterative process of variable selection based on the **Likelihood Ratio** (LR) statistic:

1. Set of variables: A, B, C, D
2. Estimate separate Logit models for each of the variables in the set
3. Choose the variable with the highest LR statistic and include it in the baseline model
4. Repeat the process until the LR statistic is below **1**

Imbens & Rubin's (2015) stepwise approach

➢ Set of variables: A, B, C, D

	LR Stat 1	LR Stat 2	LR Stat 3	End
A	**14.23**	---	---	
B	7.89	2.14	0.91	
C	11.84	**4.23**	---	
D	5.03	0.94	0.74	

➢ Imbens & Rubin's main limitations for our setup: **too many variables selected** and **highly correlated**

Modified Imbens & Rubin's (2015) stepwise approach

➢ Iterative process of variable selection based on the Likelihood Ratio (LR) statistic:

1. Set of explanatory variables: 118!
   i. Size and industry fixed effects included

…

5. Repeat the process until the LR **ratio** is below the **5% threshold**
   1. Every chosen variable has to **be statistically significat** at 5% level
   2. Every chosen variable **does not have a correlation** with some other chosen variable higher than **0.5**
   3. Any additional variable has to **improve AIC** and **AUROC** criteria
   4. Limited to a maximum of 10 explanatory variables selected

Modified Imbens & Rubin's (2015) stepwise approach

Entire dataset

Selected variables

Training data (70% of entire dataset)

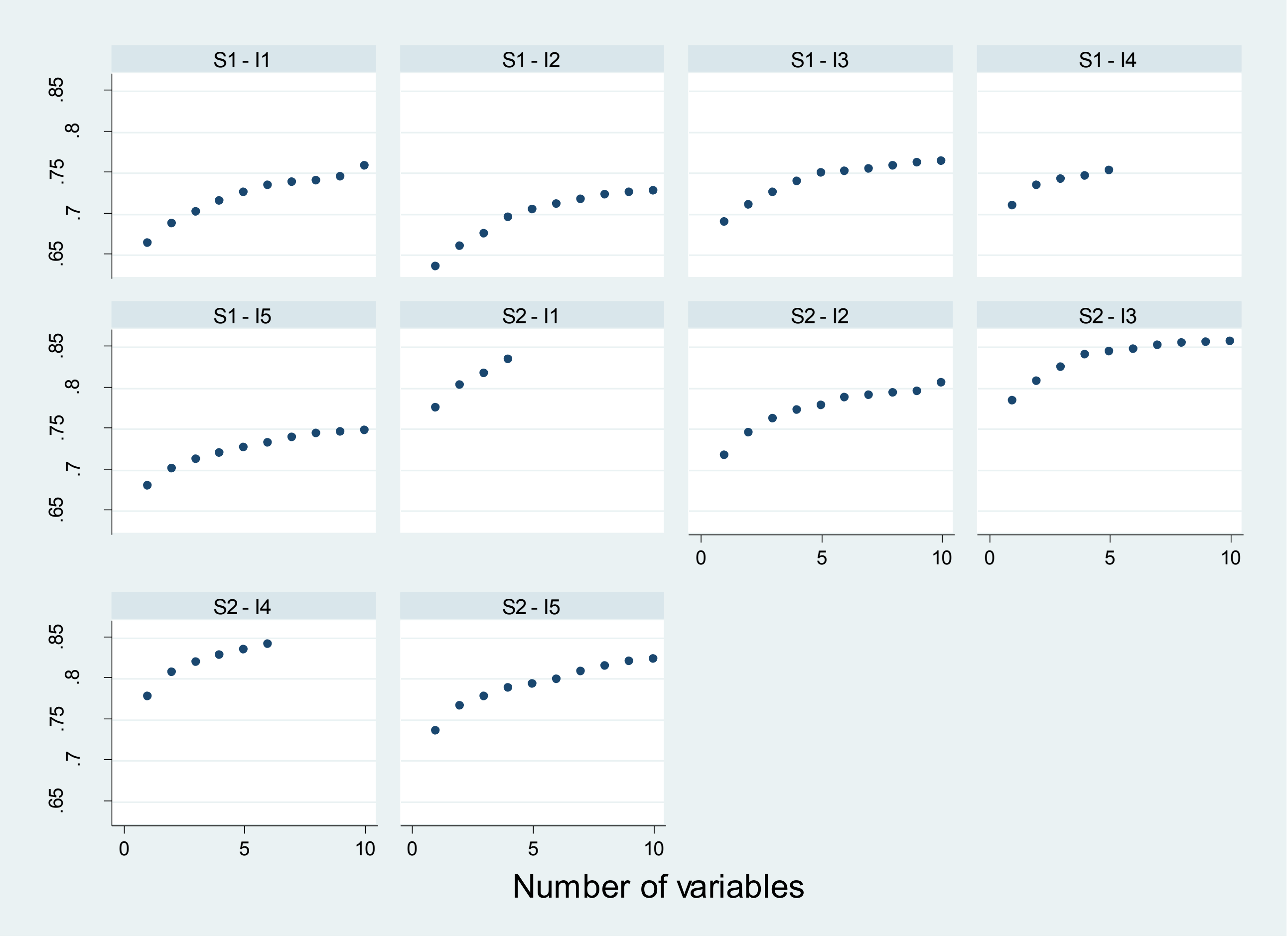
Coefficients estimation

- Rating schedule estimation
- Validation tests

Modified Imbens & Rubin's (2015) stepwise approach

Pair	Observations	Defaults Ratio	# variables	AUROC		Brier Score	
				Training	Validation	Training	Validation
S1 - I1	76417	5.11%	10	0.755	0.755	0.046	0.046
S1 - I2	103215	5.71%	10	0.726	0.726	0.051	0.051
S1 - I3	282453	4.56%	10	0.763	0.759	0.041	0.041
S1 - I4	4598	4.59%	5	0.771	0.701	0.043	0.038
S1 - I5	232945	4.48%	10	0.746	0.741	0.041	0.042
S2 - I1	98392	3.93%	4	0.830	0.837	0.035	0.034
S2 - I2	46020	6.51%	10	0.799	0.808	0.054	0.056
S2 - I3	77292	2.56%	10	0.854	0.855	0.022	0.024
S2 - I4	4319	3.22%	6	0.842	0.824	0.025	0.039
S2 - I5	61037	3.14%	10	0.823	0.818	0.029	0.028
Total	**986688**	**4.48%**	**n.a.**	**0.778**	**0.776**	**0.0402**	**0.0406**

AUROCs for each separate model*



* - the dots represent variables picked by the algorithm and do not include the fixed effects.

Variables selected

Variable	# times selected	Average rank	Coef. sign
r(EBITDA/Interest_exp)	7	1.4	-
r(Interest_exp/Fin_debt)	8	3.4	+
r(Cash Flow / Total assets)	2	1.0	-
r(Avg_pay_days)	6	3.3	+
r(Assets/Turnover)	5	4.4	-
r(Cash ratio)	6	5.3	-
r(Net Income/Total assets)	1	1.0	-
r(Equity/Fin_debt)	3	3.3	-
r(Equity/Total assets)	3	3.7	-
log(Financial debt / Total assets)	5	6.4	+
Ln(Interest Expenses/Fin_debt)	2	3.0	+
Ln(Age)	5	7.8	-
Agg. Default Rate	3	5.3	+
r(Wages / Total assets)	3	5.7	-
Ln(Cash ratio)	1	2.0	-
r(Trade Debt/Total assets)	2	4.5	+

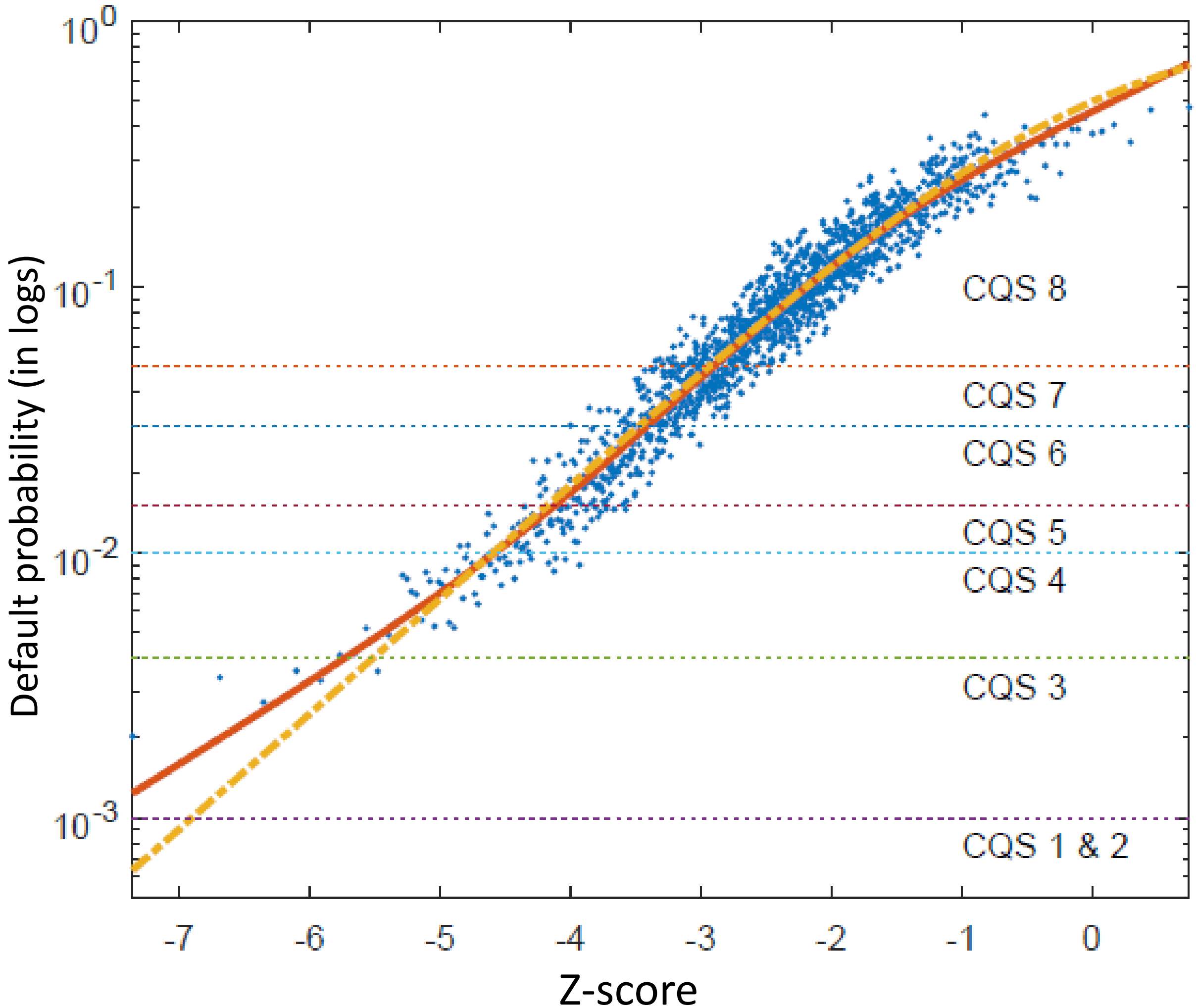
Variables selected

Variable	# times selected	Average rank	Coef. sign
Ln(Avg Invest. Turnover)	3	7.3	-
Equity/Total assets	2	6.0	-
r(Financial Leverage)	1	3.0	+
r(Value-added per worker)	2	6.0	-
r(Financial debt/ Total assets)	2	8.0	+
r(Current assets / Total assets)	2	8.0	+
r(Avg Invest. Turnover)	2	9.0	-
Cash Flow/Turnover	1	6.0	-
Credit growth	1	7.0	+
Ln(Employees)	1	7.0	+
r(Cash/Current Assets)	1	8.0	-
Nominal GDP growth	1	9.0	-
Ln(Total assets / Turnover)	1	9.0	-
r(Turnover)	1	10.0	-
log(Turnover)	1	10.0	+
Ln(Current assets / Total assets)	1	10.0	+

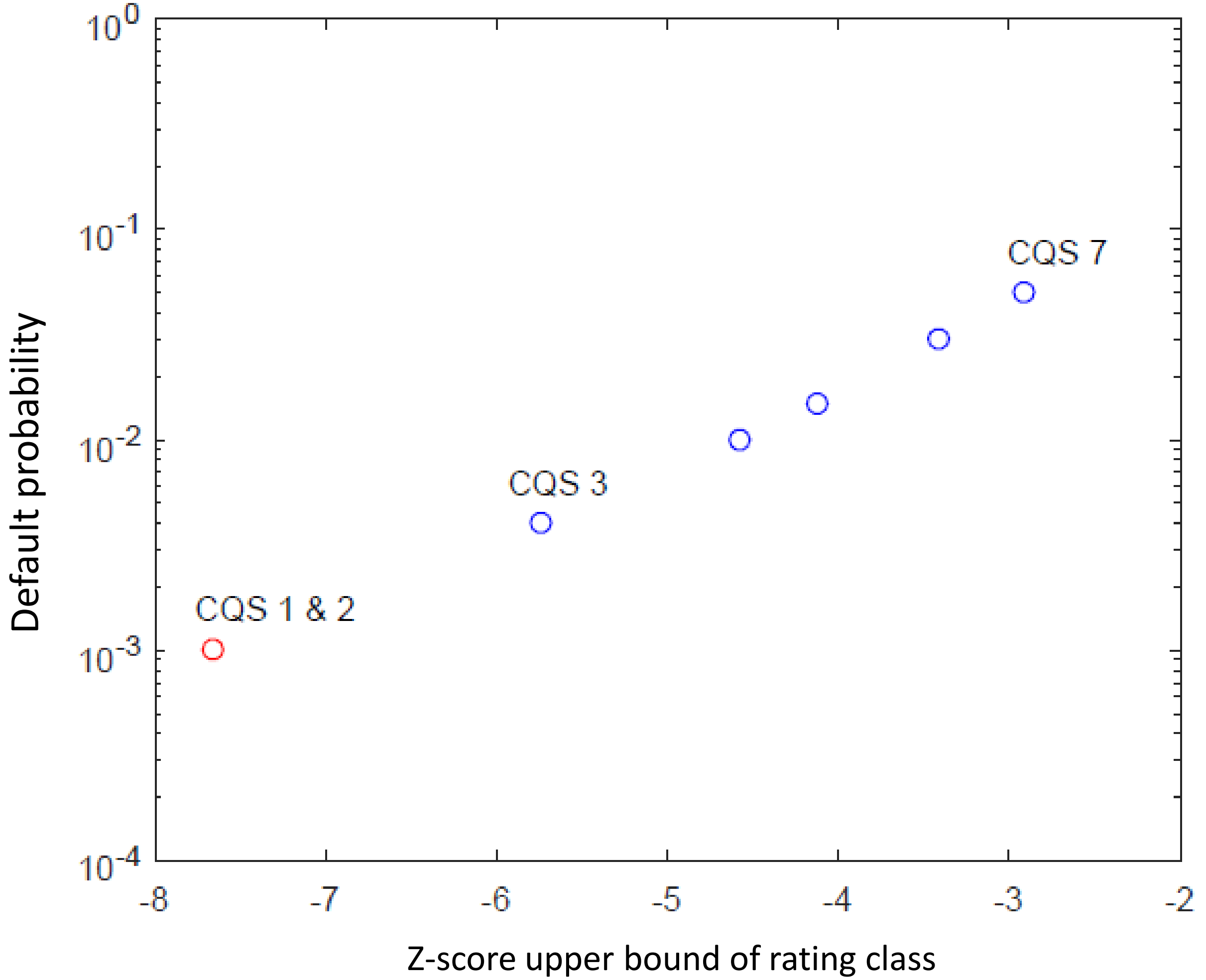
ECB’s rating schedule

<table>
<tr><th colspan="2">Masterscale (COCAS)</th><th colspan="2">Credit Quality Step (Eurosystem)</th></tr>
<tr><th>Rating Class</th><th>PD</th><th>Rating Class</th><th>PD</th></tr>
<tr><td>1</td><td>0.004%</td><td rowspan="7">1&2</td><td rowspan="7">0.10%</td></tr>
<tr><td>2+</td><td>0.010%</td></tr>
<tr><td>2</td><td>0.016%</td></tr>
<tr><td>2-</td><td>0.025%</td></tr>
<tr><td>3+</td><td>0.040%</td></tr>
<tr><td>3</td><td>0.063%</td></tr>
<tr><td>3-</td><td>0.100%</td></tr>
<tr><td>4+</td><td>0.159%</td><td rowspan="3">3</td><td rowspan="3">0.40%</td></tr>
<tr><td>4</td><td>0.250%</td></tr>
<tr><td>4-</td><td>0.394%</td></tr>
<tr><td>5+</td><td>0.615%</td><td rowspan="2">4</td><td rowspan="2">1%</td></tr>
<tr><td>5</td><td>0.951%</td></tr>
<tr><td>5-</td><td>1.457%</td><td>5</td><td>1.5%</td></tr>
<tr><td>6+</td><td>2.204%</td><td>6</td><td>3%</td></tr>
<tr><td>6</td><td>3.284%</td><td rowspan="2">7</td><td rowspan="2">5%</td></tr>
<tr><td>6-</td><td>4.814%</td></tr>
<tr><td>7+</td><td>6.923%</td><td rowspan="4">8</td><td rowspan="4">>5%</td></tr>
<tr><td>7</td><td>9.750%</td></tr>
<tr><td>7-</td><td>13.422%</td></tr>
<tr><td>8</td><td>100%</td></tr>
</table>

Empirical default distribution

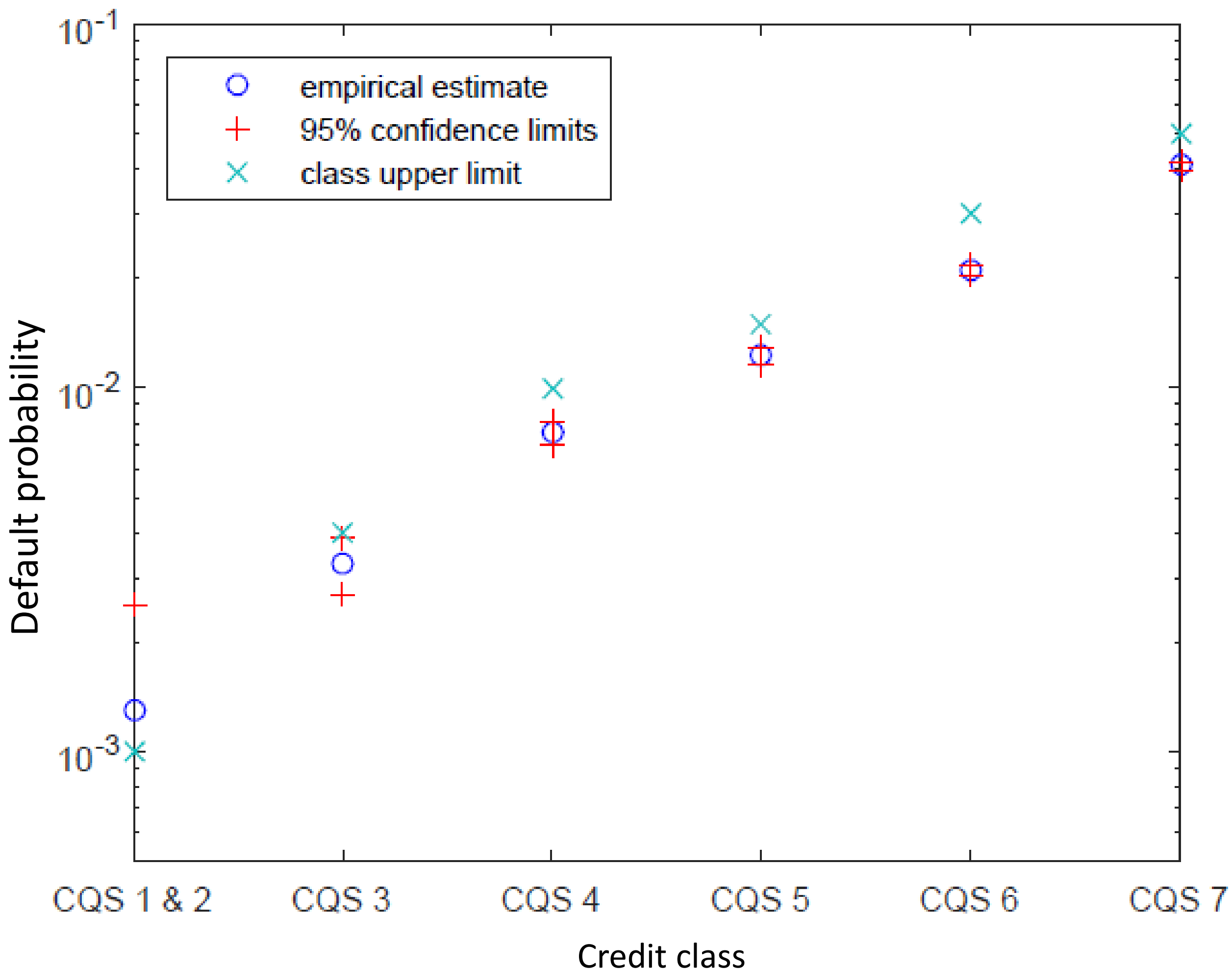


Estimated rating classes



Observed vs Reference Default Probabilities

(by rating class)



Transitions between risk classes*
(by risk classes)

	CQS in year t+1							
CQS in t	**1 & 2**	**3**	**4**	**5**	**6**	**7**	**8**	**Default**
1 & 2	45.00	**45.00**	7.78	1.11	0.67	0.40	0.04	0.09
3	3.22	**56.18**	28.89	5.45	2.78	2.67	0.80	0.32
4	0.25	9.60	**49.79**	19.34	10.03	8.37	2.62	0.73
5	0.03	2.06	21.52	**29.75**	21.88	19.13	5.64	1.19
6	0.01	0.84	8.85	18.32	27.16	**34.16**	10.66	1.78
7	0.01	0.34	3.22	6.20	13.81	**46.95**	29.47	3.40
8	0.00	0.09	0.79	1.50	3.13	19.34	**75.14**	10.41

* - condicional in the company being observed for two consecutives years in CB and not registering any credit event. All values in percentages. Rows add up to 100.

Observed vs estimated default rates and exit rates*
(by risk classes)

CQS	Exits	Default Rate			Share of
		Observed	Estimated	*Upper limit*	Total sample
1 & 2	18.33	0.09	0.10	*0.10*	0.50
3	13.57	0.32	0.26	*0.40*	5.3
4	15.63	0.73	0.73	*1.00*	14.4
5	14.97	1.19	1.26	*1.50*	11.6
6	14.28	1.78	1.86	*3.00*	12.5
7	13.79	3.40	3.37	*5.00*	25.7
8	18.56	10.4	10.23	*>5*	30.0
Total sample	15.63	4.48	4.43	*n.a.*	100

* - Exits with no credit event associated. Estimated default rates using the semi-prametric approach. Default rate for CQS 1 & 2 defined as the upper limit for the class. All values in percentages. Rows add up to 100.

Transitions between risk classes*
(by risk classes)

	CQS in year t+1							
CQS in t	**1 & 2**	**3**	**4**	**5**	**6**	**7**	**8**	**Default**
1 & 2	41.59	**48.14**	8.34	0.90	0.77	0.26	0.00	0.00
3	2.43	**56.62**	29.29	5.43	3.02	2.45	0.76	0.32
4	0.17	9.93	**49.21**	19.50	10.08	8.36	2.75	0.67
5	0.02	1.90	20.35	**31.02**	22.43	19.32	4.96	1.21
6	0.01	0.85	8.00	17.81	28.44	**34.89**	10.00	1.78
7	0.00	0.26	2.82	5.68	13.46	**48.57**	29.21	3.52
8	0.00	0.09	0.75	1.24	2.97	20.73	**74.23**	10.55

* - condicional in the company being observed for two consecutives years in CB and not registering any credit event. All values in percentages. Rows add up to 100.

Observed vs estimated default rates and exit rates*
(by risk classes)

CQS	Exits	Default Rate			Share of
		Observed	Estimated	*Upper limit*	Total sample
1 & 2	20.02	0.00	0.10	*0.10*	0.32
3	13.13	0.32	0.27	*0.40*	5.0
4	14.55	0.67	0.73	*1.00*	14.2
5	15.41	1.21	1.27	*1.50*	11.8
6	14.41	1.78	1.86	*3.00*	13.0
7	14.32	3.52	3.37	*5.00*	27.6
8	18.90	10.6	9.27	*>5*	28.1
Total sample	15.70	4.50	4.11	*n.a.*	100

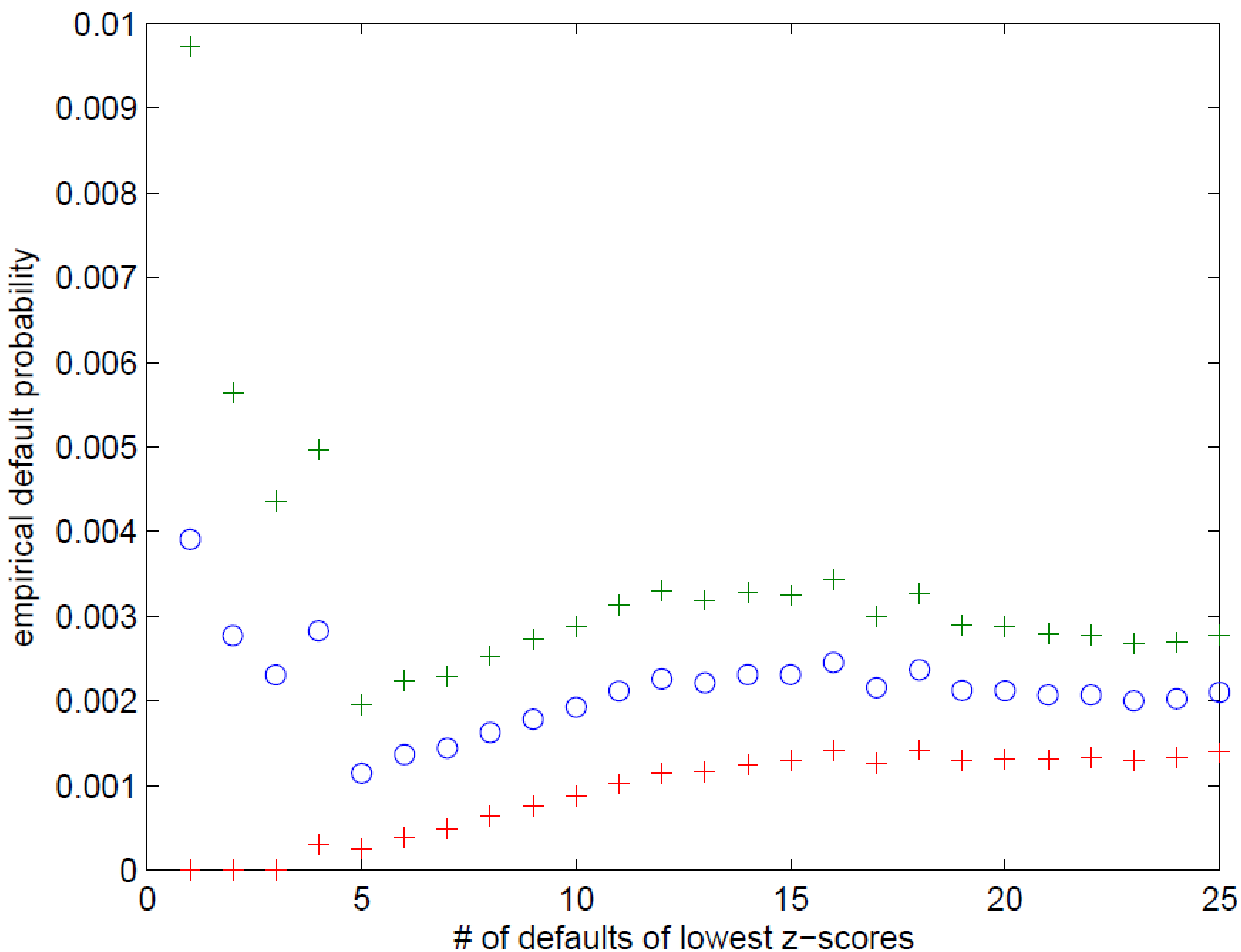
* - Exits with no credit event associated. Estimated default rates using the semi-prametric approach. Default rate for CQS 1 & 2 defined as the upper limit for the class. All values in percentages. Rows add up to 100.

Validation tests

	AUROC		Brier Score		Min-P test	
Grupo	Learning	Validation	Learning	Validation	Learning	Validation
S1 - I1	0.754	0.757	0.046	0.046	38.1%	100.0%
S1 - I2	0.729	0.720	0.051	0.051	**0.0%**	25.4%
S1 - I3	0.764	0.759	0.041	0.041	3.0%	32.5%
S1 - I4	0.746	0.759	0.043	0.038	93.3%	89.0%
S1 - I5	0.746	0.744	0.041	0.042	15.2%	100.0%
S2 - I1	0.832	0.835	0.035	0.034	88.4%	100.0%
S2 - I2	0.805	0.800	0.054	0.056	82.7%	38.7%
S2 - I3	0.855	0.849	0.022	0.024	100.0%	100.0%
S2 - I4	0.847	0.825	0.025	0.039	87.8%	**0.2%**
S2 - I5	0.822	0.822	0.029	0.028	100.0%	100.0%
Global	**0.778**	**0.775**	**0.0402**	**0.0406**	**99.9%**	**100.0%**

Support information

Default probabilities of high rating firms



Support information

$$s(\cdot) = \arg\min p \sum_{q=1}^{Q} (\log(\hat{d}_q) - s(\hat{z}_q))^2 + (1-p) \int_{\hat{z}_1}^{\hat{z}_Q} (s''(z))^2 dz$$

p – being a penalising parameter of the 2nd derivative

- with p=1 → natural cubic interpolant which passes through all the dots
- with p=0 → linear interpolant

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Özdere-İzmir, Turkey, 26 September 2016

Towards a more comprehensive understanding of corporate leverage ratios[1]

Nicolas Griesshaber, European Central Bank

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.

Towards a more Comprehensive Understanding of Corporate Leverage Ratios

Using firm-level data from Central Balance Sheet Data Offices to disentangle the role of firm, sector and region specific characteristics

Nicolas Griesshaber, European Central Bank[1]

Abstract

The current paper aims to take a more encompassing perspective on capital structures of non-financial corporations (NFCs), investigating the relative importance of firm, sector and region specific determinants of leverage. Utilising unique cross-country micro data on NFC balance sheet information for six euro area countries, obtained from Central Balance Sheet Data Offices, it explicitly takes into account the possible role played by firms' more local environment in shaping corporate financing structures. Employing cross-classified multilevel estimations to account for the hierarchical structure in the data, our findings suggest that both sector and regional characteristics are relevant to explain the variation of leverage across firms. The relative importance of these characteristics thereby seems to vary depending on the size of firms, with regional aspects being most relevant among smaller companies. Nevertheless, most of the variation across firms is still linked to firm specific differences.

Keywords: Capital Structure, Non-Financial Corporations, Regional Determinants, Balance Sheet Data, Multilevel Analysis

JEL classification: F30; F36; G32

[1] The views expressed in this paper are those of the author and do not necessarily represent those of the European Central Bank. All errors are the sole responsibility of the author. I would like to thank Annalisa Ferrando, Linda Fache Rousová, Ioannis Ganoulis, Manfred Koch, Sébastien Pérez-Duarte, Carlos Sánchez Muñoz, Livio Stracca and Caroline Willeke for their valuable comments and suggestions with respect to the current research. Contact: nicolas.griesshaber@ecb.europa.eu.

1. Introduction

As highlighted by a comprehensive ECB structural issues report on "Corporate Finance and Economic Activity in the Euro Area" (ECB 2013: 13), capital structure choices of non-financial corporations (NFCs) can have important implications for the financial stability and economic performance of the wider economy (see also Kühnhausen & Stieber 2013: 1). Moreover, companies' capital structure and financing choices are likely to play a central role for the transmission of monetary policy to the real economy, as these affect firms' access to finance and thus, their ability to seize investment opportunities. In consequence, gaining a comprehensive understanding of the underlying determinants of NFCs' financing policies, particularly in the aftermath of the financial crisis, appears of primary importance.

Such goal, however, necessitates i) availability of harmonised financial micro information on NFCs that offers sufficient data quality and coverage and ii) a more encompassing analytical approach to capital structure that accounts for both firm specific determinants as well as characteristics related to a firm's particular environment. While in the wake of the seminal study by Rajan and Zingales (1995) a substantial empirical literature on corporate capital structure has developed, existing evidence on the determinants of firms' financing choices appears far from conclusive. Moreover, most research to date is characterised by a rather narrow focus on specific factors or selective samples and thus, mostly lacks a more encompassing perspective. The current research aims to address these issues, investigating the role of firm, sector and region specific characteristics as determinants of leverage (measured as the ratio of total liabilities over assets). Building upon a vast empirical research tradition, it thereby aims to make the following main contributions.

First, it utilises a unique cross-section of harmonised large-scale NFC micro data from six euro area countries, expanding upon existing research that often focuses on single countries, small scale survey data or specific subsets of firms. The data is obtained from Central Balance Sheet Data Offices (CBSOs) as part of a pilot exercise on the value of a centralised collection of harmonised CBSO micro data, conducted by the European Central Bank (ECB).

Second, it goes beyond an exclusive focus on firm-level characteristics to also include the role of industry and regional differences. While the relevance of the former has been widely acknowledged in the literature on corporate capital structures, the latter in particular has been mostly neglected in cross-country investigations. However, regional aspects are likely to matter for firms' financing structures, providing relevant financial infrastructures as well as institutional, economic and social contexts that can affect the access to finance of NFCs. In addition, it is often argued that the recent financial crisis has reinforced regional differences within the euro area, increasing the relevance of an assessment of their economic effects. Understanding the nature, extent and origins of such possible regional differences with respect to NFCs' capital structures should be of significant relevance for policymakers as elimination of regional divergences in the access to finance are crucial for efforts towards convergence of non-financial corporations at European level (see also Palacín-Sánchez and di Pietro 2013: 3). To analyse the role of firms' respective environment, the current study distinguishes between 17 different sectors (based on main NACE rev. 2 sections) as well as 87 basic regions according to the Nomenclature of territorial units for statistics (NUTS). It will consider several sector and region specific factors that are assumed to have an impact on firms' financing decisions.

Finally, from a technical point of view, the current study explicitly considers the cross-hierarchical structure of the data, aiming to disentangle the relative importance of firms' respective industry as well as their local environment. While several existing contributions have analysed the possible role of the institutional environment and sector specific characteristics, they mostly pursue this in an isolated way (Kayo & Kimura 2011: 362), merely including dummy variables or specific characteristics of the respective environment. Meanwhile, empirical investigations that simultaneously analyse the effect of firm, sector and region specific differences while accounting for the nested structure of the data remain scarce (an exception is the multilevel study by Kayo & Kimura 2011). The present paper estimates crossed random-effects models, taking into account that intercepts may vary across sectors, regions as well as across their interaction. This allows assessing to what extent elements beyond mere firm characteristics may influence firms' financing choices and thus, their ability for future acquisition of capital. In consequence, the current study should help to provide a more comprehensive understanding of firms' capital structure, constituting an important basis for analysing economic and financial stability impacts of corporate financing and the transmission of monetary policy.

Results indeed indicate that, while most of the variation in leverage ratios across firms is linked to firm-level differences, both sector and regional characteristics are found to be of relevance (in particular with respect to the use of long-term debt). The relative importance of these characteristics seems to vary depending on the size of firms, pointing out to further differences in the transmission of monetary policy across firms. While capital structures of SMEs appear more strongly connected to their regional environment, large firms seem more affected by sectoral features.

This paper contributes to the literature that tries to gain a more encompassing perspective on corporate financing structures in the non-financial sector, confirming that firms' specific environment along with the specific characteristics of a firm are important elements that deserve a deeper analysis. It further indicates the value of a newly constructed cross-country database of harmonised firm-level information from CBSOs for such an analysis along with its monetary policy implications.

The remainder of the paper is organised as follows. Section 2 provides an overview of the main theoretical as well as empirical literature on corporate capital structure, summarising the existing evidence with respect to the main determinants of NFC leverage ratios. Section 3 introduces the firm-level data obtained from CBSOs, including a brief description of the data source as well as the conducted data adjustments. Section 4 focuses on the possible role of NFCs' industry and regional environment for the financing choices of firms, deriving the main expectations for the analysis. Section 5 describes the main variables considered in the analysis, along with their expected effects, as well as the estimation method that is employed. The results of the empirical analysis are discussed in section 6. The last section concludes.

2. Theoretical Foundations and Existing Evidence

More than half a century ago, the seminal work by Modigliani and Miller (1958) provided a starting point for a vast literature on corporate capital structure – also known as the debt-equity choice. Under the assumption of perfect and frictionless capital markets and a neutral tax system, their work suggested that financing choice has no effect on firm value as well as cost or availability of capital (Myers 2001: 81). While the logic of these results is by now widely accepted, various contributions have since relaxed the strict assumptions of Modigliani and Miller (1958), concluding that financing choices can matter. In consequence, several theories of optimal capital structure have developed. These mainly differ with respect to their relative emphasis and interpretation of certain main underlying factors that determine firms' debt-equity choices (Myers 2001: 82; ECB 2013: 40 f.).

The trade-off theory assumes that firms choose an optimal level of debt at which tax advantages of additional debt would be offset by the cost of possible financial distress (Myers 2001: 81). The pecking order theory (see Myers & Majluf 1984; Myers 1984) emphasises the role of information asymmetries between lenders and company insiders, which determine financing costs. In consequence, firms prefer the use of internal over external funds and debt over equity issuance when internal funds are not sufficient to cover expenditures. Yet another theoretical strand focuses on capital structure being determined by the benefits of debt against its agency costs – i.e. costs arising from conflicts of interest (see, e.g. Jensen & Meckling 1976; Harris & Raviv 1991: 300-301). Overall, while providing conditional theories based on different economic aspects, none of these theories seems to provide a more universal explanation of corporate financing decisions (Myers 2001: 99).

As regards existing empirical work, Rajan and Zingales (1995) conducted one of the first cross-country studies (across G7 member states), identifying firm size, growth opportunities, tangibility and profitability to be central determinants of firm leverage.[2] Since then, an increasing number of studies have empirically investigated the determinants of corporate financing structures. Existing contributions thereby predominantly focus on firm specific characteristics, largely finding a negative connection to profitability and growth opportunities and a positive relation with size and asset tangibility (e.g., among others, Ferrando et al. 2014; see also ECB 2013: 41).

In addition, a firm's age and liquidity have been brought forward as further factors that can affect corporate financing decisions, with existing evidence mostly pointing to a negative relation with leverage (e.g., among others, Michaelas et al. 1999; de Jong et al. 2008; Brav 2009; Bhaird & Lucey 2010; Kühhausen & Stieber 2014).[3] Firm risk, mostly measured by the variation in earnings or operating income, has also been found to be negatively connected to leverage in some contributions (Psillaki & Daskalakis 2009; Köksal et al. 2013). Finally, from a trade-off theory perspective, taxation may also affect corporate financing structures, leading some

2 Before then, most empirical work was almost exclusively based on US firms (Rajan & Zingales 1995: 1421).

3 La Rocca et al. (2011) find a non-linear effect for firm age.

studies to account for the possible effect of the effective tax rate and non-debt tax shields (Titman & Wessels 1988; Michaelas et al. 1999; Sogorb-Mira 2005; de Jong et al. 2008; Degryse et al. 2012; Köksal et al. 2013). However, resulting empirical evidence remains mixed and inconclusive.

Besides firm-specific determinants, some contributions have focused on the role of industry characteristics (e.g. McKay & Phillips 2005; La Rocca et al. 2011; Degryse et al. 2012; Kühnhausen & Stieber 2014). However, this often is restricted to the mere inclusion of industry dummies (e.g. Kester 1986; Titman & Wessels 1988; La Roca et al. 2011; see also Kayo & Kimura 2011: 360), mostly revealing significant variation across sectors. One common explanation for such differences is that managers take industry benchmarks such as the median leverage into account when choosing their own debt structure (Frank and Goyal 2009: 8). Indeed, studies using median leverage ratios to capture target capital structures of industries show a consistently positive connection to firms' debt ratios (e.g. Hovakimian et al. 2001; Frank and Goyal 2009; Degryse et al. 2012; Köksal et al. 2013; Kühnhausen & Stieber 2014). Besides median leverage, industries' growth environment (Frank & Goyal 2009; Kühnhausen & Stieber 2014) and concentration (MacKay & Phillips 2005; Kayo & Kimura 2011) have also been found to affect leverage ratios.[4]

Some cross-national studies have also investigated the possible effect of the institutional context and other country specific factors, showing that some differences in corporate financing structures reflect differences in firms' economic, institutional or cultural environment (e.g. Rajan & Zingales 1995; Demirguç-Kunt & Maksimovic 1999; de Jong et al. 2008; Psillaki & Daskalakis 2009; Öztekin & Flannery 2012; Kühnhausen & Stieber 2014). Exploring the relative importance of country characteristics, Fan et al. (2012) indicate that the country of residence appears to constitute a more important determinant of firms' capital structures than their industry affiliation. Country-level factors often associated to the use of debt financing include economic development and growth, tax policy as well as inflation (which decreases the relative value of debt while increasing the value of tax deductions from debt financing; see, e.g., Booth et al. 2001; de Jong et al. 2008, Frank & Goyal 2009; Fan et al. 2012; Köksal et al. 2013; Kühnhausen & Stieber 2014). The effectiveness and development of the financial system as well as developments in capital markets are also argued to be important determinants of corporate financing structures as financial markets and intermediaries provide direct sources of capital as well as mechanisms to ensure access to firm information for investors (Demirguç-Kunt & Maksimovic 1999: 2108; for the role of capital market developments, see also Fan et al. 2012; Köksal et al. 2013; Kühnhausen & Stieber 2014). However, empirical research with respect to specific characteristics and indicators in this regard remains mixed and far from conclusive. Finally, countries' legal tradition, the effectiveness of the legal system as well as the quality of public governance and thus, the enforcement of property and investor rights are often argued to be of high relevance. Indeed, Fan et al. (2012), among others, show the strength of the legal system and public governance to matter for corporate capital structure, finding weaker laws and higher corruption to be associated to higher debt ratios with shorter debt maturity while countries with explicit bankruptcy codes have higher debt ratios with longer maturities. Overall, these contributions have revealed

4 For further industry specific variables not mentioned in this chapter, see for instance MacKay and Phillips (2005) and Kayo and Kimura (2011).

a significant role of the residential context of firms in regard to their financing choices. Nevertheless, research on the role of the economic, institutional and socio-cultural environment thus far remains mostly at the level of countries and thus, usually neglects the possible impact of the more local environment.

Only recently, characteristics related to the local environment of firms have received some attention. La Rocca et al. (2010), Palacín-Sánchez and di Pietro (2013) and Palacín-Sánchez et al. (2013) show for Italian and Spanish regions, respectively, that leverage ratios as well as the role of firm-level determinants varies across regions and that development and structure of the regional financial system as well as regional economic conditions affect SMEs' capital structure. However, these studies are restricted to single countries, leaving the question whether certain regional characteristics affect firms' financing structures beyond an individual country setting unaddressed.

Finally, more encompassing research, which fully accounts for the different levels that might influence firms' financing decisions and which addresses the hierarchical structure of the underlying firm level data remains scarce. One exception is Kayo & Kimura's (2011) multilevel study on the role of industry and country differences for corporate capital structure (measured as the ratio of long-term debt to total assets). Using panel data for 17,061 NFCs from 40 countries over a period from 1997 to 2007 and employing mixed random effects estimation, they show that, although industry and country differences account for less variance in firm leverage than firm and time specific factors, their effect is far from negligible.

Strongly building upon the approach by Kayo and Kimura (2011), the current research takes a more regional perspective with respect to the geographical and institutional context instead of focusing on overall differences between countries. It further utilises more extensive, detailed and comprehensive data on NFCs' balance sheets for selected euro area countries, sacrificing a larger cross-section of countries in exchange for a higher coverage of the non-financial sector in the respective countries as well as high quality and depth of the firm-level data.

3. Data

The current analysis draws on a unique cross-country dataset of harmonised firm-level balance sheet information of NFCs from six euro area countries. The data stems from micro data underlying the Bank for the Accounts of Companies Harmonized (BACH) database and was obtained from Central Balance Sheet Data Offices (CBSOs) in the respective countries as part of an ECB pilot exercise on the value of a centralised collection of NFC micro data. BACH is a publicly available meso-aggregated database of the European Committee of Central Balance Sheet Data Offices (ECCBSO). It publishes non-consolidated accounting information of non-financial incorporated enterprises for currently 11 European countries, aggregated separately in each country by business sector and enterprise size.

Financial items are mostly based on common templates which have been harmonised to increase cross-country comparability.[5]

Six of the eleven national providers currently participating in BACH (i.e. Belgium, Spain, France, Italy, Portugal and Slovakia) agreed to provide the underlying annual firm-level data for their respective countries, resulting in a unique cross-country dataset of large scale firm-level data that has not been compiled at this level before. While the obtained data provides a time series dimension, the resulting cross-country panel data is rather diverse and unbalanced across countries and does only cover a rather short period (mostly 2009-2013). With respect to the current analysis, this limits the sample as well as the explanation power of the time dimension while adding more complexity to the estimations. Moreover, capital structure is expected to be rather stable across a shorter period of time (for empirical support, see, e.g., Lemmon et al. 2008).[6] Thus, in a first step, only a cross-section of NFCs is used instead of the full panel data. The data is pooled over time with each observation containing the latest record available for the respective firm. Only annual records from 2011 or later are considered.

Furthermore, only observations with non-missing information regarding all main variables central to the analysis are included. In addition, the sample is restricted to those firms with leverage ratios between 0 and 1 (following Kühnhausen & Stieber 2014: 7) in order to exclude influential outliers and observations with implausible values. The data was further adjusted to only contain observations with profitability values between -1 and 1 and tangibility and liquidity ratios between 0 and 1 (again following Kühnhausen & Stieber 2014). A description of the individual measures mentioned here is given in section 5 below. The final cross-section of NFCs from Belgium, Spain, France, Italy, Portugal and Slovakia analysed in the current study amounts to a total of 1,969,284 companies.

4. Accounting for Differences between Industries and Regions

The present analysis particularly considers that firms' financing decisions and capital structure may not be purely determined by intrinsic characteristics of the firm, but are likely to be influenced by their respective environment.

As discussed in section 2, various studies on corporate capital structures have previously highlighted the existence of significant variation in leverage ratios across sectors of activity. According to Frank and Goyal (2009: 8), two main reasons for such variation can be distinguished. First, managers might orient themselves along industry benchmarks when setting their own leverage ratios, treating such benchmarks as target capital structures. Second, companies within the same industry are likely exposed to common forces that affect their financing decisions, which may reflect different industry characteristics such as the nature of

5 For a detailed description of the BACH database as well as its underlying national data providers, refer to BACH Working Group (2015).

6 Preliminary analysis using the panel data shows that including a time dimension does not seem to add considerable explanation power to the analysis.

competition or industry heterogeneity in the types of assets, business risk, technology or regulation. Simerli and Li (2000) further point out that environmental factors may similarly affect corporate strategies of all organisations of a given industry (see Kayo & Kimura 2011: 360). In addition, industries can also differ regarding the type of firms that are predominantly active in them, possibly implying different financing strategies between different sectors due to the specific characteristics of firms in the respective industries. Overall, this leads to the expectation that a considerable part of variation in corporate leverage ratios across NFCs should be due to differences between industries, which likely reflect both differences in the composition of firms across sectors as well as specific industry characteristics that influence individual financing decisions. In consequence, it seems not only necessary to investigate the role of specific industry characteristics, but to also aim at establishing the relative importance of overall sector differences.

Sector differences are taken into account by distinguishing between 17 main sections based on the Statistical Classification of Economic Activities in the European Community (NACE, rev.2).[7] All observations from companies indicated as active in the financial sector (i.e. mostly holding companies) are excluded. In addition, firms from sector O – i.e. Public Administration and Defence; Compulsory Social Security – are dropped from the final analysis due to only 6 companies in the sample being active in this sector.

In addition to the role played by sectors, the current research focuses on specific characteristics of firms' local environment (i.e. the region) as a relevant factor affecting the capital structure of firms in a cross-country setting. While most existing research on the role of the institutional context and the regional environment concentrates on the level of countries (see section 2), some contributions have highlighted the existence of institutional differences at the local level, which are likely to have crucial impacts on corporate financing decisions (see La Rocca et al. 2011: 113). Moreover, development and infrastructure of regional financial sectors are likely to differ, which may strongly influence access to external financing for various firms (see also Palacín-Sánchez and di Pietro 2013: 5). Finally, economic forces and social factors can also vary considerably across local environments instead of being stable across geographic areas of the same country. It thereby appears reasonable that firms are often rather affected by these regional forces instead of country aggregates. Hence, regional differences should constitute relevant influences on firms' financing decisions, particularly for companies operating purely in a more local environment.

However, the role of regional characteristics may differ given the size of firms. As Palacín-Sánchez and di Pietro (2013: 5) argue, regional divergences in financial sectors would decrease in their relevance the better the possibility for firms to access any financial market. While large firms are likely to have access to wider financial markets across regional borders, smaller firms are often restricted to their more immediate environment and have limited access to financial companies operating in other regions. Thus, regional factors should be of particular relevance

[7] While information on the NACE classification provided in the BACH micro data from CBSOs allows for a more detailed sector breakdown up to the four digit level, such detailed view would reduce the number of cases in some sectors considerably, particularly when considering the interaction between sectors and regions.

for financing decisions of smaller firms, while larger corporations should be rather affected by broader environments such as features of the overall industry.

The present study will distinguish between regions according to the Nomenclature of territorial units for statistics (NUTS), focusing mainly on the NUTS 2 level, which corresponds to basic regions for the application of regional policies. NUTS classifications were mostly derived from the postal code utilising conversion tables from Eurostat. For Portugal, where information on the NUTS region was available with a high coverage, no postal code to NUTS conversion was conducted.

5. Variables and Estimation

After establishing the final sample as well as the distinction between different sectors and regions, the current chapter concentrates on the main variables of the analysis as well as the analytical method that is employed. The former includes a thorough discussion of the main explanatory factors considered, providing details on their operationalisation and expected connection to firms' financing structures.

Dependent Variables – Firm Leverage

To analyse firms' capital structure, *leverage* – measured in this paper as the ratio of total liabilities to total assets – will serve as the main dependent variable that captures a company's respective overall debt versus equity choice (where equity equals total assets minus liabilities). This is in line with a large part of the previous literature on NFC capital structures (e.g. MacKay & Phillips 2005; Palacín-Sánchez & di Pietro 2013; Palacín-Sánchez et al. 2013; Kühnhausen & Stieber 2014).[8] Figures 5.1 to 5.4 illustrate median leverage ratios across NUTS 2 regions for the six pilot countries, separately by firm size. Firms are thereby distinguished into micro, small, medium and large firms based on their total assets (applying the thresholds as set out in the European Commission Recommendation 2003/361/EC of 6 May 2003).[9]

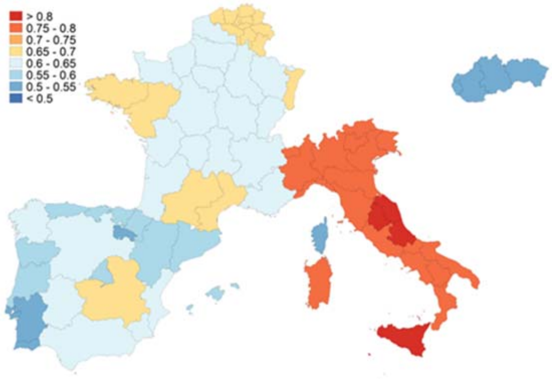
As can be observed, leverage ratios seem to differ across regions, although differences between countries seem to dominate. In general, median leverage ratios appear to be smaller across most French, Spanish and Portuguese regions, while they seem to be largest among regions in Southern Italy. At the same time, clear differences across size classes can be observed, with an overall tendency towards lower debt financing with increasing firm size. In line with the argumentation of Palacín-Sánchez et al. (2013: 508), regional differences seem to be more pronounced for SMEs compared to large firms. Moreover, differences between size classes seem to vary across regions. Whereas leverage ratios seem to be rather consistent across size classes among French regions, differences are more pronounced in Slovakia, central Spain and in particular the north of Italy.

8 Please note that the overall leverage measure chosen here differs from the sum of short- and long-term debt over total assets (often considered as financial leverage) as, along with both short- and long-term debt, it further includes provisions, trade payables, current payments received on account of orders as well as deferred liabilities.

9 Total assets are used here as other indicators such as the number of employees or net turnover contain missing information for a relatively large fraction of observations in the sample.

Figure 5.1: Median leverage – Micro firms

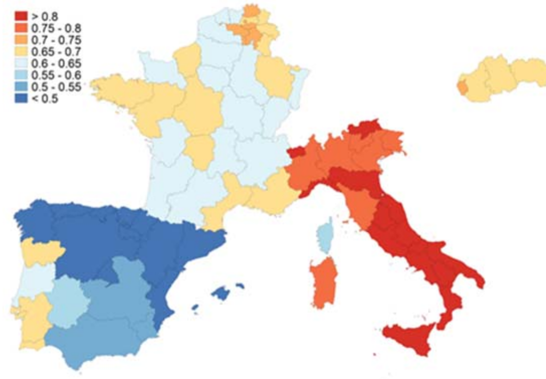
(by NUTS 2 region)



Note: Micro firms are defined as those firms with less than EUR 2 million in total assets.

Figure 5.2: Median leverage – Small firms

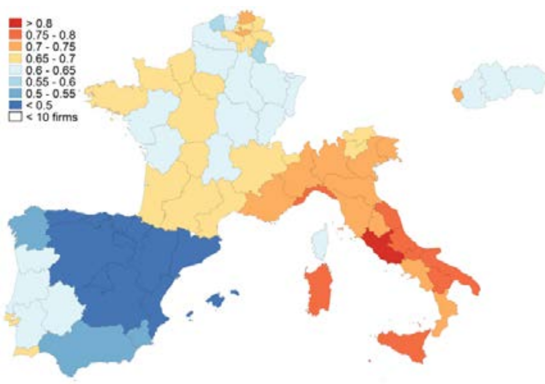
(by NUTS 2 region)



Note: Small firms are defined as those firms with EUR 2 – 10 million euros in total assets

Figure 5.3: Median leverage – Medium firms

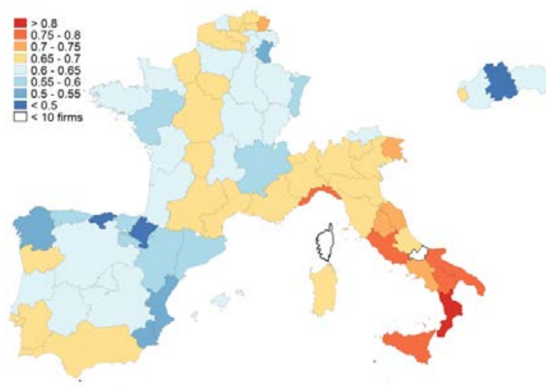
(by NUTS 2 region)



Note: Medium-sized firms are defined as those firms with EUR 10 to 43 million in total assets

Figure 5.4: Median leverage – Large firms

(by NUTS 2 region)



Note: Large firms are defined as those firms with more than EUR 43 million in total assets

In addition to overall leverage, further analysis will focus on the maturity of financial debt, distinguishing between short- and long-term financial liabilities over total assets (see also, among others, Demirgüç-Kunt & Maksimovic 1999; Palacín-Sánchez et al. 2013; Kühnhausen & Stieber 2014).

Explanatory Variables – Firm, Sector and Regional Characteristics

Explanatory variables will first of all include the main firm characteristics identified in the literature (i.e. firm size, age, asset structure, profitability and liquidity). Table 5.1 gives an overview of the explanatory variables included in this study, along with their indicators and expected relationship with leverage.

Table 5.1: Overview of main explanatory factors – Measurement & Expected Effect

Variable	Indicator & Operationalisation	Expected effect
Firm level		
Firm size	Log of total assets	+
Firm age	Log of firm age in years	-
Asset structure/Tangibility	Tangible / Total assets	+
Profitability	Net operating profit (EBIT) / Total assets	-
Liquidity	Total cash & cash equivalents / total assets	-
Sector level		
Growth	Median growth in net turnover	-
Concentration	Herfindahl-Hirshman Index: Sum of squared ratios of firm turnover to total industry turnover	+,-
Regional level		
GDP	Log GDP 2012 (at current prices; NUTS 2; from Eurostat)	+
Urbanisation; Infrastructure	Population Density (NUTS 2; from Eurostat)	+
Industry concentration	Herfindahl-Hirshman Index: Sum of squared ratios of total industry turnover per region over total regional turnover	+,-
Level of generalised trust	Question A3 from European Social Survey on the degree to which most people can be trusted (individual scores lie on a scale from 0 (you cannot be too careful) to 10 (most people can be trusted) Final measure: Regional % of respondents with trust score 7 or higher.	-
Regional industry concentration	Herfindahl-Hirshman Index: Sum of squared ratios of firm turnover to total industry turnover by NUTS 2 region	+,-

Firm size is one of the main determinants of firms' capital structure found in the existing literature. Larger firms are thereby often assumed to be more established, diversified and less prone to bankruptcy, leading them to be more highly leveraged as size serves as an inverse proxy of bankruptcy risk (Titman & Wessels 1998: 6; Kühnhausen & Stieber 2014: 8 f.). However, Titman and Wessels (1998: 6) also argue that the cost of issuing debt and equity securities is related to firm size with small firms paying more to issue new equity and long-term debt. In consequence, smaller firms should be more leveraged with an inclination to short-term debt (Titman & Wessels 1998: 6). Moreover, size can be a proxy for the degree of information outside investors have, which should imply a preference for equity (Rajan & Zingales 1995: 1451; Psillaki & Daskalakis 2009: 325). Despite these ambiguities in existing theoretical argumentations, empirical evidence mostly finds a positive relationship between firm size and leverage (exceptions are Kester 1986; Titman & Wessels 1988 and Heyman et al. 2008). For the current analysis, firm size is measured as the logarithm of total assets (see also, among others, Michaelas et al. 1999; Fama & French 2002; Flannery & Rangan 2006; Brav 2009; Frank & Goyal 2009; Degryse et al. 2012; Fan et al. 2012). Total assets are used instead of alternative indicators of firm size such as turnover or the number of employees, as the latter show relatively high fractions of missing observations for some countries (mostly for small companies), which would reduce as well as distort the final sample considerably.

Firm age is expected to be negatively connected to leverage as young firms tend to be strongly based on external financing, while older firms are likely to increasingly rely on accumulated retained profits (Michaelas et al. 1999: 116; Bhaird & Lucey 2010: 361). Firm age is measured as the natural logarithm of the difference (in years) between the respective reference year and the year of incorporation.

Firms' *asset structure* is also taken into account, using the ratio of tangible to total assets (see also Brav 2009; Frank & Goyal 2009; Psillaki & Daskalakis 2009; Degryse et al. 2012). Larger proportions of tangible assets on a firm's balance sheet imply more assets that can be placed as collateral, which should further increase firms' ability to acquire loans (Rajan & Zingales 1995: 1451; Kühnhausen & Stieber 2014: 10). Tangible assets are further assumed to be more easily assessed and valued by outsiders than intangible ones, mitigating expected distress and debt-related agency costs. Hence, one would expect a positive connection with leverage.

Profitability is also widely considered to be strongly related to leverage with existing evidence consistently suggesting a negative connection (see section 2). Following a pecking order argumentation, more profitable firms should have more internal financing available and thus, should use these funds rather than debt to finance new investments in order to minimise costs from information asymmetries (Rajan & Zingales 1995: 1451; Psillaki & Daskalakis 2009: 325).[10] In line with several previous contributions (e.g. Fama & French 2002; Sogorb-Mira 2005; Flannery & Rangan 2006; Psillaki & Daskalakis 2009), profitability is captured using the ratio of net operating profit (EBIT) over total assets.

Finally, *liquidity* is assumed to affect leverage as cash and other liquid assets can function as internal funds that, according to the pecking order theory, are likely to be utilised first instead of debt (de Jong et al. 2008: 1961). Thus, liquidity should be negatively related to leverage (see Brav 2009; Kühnhausen & Stieber 2014). Liquidity is measured as the amount of cash equivalents over total assets (see also Brav 2009; Kühnhausen & Stieber 2014).

Besides these firm-level factors, certain characteristics of firms' respective industries (based on NACE rev 2) are also considered. These will include *industry growth* captured by median growth in turnover across firms active in the same NACE section as well as *industry concentration*. For the latter, a Herfindahl-Hirshman index will be constructed (following Kayo & Kimura 2011), defined as the sum of squared market shares (i.e. the ratio of a firm's net turnover over total turnover of their respective industry) of firms within a given NACE section.

Industry growth should be negatively related to leverage as firms in low-growth industries should use debt for "its disciplinary function in avoiding the misuse of free cash flows", while firms in high-growth industries have "incentives to signal that they do not engage in adverse selection and moral hazard costs" (e.g. through underinvestment and asset substitution) and thus, to carry less leverage (La Rocca et al. 2011: 113). Meanwhile, previous studies on the role of industry concentration have usually assumed a positive connection with leverage ratios, due to differences in profitability, size and firm risk between firms in highly and lowly concentrated industries (Kayo & Kimura 2011: 361). However, existing empirical evidence on the connection of industry concentration and leverage remains mixed (see, e.g., MacKay & Philips 2005 for a positive, Kayo & Kimura 2011 for a negative relationship).

[10] However, from a trade-off theory perspective, profitable firms are expected to use more debt financing in order to capitalise on tax shield benefits of debt (Psillaki & Daskalakis 2009: 325; see also Harris & Raviv 1990).

In addition to industry specific factors, some characteristics of the local region are also included in the analysis. *Regional GDP* is considered to capture the level of economic development, while *population density* by region serves as a proxy for urbanisation and local infrastructure. Both are expected to improve the access to external financing and thus to be related to higher leverage ratios. Both measures refer to the NUTS 2 region level and are obtained from Eurostat.

Industry structure is also expected to play a relevant role for corporate financing decisions at regional level as one would expect notable differences between regions dominated by certain industries and those regions with a more diversified non-financial sector economy. A region's industry structure is measured using a Herfindahl-Hirshman index across industries in each region. Thus, it is defined as the sum of squared shares of individual industries in total regional turnover.

A more social factor that may affect costs related to information asymmetries for different forms of financing is *trust*. The current study will thereby focus on the concept of generalised rather than particularised trust.[11] Generalised trust has been widely argued to have various positive economic externalities as it reduces transaction costs and facilitates economic interactions (Alesina & La Ferrara 2002: 207, Uslaner 2003: 44). More specifically, generalised trust should reduce the need and effort to obtain additional information regarding the reliability of counterparts in financial and economic interactions (Knack & Keefer 1997: 1252). Higher levels of generalised trust should therefore mitigate the importance of information asymmetries and thus should increase the use of long-term over short-term debt and equity over debt financing. The regional level of generalised trust is obtained from the sixth wave of the European Social Survey (ESS) conducted in 2012.[12] The current research thereby draws on question A3 of the ESS asking respondents whether they would say "that most people can trusted, or that you can't be too careful in dealing with people" (see ESS Round 6 Main Questionnaire). Respondents are asked to answer on a scale from 0 (can't be too careful) to 10 (most people can be trusted). The percentage of respondents in each NUTS 2 region with a trust score of 7 or higher is thereby taken as the final measure of generalised trust at the regional level. Regional trust scores at NUTS 2 are replaced by aggregates at NUTS 1 for regions with less than 30 respondents.[13]

Finally, industry concentration is also considered at the regional level. Specific characteristics of a firm's respective industry may not only have a general effect on

[11] While particularised trust is based on personal knowledge and restricted to a specific social unit (Freitag et al. 2009: 498), generalised trust is based on the assumption that most people are part of the own moral community (Uslaner 2003). Therefore, it is independent of specific persons or groups and thus, can rather be understood as an estimate of the trustworthiness of the average person (Coleman 1990: 104; Robinson & Jackson 2001: 119, Paxton 2007: 48; Griesshaber & Geys 2012: 58).

[12] See ESS round 6 documentation report for technical details.

[13] Apart from the regional characteristics considered here, other factors of the regional environment in which firms are operating may be of importance. In particular the regional institutional context, the financial infrastructure and a measure of financial deepening at regional level might constitute relevant determinants of firms' financing decisions (see Palacín-Sánchez & Di Pietro 2013; Palacín-Sánchez et al. 2013). However, good indicators of these factors such as the number of bank branches per 100,000 inhabitants in each region, utilised in previous country specific studies (e.g. La Rocca et al. 2010, Palacín-Sánchez et al. 2013), could not be obtained on a comparable basis for all countries of the current study. An assessment regarding the role of such factors in a cross-country setting is thus left to future research.

firms' capital structure across geographical units. Instead, firms may also be strongly affected by their more local industry environment to which individual firms adjust their financing decisions. *Regional industry concentration* is computed as before (via a Herfindahl-Hirshman index), but separately for each NUTS 2 region.

Statistical Estimation

Given the hierarchical structure of the data (firms are nested in both sectors and regions), cross-classified multilevel models are employed. Ignoring such a hierarchical structure in the data would increase the risk of incorrect standard as well as type I errors since residuals might be correlated across observations from the same industry or region (Kreft & de Leeuw 1998: 9; Steenbergen & Jones 2002: 219 f.). Conducting multilevel estimations explicitly accounts for the possibility that intercepts may vary between industries, regions as well as their interaction. It further allows controlling for the effect of sector and region specific factors absent of the assumption that these factors explain all existing variation between sectors and regions. Sectors and regions are thereby introduced at the same level since one cannot establish a clear hierarchy between the two.

In a first step, variance component models are estimated to assess the relative importance of each level regarding the overall variance of leverage. The basic model can be set up as follows, starting with the firm-level (subscripts i for firm, j for industry and k for region).[14]

$$Lev_{ijk} \quad = \beta_{0jk} + \varepsilon_{ijk} \tag{1.1}$$

where the leverage ratio of firm i within sector j and region k is a function of mean leverage β_{0jk} of industry j in region k plus an error term ε_{ijk}. As mentioned above, it seems rather unlikely that financing choices of firms from the same sector or region are completely independent. Therefore, in a next step, a second level will be introduced by modelling the mean leverage of industry j in region k (β_{0jk})

$$\beta_{0jk} \quad = \beta_{000} + \delta_{0j0} + \zeta_{00k} + \vartheta_{0jk} \tag{1.2}$$

where β_{000} reflects the grand mean of the sample and δ_{0j0} and ζ_{00k} represent the industry and region specific error components, respectively. In addition, a random interaction term ϑ_{0jk} is introduced, reflecting all existing combinations of sector and region.[15] Substituting (1.2) into (1.1) then gives the complete mixed effects model.

$$Lev_{ijk} \quad = \beta_{000} + \delta_{0j0} + \zeta_{00k} + \vartheta_{0jk} + \varepsilon_{ijk} \tag{1.3}$$

The variance of the respective level-specific error terms δ_{0j0}, $\zeta_{00k,}$ ϑ_{0jk} and ε_{ijk} finally reflect the relative importance of these levels with respect to firm leverage. The former (i.e. δ_{0j0}, $\zeta_{00k,}$) remain constant across firms from the same sector and region,

14 The employed method and its discussion in this chapter are strongly based on Kayo and Kimura (2011: 363 f.).

15 A likelihood ratio test to compare this specification with an additive random-effects model excluding a random interaction supports the inclusion of an interaction term between sectors and regions for all considered debt ratios.

respectively, while ϑ_{0jk} is assumed to be independent from the other error components as well as across combinations of sector and region (see also Rabe-Hesketh and Skrondal 2008: 485). The firm-level residuals represent the deviation of a firm's specific leverage ratio from the mean for sector j and region k, and are assumed to be independent across firms, sectors, regions as well as the interaction of sectors and regions.

Following the estimation of this basic ('empty') specification, explanatory factors at firm, sector and regional level are introduced in a next step. The main random intercept model is thereby derived as before, with firm specific predictors included in the firm-level specification (1.1).

$$Lev_{ijk} = \beta_{0jk} + \beta_{1jk} \cdot Size_{ijk} + \beta_{2jk} \cdot Age_{ijk} + \beta_{3jk} \cdot Tangibility_{ijk} + \beta_{4jk} \cdot Profitability_{ijk} + \beta_{5jk} \cdot Liquidity_{ijk} + \varepsilon_{ijk} \tag{2.1}$$

The sector and region specific variables as well as the measure of industry concentration within regions are then included as determinants of the random firm-level intercept.

$$\beta_{0jk} = \beta_{000} + \beta_{01k} \cdot Ind\_Growth_j + \beta_{02k} \cdot Ind\_Concentration_j + \beta_{0j1} \cdot Reg\_GDP_k + \beta_{0j2} \cdot Reg\_PopDensity_k + \beta_{0j3} \cdot Reg\_IndStructure_k + \beta_{0j4} \cdot Trust_k + \beta_{011} \cdot RegInd\_Concentration_{jk} + \delta_{0j0} + \zeta_{00k} + \vartheta_{0jk} \tag{2.2}$$

Please note that by retaining the specific error components of industry, region and their interaction (i.e. δ_{0j0}, ζ_{00k} and ϑ_{0jk}) one takes into account that the region- and sector-level factors considered in the model may not completely explain all existing variation in the intercepts. Consolidating specifications (2.1) and (2.2) then results in the full random intercept model (2.3), where leverage of firm i of sector j in region k is a function of the mean intercept plus firm, sector and region specific covariates and their respective random errors. Thereby, it is assumed that the firm-level effects $\beta_{1jk} - \beta_{5jk}$ are fixed across sectors and regions (i.e. $\beta_{pjk} = \beta_{p00}$ for p = 1, 2, … , 5), while sector specific effects are fixed across regions and vice versa ((i.e. $\beta_{0pk} = \beta_{0p0}$ for p = 1, 2; $\beta_{0jp} = \beta_{00p}$ for p = 1, 2, …, 4; see also Steenbergen and Jones 2002: 229).

$$Lev_{ijk} = \beta_{000} + \beta_{100} \cdot Size_{ijk} + \beta_{200} \cdot Age_{ijk} + \beta_{300} \cdot Tangibility_{ijk} + \beta_{400} \cdot Profitability_{ijk} + \beta_{500} \cdot Liquidity_{ijk} + \beta_{010} \cdot Ind\_Growth_j + \beta_{020} \cdot Ind\_Concentration_j + \beta_{001} \cdot Reg\_GDP_j + \beta_{002} \cdot Reg\_PopDensity_k + \beta_{003} \cdot Reg\_IndStructure_k + \beta_{004} \cdot Trust_k + \beta_{011} \cdot RegInd\_Concentration_{jk} + \delta_{0j0} + \zeta_{00k} + \vartheta_{0jk} + \varepsilon_{ijk} \tag{2.3}$$

where β_{000} constitutes the overall mean intercept, $\beta_{100} - \beta_{500}$ reflect the firm-level effects on leverage for firm size, age, tangibility, profitability and liquidity, β_{010} and β_{020} stand for the sector specific effects of industry growth and concentration and $\beta_{001} - \beta_{004}$ represent the region-level effects of regional GDP, population density, a region's industry structure and trust. β_{001} finally reflects the effect of sector concentration within regions. As before, δ_{0j0}, ζ_{00k}, ϑ_{0jk} and ε_{ijk} constitute the level-specific error terms.

All models are estimated using maximum likelihood estimation and only non-missing observations regarding all relevant variables of the analysis are included in each model. All models were tested for possible multi-collinearity among covariates. However, pairwise correlations between explanatory variables are found to be lower than 0.5 in all cases. Moreover, estimated variance inflation factors (VIFs) remain well below common thresholds and thus, do not show any indication of possible multi-collinearity.

6. Empirical Findings

Discussion of the main results obtained through estimation of the models specified in section 5 first concentrates on overall firm leverage (i.e. the ratio of total liabilities over total assets). Table 6.1 reports the results of the corresponding crossed random-effects estimations. Model 1 thereby refers to the empty specification in order to decompose the variances of the level-specific random errors, while model 2 adds firm, sector, region and sector-region specific characteristics as explanatory variables. Estimations are based on a cross-section of 1,969,284 firms from 17 different NACE sections and 87 different NUTS 2 regions (located in BE, ES, FR, IT, PT and SK).

Results for the variance decomposition indicate that a vast proportion of variance in leverage ratios is allocated at the firm-level, suggesting that it is mainly intrinsic factors of firms that seem to drive financing decisions (see also Kayo & Kimura 2011: 365). From the point of European economic integration and monetary union, the high relevance of firm specific differences compared to regional ones seems reassuring as strong regional differences should not persist when aiming towards convergence of NFCs (SMEs in particular) by improving overall access to finance across the whole euro area (Palacín-Sánchez & di Pietro 2013: 3). Nevertheless, region and sector differences still seem to matter to some degree with the intra-class correlation for firms from the same region and sector amounting to 0.1. Regional differences thereby seem to be more relevant than industry characteristics, which appear to be of minor importance.

After establishing the relative importance of the different levels in regard to the overall variation in leverage ratios, subsequent inclusion of explanatory variables indicates which firm, sector and region specific characteristics pose relevant impacts on firms' leverage ratios and can explain some of the variance in leverage found at the respective levels. Results for the main firm-level variables are thereby mostly in line with large parts of the empirical literature, confirming the theoretical expectations derived in section 5. Firm size and asset tangibility are both found to be positively connected to leverage, supporting the view that firms of larger size or with more tangible assets signal lower bankruptcy risk and can post relatively more collateral against debt, which improves their access to debt financing. Similarly, findings show the expected negative links for firm age, profitability and liquidity.

Table 6.1: Multilevel analysis I – The determinants of firm leverage

Dep. Variable: Firm Leverage	(1)	(2)
Firm level		
Log of total assets		0.0209***
		(0.0001)
Log of firm age		-0.0766***
		(0.0002)
Profitability		-0.144***
		(0.001)
Tangibility		0.00239**
		(0.0008)
Liquidity		-0.355***
		(0.0009)
Industry level		
Concentration		-0.145*
		(0.061)
Median growth in turnover		-0.583
		(0.370)
Region level		
Population density 2012		-1.14e-05*
		(5.69e-06)
Log of GDP 2012		0.0342***
		(0.007)
Industry structure		-1.4e-05*
		(5.5e-06)
Trust		0.000159
		(0.0007)
Industry concentration by region		-0.0266*
		(0.013)
Constant	0.599***	0.388***
	(0.0117)	(0.069)
Number of Firms	1,969,284	1,969,284
Number of Sectors	17	17
Number of Regions (Nuts 3)	87	87
Number of Sectors by Region	1,460	1,460
Variance decomposition (in % of residual variance)		
Variance: Sector-level	1.4%	1.0%
Variance: Region-level	6.7%	4.2%
Variance: Sector x Region	2.2%	2.2%
Variance: Firm-level	89.7%	92.6%

The table reports the results of the crossed random intercept models specified in section 5 when using overall leverage (i.e. total liabilities/assets) as the dependent variable. Non-standardised regression coefficients are reported with standard errors in parentheses.

Significance Levels: * < 0.05, ** < 0.01, *** < 0.001

As regards the role of the sector specific characteristics considered in the analysis, firms in more highly concentrated industries appear to have lower leverage ratios. This supports the finding of Kayo and Kimura (2011) rather than MacKay and

Philips (2005). The effect of industry growth also seems to be negative (yet insignificant). Turning to the results for the regional factors, firms in regions with higher economic development seem to have higher leverage ratios. Meanwhile, negative effects are found for population density and industry structure, which nevertheless remain rather marginal. Regarding the regional level of trust, the obtained positive connection with leverage is also small and insignificant. Finally, industry concentration also seems to matter within regions. Firms operating in regional industries that are more concentrated thereby seem to have lower leverage ratios, which again partially supports the finding of Kayo and Kimura (2011).

Overall, the included covariates explain around 40% of the part of variation in firm leverage that is due to differences across sectors. However, the share of variation in leverage allocated at the level of sectors in general is rather small, causing the value added through the considered sector characteristics to remain limited. With respect to regional differences, the model is able to explain close to half of the variance allocated at this level. Thereby, a considerable amount is explained by the firm-level variables, suggesting that regions differ in regard to their population of firms, which in turn explains some of the differences in capital structures across regions. Nevertheless, the considered region specific variables provide further explanatory value, supporting the view that there are specific features of the regional environment that can affect corporate financing choices.

Exploring Differences between Size Classes

As mentioned in section 4, the role and relative importance of firm, industry and regional differences may differ depending on the size of firms. Smaller companies might be more restricted to local financial markets and more likely affected by the features of the local economy and their respective regional industry. Larger firms, meanwhile, should have higher capabilities of operating across regional boundaries and thus, should be less constrained by regional characteristics. Instead, those firms should rather be affected by broader developments and features regarding their markets and industries.

Table 6.2: Distinguishing by firm size – Variance Decomposition

Dep. Variable: Firm Leverage	Micro	Small	Medium	Large
Number of Firms	1,627,649	262,105	61,171	18,359
Number of Sectors	17	17	17	17
Number of Regions (Nuts 3)	87	87	87	87
Number of Sectors by Region	1,452	1,420	1,282	1,001
Variance decomposition (in % of residual variance)				
Sector-level	1.1%	2.0%	4.2%	6.0%
Region-level	6.1%	12.7%	8.5%	3.4%
Sector x Region	2.1%	3.2%	4.1%	2.7%
Firm-level	90.7%	82.1%	83.2%	87.9%

The table reports the estimation results of the empty crossed random intercept models when using overall leverage (i.e. total liabilities / total assets) as the dependent variable. Distinction by size is based on total assets – i.e. Micro: < EUR 2 million; Small: EUR 2-10 million; Medium: EUR 10-43 million; Large: > EUR 43 million.

Table 6.3: Distinguishing by firm size – Multilevel analysis

Dep. Variable: Firm Leverage	Micro	Small	Medium	Large
Firm level				
Log of total assets	0.0429***	-0.0140***	-0.00387	0.00412*
	(0.0002)	(0.001)	(0.002)	(0.002)
Log of firm age	-0.0833***	-0.0666***	-0.0461***	-0.0247***
	(0.0002)	(0.0006)	(0.001)	(0.002)
Profitability	-0.152***	-0.389***	-0.422***	-0.445***
	(0.001)	(0.005)	(0.010)	(0.018)
Tangibility	0.00973***	-0.0807***	-0.0628***	-0.0362***
	(0.0009)	(0.002)	(0.004)	(0.007)
Liquidity	-0.328***	-0.388***	-0.333***	-0.171***
	(0.001)	(0.004)	(0.009)	(0.019)
Industry level				
Concentration	-0.122	-0.0798	-0.213	-0.262*
	(0.065)	(0.078)	(0.116)	(0.132)
Median growth	-0.560	-0.129	-0.629	-1.084
(in turnover)	(0.394)	(0.474)	(0.699)	(0.770)
Region level				
Population density 2012	-9.67e-06	-1.37e-05	-2.49e-06	-4.48e-06
	(5.04e-06)	(9.48e-06)	(9.38e-06)	(6.37e-06)
Log of GDP 2012	0.0273***	0.0324**	0.0266*	0.0220**
	(0.006)	(0.011)	(0.010)	(0.007)
Industry structure	-1.01e-05*	-1.19e-05	-1.12e-05	-3.66e-06
	(4.84e-06)	(9.08e-06)	(8.05e-06)	(4.85e-06)
Trust	0.00046	-0.00128	-0.00209*	-0.00121
	(0.0006)	(0.001)	(0.001)	(0.0006)
Industry concentration	-0.0101	-0.0446*	-0.00883	0.0140
by region	(0.013)	(0.022)	(0.032)	(0.041)
Number of Firms	1,627,649	262,105	61,171	18,359
Number of Sectors	17	17	17	17
Number of Regions (Nuts 3)	87	87	87	87
Number of Sectors by Region	1,452	1,420	1,282	1,001
Variance decomposition (in % of residual variance)				
Sector-level	1.1%	1.7%	3.5%	4.6%
Region-level	3.3%	12.1%	8.9%	2.8%
Sector x Region	1.9%	4.0%	5.1%	3.4%
Firm-level	93.7%	82.3%	82.6%	89.2%

The table reports the estimation results of the crossed random intercept models specified, when using overall leverage (i.e. total liabilities / total assets) as the dependent variable. Distinction by size is based on total assets – i.e. Micro: < EUR 2 million; Small: EUR 2-10 million; Medium: EUR 10-43 million; Large: > EUR 43 million. Non-standardised regression coefficients are reported, standard errors in parentheses.

Significance Levels: * < 0.05, ** < 0.01, *** < 0.001

To further investigate such possible differences, firms are distinguished into four categories based on their size in terms of total assets (i.e. micro, small, medium and large) and the above models are re-estimated separately for each sub-sample. Results of the variance components and multilevel models are reported in table 6.2 and 6.3, respectively. As can be observed, the relative importance of industry and region differences indeed seems to vary with firm size. Although most of the variance in leverage across all size classes still appears due to firm specific differences, regional characteristics seem to be of higher relevance among small and medium-sized companies compared to larger firms. In particular among companies with EUR 2 to 10 million in total assets, differences between regions independent of differences between industries seem to account for 12.7% of the variance in leverage (with slightly lower intra-class correlations for firms from the same region but different sectors among the samples of micro and medium-sized firms). In contrast, the relative importance of the industry level is found to increase with firm size. Both findings confirm the above expectations that smaller firms are more affected by their local environment, while overall industry differences seem to matter mostly for large companies.

Including explanatory variables in the estimations by size class shows that the previously identified negative connections for firm age, profitability and liquidity consistently hold across all size classes. The positive relationship between tangibility and leverage revealed for the full sample seems to only hold for the sub-sample of micro firms with less than EUR 2 million in total assets. In contrast, among all other size classes, firms with relatively more tangible assets on their balance sheet appear to have lower debt ratios.

As before, the coefficient for industry concentration is found to be negative yet insignificant in most estimations. The only exception is among large firms where the effect becomes significant at a 5% level, again supporting the idea that overall industry characteristics such as concentration are most influential among larger firms. The relationship between median industry growth and individual firm leverage, meanwhile, is not found to be significant among any size class.

Regarding regional specific variables, only GDP seems to be consistently (positively) associated with firm leverage across all size classes. Interestingly, trust is found to be negatively connected to firm leverage among medium-sized companies, possibly suggesting that in high trust environments availability of equity financing improves. Meanwhile, small firms active in industries with higher concentration in the respective region choose lower debt financing. Not surprisingly, it is among those size classes with larger shares of variance being allocated at the level of regions, where significant effects for regional variables are more likely found.

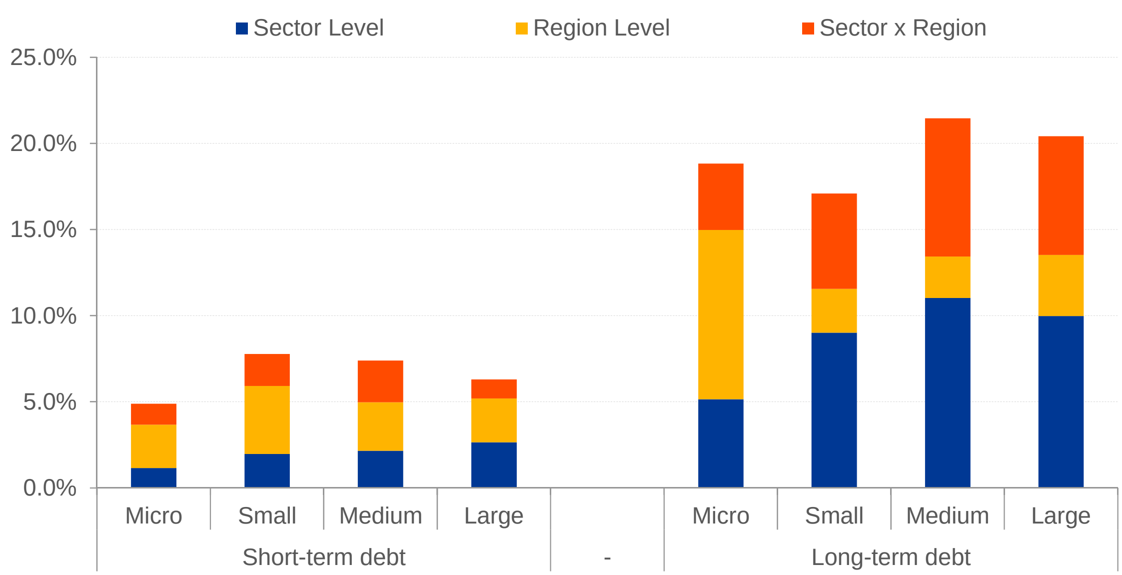
Distinguishing between Short- and Long-Term Debt

Several studies on the determinants of corporate capital structures have accounted for the maturity of debt, highlighting that the underlying reasons for the use of short-term versus long-term debt financing are likely to differ significantly (e.g., among others, Fan et al. 2012). The present study therefore re-estimates the previous models separately for short- and long-term liabilities. Estimations again are conducted individually for each size class.

Figure 6.1 shows the results of the variance decomposition by size class for both types of debt financing, whereas the full models including all covariates considered in the current analysis are reported in table 6.4. Results thereby indicate that firms' relative use of short-term debt financing does not seem to be considerably connected to region or sector specific characteristics. Instead, variation in short-term leverage ratios seems to be almost exclusively due to firm specific differences. There further do not seem to be notable differences between size classes. On the other hand, differences between regions and sectors seem to be of some relevance with respect to the use of long-term leverage, jointly accounting for around 17-22% of the variance in the dependent variable across the different size classes. As before, regional differences seem to matter most for smaller firms (micro firms in particular), while industry differences appear more important with increasing firm size. Furthermore, industry differences do not only seem to affect long-term debt financing across regions but also appear to matter at the local level.

Figure 6.1: Short- and long-term debt

Variance decomposition (by firm size)



The graph illustrates the results of the variance components estimations, using ratios of short- and long term liabilities over total assets as dependent variables. The models are separately estimated for firms of different size classes.

Regarding the role of specific firm-level factors, firm size, age, profitability, tangibility as well as liquidity appear consistently negatively related to short-term leverage. Overall, these findings are in line with most theoretical expectations (see section 5), supporting the view that smaller as well as less established firms should encounter higher costs of long-term debt and equity financing and thus, are more likely to opt for short-term financing. Higher profitability as well as higher liquidity should increase the availability of retained earnings to finance investment, which is supported by the obtained negative relation. Meanwhile, relatively more tangible assets that can be posted as collateral are likely to facilitate access to long-term financing, as confirmed by the opposed effects obtained for short- and long-term financing. The latter most likely also explains the opposed effects found for tangibility with respect to overall leverage across size classes (see above).

Table 6.4: Short- and long-term debt – Including explanatory factors (by firm size)

	DV: Short-term debt / Total assets				DV: Long-term debt / Total assets			
	Micro	Small	Medium	Large	Micro	Small	Medium	Large
Firm level								
Log of total assets	-0.007***	-0.017***	-0.004*	-0.007***	0.020***	-0.004***	0.002	0.018***
	(0.0002)	(0.0008)	(0.002)	(0.001)	(0.0001)	(0.0009)	(0.002)	(0.001)
Log of firm age	-0.027***	-0.007***	-0.003***	0.003*	-0.021***	-0.0426***	-0.0320***	-0.0250***
	(0.0002)	(0.0005)	(0.0009)	(0.002)	(0.0002)	(0.0005)	(0.001)	(0.002)
Profitability	-0.0345***	-0.131***	-0.151***	-0.126***	-0.055***	-0.094***	-0.127***	-0.165***
	(0.001)	(0.004)	(0.008)	(0.013)	(0.0009)	(0.004)	(0.008)	(0.016)
Tangibility	-0.057***	-0.124***	-0.122***	-0.110***	0.230***	0.242***	0.248***	0.226***
	(0.0008)	(0.002)	(0.003)	(0.005)	(0.0006)	(0.002)	(0.003)	(0.006)
Liquidity	-0.184***	-0.185***	-0.164***	-0.119***	-0.077***	-0.231***	-0.209***	-0.148***
	(0.0009)	(0.003)	(0.007)	(0.014)	(0.0007)	(0.003)	(0.007)	(0.016)
Industry level								
Concentration	-0.043	-0.030	-0.067	-0.023	-0.056	-0.066	-0.103	-0.201
	(0.060)	(0.051)	(0.046)	(0.063)	(0.065)	(0.085)	(0.108)	(0.122)
Median growth (in turnover)	-0.249	0.030	0.168	-0.261	0.276	0.037	-0.275	-0.036
	(0.360)	(0.305)	(0.265)	(0.339)	(0.396)	(0.517)	(0.651)	(0.714)
Region level								
Pop. density 2012	-4.4e-06	-3.3e-06	4.5e-06	1.8e-06	2.5e-07	-1.5e-06	2.8e-06	3.3e-06
	(2.9e-06)	(4.1e-06)	(4.0e-06)	(3.7e-06)	(4.7e-06)	(5.0e-06)	(5.5e-06)	(7.3e-06)
Log of GDP 2012	-0.003	-0.006	-0.009*	-0.012**	0.026***	0.031***	0.021**	0.016
	(0.003)	(0.005)	(0.00427)	(0.00444)	(0.006)	(0.006)	(0.006)	(0.008)
Industry structure	5.1e-06	9.2e-06*	1e-05***	1.2e-5***	-2e-05***	-2e-5***	-2e-5***	-1.1e-05*
	(2.7e-06)	(3.7e-06)	(3.1e-06)	(2.8e-06)	(4.6e-06)	(4.5e-06)	(4.4e-06)	(5.6e-06)
Trust	0.001***	0.0006	0.0004	0.0008*	-0.002***	-0.002***	-0.002***	-0.002**
	(0.0003)	(0.0005)	(0.0004)	(0.0004)	(0.0006)	(0.0006)	(0.0005)	(0.0007)
Industry concentr. by region	-0.023*	-0.016	-0.004	-0.004	0.014	-0.025	-0.022	-0.064
	(0.010)	(0.015)	(0.020)	(0.026)	(0.012)	(0.020)	(0.028)	(0.039)
Firms	1,627,649	262,105	61,171	18,359	1,627,649	262,105	61,171	18,359
Sectors	17	17	17	17	17	17	17	17
Regions	87	87	87	87	87	87	87	87
Sectors by Region	1,452	1,420	1,282	1,001	1,452	1,420	1,282	1,001
Variance Decomposition								
Sector-level	1.2%	1.2%	1.0%	1.6%	2.0%	3.0%	4.9%	4.9%
Region-level	1.2%	3.4%	2.5%	1.9%	5.1%	4.2%	3.7%	5.0%
Sector x Region	1.1%	1.9%	2.5%	0.8%	3.2%	5.4%	7.2%	7.1%
Firm-level	96.5%	93.5%	94.0%	95.7%	89.7%	87.4%	84.2%	83.0%

The table reports the results of the crossed random intercept estimations, using ratios of short- and long term liabilities over total assets as dependent variables. The models are separately estimated for firms of different size classes. Distinction by size is based on total assets – i.e. Micro: < EUR 2 million; Small: EUR 2-10 million; Medium: EUR 10-43 million; Large: > EUR 43 million. Standard errors are reported in parentheses.

Significance Levels: * < 0.05, ** < 0.01, *** < 0.001

The rationale for the effect of firm age, profitability and liquidity should apply to both short- as well as long-term leverage. Hence, the consistently negative connections with long-term leverage are again in line with expectations. Contrary to short-term debt, firm size appears mostly positively connected to the use of long-term debt (except for the sample of small firms where a slightly negative relationship is obtained), broadly supporting previous findings in the literature.

As the overall relevance of region and sector differences with respect to the use of short-term debt appears to be fairly limited, it is not surprising that industry and region specific factors considered in the analysis are mostly not found to have a considerable and significant effect on this type of debt financing. Exceptions are significant negative effects for regional GDP among medium and large firms and a positive effect of regional trust on the use of short-term debt among micro and large companies. With respect to long-term debt, SMEs show increased use in regions with higher economic development. Higher levels of trust existing in the local community seem connected to lower relative usage of long-term debt.[16] Overall, while regional and sector characteristics appear to matter quite significantly for firms' decisions regarding the use of long-term debt, the considered regional variables only seem to explain a limited part of this role. In consequence, future analysis needs to further investigate potential alternative factors related to companies' industry and regional environment that may be of relevance.

The Issue of Zero Leverage Ratios

One issue often raised with respect to the analysis of leverage ratios concerns the fact that many firms may not use any debt, implying a large share of companies with leverage ratios of zero in the sample. Neglecting the special nature and possible extent of these zero leverage ratios may therefore result in a misspecification of the estimated models (see also Ramalho & da Silva 2009: 628-630). The current section focuses on the possible issue of large fractions of firms with zero leverage ratios, distinguishing them from firms with non-zero debt ratios.

However, the percentage of firms with leverage ratios of zero appears rather low in the case of overall leverage as well as short-term debt. Thus, their effect on the previously reported results for these types of debt financing should be limited. Indeed, results remain overall robust when restricting the previous estimations only to those firms with non-zero leverage in these cases (available upon request).

The case of long-term debt ratios seems to be different, as almost 40% of the firms appear to hold no long-term debt on their balance sheet. In this case, the results of the previous linear hierarchical estimations run the danger of being biased. In consequence, a two-part approach is adopted, separately estimating logistic regressions of having non-zero long-term debt in a first step, followed by a re-estimation of the previous crossed random-effects model exclusively for those firms with a long-term debt ratio larger than zero. For the first part, simple logistic estimations are conducted, including sector and region dummies when no other

16 One explanation could be the increased use of equity financing as higher trust might reduce costs related to information asymmetries.

region or sector specific variables are considered and allowing error terms to be clustered by combinations of region and sector.[17]

Results indicate that the probability of having non-zero long-term debt seems to vary notably across regions (available upon request). Besides differences in the composition of firms and the possible impact of regional characteristics, this may also point to different treatment of missing information in the data across countries. Obtained results for the firm-level covariates in the logit regressions further show that zero-leverage ratios are more likely for smaller, less profitable companies with relatively less tangible assets.

The hierarchical estimations for long-term debt conditional on having non-zero leverage show that sector differences seem to play a more considerable role than before, while the proportion of variance explained purely at the regional level independent of sector differences is reduced. Hence, the importance of overall regional differences appears diminished when accounting for the fact that the occurrence of zero leverage ratios explains some of the previously found variation across regions. Nevertheless, the relative importance of sector and regional characteristics still continues to differ across size classes, with the former being more relevant among smaller and the latter more important among larger firms. In consequence, differences between regions as well as between industries at regional level continue to matter, in particular among SMEs.

8. Conclusion

The present paper investigated the role and relative importance of firm, sector and region specific determinants of leverage ratios, aiming to provide a more comprehensive perspective on corporate capital structures. It used cross-country micro data on NFC balance sheet information from six euro area countries, collected for the first time at the European Central Bank. The paper particularly explored to what extent elements beyond mere firm characteristics, related to firms' more immediate environment (i.e. industries and regions), may influence financing choices of NFCs and their access to capital.

The empirical results show that the major part of variation in corporate leverage ratios appear to be related to differences at the firm-level, suggesting that it is the individual characteristics of the firm that strongly drive NFCs' financing structures. Findings with respect to the main firm-level factors are thereby in line with previous contributions, confirming the expected effects for firm size (+), age (-), profitability (-), asset tangibility (+) and liquidity (-). Nevertheless, both sector and regional characteristics are found to be of some relevance (in particular with respect to long-term debt). Moreover, the relative importance of differences between sectors and regions seems to vary depending on the size of firms. Firms' more local environment thereby appears to be particularly relevant with respect to financing structures of small and medium-sized companies, while overall industry characteristics play a more significant role among larger firms. In consequence, the

[17] Please note that the employed two-part approach consisting of independent estimations implicitly assumes that the error terms between the separate estimations are uncorrelated.

respective environment of firms seems to matter when it comes to NFCs' financing strategies and thus, should not be neglected in a more encompassing analysis of corporate financing in the euro area.

The main implications of these results are twofold. On one hand, the relative importance of firm specific characteristics indicated in the analysis reassures European efforts towards convergence of NFCs by improving overall access to finance across the whole euro area. On the other hand, regional differences (also between industries) still seem to exist, making it important for policymakers to gain a profound understanding of the nature, extent and origin of these differences as well as their importance for NFCs' access to external financing.

Despite the importance of the conducted analysis, the present results must be qualified. First, the analysis of this paper purely relied on cross-sectional data of annual balance sheet information between 2011 and 2013. While this offers a valuable starting point for a more comprehensive assessment regarding the relative importance of firm, sector and regional determinants of leverage, future investigations need to test the robustness of the results using panel data. As the micro data obtained for the ECB pilot on NFC balance sheet information seems only partially suited for such an analysis (due to its limited time span and its unbalanced character), alternative data sources need to be explored in this regard. This further appears important as the data utilised for the pilot exercise is (with some few exceptions) limited to the post-crisis period. In consequence, additional analysis needs to be conducted on an extended time-series to investigate possible changes occurring in the aftermath of the financial crisis.

Second, the micro data obtained from CBSOs only covers six euro area countries, making generalisations to the wider euro area rather difficult. Future investigations should therefore complement this data with a wider country sample. This further allows distinguishing the role of regions from the wider country context. However, with respect to such data, the availability and quality of NFC reference information, which allows the incorporation of a regional perspective, appears crucial.

Third, while the current results have pointed to some relevance of differences in firms' respective industry and regional environments, the importance of the considered sector and region specific factors has remained limited. Therefore, further investigations should particularly aim at identifying possible alternative characteristics of regions and industries that may play a role regarding the debt-equity structures of NFCs. Thereby, a specific focus should be put on the structure and size of the financial sector existent at the regional level, necessitating the collection of appropriate indicators that are comparable across countries. Finally, differences at the level of industries and regions may not only influence corporate capital structures directly by affecting firms' access to external finance, but might also have an impact on the effect of firm specific determinants. While such possible indirect effects of contextual factors have been previously investigated with respect to sector and country specific characteristics, future analysis should also explore the possibility of cross-level interaction effects at the regional level.

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IFC-ECCBSO-CBRT Conference on *"Uses of Central Balance Sheet Data Offices' information"*

Co-organised by the IFC, the European Committee of Central Balance Sheet Data Offices (ECCBSO) and the Central Bank of the Republic of Turkey (CBRT)

Özdere-İzmir, Turkey, 26 September 2016

Towards a more comprehensive understanding of corporate leverage ratios[1]

Nicolas Griesshaber, European Central 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.

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Towards a more Comprehensive Understanding of Corporate Leverage Ratios

Using firm-level data from Central Balance Sheet Data Offices to disentangle the role of firm, sector and region specific characteristics

Joint IFC/ECCBSO/CBRT Conference on the "Uses of Central Balance Sheet Data Offices Information"

26 September 2016

Overview

Understanding capital structures is primary goal at the ECB

- **Financing choices** of **non-financial corporations** (***NFCs***) can have important "*repercussions for the stability and performance of the wider economy*"

ECB structural issues report on Corporate Finance and Economic Activity in the Euro Area (ECB 2013: 13)

- Central role for transmission of monetary policy:

  Financing structure of firms affects how monetary policy operates

➢ Comprehensive understanding of the underlying determinants of NFCs' financing policies & their impact on the access to additional funds of high importance

  ➢ Requires harmonised financial micro information on NFCs

  ➢ Necessitates a more encompassing analytical approach

Existing evidence

- Following the study of Rajan & Zingales (1995), a vast body of empirical research on the determinants of firms' capital structure has developed
  - ➢ *Strong focus on firm characteristics (profitability, growth opp., size, asset tangibility)*

- Additional focus on the role of industry as well as institutional and country factors

  (e.g.McKay & Phillips 2005; de Jong et al. 2008; Psillaki & Daskalakis 2009; La Rocca et al. 2011; Degryse et al. 2012; Öztekin & Flannery 2012; Kühnhausen & Stieber 2014)

- Recently, characteristics related to the local environment received some attention

  (see La Rocca et al. 2010, Palacín-Sánchez et al. 2013 on Spanish and Italian regions, respectively)
  - ➢ Analytical framework beyond single country setting missing to date

- More encompassing frameworks that fully account for the different levels and their relative importance are rare
  - ➢ Exception: Multi-level study by Kayo & Kimura (2011)

Research Focus

Disentangle the effect of firm, sector and regional specific characteristics on NFC capital structures (i.e. leverage)

Main Contributions:

- Uses new firm-level dataset of harmonised balance sheet information of NFCs from six EA countries
- Considers the role played by firms' more local environment
- Accounts for hierarchical structure in the data

Accounting for firms' respective environment

- Previous studies found sign. variation in capital structures across sectors of activity
  - Managers orient themselves along industry benchmarks
  - Companies likely exposed to common forces
  - Industries differ in their population of firms
  - ➢ Considerable part of variation in leverage ratios should be due to industry differences

- Regional environment can also matter (research so far focused on country-context)
  - Institutional contexts & financial sectors can differ between local regions
  - Economic forces and social factors likely to vary across local environments
  - ➢ Regional forces should be relevant with respect to firms financing decisions

- Ability to access any financial market reduces relevance of regional divergences
  - Larger firms have access to wider financial markets; small companies restricted to more immediate environment
  - ➢ Relevance of firms' particular environments should differ depending on size of firms

Using data from Central Balance Sheet Data Offices (CBSOs)

- Bank for the Accounts of Companies Harmonized database (BACH)
  - Non-consolidated accounting information for 11 countries
  - Meso-aggregated in each country by sector and firm size
  - Harmonised templates to increase comparability across countries

➢ 6 countries agreed to provide annual micro data
  - BE, ES, FR, IT, PT and SK
  - More than 3.2 million companies
  - Annual data from 2009 to 2013 (from 2008 for BE, SK; 2004 for PT)

- Obtained as part of an ECB pilot exercise on the value of centralised collection of NFC micro data, which aims to evaluate
  - the characteristics of such data
  - its value in comparison to data from commercial providers (i.e. Bureau van Dijk's Amadeus database)
  - its analytical value for ECB purposes (monetary policy; macro prudential; financial stability; micro supervisory)

Data Adjustments & Final Sample

- Restriction to cross-section data – Pooled for 2011-2013 (latest record available)
  - Panel data diverse and unbalanced; covers only short period
  - Capital structure expected to be rather stable across shorter period

- Main industry sections are distinguished
  - based on Statistical Classification of Economic Activities in the EC (NACE, rev. 2)

- Regions are distinguished based on Nomenclature of Territorial Units for Statistics (NUTS; level 2)
  - Derived from postal code and region information in the BACH data

Data Adjustments & Final Sample

- Final Sample of 1,969,284 NFCs across
  - 6 countries
  - 17 Sectors
  - 87 NUTS 2 regions
  - 1,460 region sector combinations

Dependent Variables

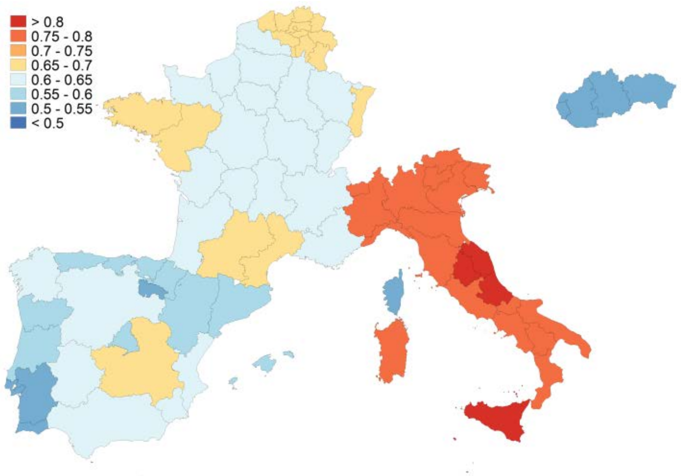
- Firm leverage = Ratio of total debt to assets

- further analysis will also distinguish between different forms of financial debt:
  - *Short- vs. Long-term debt (over total assets)*

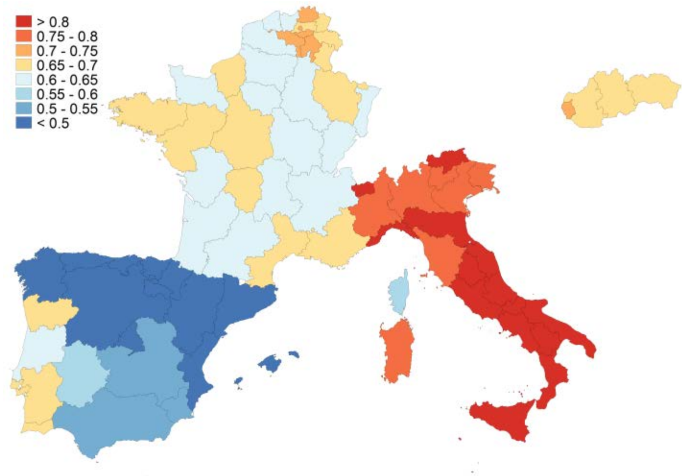
Regional median leverage by firm size

(Leverage = Total liabilities / Total assets; NUTS 2 level)

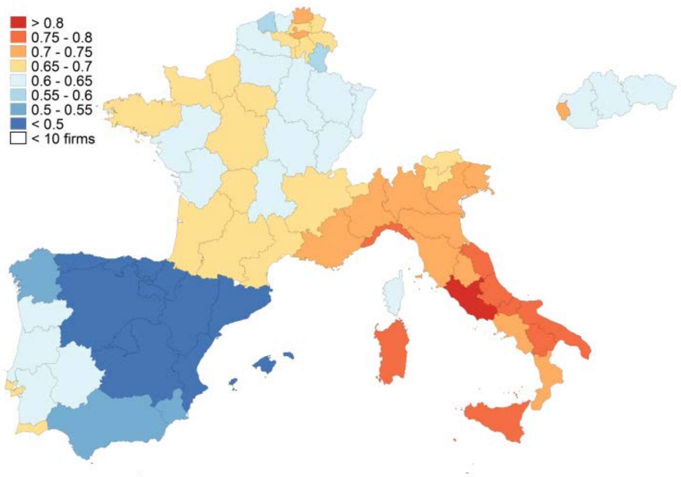
Micro firms: Total assets < 2 million €



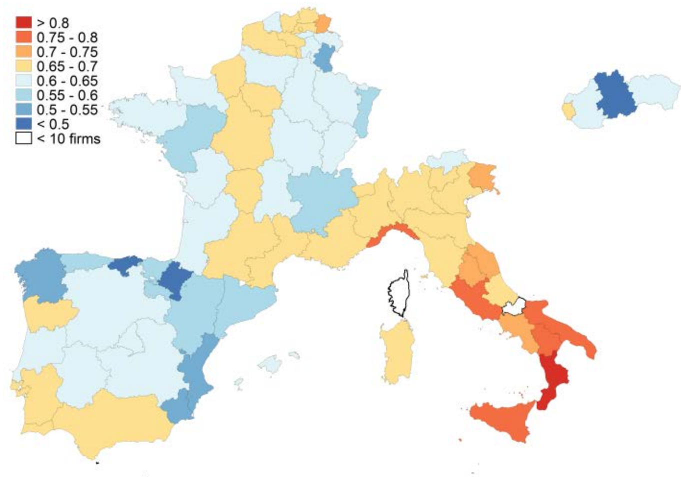
Small firms: 2 - 10 million € in total assets



Medium firms: 10 - 43 million € in total assets



Large firms: Total assets > 43 million €



Main Explanatory Variables

Type	Variable	Expected effect
Firm specific	Firm size (Log of Total Assets)	(+)
	Firm age (Log of Years since Incorporation)	(-)
	Profitability (Net Operating Profit / Total Assets)	(-)
	Tangibility (Tangible / Total Assets)	(+)
	Liquidity (Cash & Cash Equivalents / Total Assets)	(-)
Industry specific (based on NACE rev. 2)	Sector Growth (Median Growth in Turnover)	(-)
	Concentration (Herfindahl-Hirshman index)	(+,-)
Region specific (distinction based on NUTS classification; level 2)	Log of GDP 2012 (at current prices, from Eurostat)	(+)
	Population Density (from Eurostat)	(+)
	Industry Structure (sum of sq. ratio of regional industry to region turnover)	(+,-)
	Trust (% of people with high generalised trust; European Social Survey)	(-)
Industry by Region	Regional Industry Concentration (Herfindahl-Hirshman index)	(+,-)

Estimation Method

- Estimation has to account for the hierarchical structure in the data

- Cross-classified multilevel estimations are employed
  - Allowing intercepts to vary across business sectors, regions as well as their interaction

(see Kayo & Kimura 2011 for a similar approach)

$$Lev_{ijk} = \text{Function}(\text{Size, Age, Profitability, Tangibility, Liquidity, Industry growth, Industry concentration} \\ \text{Regional GDP, Regional population density, Regional industry structure, Regional trust,} \\ \text{Regional industry concentration}) + \boldsymbol{\delta_{0j0}} + \boldsymbol{\zeta_{00k}} + \boldsymbol{\vartheta_{0jk}} + \varepsilon_{ijk}$$

δ_{0j0} - Sector specific error term

ζ_{00k} - Region specific error term

ϑ_{0jk} - Interaction term (sector x region specific error term)

(subscrips i for firm, j for industry and k for region)

Variance Decomposition - Leverage

(Empty crossed random-effects model; including interaction)

Dep. Variable: Leverage	All firms	Micro	Small	Medium	Large
Fixed Part					
Constant (β_{000})	0.599***	0.600***	0.602***	0.596***	0.603***
Number of Firms	1,969,284	1,627,649	262,105	61,171	18,359
Number of Sectors	17	17	17	17	17
Number of Regions (Nuts 2)	87	87	87	87	87

Random Part:					
Variance Decomposition (in % of total)					
Sector-level (δ_{0j0})	1.4%	1.1%	2.0%	4.2%	6.0%
Region-level (ζ_{00k})	6.7%	6.1%	12.7%	8.5%	3.4%
Sector x Region (ϑ_{0jk})	2.2%	2.1%	3.2%	4.1%	2.7%
Firm-level (ε_{ijk})	89.7%	90.7%	82.1%	83.2%	87.9%

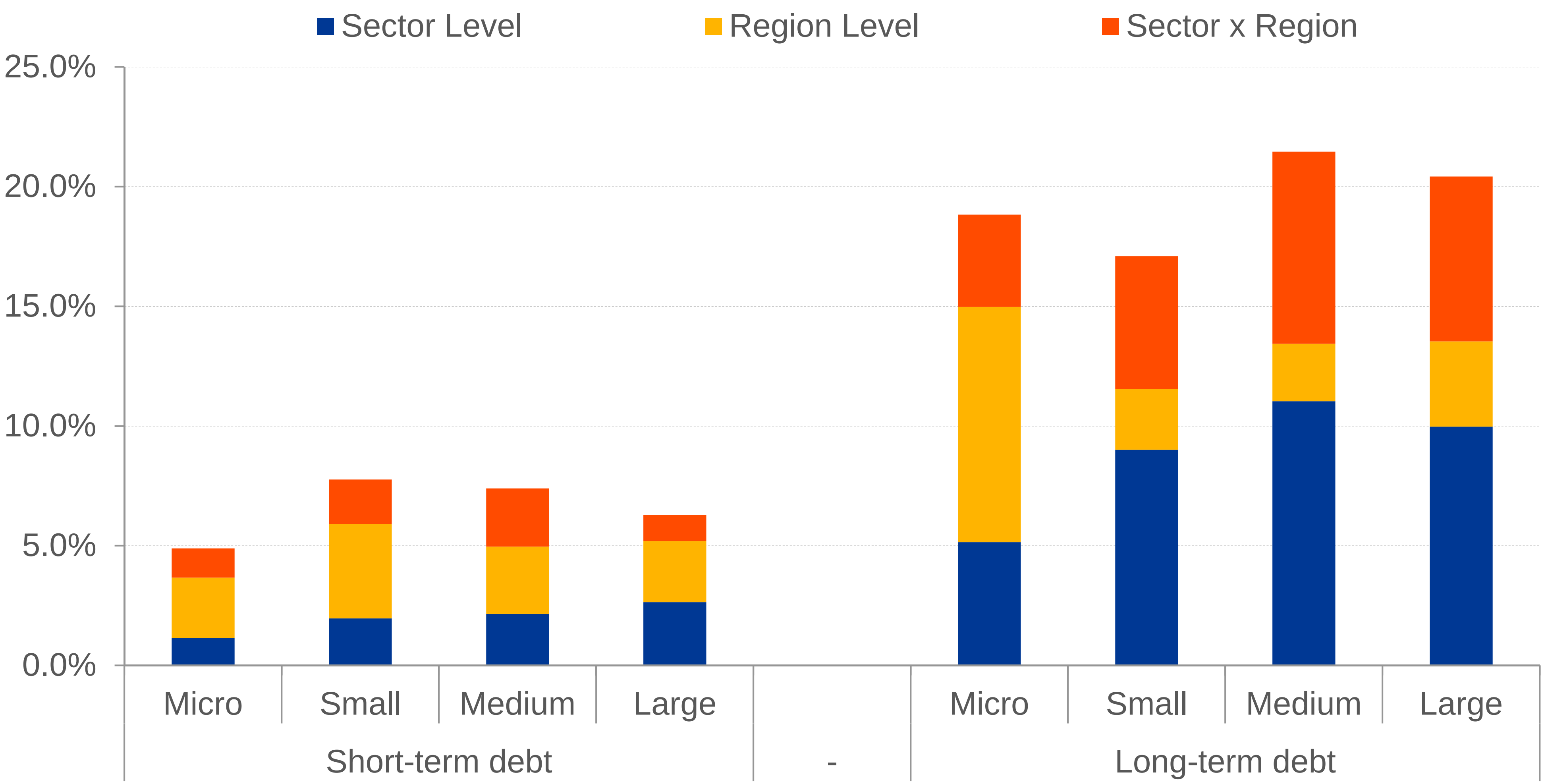
The Determinants of Leverage

(Crossed random-effects models including explanatory variables; sign. level: < 5%)

Dep. Variable: Leverage	All firms	Micro	Small	Medium	Large
Firm level					
Log of Total Assets	(+)	(+)	(–)	n.s	(+)
Log of Firm Age	(–)	(–)	(–)	(–)	(–)
Profitability	(–)	(–)	(–)	(–)	(–)
Tangibility	(+)	(+)	(–)	(–)	(–)
Liquidity	(–)	(–)	(–)	(–)	(–)
Industry Level					
Concentration	(–)	n.s.	n.s.	n.s.	(–)
Median growth (in turnover)	n.s.	n.s.	n.s.	n.s.	n.s.
Region Level					
Log of GDP (2012)	(+)	(+)	(+)	(+)	(+)
Population Density	(–)	n.s.	n.s.	n.s.	n.s.
Industry Structure	(–)	(–)	n.s.	n.s.	n.s.
Level of Generalised Trust	n.s.	n.s.	n.s.	(–)	n.s.
Regional Industries					
Industry Concentration by Region	(–)	n.s.	(–)	n.s.	n.s.
Number of Firms	1,969,284	1,627,649	262,105	61,171	18,359

Short- vs. Long-Term Debt Ratios

(Variance decomposition based on empty crossed random-effects model)



Note: Graph displays variances of level specific error components (in % of total variance); Residual variances due to firm-level differences

The Determinants of Leverage

(Crossed random-effects models including explanatory variables; sign. level: < 5%)

	Short-Term Debt				Long-Term Debt			
Dep. Variable: Leverage	**Micro**	**Small**	**Medium**	**Large**	**Micro**	**Small**	**Medium**	**Large**
Firm level								
Log of Total Assets	(–)	(–)	(–)	(–)	(+)	(–)	n.s	(+)
Log of Firm Age	(–)	(–)	(–)	(+)	(–)	(–)	(–)	(–)
Profitability	(–)	(–)	(–)	(–)	(–)	(–)	(–)	(–)
Tangibility	(–)	(–)	(–)	(–)	(+)	(+)	(+)	(+)
Liquidity	(–)	(–)	(–)	(–)	(–)	(–)	(–)	(–)
Industry Level								
Concentration	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.
Median growth (in turnover)	(–)	n.s.	n.s.	(–)	n.s.	n.s.	n.s.	n.s.
Region Level								
Log of GDP (2012)	n.s.	n.s.	(–)	(–)	(+)	(+)	(+)	n.s.
Population Density	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.
Industry Structure	(+)	(+)	(+)	(+)	(–)	(–)	(–)	(–)
Level of Generalised Trust	(+)	n.s.	n.s.	(+)	(–)	(–)	(–)	(–)
Regional Industries								
Industry Concentration by Region	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.
Number of Firms	1,627,649	262,105	61,171	18,359	1,627,649	262,105	61,171	18,359

Main findings and implications

- Major part of variation in corporate leverage ratios related to the firm level

- Yet, both sector and regional differences seem to be of some relevance
  - ➢ Relative importance varies depending on the size of firms

➢ Important to understand nature, extent and origin of differences between firms' respective environments and their importance for NFCs access to finance

Implications for Future Research

- Adding time-series dimension (covering both pre- and post-crisis data)
  - ➢ Pilot data only partially suited (limited time span; unbalanced character)

- Widen country coverage to enable generalisations to the wider EA
  - Further allows to better distinguish role of regions from wider country context

- Explore alternative region & sector characteristics that play a role
  - ➢ Further investigate the possible existence of cross-level interaction effects

Thank you very much!

Questions & Comments

are welcome

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Özdere-İzmir, Turkey, 26 September 2016

Corporate sector financials from financial stability perspective[1]

Gülcan Yildirim Güngör, Merve Demirbaş Özbekler
and Tuba Pelin Sümer, CBRT

[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.

Corporate Sector Leverage From Financial Stability Perspective[1]

Gülcan Yıldırım Güngör[2], Tuba Pelin Sümer[3] and Merve Demirbaş Özbekler[4]

Abstract

Non-financial companies' indebtedness has risen substantially following global financial crisis era due to increasing global risk appetite and capital inflows towards developing economies. However, reversal of capital flows owing to lower growth prospects of emerging countries, concerns about expansionary monetary policies of developed economies and surged in global risk aversion resulted in higher funding cost for emerging markets' corporate sectors. In order to analyze potential systemic risk stemming from corporate sector's foreign currency risk and roll-over capability, indebtedness should be monitored closely from sustainable financial stability perspective. This study aimed to estimate optimal debt level for non-financial companies listed on Borsa Istanbul Stock Exchange and estimated leverage ratio stood at reasonable levels in spite of the significant increase in indebtedness since global crisis. Even if indebtedness of corporate sector is assumed to be at reasonable levels, non-financial companies' prudential approach for debt sustainability is considered to be important in terms of systemic risk mitigation. Moreover, since this study was conducted for aggregated terms for company sample, sector and company specific factors should also be considered to estimate optimal leverage ratio specifically.

Keywords: Non-financial companies, leverage, financial stability, capital structure

JEL classification: G30, G32, F65

Content

[1] The views expressed are those of the authors and not necessarily reflect the views of the Central Bank of the Republic of Turkey. The authors thank to Uğur Çıplak for valuable comments for this study.

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1. Introduction

After the global financial crisis, expansionary monetary policies of developed countries resulted in search for high yield opportunities, increase in risk appetite and acceleration in capital flows to emerging countries partially due to high growth prospects of developing economies. Along with increased liquidity, interest rates scaled down and funding conditions became favorable which triggered corporate sector indebtedness in these countries. Köksal and Orman (2015) indicated the significant relationship between capital flows and leverage of Turkish non-financial firms, where capital flows boosting especially leverage of large private non-manufacturing firms. In line with enriched liquidity conditions and favorable funding environment since 2008, debt to GDP ratio increased in developing countries where economic activity has been predominantly financed by banking sector. Although higher leverage might be perceived as an indication of access to finance, exchange rate management or debt turnover capacity needs to be properly analyzed for robust and sustainable financial stability.

Contrary to the abovementioned favorable financial environment, due to concerns about expansionary monetary policies of developed economies, increased global risk aversion and lower growth prospects of emerging countries, global capital flows changed its direction back to developed economies since 2013. This caused raise in borrowing costs in emerging economies, as lower global liquidity put pressure on firms' debt roll-over and repayment capacity. In this regard, even if companies' indebtedness might be at sustainable levels, it is vital for firms to consider prudential leverage approach to mitigate systemic risk.

Companies may prefer to use debt to some extent considering tax benefits but they might also be exposed to higher risk premiums due to additional debt. Since non-financial companies constitute majority of banking sector loan borrowers, corporate credit quality, loan standards and lending conditions have significant influence on maintenance of healthy economic activity. On the other hand, fragilities that may arise from corporate sector may leap into the banking sector by causing vulnerabilities and systemic risk.[5] For instance, Lindner and Jung (2014) emphasized that firms operating in India with high leverage are vulnerable to systemic shocks therefore cautionary policies should be taken to sustain banks as the driving force in the economy.

This study aims to examine the optimal mixture of debt and equity to sustain financially sound, profitable and robust corporate sector that can stimulate economic activity by using data of non-financial companies (NFC) listed on Borsa Istanbul stock exchange. In this regard, interaction between global liquidity conditions and corporate indebtedness are initially examined. Consequently, main capital structure theories -irrelevance theory, trade off theory and pecking order theory- and their arguments regarding firm value and leverage relation are discussed. Then, factors affecting company's debt/equity preferences and borrowing costs are mentioned. In the last part, optimal leverage ratio is investigated for non-financial companies listed on Borsa Istanbul via weighted average cost of capital method.

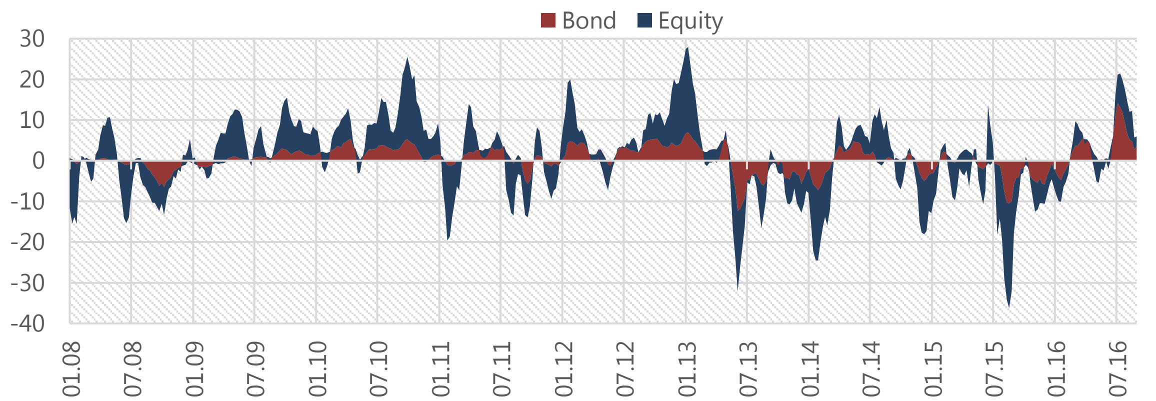
[5] Acharya et al (2015), Lindner and Jung (2014), Kılıc (2014), Aydın et al (2006)

2. Corporate Sector Indebtedness

To alleviate the effects of global financial crisis, developed economies conducted expansionary monetary policies. As global liquidity increased with these policies, emerging market economies made use of the advantages offered by higher capital inflows searching for high yield. In line with enriched liquidity conditions and favorable funding environment, corporate sector debt to GDP ratios have increased in developing economies where economic activity is predominantly financed by banking sector. While banking sector stands as the primary financial intermediary for these countries, recently bond issuance also gained importance for corporate sector finance.

Favorable global risk appetite and high yield return opportunities in developing economies have led corporate sector to benefit from low funding cost environment and to undertake more exchange rate risk due to foreign currency denominated liabilities. Increasing leverage by non-financial companies was attributed as a favorable development since it promoted economic growth and increased financial deepening.

Capital Flows to Emerging Markets
(Million USD, 4-Week Moving Sum) Graph 1



Source: EPFR

However, starting from second quarter of 2013, capital flows changed its direction back into hard currencies. Thus, developing economies had to face with reversed cash flows due to surged global risk aversion, concerns about continuity of easing monetary conditions and lower growth prospects for emerging economies[6]. In this response, local currencies of emerging markets depreciated against hard currencies and funding costs scaled up which resulted in increased currency and interest risk on developing countries' NFC balance sheets and jeopardized profitability due to weakened roll-over capability and high exchange loss.

Credit risk indicators and exchange rates pointed out surge in debt burden of emerging countries' corporate sector while bond returns tended to be flat since 2013 year end. Even though JP Morgan EMBI+ recorded remarkable increase after global

[6] Capital Flows to Emerging Market Economies, Institute of International Finance

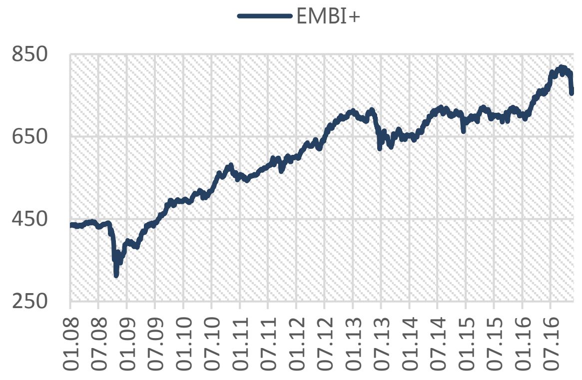
financial crises and preserved its increasing trend till 2013, the index tended to became flat between 2013-2015 periods. On the other hand, due to the deceleration in capital flows majority of emerging country currencies depreciated against US dollar. Local currency depreciation especially for Russian Ruble and Brazilian Real recorded more volatile developments while Chinese Yuan performed better primarily owing to its country specific prospects.

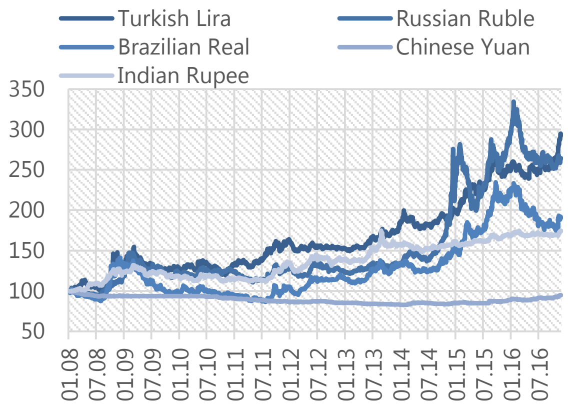
These unfavorable developments jeopardized external borrowings and triggered FX risk for companies especially those without financial and natural hedge but having high net FX open position. From financial stability perspective, it is worth to mention that since corporate loans are generally the major asset of banking sector balance sheets in developing countries, these fragilities had reflections on banking sector asset quality and financials[7]. Within this scope, the magnitude of reliance on foreign sources by banks gains importance regardless of dynamics of corporate sector and the country's economic fundamentals.

Emerging Market Financials

Graph 2

EMBI+	Exchange Rates (Against USD, Indexed Base Year=2008)



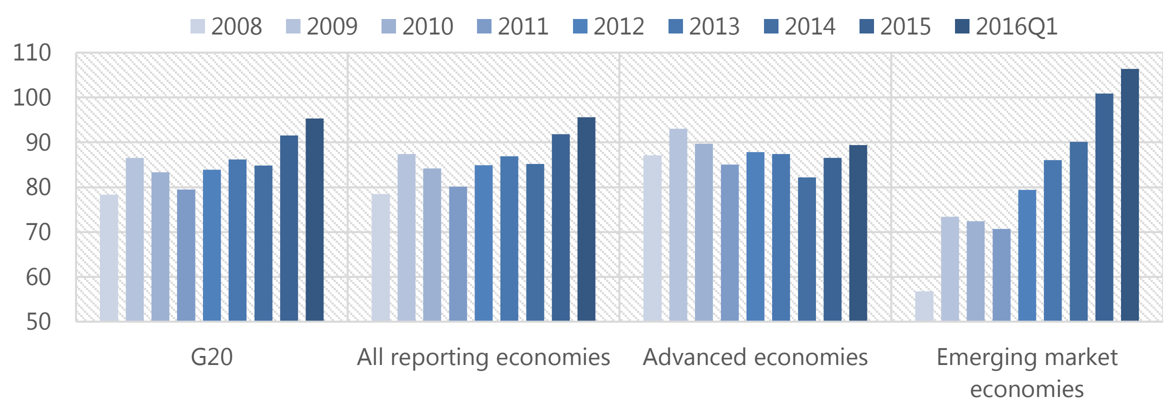


Source: Bloomberg

NFC loans to GDP ratio preserved a flat trend for mature economies while it recorded a tremendously increasing tendency for emerging economies particularly due to their continuing financial deepening process and abovementioned global funding conditions. In general developing economies benefited from favorable funding environment and NFCs borrowed with lower interest rates. In particular, Chinese share from capital flows and jump in corporate borrowing should be analyzed separately considering its country unique growth prospects.

[7] IMF Global Financial Stability Report, October 2015, Chapter Three: Corporate Leverage in Emerging Markets

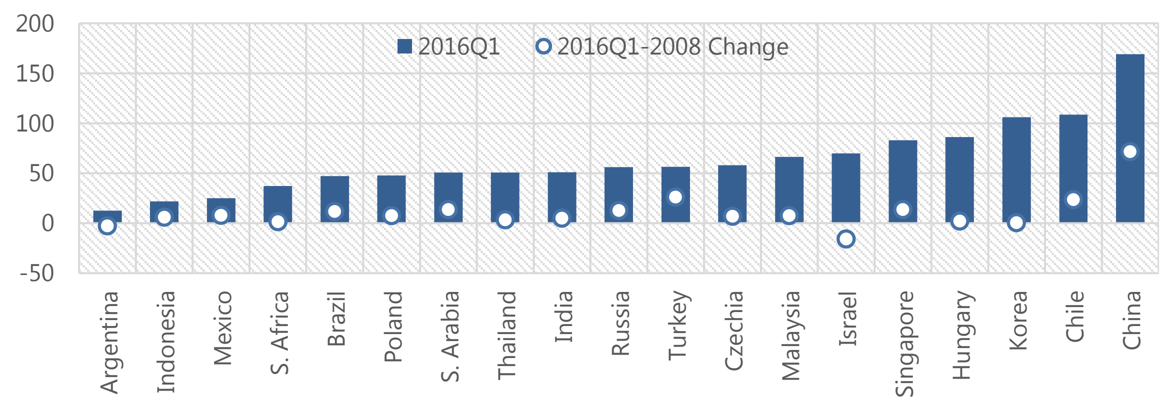
Non-Financial Company Credit (% GDP) Graph 3



Source: BIS
Based on conversion to US dollars at market exchange rates.

In the country specific NFC leverage framework, as mentioned above China's case is obviously stronger compared to peer countries. Compared to the global financial crisis period Chinese corporate sector increased its financial indebtedness enormously which might be attributable to relatively higher growth prospect of the country. Chilean and Korean companies also follow Chinese companies in terms of loan to GDP ratio. On the other hand, even though Turkish corporate sector companies recorded high increase after favorable liquidity conditions, credit to GDP ratio is at reasonable levels compared to peer group countries. In this regard, continuing financial deepening process should be taken into consideration while assessing leverage surge.

NFC Credit (% of GDP) Graph 4



Source: BIS

In an economic environment where NFC finance is predominantly provided by financial sector, particularly banking sector, roll-over capability and funding cost management gain more importance. Financial fragilities derived from NFCs balance sheets and debt repayment capacity also bring out concerns about financial stability. Given the evident importance of systemic and contagion risks, preserving optimal share of equity finance is vital to mitigate interest and currency risk for corporate financials.

3. Capital Structure Theories and Firm Preferences for Leverage

Value of a firm can be basically described as net present value of future cash flows of the company. In order to discount future cash flows, weighted average cost of capital (WACC) is generally used. Basically, WACC is the weighted average of cost of equity and cost of debt where weights are determined by value of debt and equity (Brealey and others, 2011). The capital structure gains importance in terms of company survival and debt roll-over (Lynch, 2009).

The fundamental study on capital structure which is also known as the irrelevance theory by Modigliani and Miller (1958), states that firm value or WACC is indifferent from the mixture of debt and equity in an efficient environment without taxes, dividends, bankruptcy cost and agency conflicts. According to the irrelevance theory, if company's debt to asset ratio increases by one percent than it only means one percent decrease in equity's share in firm balance sheet size. However, this share transition do not cause any change in cost of capital and firm value. The irrelevance theory was also improved by incorporating tax shields in firm value calculation, such that the firm value increases continuously along with debt usage (Modigliani and Miller, 1963). Fundamental drawback in this theory is thought to be the underestimation of financial distress such as bankruptcy and agency costs (Frank and Goyal, 2007).

As Modigliani and Miller stated to increase debt share to benefit from tax advantage, Kraus and Litzenberger (1973) mainly counter argued this capital mix via proposing Trade-off Theory which considers a balance between bankruptcy cost and tax benefits of debt. According to this approach, firm value might be optimized by considering tax shield of debt and financial distress such as bankruptcy costs and non-bankruptcy costs. While increasing indebtedness to some extent might be a positive aspect in terms of replacing expensive equity to reduce WACC; on the contrary side high leverage might create weaknesses such as additional financial risk, higher risk premiums and higher equity return desire which put pressure on WACC to scale up. In this regard, firm value is a combination of the present value of all equity financed firm plus the present value of tax shield minus the present value of financial distress cost (Brealey and others, 2011). This approach also has some weaknesses such as complex tax code, whether bankruptcy costs are transferable and/or fixed, and the structure/magnitude of transaction costs (Frank and Goyal, 2007)

Another milestone approach for capital structure is Pecking Order Theory introduced by Myers (1984) and with co-author Majluf (1984) which emphasizes preferring internal funds to external funds and debt to equity in case of external finance. In the trade-off theory, firm's decision is a trade-off between tax advantage and leverage-related costs. Pecking order theory argues that adverse selection implies retained earnings to be more favorable than debt. The ordering may stem from a variety of sources including agency conflicts and taxes. Myers and Majluf (1984) stated that in case of stable economic cycles, trade-off theory is appropriate for large-scale firms, on the other hand for unstable economic cycle pecking-order theory works better for small-scale firms

In the literature, there are several studies investigating which capital structure theory best explains financing choices of corporates, although conclusions are mixed. Shyam-Sunder and Myers (1999) make use of two models to compare the fit of pecking-order theory and trade-off theory. In the model for pecking-order theory, they model long-term debt as a function of financing deficit of the company. On the other hand, for trade-off theory, they make use of a target adjustment model, where the firm issues debt as it departs from its optimal debt level. The authors showed that pecking-order theory has much explanatory power than trade-off theory. By incorporating debt capacity into the model of Shyam-Sunder and Myers (1999), Lemmon and Zender (2010) indicated that pecking order theory describes the choice of corporates better. If it is possible firms prefer to use their internal funds to retire debt and reduce leverage while concerns over debt capacity is the reason to issue equity. On the other hand, Frank and Goyal (2003) tested performance of pecking-order theory for American firms and showed that equity issuance is more closely related with financing deficit compared to debt issuances which violates the pecking-order theory. Similarly, Köksal and Orman (2015) tested the suitability of trade-off and pecking order theory for Turkish non-financial companies and showed that trade-off theory explains the capital structure of large private non-manufacturing firms better and pecking-order theory performs best for small public firms in the manufacturing sector. While conventional capital structure theories only consider debt, equity and internal sources as funding streams, Shimpi (2004) showed that insurative leverage (proportion of contingent capital) and risk leverage (proportion of transferred risk) are also important streams to consider along with financial leverage.

Besides the studies focusing on capital structure theory tests, there is a group of articles exploring the factors affecting firm leverage. Karaşahin and Küçüksaraç (2016) examined capital structure determinants of Turkish non-financial firms listed on Borsa Istanbul. In this study, the effect of firm and industry specific factors and macroeconomic variables on short-term and long-term leverage ratios of non-financial companies was investigated. The authors showed that size and tangibility have positive relation with long-term leverage ratio; while on the other hand, profitability and liquidity have negative relation with short-term leverage ratio. Frank and Goyal (2009) studied capital structure preferences of American firms and showed that as asset size, tangibility and expected inflation increases firm leverage increases and as profitability and market-to-book asset ratio increases leverage decreases. Compatible with the literature, Köksal and Orman (2015) found that firm leverage is positively correlated with firm size, potential debt tax shields, median of industry debt ratios, and inflation, and negatively correlated with profitability, business risk, and real GDP growth for Turkish non-financial companies.

On the other hand, there are also studies on the relation between cost of borrowing and leverage. Mizen and Tsoukas (2012) explored firm characteristics and financial crisis on the borrowing premiums of Asian countries. They pointed out that firms with lower leverage and higher Z-scores (lower probability of bankruptcy) have lower borrowing cost in the bond markets. Altunok and Fendoğlu (2015) studied determinants of bank loan rates for Turkish non-financial companies and showed that borrowing cost decreases as leverage decreases, tangible asset ratio and asset size increases. Moreover, increase in policy rates and decrease in global capital flows has increasing effect on borrowing costs.

In order to model deviation from optimal debt level in their trade-off theory test, Shyam-Sunder and Myers (1999) used historical average of leverage ratio to represent the optimal leverage ratio. On the other hand, Jalilvand and Harris (1984) used three-year moving average for firm leverage. Although, Damodaran (2012) conducted analysis for optimal leverage ratio of a firm, any specific study focusing on optimal leverage ratio estimation for a specific country was not encountered.

4. Optimal Leverage Ratio: Turkish NFC Case

Debt and equity are main funding sources for a company. Firms generally prefer to raise capital via debt issuances since interest payments are tax deductible. However, as the debt to asset ratio of a firm increases, cost of debt also increases since firms are perceived to be riskier in the market. On the other hand, although equity is more expensive compared to debt, firms may prefer to issue equity which does not need to be paid back in financially unfavorable times when earnings are declining. In order to maximize firm value, corporates select a mix of debt and equity which minimizes their weighted average cost of capital. This section aims to find optimal leverage ratio for NFCs listed on Borsa Istanbul in Turkey.

Data and Indicators

Weighted average cost of capital for a firm can be expressed by the following formula, where $WACC, r_e, r_D\ E, D$ denote weighted average cost of capital, cost of equity, cost of debt, equity and debt level respectively.

$$WACC = r_e(\frac{E}{(D+E)}) + r_d(\frac{D}{(D+E)})(1 - tax\ rate)$$

In order to find out the optimal leverage ratio which corresponds to the minimum level of weighted average cost of capital; cost of equity and cost of debt are needed to be modelled as a function of leverage ratio. In this regard, cost of equity can be modelled via using capital asset pricing model (CAPM):

$$r_e = r_f + Beta\ (r_m - r_f)$$

where r_f *and* r_m denote risk-free return and market return respectively. As debt level increases, equity also becomes riskier since default risk of the company rises. Therefore, beta coefficient increases which brings up cost of equity. Industry index of Turkey (XUSIN Index) consisting of 146 firms is used to represent corporate sector in this study. For the market return, daily return of BIST100 Index (XU100 Index) is used. Sensitivity of the industry index to the price changes in the market index which is called as beta is calculated via the following formula:

$$Beta_{levered} = \frac{Covariance\ (r_m, r_i)}{Var\ (r_m)}$$

where r_i denotes return of the industry index. Beta coefficient was estimated as 0.77 using daily returns of industry and market index in 2015. However, it is worth to note that beta coefficient does not change significantly if the daily returns in the 2011-2015 period is used. The estimated beta coefficient which is 0.77 is indeed the levered beta coefficient corresponding to the leverage ratio of the firms represented in the industry index which has 54% debt to asset ratio as of 2015 year-end. In order to calculate cost of equity for various leverage ratios, it is needed to calculate levered beta coefficient for differing debt to equity ratios via the following formula.

$$Beta_{unlevered} = (\frac{Beta_{levered}}{(1+\frac{D}{E}*(1-tax\ rate))})$$

After calculating levered beta stream, cost of equity for increasing debt to asset ratio was derived with CAPM formula. Average of 3 month government bond annual rate in 2015 was used to denote the risk-free rate which is 9.9%. Fernandez et al. (2015) collected market risk premiums used in 41 countries in 2015 with a survey.

9.3% is used in this study as the market risk premium for Turkey as suggested by Fernandez et al. (2015).

There are alternative approaches for modelling cost of debt as a function of leverage ratio. As an example, Damodaran (2012) suggested to model cost of debt using interest coverage ratio (ICR). The author derived the spread and ICR relation using US corporate bond issuances. There is negative relation between ICR and spreads, as ICR decreases cost of borrowing increases. According to his methodology, as the debt level of corporate increases, interest expenses rise which causes ICR to decelerate and spread to increase. The approach that Damodaran (2012) used might not be applicable for now in Turkey since local corporate bond market recently started to operate actively. Moreover, ICR is not the only factor to determine cost of borrowing. Therefore, in this article, cost of borrowing is modelled as a function of firm characteristics. The relation between cost of borrowing and firm characteristics for Turkish NFCs was initially examined by Altunok and Fendoğlu (2015). Considering main findings of mentioned study, independent variables were determined and improved. In this regard, this study focuses on NFCs listed on the Borsa Istanbul and matches their financial ratios with loan interest rates. To represent the general interest rate in the market, benchmark rate was used and difference between loan interest and benchmark rate was derived as the dependent variable and called as spread. Then, the spread of cost of borrowing for a corporate could be modelled via the following linear regression.

$$Spread = \beta_0 + \beta_1 \log(assets) + \beta_2(leverage) + \beta_3(current\ ratio) + \beta_4(ROE) + \beta_5(stock\ turnover) + \beta_6(sales\ growth)$$

Assets stands for total asset size of the company, leverage is debt to equity ratio, current ratio is calculated by dividing short-term assets to short-term liabilities, return on equity (ROE) is the ratio of annualized net profit over four quarter average equity. Stock turnover ratio is calculated as division of annualized cost of goods sold to four quarter average inventory level.

Data includes TL loan rates that were originated in 2016 for 262 non-financial firms listed on the exchange. To eliminate maturity factor on loan rates, loans that only have a maturity of 3 months to 2 years are considered. Descriptive statistics of the variables used in the regression are given in the following table.

Descriptive Statistics

Table 1

	Mean	Std Dev.	Minimum	Maximum
Loan Rate -Benchmark Spread	3.68	2.45	-4.63	8.75
Log Asset	8.54	0.64	6.93	10.42
Leverage	1.73	0.86	0.16	3.96
Current Ratio	1.38	0.53	0.22	5.22
ROE	0.06	0.19	-0.98	0.66
Stock Turnover Ratio	7.24	14.89	0.03	181.28
Sales Growth	0.12	0.25	-0.65	2.46
# of Observation	1,371			

Source: CBRT, Public Disclosure Platform, Finnet

Regression results indicate that asset size, debt to equity ratio, return on equity and current ratio are significant factors affecting cost of borrowing. As the asset size, current ratio and return on equity decreases while debt to equity ratio increases, cost of borrowing increases.

Regression Results			Table 2
	1	2	3
Log Asset	-0.5821***	-0.5999***	-0.4456***
	(0.0989)	(0.0988)	(0.1071)
Leverage	0.8074***	0.8305***	0.5528***
	(0.0737)	(0.0739)	(0.0875)
Sales Growth		-0.7332***	-0.1807
		(0.2496)	(0.2721)
Current Ratio			-0.4544***
			(0.1336)
ROE			-1.6736***
			(0.4054)
Stock Turnover Ratio			0.0046
			(0.0042)

Source: CBRT, Public Disclosure Platform, Finnet

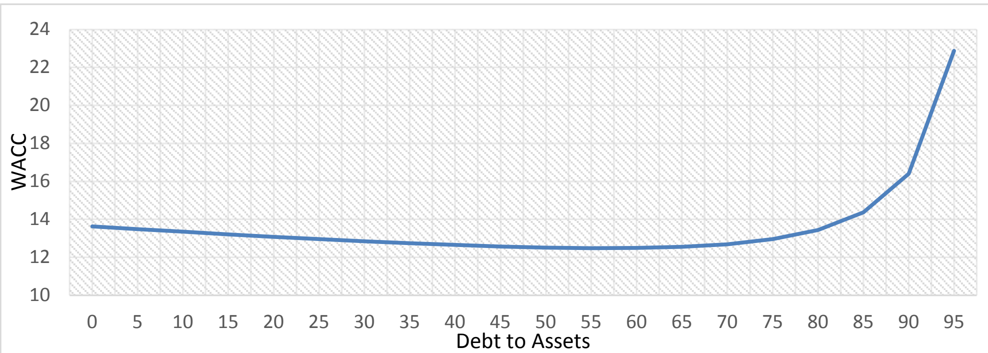
In order to estimate cost of debt, coefficient between spread and debt to equity ratio is used for different leverage ratios. Since firm value maximizes with the lowest cost of capital, optimal debt and equity mix is determined at lowest cost of capital level.

Optimal Debt Level Analysis

Cost of debt and cost of equity relation for various debt to asset ratios indicate that optimal leverage ratio for NFCs examined in this study hovers around 55-65% while actual leverage ratio of the firms represented in the industry index is 54% as of 2015 December.

Optimal Debt to Assets Ratio

Graph 5



Source: PDP, Finnet, CBRT, author calculations

Difference between estimated optimal and actual leverage ratio for these companies might be partially due to agency costs which are not considered in the WACC method. Conflicts between shareholders and debt holders cause agency cost of debt. Shareholders of companies near bankruptcy might prefer risky investments while debt holders knowing that shareholders will opt for riskier projects might ask for higher yields. On the other hand, as described by Jensen and Meckling (1976) agency cost of equity is associated with the "separation of ownership and control". Managers may prefer to take suboptimal decisions to increase their personal benefits besides maximizing the value of the firm which cause shareholders to ask for higher returns. Depending on the magnitude of agency cost of debt and equity, corporates may deviate from optimal leverage ratio based on WACC approach.

Moreover, different theories may also indicate varying optimal leverage ratios for different sectors. Karaşahin and Küçüksaraç (2016) showed that industry-specific factors have significant effects on firm leverage determination. On the other hand, Frank and Goyal (2007) stated that capital structure preferences of private firms, small public firms and large public firms might differ. Although, large public companies may prefer to use retained earnings and corporate bonds, small public firms fund themselves particularly with equity finance. Therefore, optimal leverage ratio analyses should be enriched with consideration of sectoral differences and company size.

5. Conclusion and Assessments

In this study, non-financial companies' increasing indebtedness following global crisis era was analyzed considering global risk appetite and capital inflows to developing countries. Even though scaling up leverage ratios might be attributable to continuing financial deepening process and improved corporate sector financial access, potential systemic risk stemming from corporate sector's financials should be monitored closely for sustainable financial stability. High reliance on foreign sources rather than equity finance may result in vulnerable NFC financials regardless of dynamics of corporate sector and the country's economy itself.

On the Turkish corporate sector side, current leverage ratios stand at reasonable levels although Turkey is amongst the countries which recorded significant increase in indebtedness since global crisis. Turkish NFCs' limited level of indebtedness before the increase in global liquidity; and deepening domestic financial system has decisive role in this development. In this study, optimal leverage ratio of NFCs listed on Borsa Istanbul was examined via weighted average cost of capital method. This study pointed out that leverage ratio of NFCs examined in this analysis hovers around estimated indebtedness levels. However, even if indebtedness of non-financial corporate sector is assumed to be at reasonable levels, prudential approach for firms' debt sustainability is considered to be important in terms of systemic risk mitigation. Moreover, this study was conducted for aggregated term while sector/company specific factors should also be considered to estimate optimal leverage ratio specifically for further studies.

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Özdere-İzmir, Turkey, 26 September 2016

Corporate sector financials from financial stability perspective[1]

Gülcan Yildirim Güngör, Merve Demirbaş Özbekler
and Tuba Pelin Sümer, CBRT

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

TÜRKİYE CUMHURİYET MERKEZ BANKASI

Corporate Sector Financials from Financial Stability Perspective

Corporate Sector Financials: Overleveraged?

Central Bank of the Republic of Turkey

Gülcan YILDIRIM GÜNGÖR, Merve DEMİRBAŞ ÖZBEKLER, Tuba Pelin SÜMER

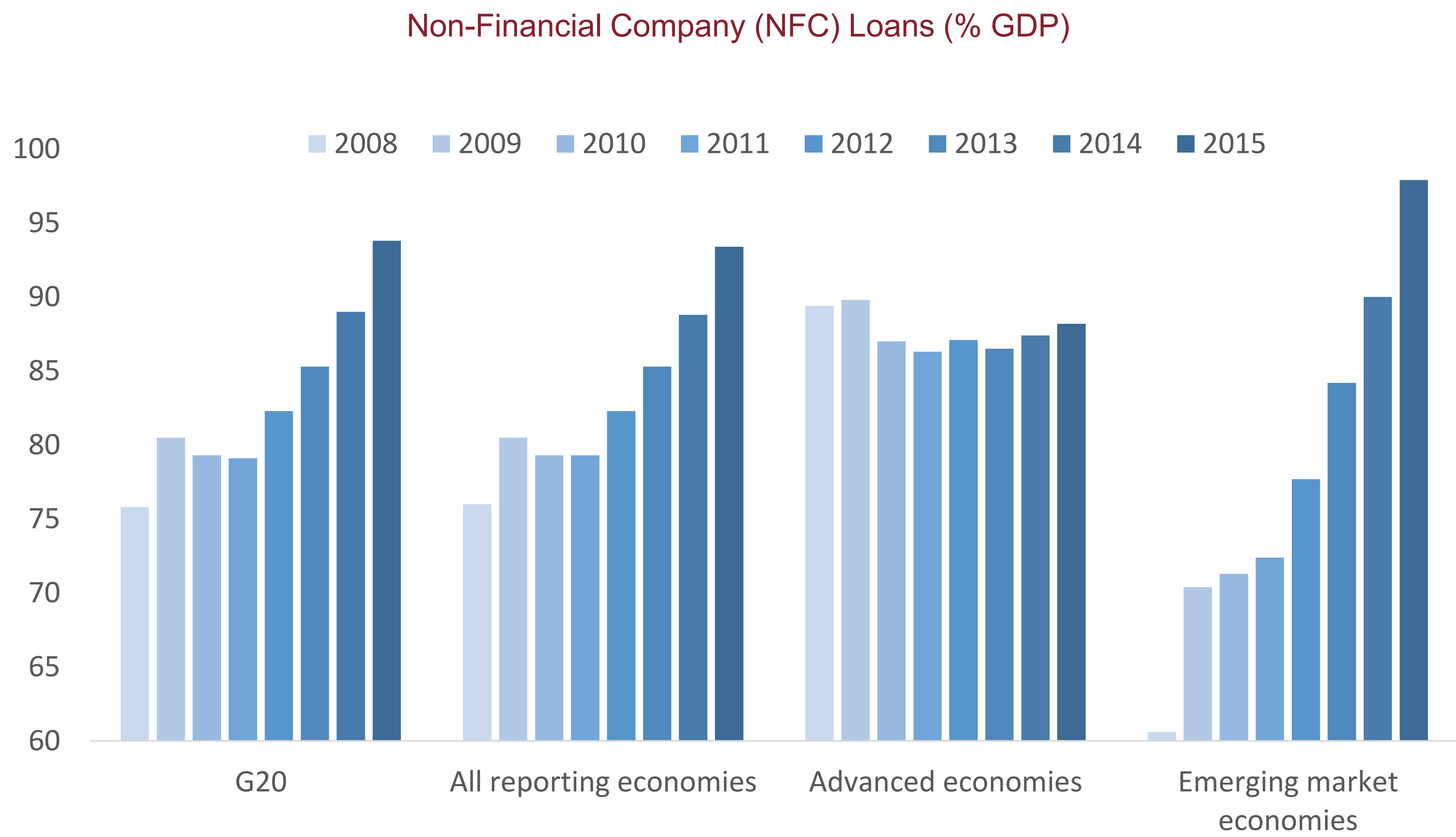
Izmir/ September 2016

AGENDA

- Corporate Sector Indebtedness
- Global Capital Flows and Optimal Debt/Assets Ratio
- Liquidity and Profitability
- Key Takeaways

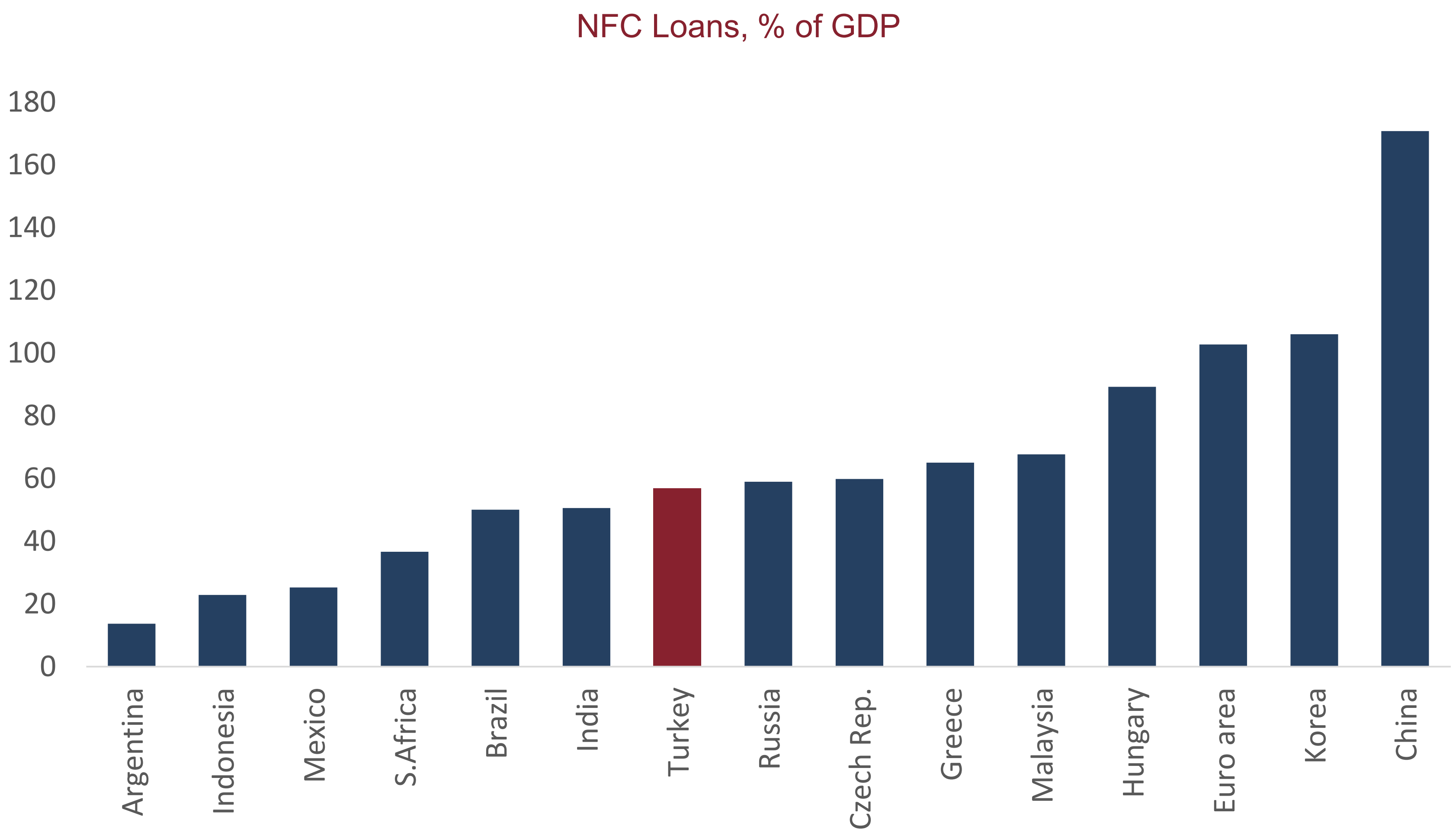
- Corporate Sector Indebtedness
- Global Capital Flows and Optimal Debt/Assets Ratio
- Liquidity and Profitability
- Key Takeaways

Corporate sector indebtedness, especially in emerging market economies, tended to scale up due to increased capital inflows.



Source: BIS (Based on conversion to US dollars at PPP exchange rates)

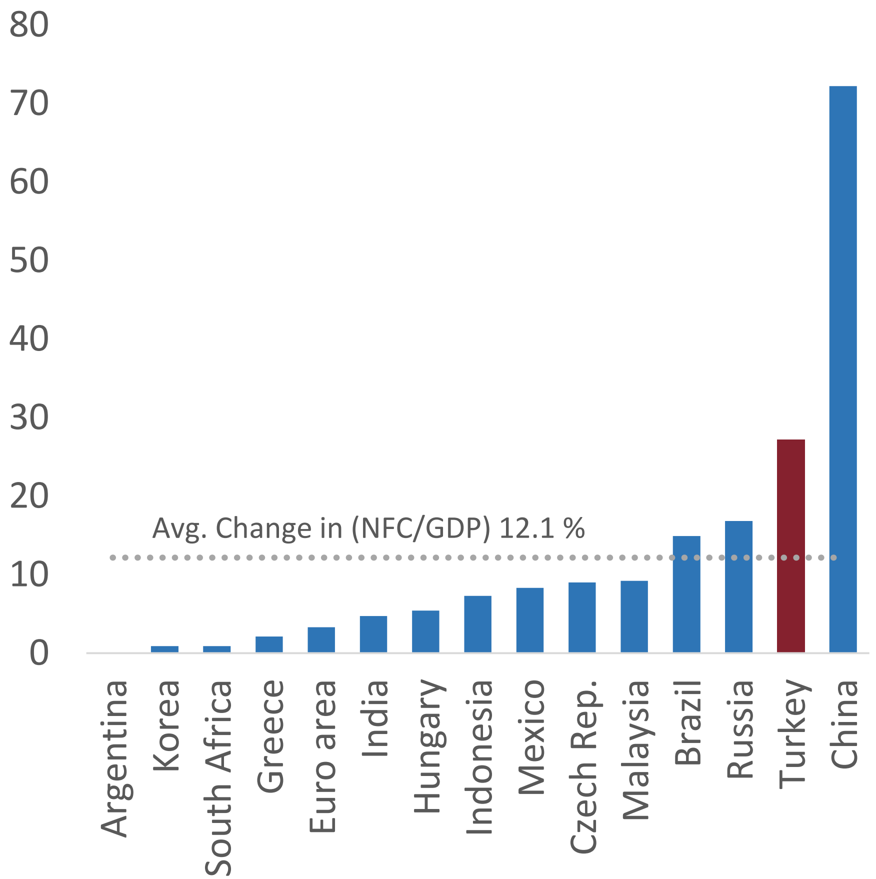
NFC debt to GDP ratio is at reasonable levels in Turkey while emerging country corporate indebtedness is gaining global attention.



Source: BIS (Aggregates based on conversion to US dollars at market exchange rates)

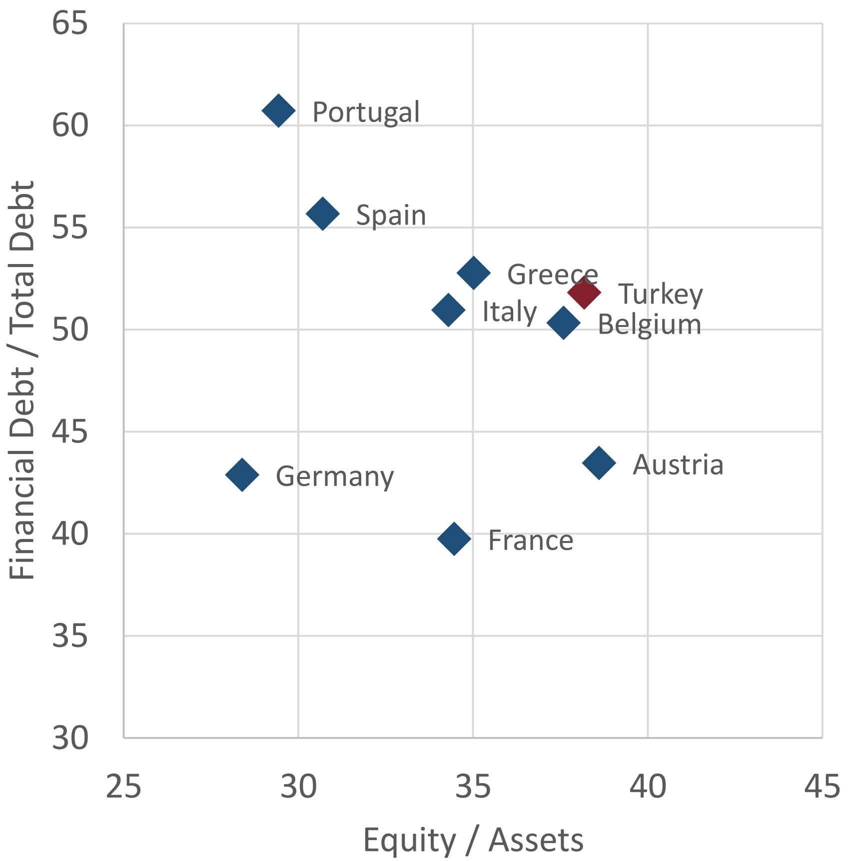
However, after global financial crises NFC debt seems to increase.

Δ(NFC Loan/GDP) Ratio Between 2008-2015 (%)



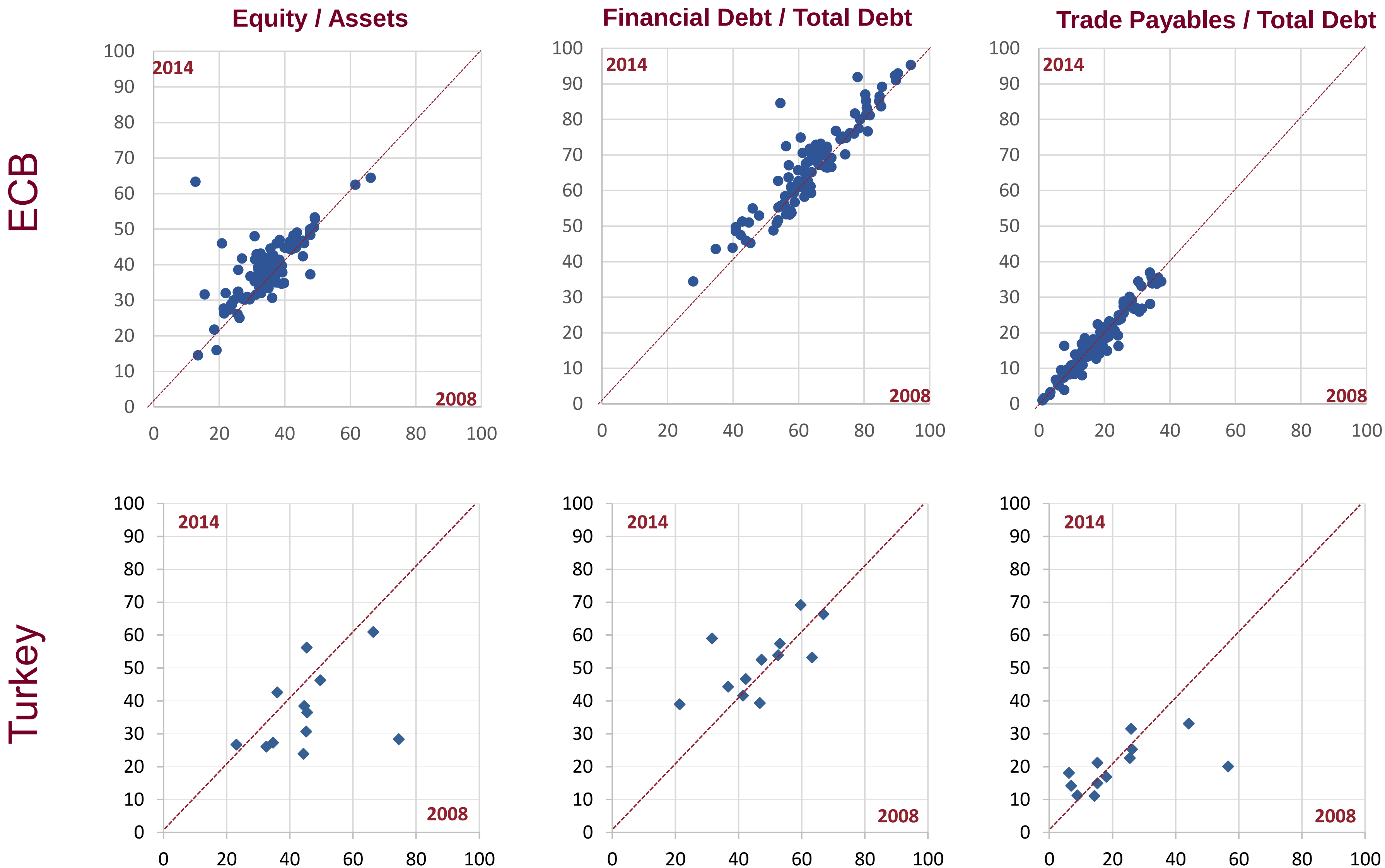
Source: BIS (As of 2015)

Funding Structure (%)[1]



Source: ECCBSO, CBRT (As of 2014)
1) Turkey: CBRT Company Accounts

Financial debt share increases both for European and Turkish NFCs.

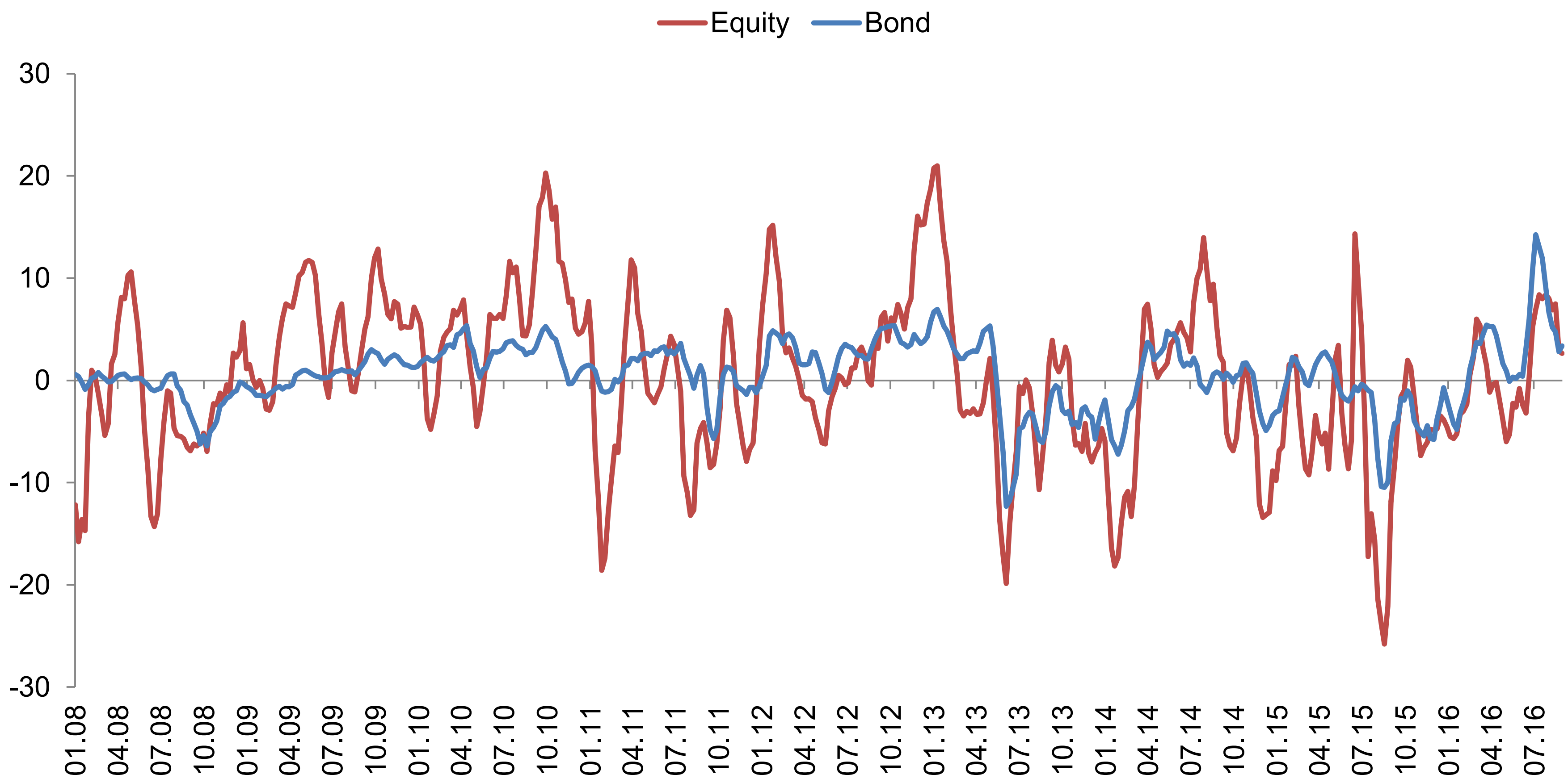


Source: ECCBSO, CBRT (As of 2014)

- Corporate Sector Indebtedness
- Global Capital Flows and Optimal Debt/Assets Ratio
- Liquidity and Profitability
- Key Takeaways

Portfolio flows to emerging economies play crucial role for funding cost and leverage.

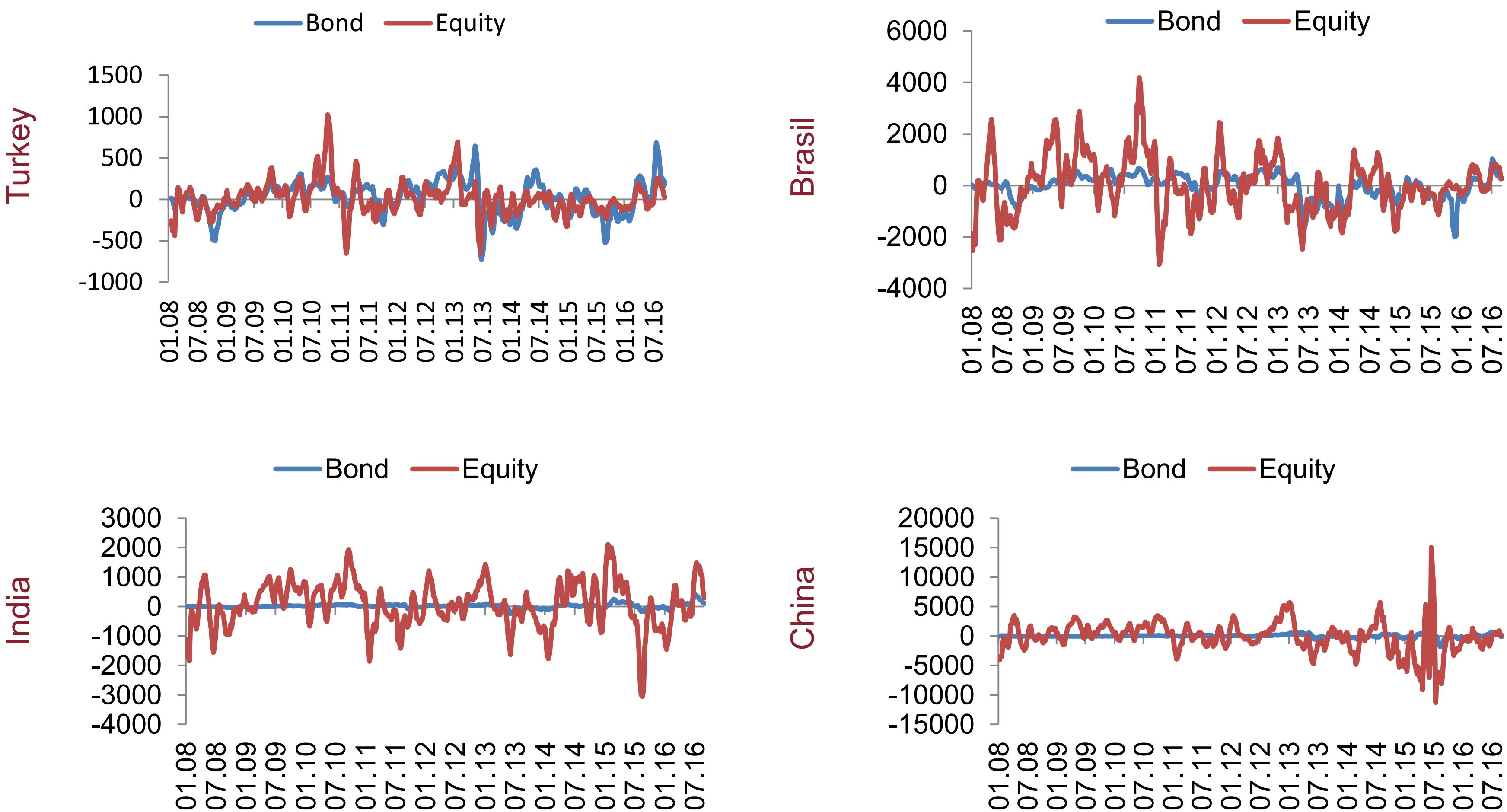
Capital Flows to Emerging Markets
(Million USD, 4-Week Moving Sum)



Source: EPFR

Portfolio flows to emerging economies play crucial role for funding cost and leverage.

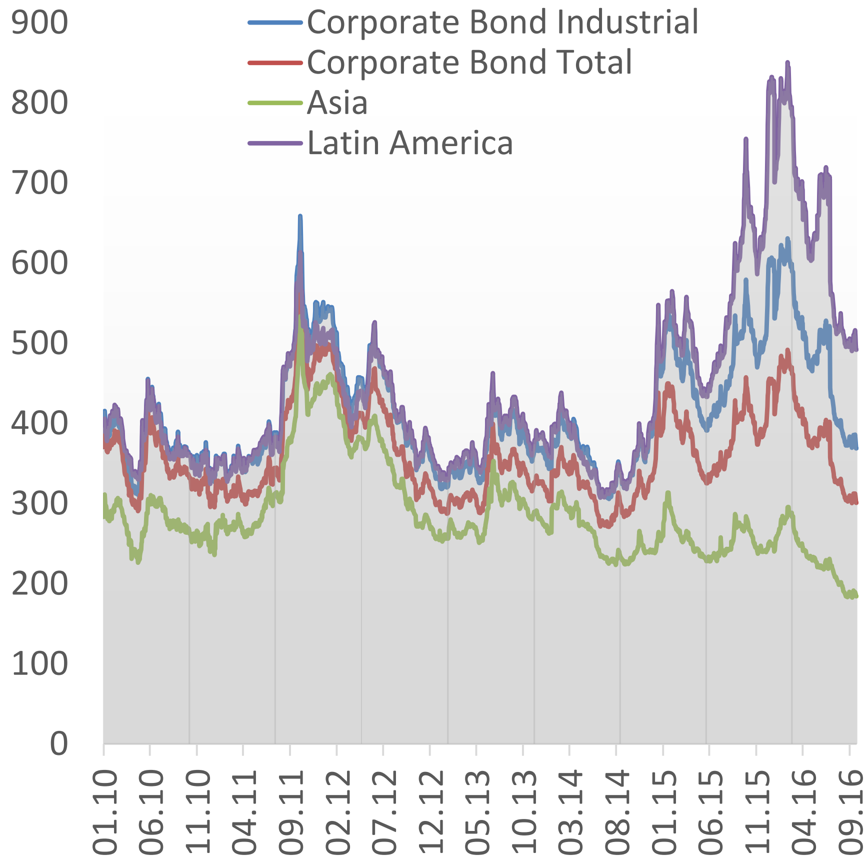
Capital Flows to Emerging Markets (Million USD, 4-Week Moving Sum)



Source: EPFR

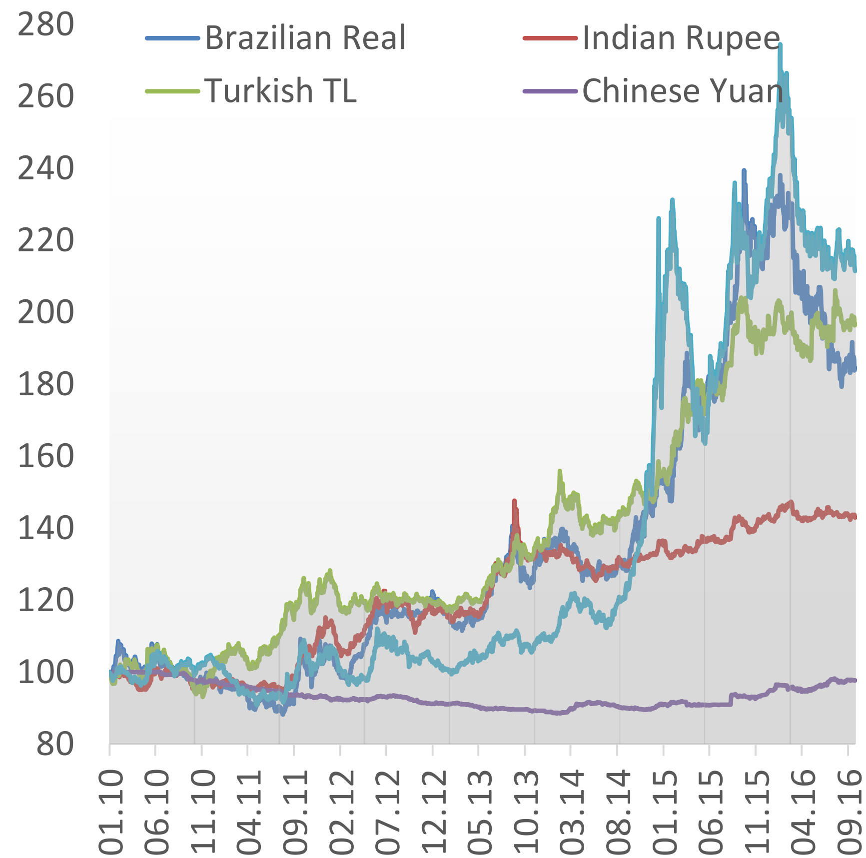
In case of acceleration in risk premiums and reverse capital flows, cost of funding increases for emerging economy NFCs.

Credit Suisse Risk Premium Indicators



Source: Bloomberg

Exchange Rates (Against USD)[1]



Source: Bloomberg
1. Indexed to base year 2010

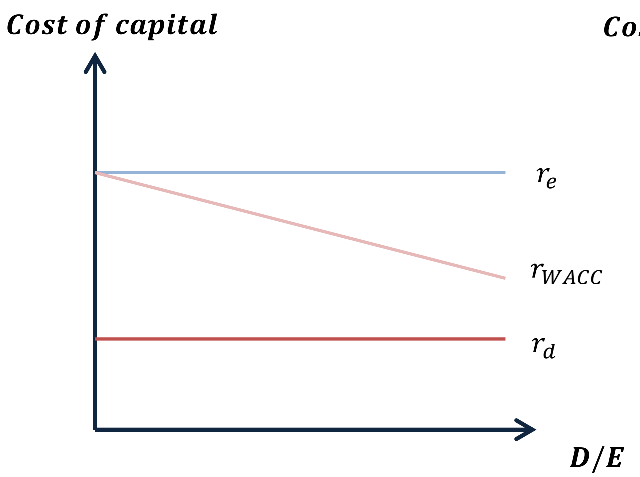
Capital Structure Theories

Weighted Average Cost of Capital = **Cost of Equity** + **Cost of Debt**

- Net Income Approach
- Modigliani&Miller Approach
- Traditional Approach

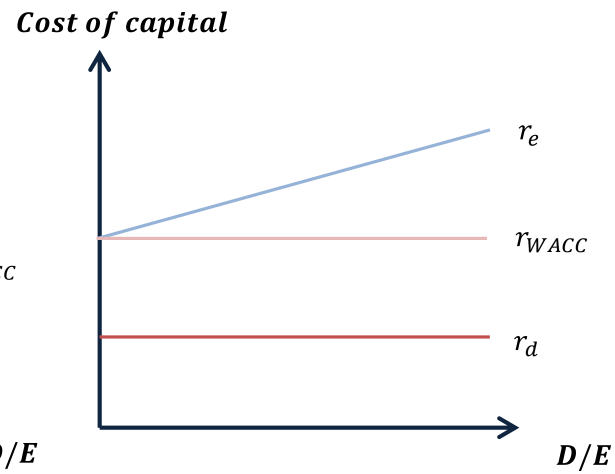
Capital Structure Theories

Net Income Approach



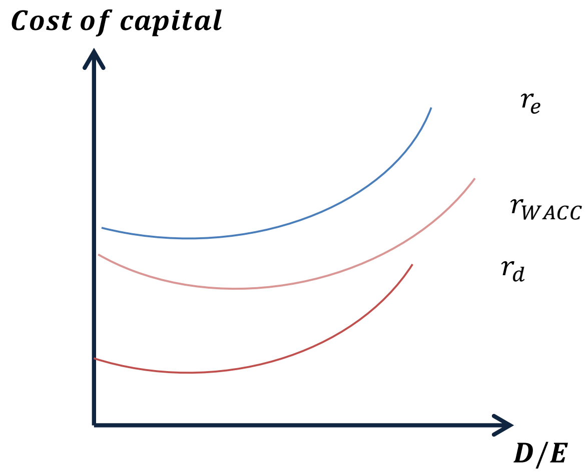
- Leverage increase will not affect investors' confidence levels.
- Rd is less than Re
- No taxes.

Modigliani &Miller Approach



- Firm value is irrelevant to the capital structure but growth prospect.
- No taxes and bankruptcy cost
- Symmetric information.
- The cost of borrowing is the same for investors as well as companies.
- Debt financing does not affect companies EBIT.

Traditional Approach



- Optimal debt to equity ratio exists at which the WACC is the lowest and the market value of the firm is the highest.
- Changes in the financing mix can bring positive change to the value of the firm at certain levels.

Optimal Leverage – Cost of Capital Approach

Weighted Average Cost of Capital

$$WACC = r_e(\frac{E}{(D+E)}) + r_d(\frac{D}{(D+E)})(1 - Tax)$$

- **Cost of Equity**
  - Industry index consisting of 146 firms to represent corporate sector
  - BIST100 Index is used as the market index

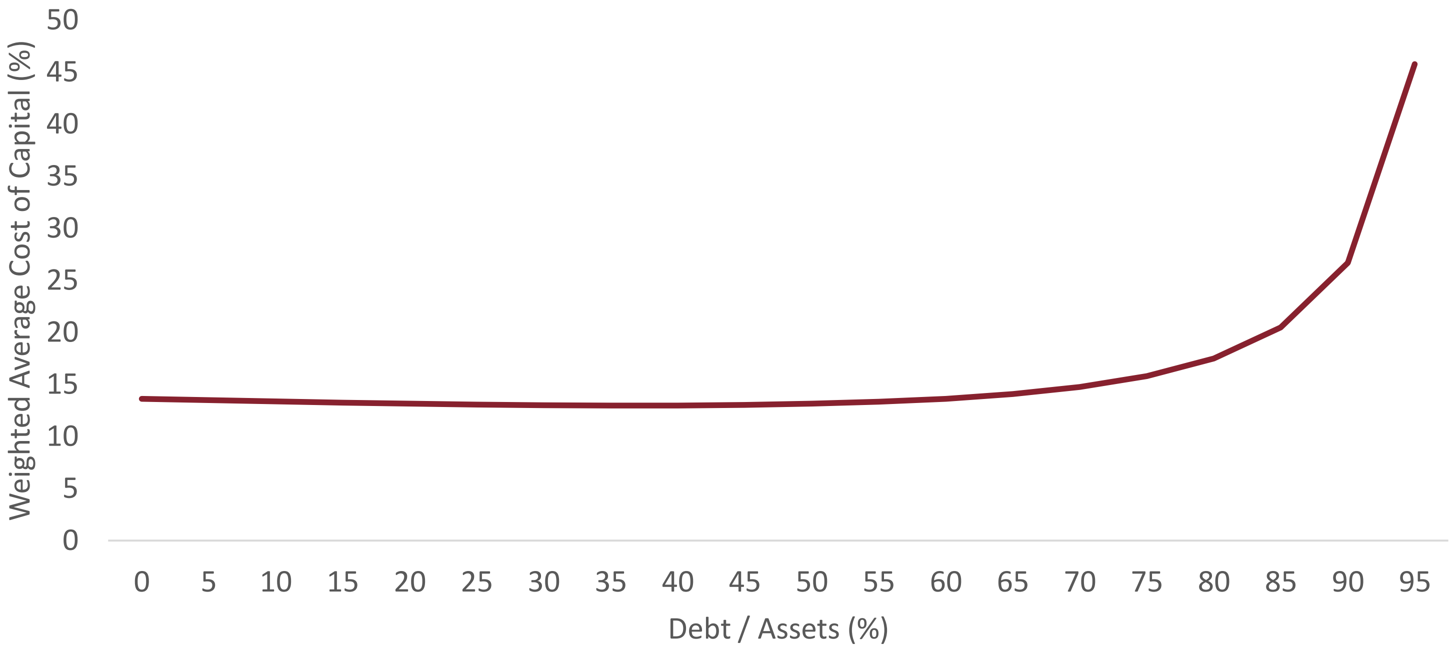
$$r_e = r_f + Beta(r_m - r_f)$$

$$Beta_{unlevered} = (\frac{Beta_{levered}}{(1 + \frac{D}{E} * (1 - tax))})$$

- **Cost of Debt**
  - Cost of borrowing for different leverage ratios*

*CBRT Research Notes in Economics, 2015, Factors Affecting Corporate Cost of Borrowing

Optimal Corporate Debt to Equity Ratio

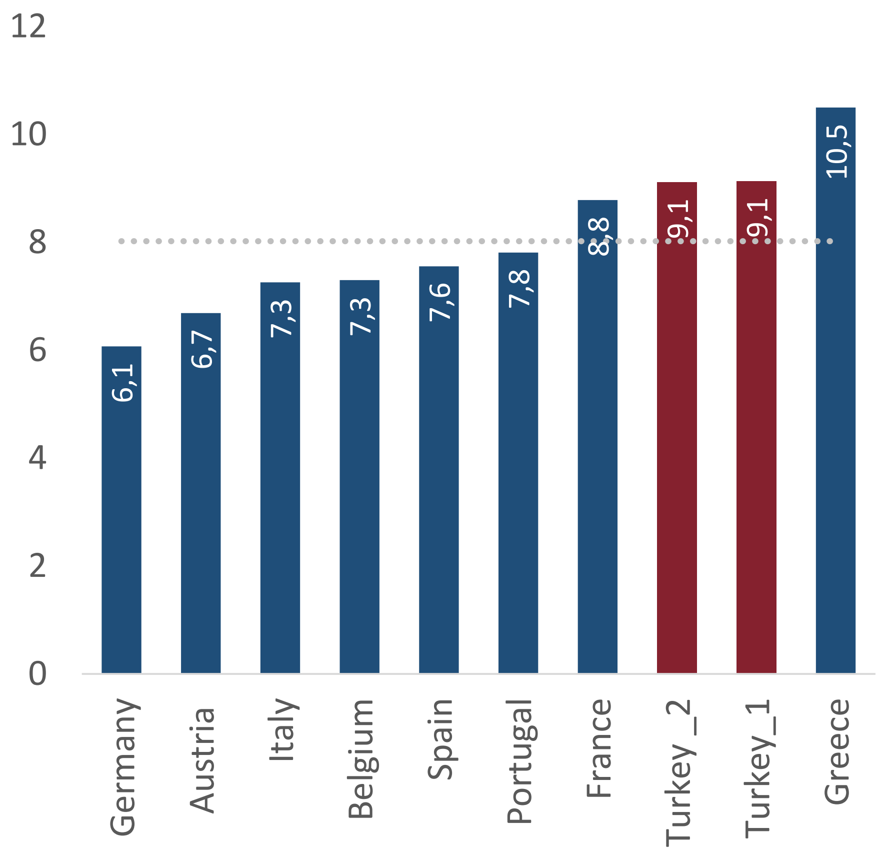


- Conflicts between shareholders and debt holders
  - Agency cost of debt : Shareholders near bankruptcy prefer risky investments
- Conflicts between shareholders and managers
  - Agency cost of equity: Managers may prefer to take suboptimal decisions to increase their personal benefits besides maximizing the value of the firm .

- Corporate Sector Indebtedness
- Global Capital Flows and Optimal Debt/Assets Ratio
- **Liquidity and Profitability**
- Key Takeaways

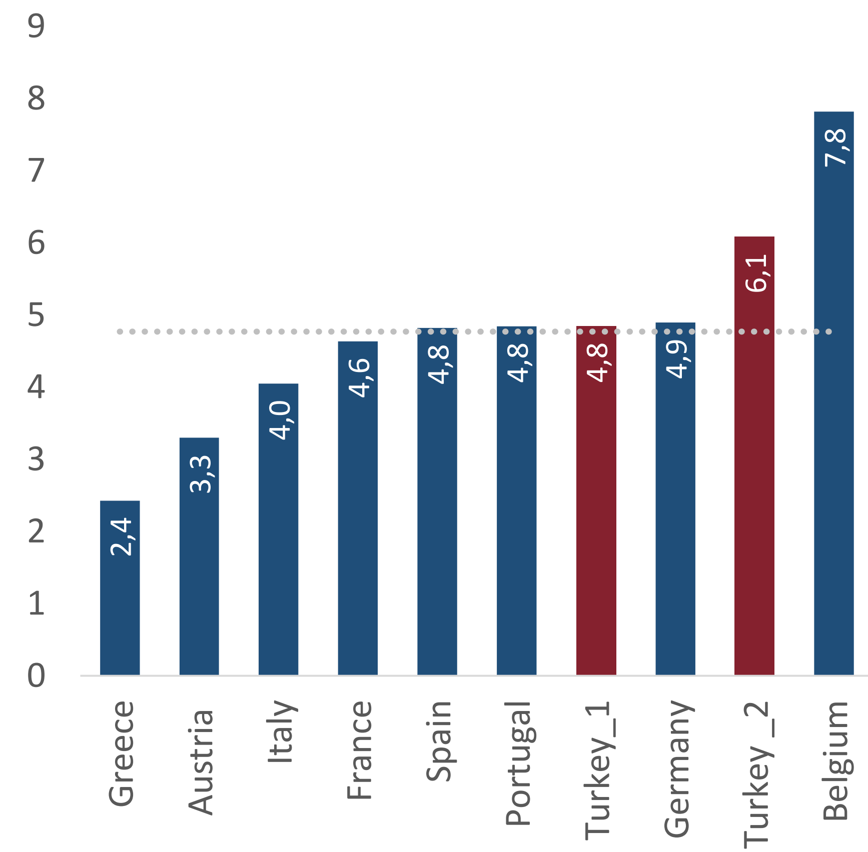
High liquidity and profitability ratios

Cash, % of Assets[1]



Source: ECCBSO, CBRT and GBS
1) Turkey_1: GBS , Turkey_2: CBRT Company Accounts

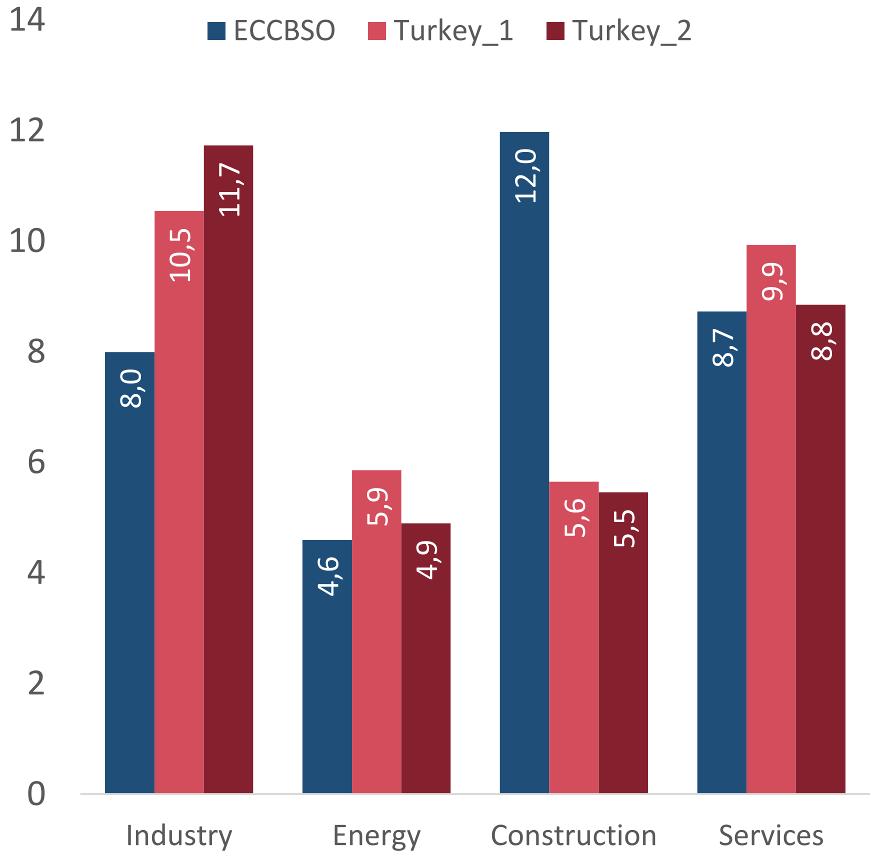
EBT, % of Assets[1]



Source: ECCBSO, CBRT and GBS
1) Turkey_1: GBS , Turkey_2: CBRT Company Accounts

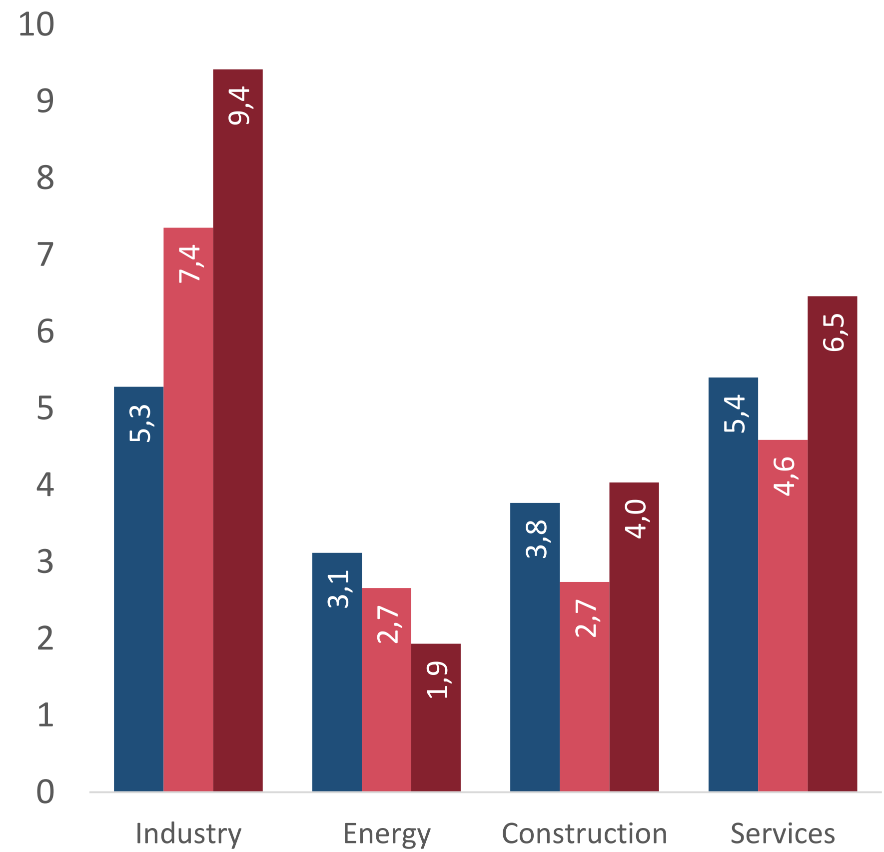
Strong liquidity and profitability ratios especially for industry and services sectors

Cash,% of Assets[1] By Sector



Source: ECCBSO, CBRT and GBS
1) Turkey_1: GBS , Turkey_2: CBRT Company Accounts

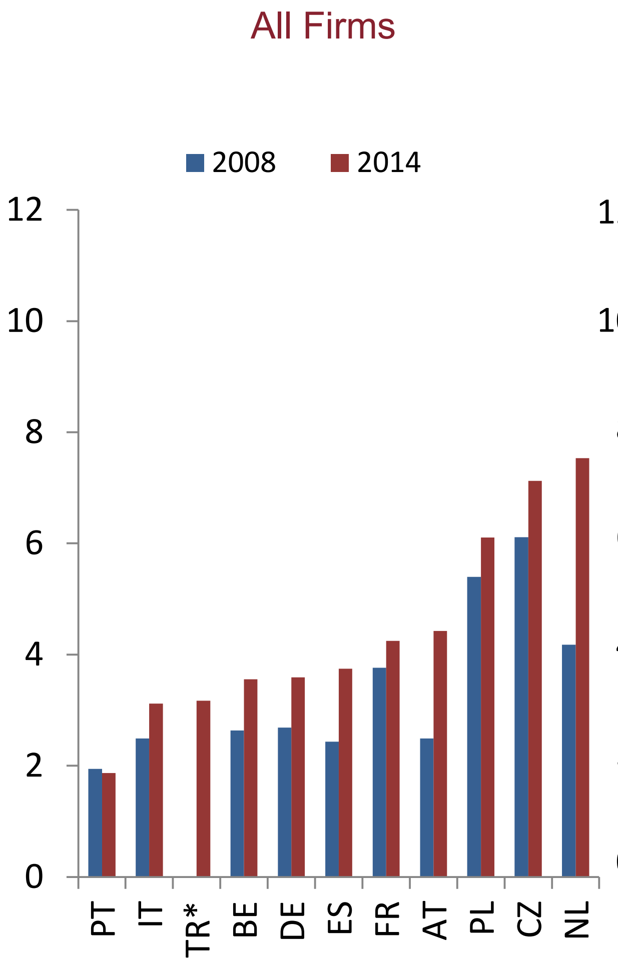
EBT, % of Assets[1] By Sector

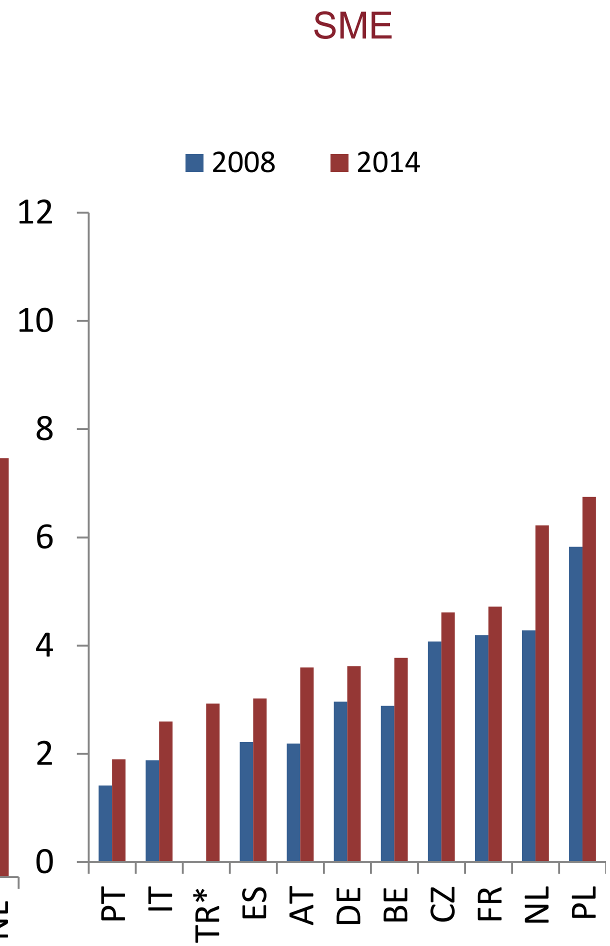


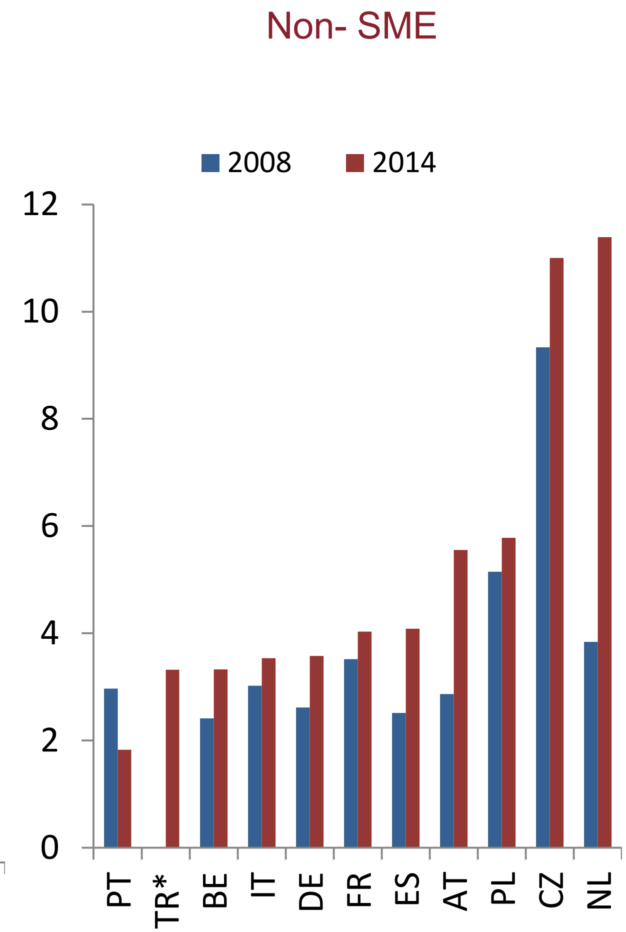
Source: ECCBSO, CBRT and GBS
1) Turkey_1: GBS , Turkey_2: CBRT Company Accounts

Interest coverage ratio for Turkish corporates is similar to most of European countries.

EBIT/ Interest Expense*







Source: ECCBSO and GBS

* Interest expense to financial expense ratio for 2015, collected from independent audit reports is used to calculate interest expense 2014.

AGENDA

- Corporate Sector Indebtedness
- Global Capital Flows and Optimal Debt/Assets Ratio
- Liquidity and Profitability
- Key Takeaways

- NFC leverage in emerging economies increased following global financial crisis due to increased liquidity and favorable funding conditions.
- Financial liabilities share within total debt increases consistent with improving NFC financial access and financial sector deepening.
- In case of capital outflow movements, emerging NFC exposure increases both through interest and foreign currency risk.
- Thus, corporate sector should consider possible finance fragilities while determining optimal debt to equity ratio.
- Profitability and liquidity remains high especially for industry and services sectors.

TÜRKİYE CUMHURİYET MERKEZ BANKASI

Corporate Sector Financials from Financial Stability Perspective

Corporate Sector Financials: Overleveraged?

Central Bank of the Republic of Turkey
Gülcan YILDIRIM GÜNGÖR, Merve DEMİRBAŞ ÖZBEKLER, Tuba Pelin SÜMER
Izmir/ September 2016

Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

IFC-ECCBSO-CBRT Conference on *"Uses of Central Balance Sheet Data Offices' information"*

Co-organised by the IFC, the European Committee of Central Balance Sheet Data Offices (ECCBSO) and the Central Bank of the Republic of Turkey (CBRT)

Özdere-İzmir, Turkey, 26 September 2016

The use of accounting information to estimate indicators of customer and supplier payment periods[1]

Merve Artman, CBRT, and Luis Ángel Maza, Bank of Spain

[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 Use of Accounting Information to Estimate Indicators of Customer and Supplier Payment Periods

Conference “Uses of Central Balance Sheet Data Offices´ Information”

IFC / ECCBSO / CBRT
Özdere-Izmir, September 26th, 2016

Merve Artman
Central Bank of the Republic of Turkey and Financial Statement Analysis Working Group, ECCBSO

Luis Ángel Maza
Banco de España and Financial Statement Analysis Working Group, ECCBSO

OUTLINE

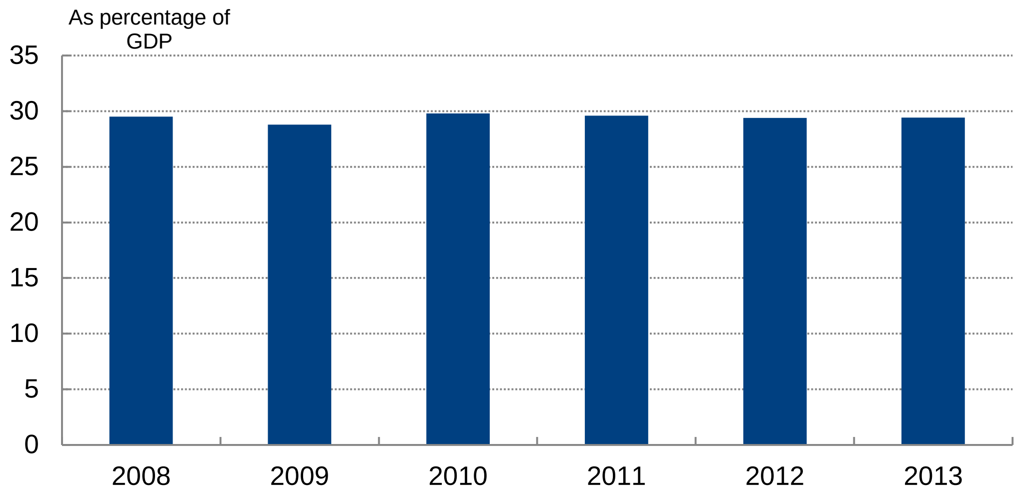
1. Motivation
2. Data Sources and Methodology
3. Empirical Results
4. Conclusions

OUTLINE

1. Motivation
2. Data Sources and Methodology
3. Empirical Results
4. Conclusions

• **Trade credits play a major role in the financing of European companies**, on average the outstanding amount of this type of financing **is close to 30 % of GDP.**

Trade credits in Euro area



Source: Eurostat (Financial accounts of the Euro area).

•However, the **trade credits** often played only a **secondary role in financial statement analysis and the statistical information system** in the past.

•This study aims at giving an insight into the importance of **trade credits** in the **member countries of the ECCBSO Financial Statements Analysis Working Group**, that is Belgium, Germany, Spain, France, Italy, Poland, Portugal and Turkey

1. Motivation (and II)

• In order to analyze trade credits based on financial statements data, the **ratios Days Sales Outstanding (DSO) and Days Payable Outstanding (DPO)** are used.

•Not only **average or median** ratios are calculated, the study wants to particularly inform about the **full distribution of the ratios.**

•Using **Kernel Density Estimations (KDE)**, as this method allows for the most comprehensive representation of the distributions

•In order to study the **differences** in DSO and DPO **distributions:**

- ❑ ***between countries and sectors.***
- ❑ and ***trends*** *in the aftermath of the* ***2008-2009 financial crisis.***

OUTLINE

1. Motivation
2. Data Sources and Methodology
3. Empirical Results
4. Conclusions

2. Data Sources and Methodology (I)

•The study makes use of the **large datasets from each national ECCBSO**. They are very similar to the national contributions to the BACH database.

•Highest coverage rates can be observed for **Italy, Belgium and Portugal**, implying that these data samples more or less contain the total population of companies.

	Manufacturing		Construction		Trade	
	Coverage rate [%] in terms of …					
	… firms	… sales*	… firms	… sales*	… firms	… sales*
Belgium	97.2	99.7	99.5	99.5	99.6	99.6
France	47.4	84.1	26.4	77.5	38.5	87.6
Germany	14.6	73.6	7.0	38.8	9.4	61.7
Italy	100.0	100.0	100.0	100.0	100.0	100.0
Poland	8.7	78.6	2.6	39.7	3.3.	47.4
Portugal	97.5	99.5	96.8	98.8	96.7	99.3
Spain	51.3	65.3	57.0	39.0	38.5	69.2
Turkey	1.0	49.3	0.6	14.3	0.2	21.8

2. Data Sources and Methodology (II)

- **Population**:
  - ❑*Almost 100% of companies included in the samples of this study have a legal form of **corporation or cooperative.***
  - ❑***Sole proprietorships are not included**.*

- **Time horizon**:
  - ❑ *From 2000 to 2013.*

- **Type of financial statements**:
  - ❑ *Individual financial statements .*
  - ❑*Mostly national generally accepted accounting principles (GAAP).*
    - ❑Although national GAAPs have the Fourth Council Directive as common ground
    - ❑ In some countries (such as PT and ES), the most recent GAAP are very close to IFRS in recent years.

- **Sectoral coverage**:
  - ❑ *Manufacturing*
  - ❑ *Construction*
  - ❑*Trade*

2. Data Sources and Methodology (III)

- **Size classes**:

  - *This report follows the EU Commission Recommendation concerning the definition of* ***micro, small, medium-sized and large enterprises****. However,* ***only the turnover criterion is applied*** *because in some of our samples the data on the number of employees is not available or is of insufficient quality.*

  - *The* ***thresholds*** *used for defining micro, small, medium-sized and large corporations are €2 million, €10 million and €50 million of turnover respectively.*

  - *But deflated using the* ***Harmonized Index of Consumer Prices (HICP) of the Euro area****. Year 2010 was selected as the base year for calculations.*

  - ***For Poland and Turkey****, the thresholds' values expressed in their national currencies, converted by using each country's real effective exchange rate versus the euro area-18 trading partners (REER).*

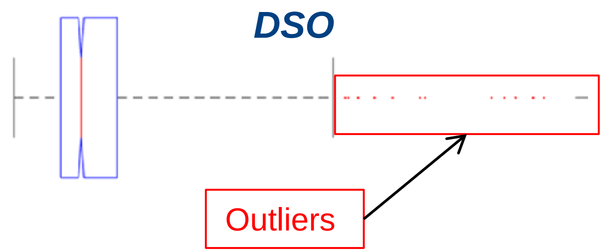
2. Methodology and Data Sources (IV)

- **Outliers**:
  - ❑*Exclusion of anomalous microdata ("outliers") with **Box-Plot method (k=6)**:*

Algebraically:

$$[Q_1 - k(Q_3 - Q_1), Q_3 + k(Q_3 - Q_1)]$$

Graphically:



- **Rejection of micro size class:**
  - ❑*Micro-corporations have been excluded from the "total size class" , due to are not directly compared between the countries.*

Number of companies in national samples, 2012

All sectors	Belgium	Germany	France	Spain	Italy	Poland	Portugal	Turkey
Small	3.216	13.418	53.315	20.201	40.073	7.915	8.313	2.281
Medium-sized	3.962	10.324	16.567	3.707	15.254	3.715	1.943	2.547
Large	1.353	4.764	4.542	906	3.847	1.264	433	1.105
Total	8.531	28.506	74.424	24.814	59.174	12.894	10.689	5.933
for information								
Micro	1.921	10.931	68.474	192.967	15.457	7.279	128.170	744

2. Methodology and Data Sources (V)

- **Two classic ratios** offer an indication of the liquidity of trade debts and receivables,
- FSA WG decided on a **net approach** (net amount of money exchanged with the clients/suppliers of the companies by **prepayments**).

Days Sales Outstanding (DSO) generally tells the number of days the average customer trade receivable is “on the books

Numerator	360 x (Trade receivables – customer prepayments)
Denumerator	Net turnover

Interpretation: The lower DSO , the sooner the firm tends to be paid by its customers

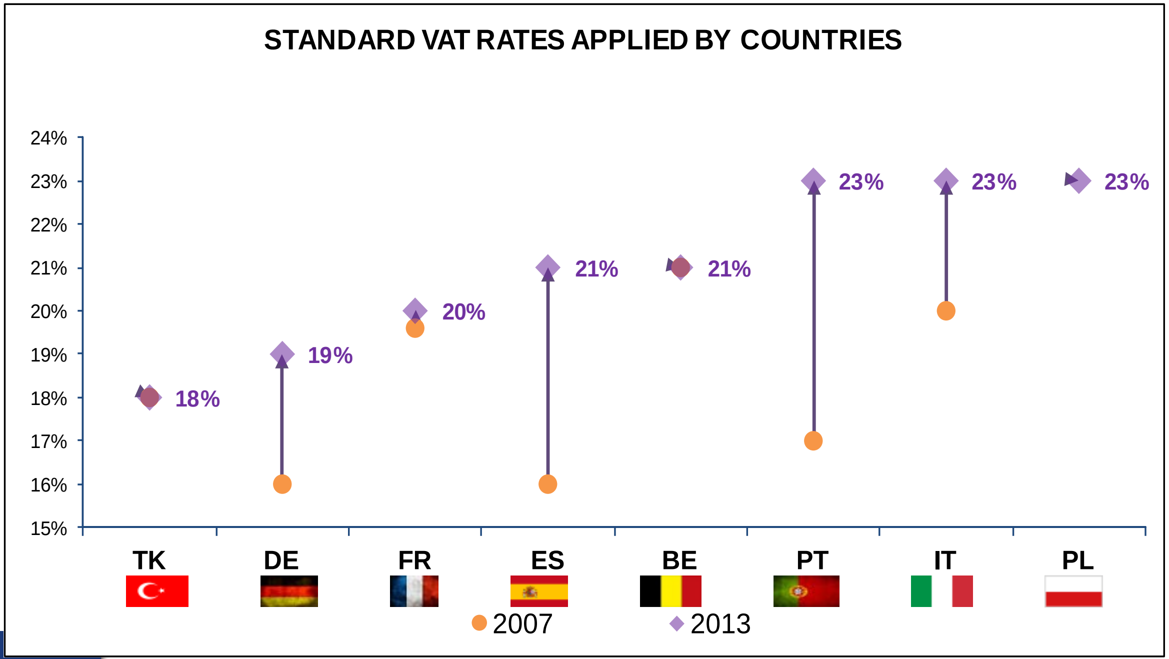
Days Payable Outstanding (DPO) explains a company’s pattern of payments to suppliers

Numerator	360 x (Trade payables – Advances to suppliers)
Denumerator	Purchases

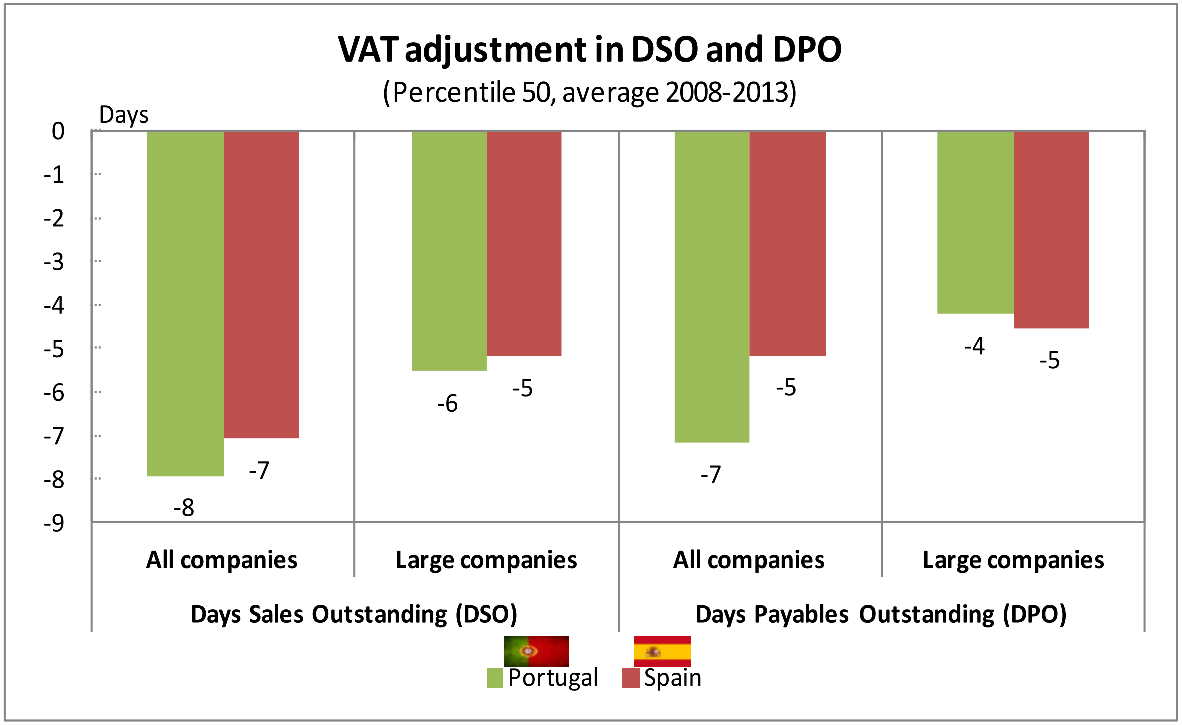
Interpretation: The more timely a company pays its trade credit the lower the DPO figure.

FSA Working Group
eccbso
European Committee of Central Balance Sheet Data Offices

- This traditional approach in DSO and DPO definitions may result in **some bias** due to the inconsistency between the numerator and the denominator **in relation to indirect taxes**.
- While **turnover and purchases do not include indirect taxes**, the balance sheet **trade credit items** (receivables and payables accounts) **do include indirect taxes.**
- The report analyses the **impact of VAT on DSO and DPO** in the context of an **international and an over-time comparison.**



- The information on indirect taxes for **Portugal and Spain is used to measure the magnitude of the bias** in DSO and DPO measurement**:**
  - The VAT correction to the median of the **DSO** indicator for **PT was 8 days**, while it was slightly lower in **ES (7 days)**.
  - With regard to the median DPO, the VAT corrections reduced the payment periods by **7 days in PT** and by **5 in ES.**



The **problem** of lack of consistency between the numerator and denominator may **not be relevant if the VAT rates keep stable over time.**

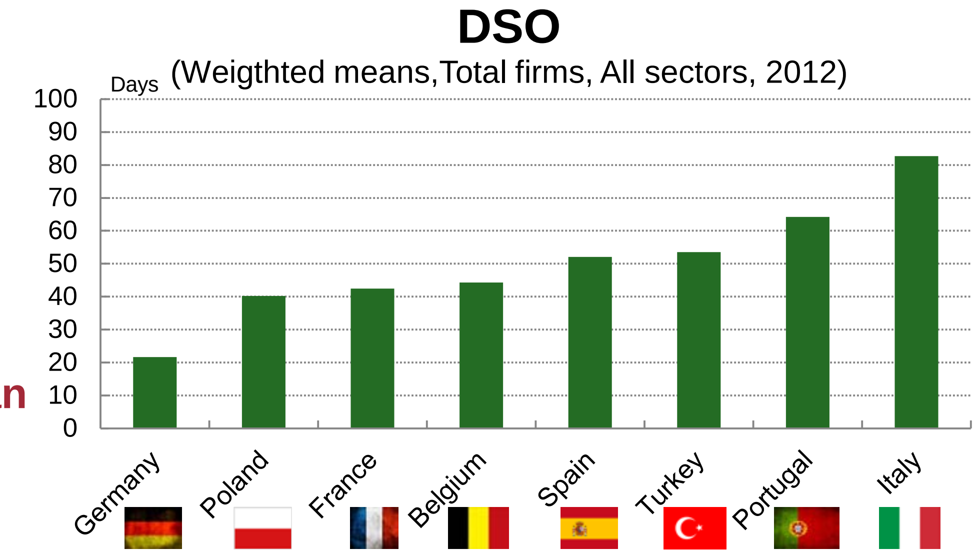
However, if these modifications in tax rates levels happened, **some breaks in the evolutions of DSO and DPO would come up**.

OUTLINE

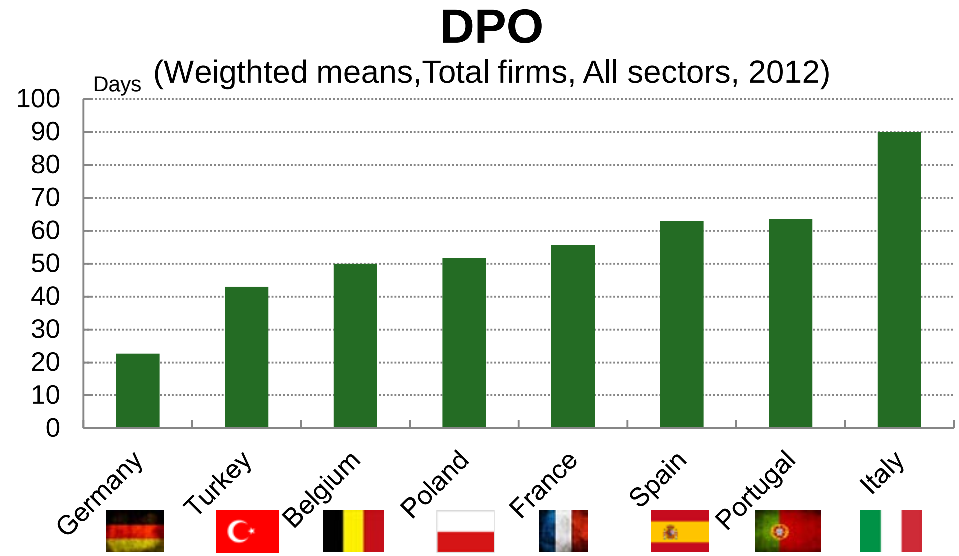
3. Empirical Results (I)

There are **considerable differences** in DSO and DPO figures **between countries** (weighted average).

- **DSO:** in **Germany,** the collection behavior is around 20 days, while **Italian** companies receive quite late their trade receivables (80 days).



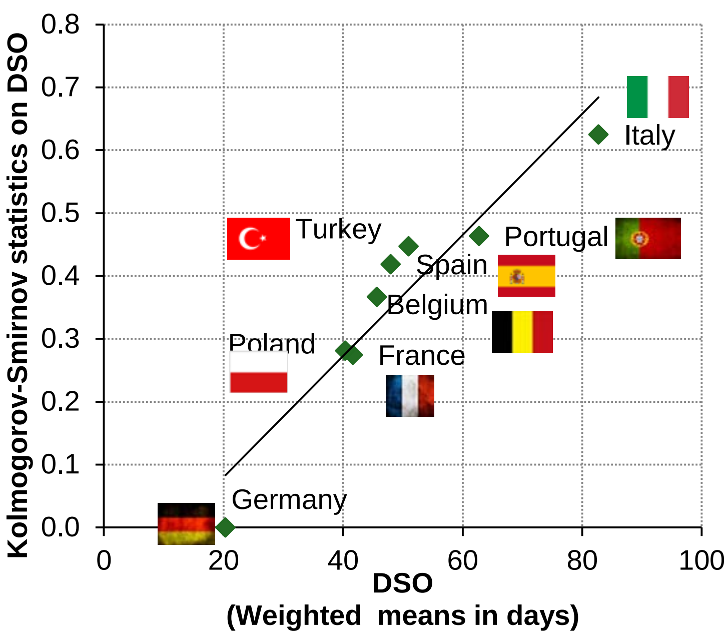
- **DPO**: similar differences are observable when interpreting payment figures

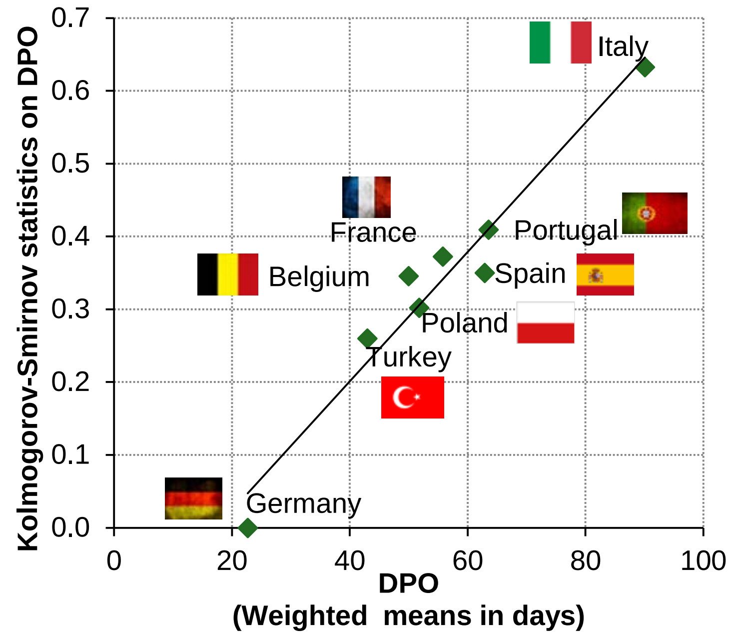


3. Empirical Results (II)

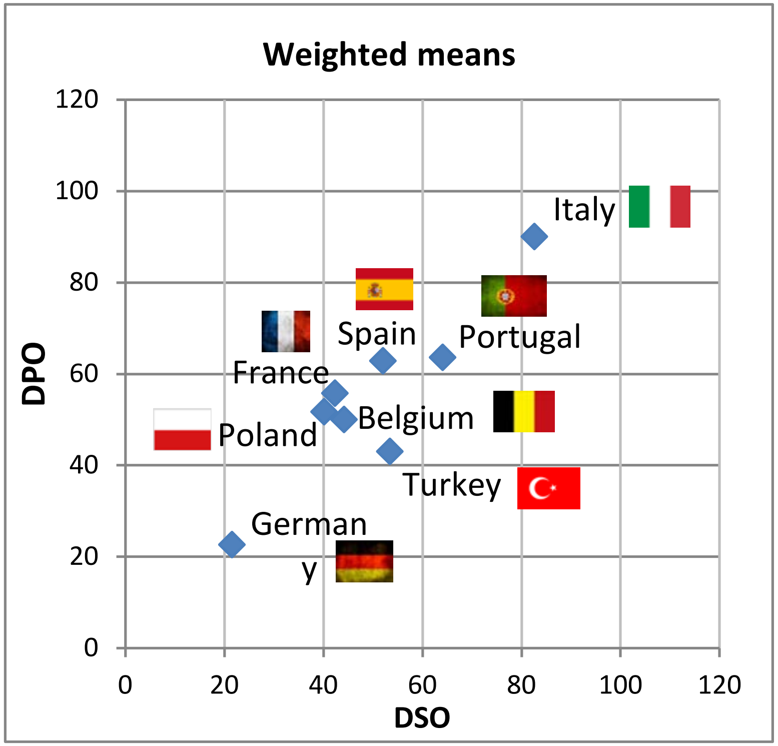
As **complement** to the analysis of the differences between countries based on weighted means, it has been worked out the distance of the DSO and DPO estimated distribution function of the each national sample versus the other countries, by the calculations of the **Kolmogorov-Smirnov statistics** (KS).

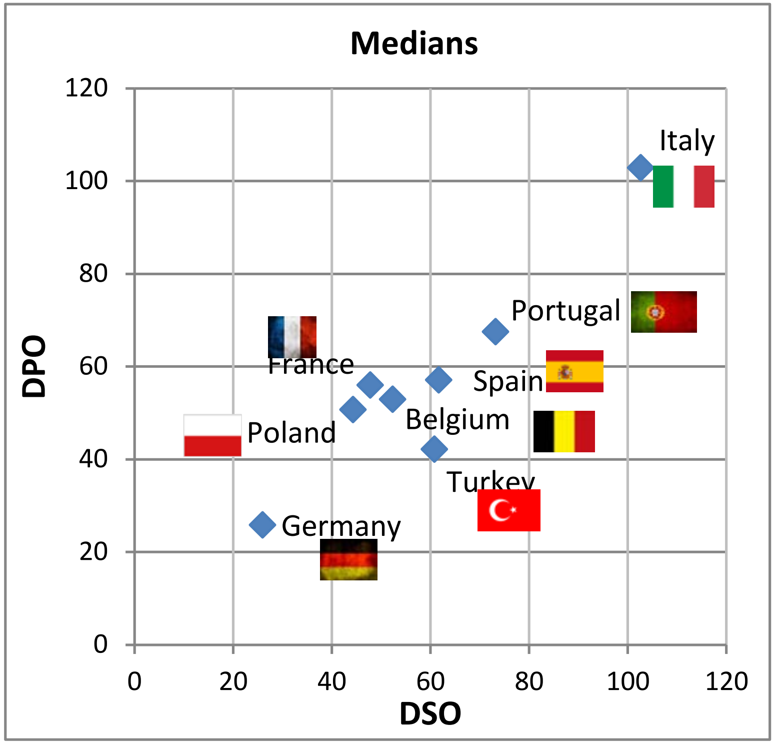
The KS statistics of all countries calculated against German samples of DSO and DPO show a **positive correlation between this measure of divergence and weighted means**. These results **would suggest the robustness of the weighted means in order to identify the aggregated behaviour of firms by countries**





For all combinations of weighted average and median values, DSOs and DPOs are **positively and closely linked**: the higher the DSO, the higher the DPO, and conversely.

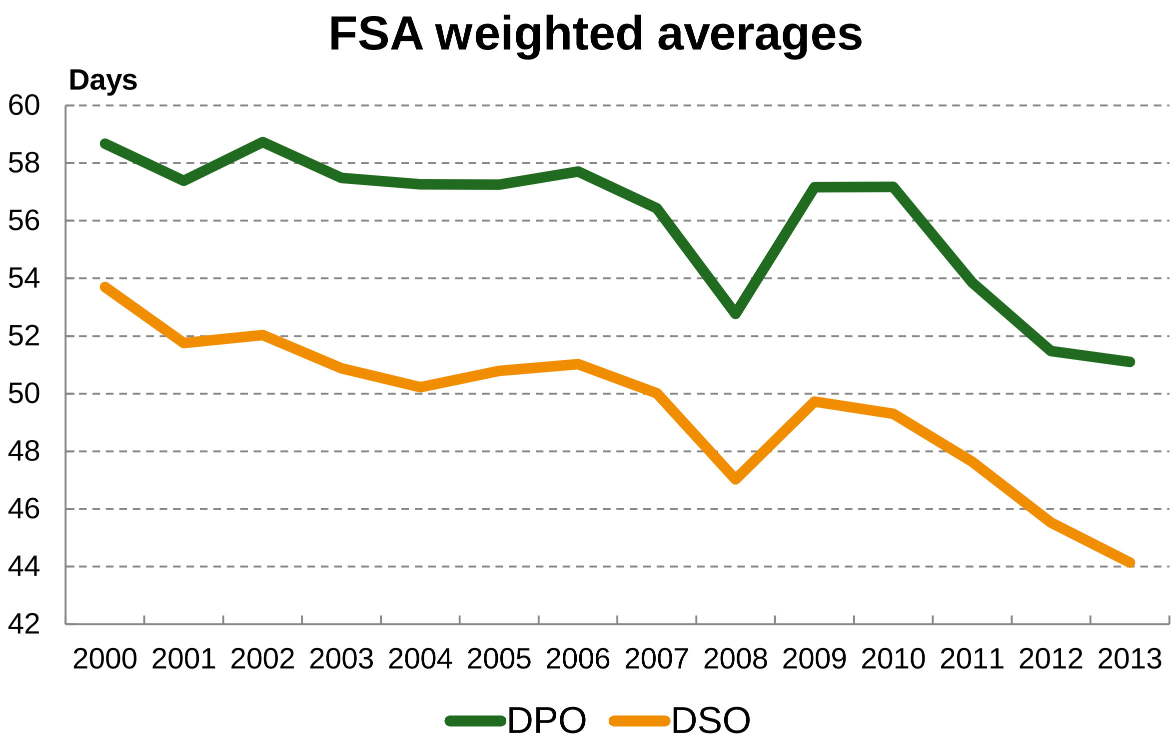




We observe a significant positive correlation between DSO and DPO using firm level data too.

3. Empirical Results (IV)

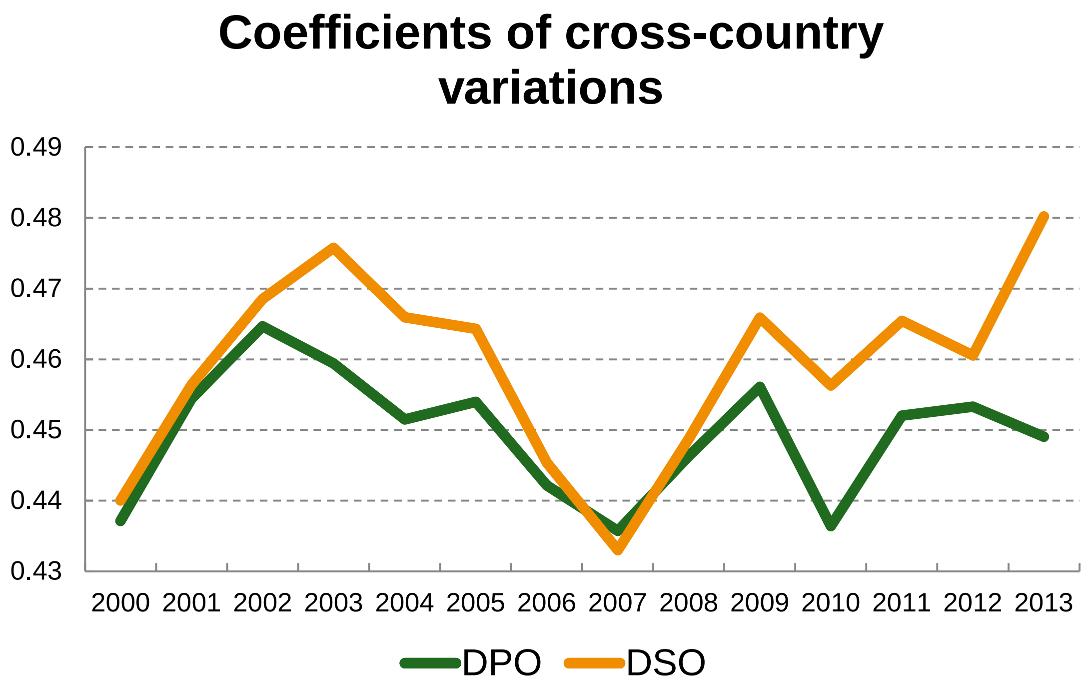
With the aim of summarizing the national information in **synthetic indicators**, aggregates of **all the countries in the WG FSA for DSO and DPO** have been built as **averages of eight countries**, as a function of the **GDP of each economy**.



- The FSA average DSO and DPO ratios show a clearly **downward trend** between 2000 and 2013, with the lowest levels being reached in last year.

- **This trend could lay**, mainly, the reduction of periods in countries with the longest DSO and DPO, as a result of the **process of economic integration of Europe** and the certain economic policy measures (such as the **European Directive on Late Payment**)

To measure the **dispersion** of DSO and DPO of the individual countries around the FSA averages, **coefficients of variation are calculated**.

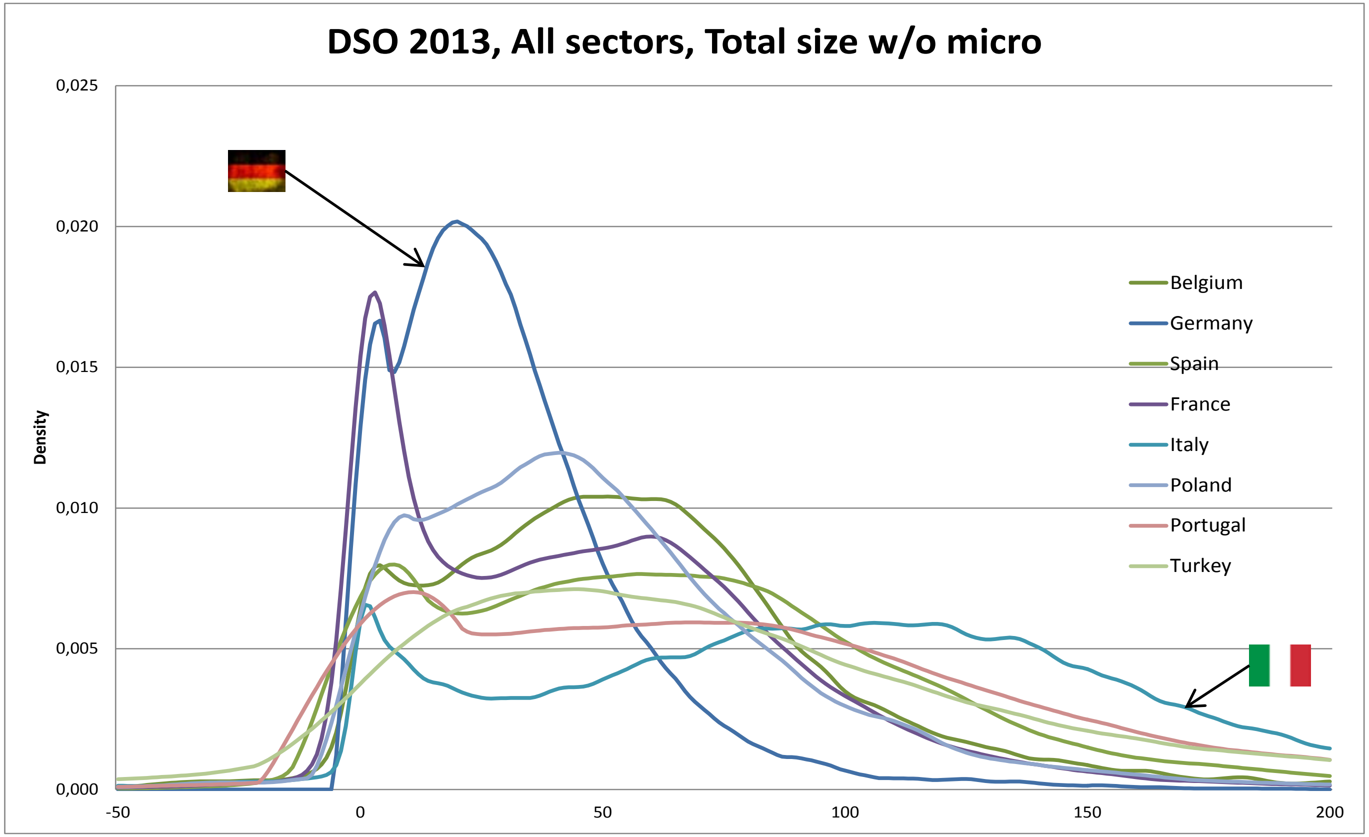


- These weighted cross country **coefficients of variation** are computed as the weighted (by the respective GDP) standard deviation of DSO and DPO across countries divided by the FSA averages.

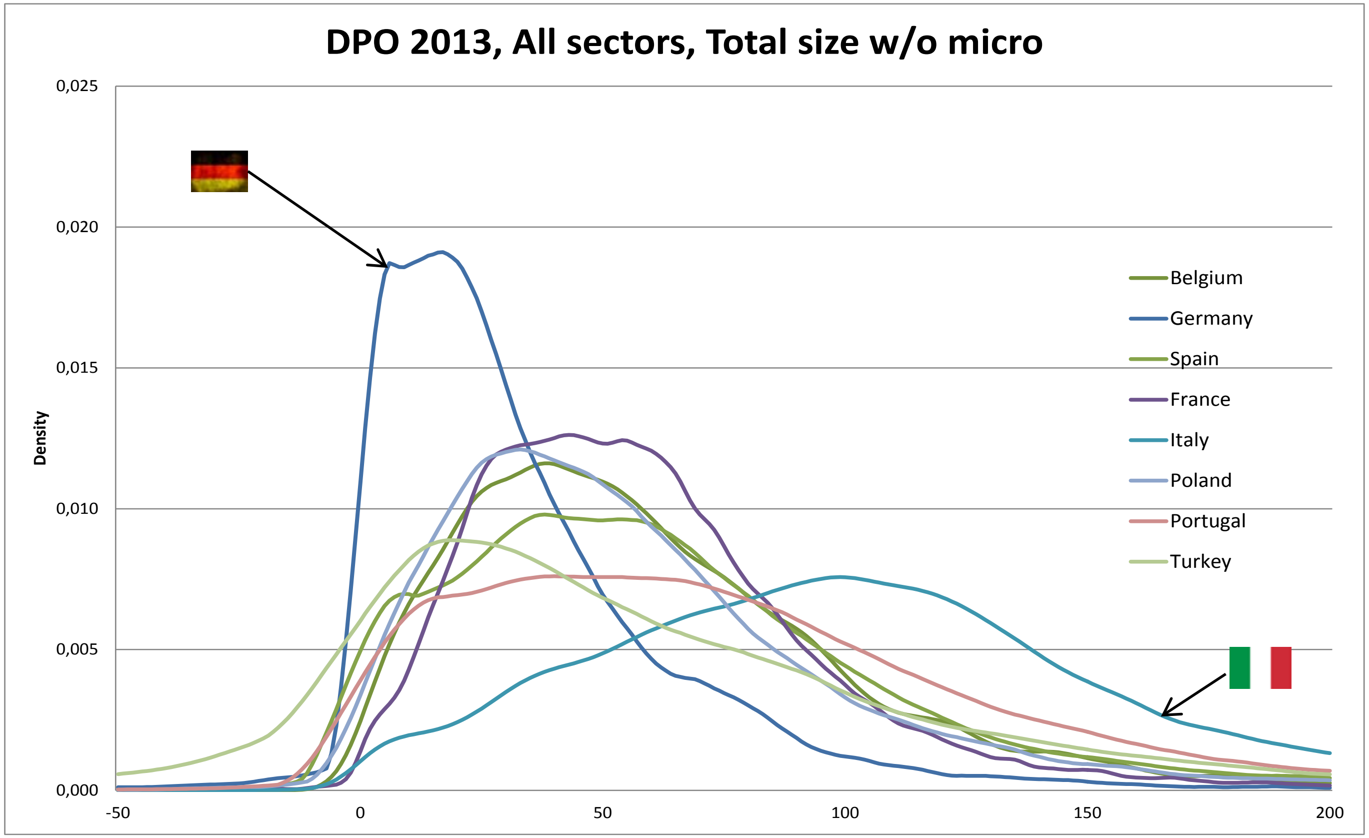
- After 2007, a trend has been observed towards **increasing the heterogeneity in the national behaviour** of customer-collection and supplier-payment periods , **due to likely substantial differences in the macroeconomic consequences of the crisis**.

3. Empirical Results (VI)

Analyzing distributions with the help of **Kernel Density Estimations (KDE)**



3. Empirical Results (VII)



Germany presents KDE functions somehow different from the other countries. Its functions are more left- hand sided than the other countries' ones, which are more evident in DSO density functions. In the opposite direction are the Italian KDE.

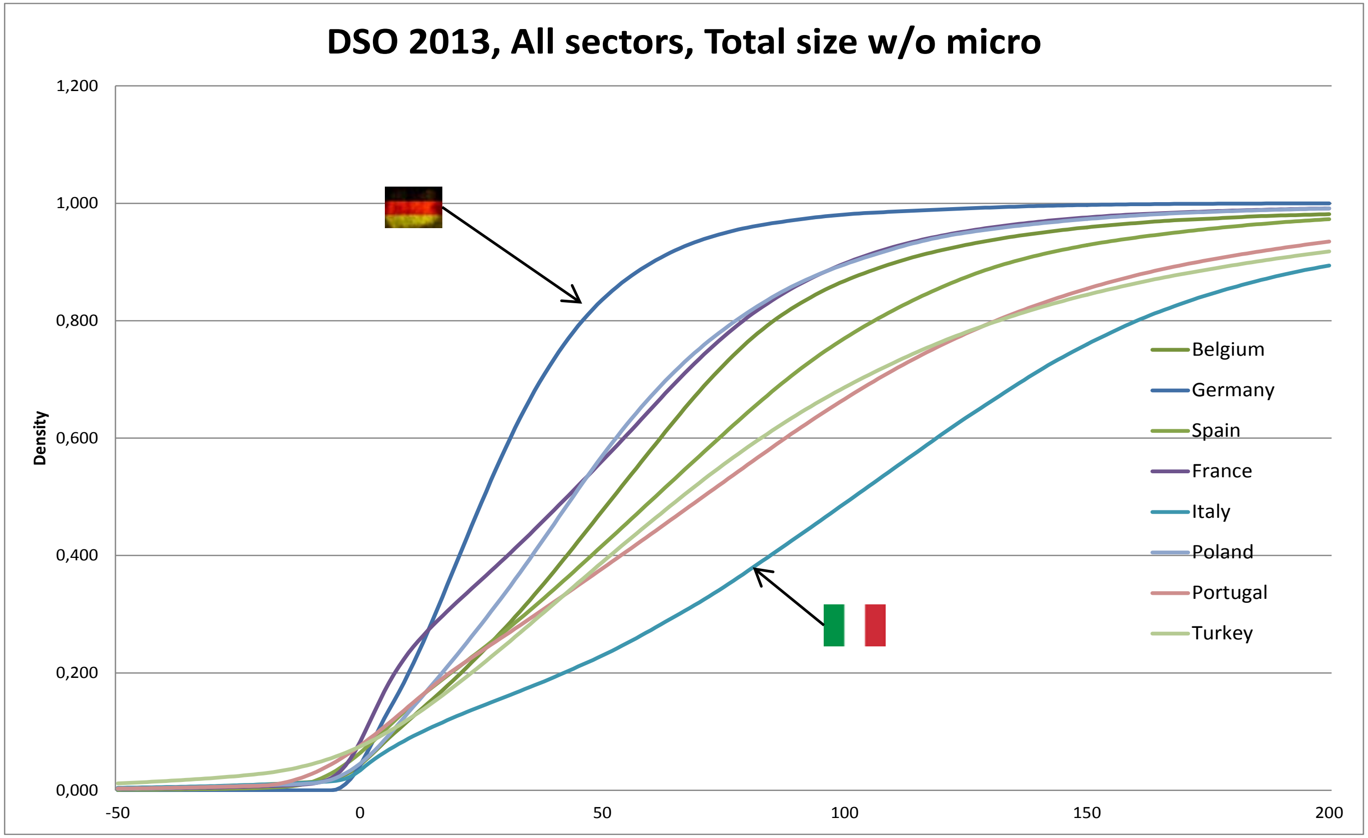
3. Empirical Results (VIII)

Outlier Analysis for KDE Estimates: Some factors for the densities beyond -100 and 500 according to sectors:

CONSTRUCTION	MANUFACTURING	TRADE
• Contracting companies • Completion method for accounting • Interim payment problems • Lump sum accounting records for separate projects	• Long term manufacturing • International contracts-exchange rate risk • Sub-group companies-access to finance problem	• Long term energy investments • Long term contracts about machine trade • Working with dealers

3. Empirical Results (IX)

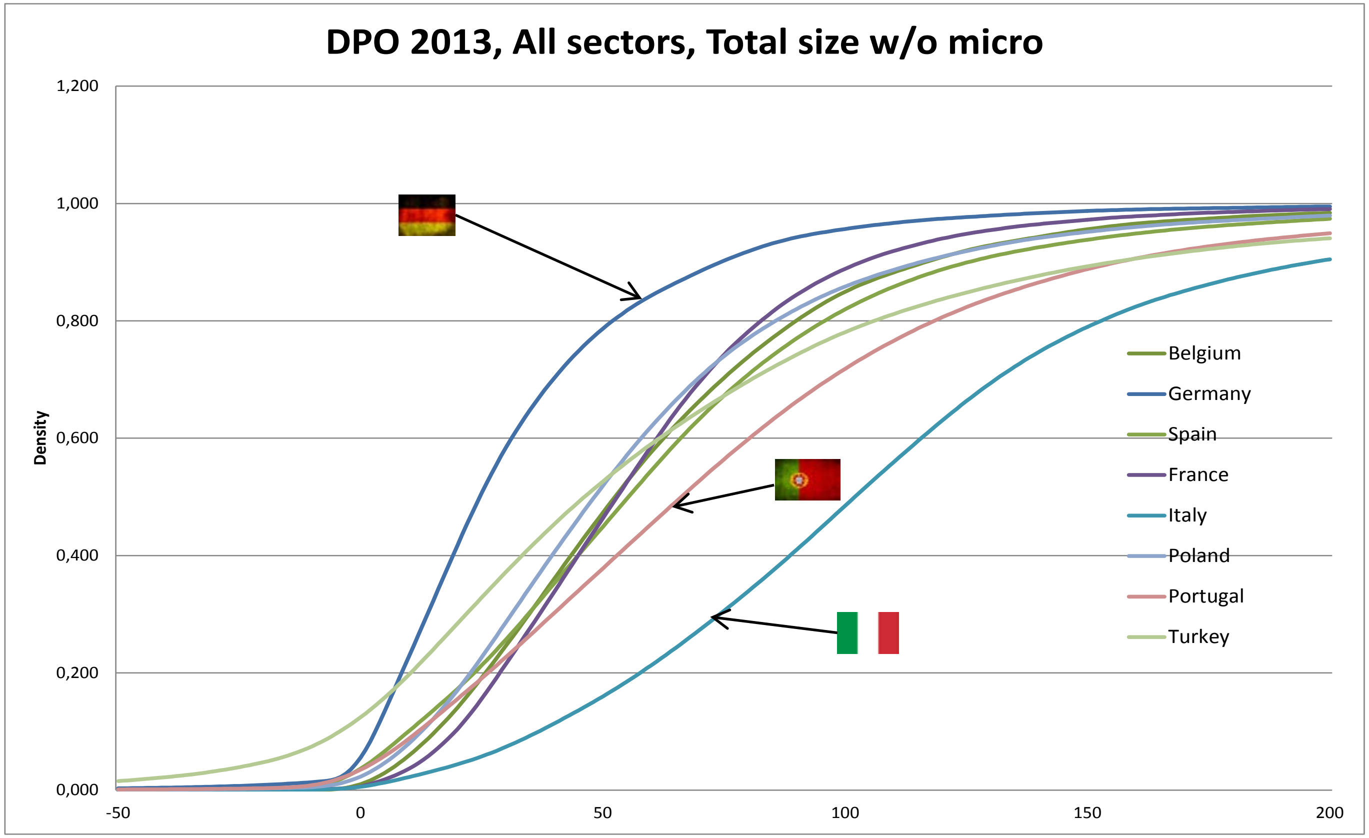
Accumulated Kernel Density Estimations show similar ranking by countries in DSO….



3. Empirical Results (X)

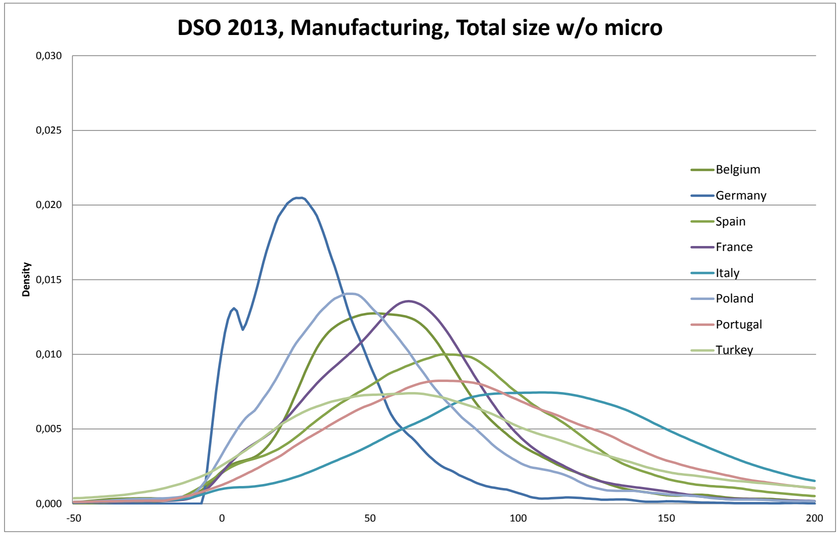
…. and DPO. These **differences** might be related with, for instance,:

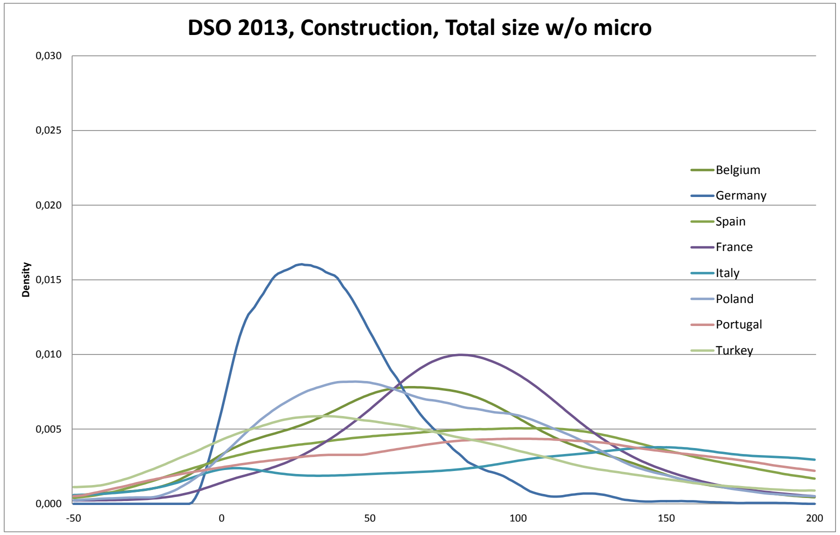
- **different commercial negotiating policies,**
- **corporation structure,**
- **general different payment culture.**

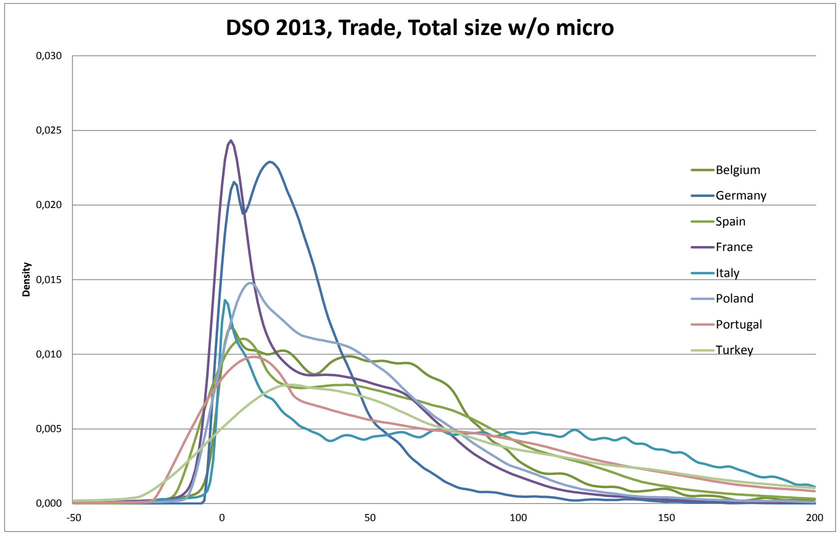


3. Empirical Results (XI)

The presented **differences** between countries remain applicable to the **main activity sectors in DSO…**







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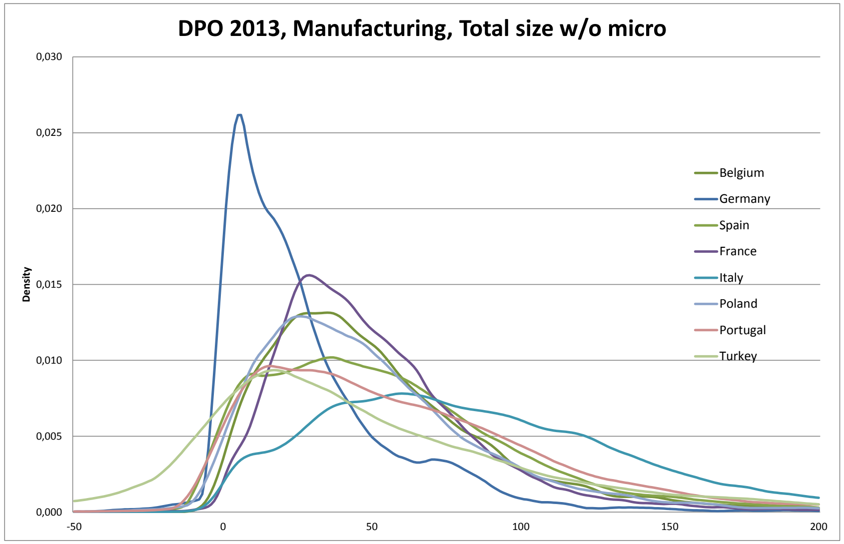
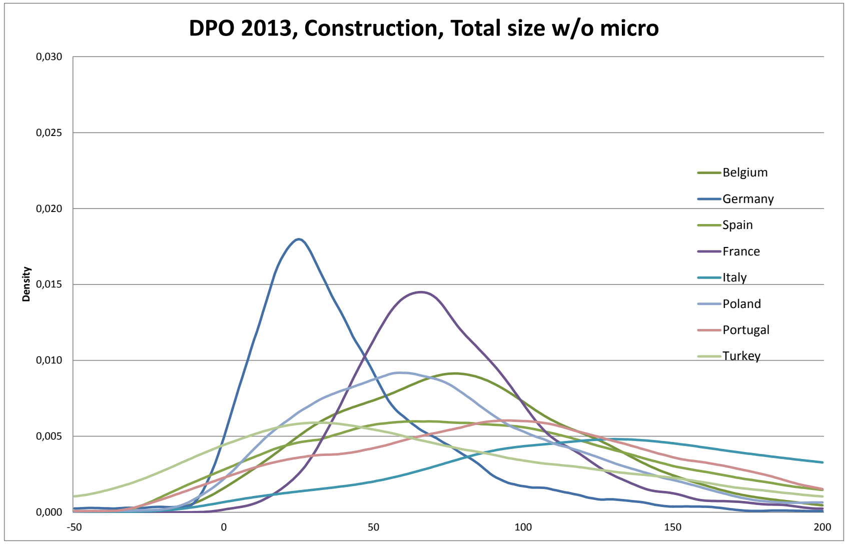
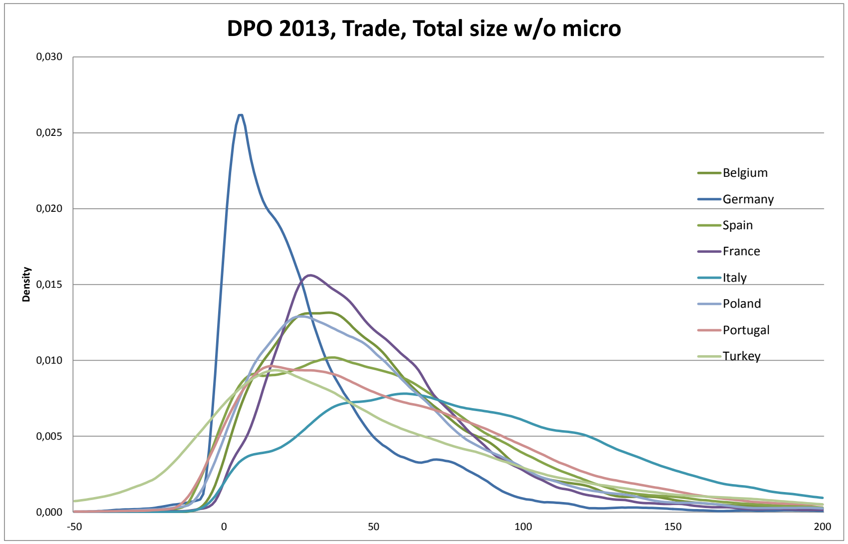
3. Empirical Results (XII)

…. and DPO

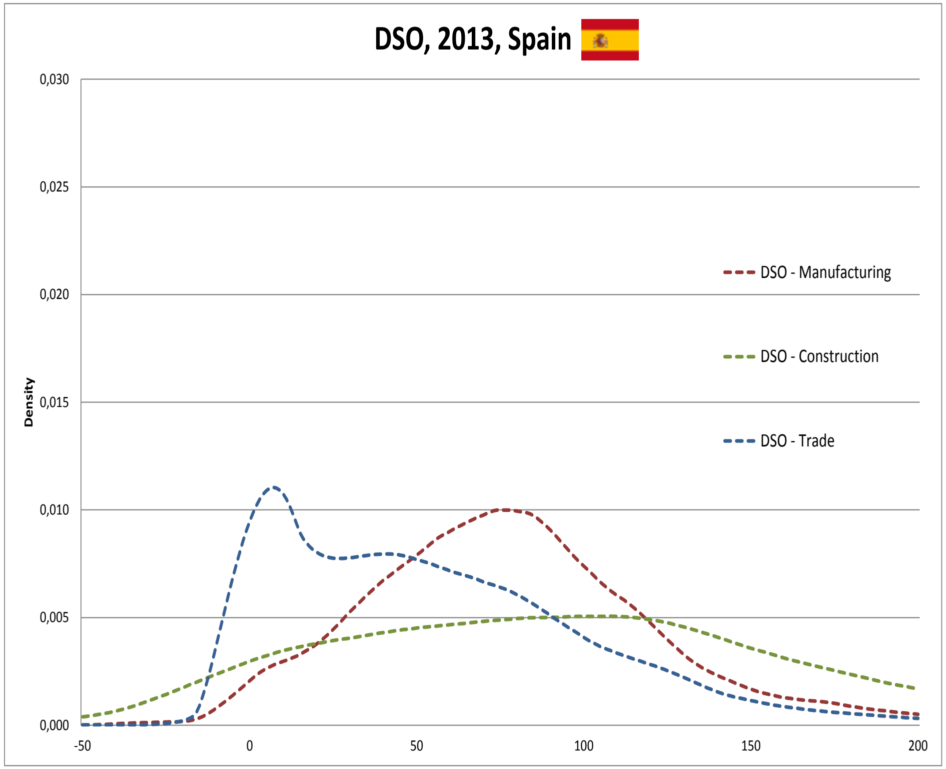


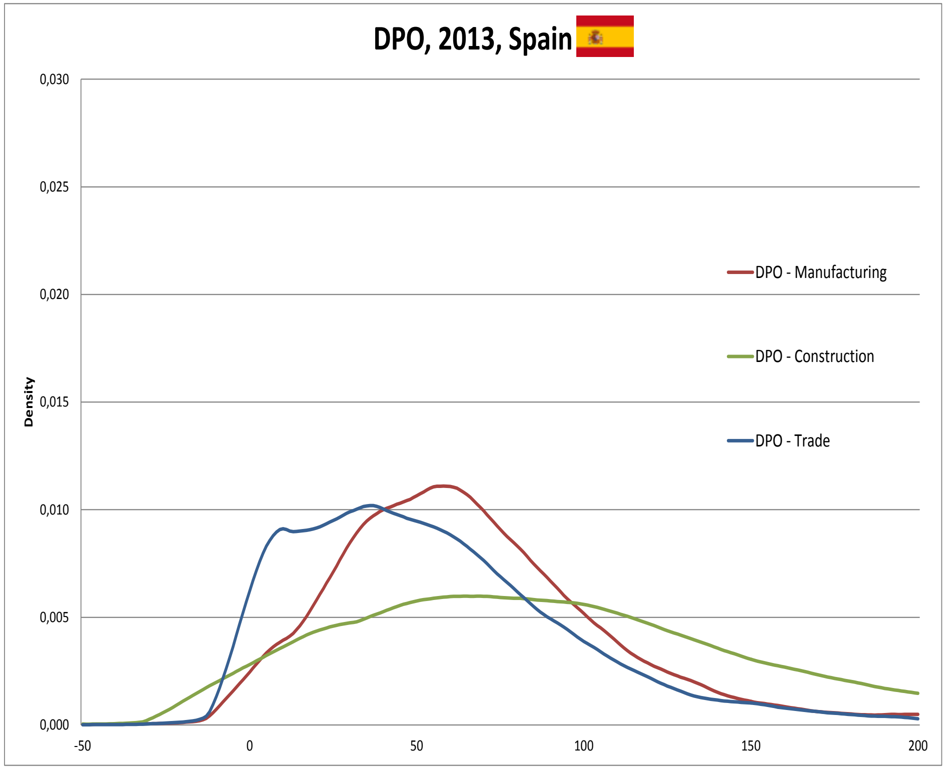




3. Empirical Results (XIII)

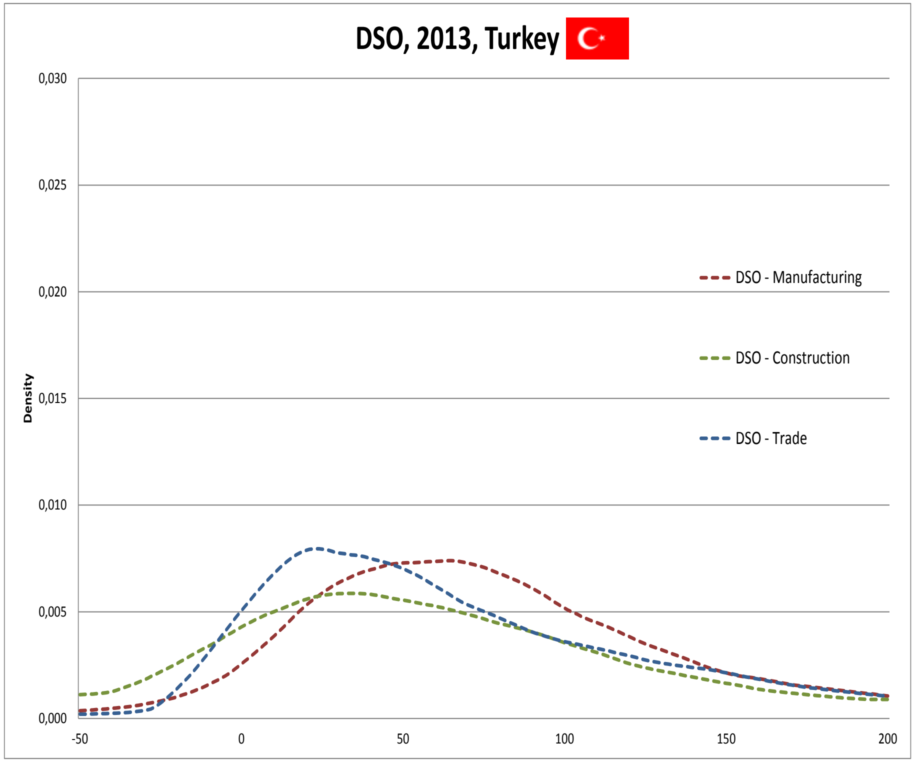
The sectoral differences are more obvious in the comparison for a specific country.
For example in Spain and Turkey.

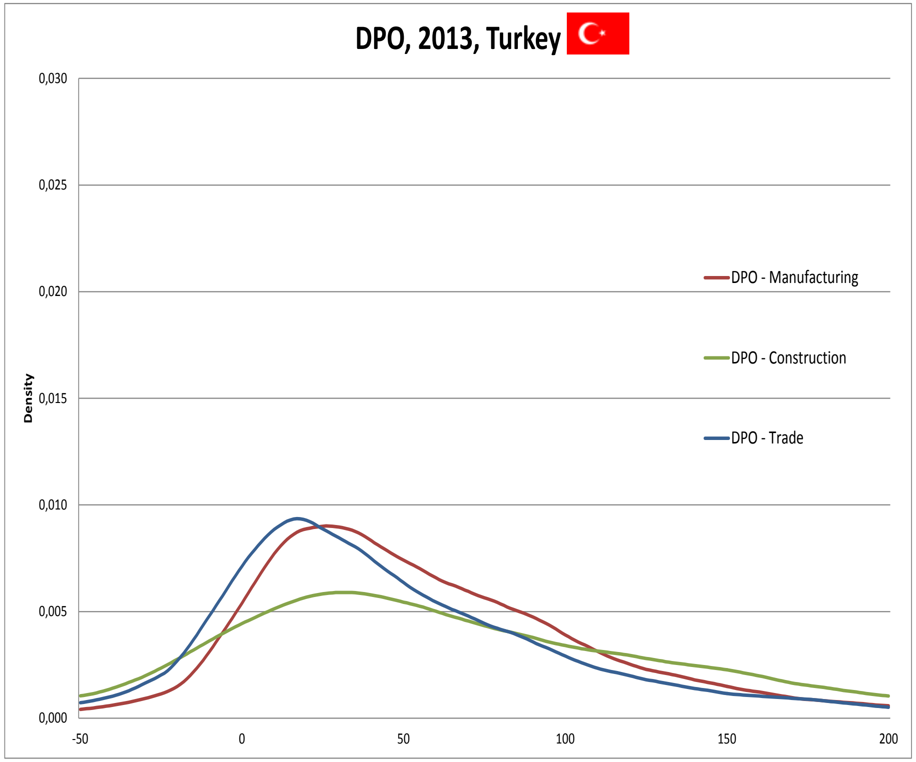




For the **Spanish firms**, across the sector of activity, the KDE depict that the longest DSO and DPO occurred in the construction sector, where the highest values of density are located above 100 days in 2013. The shortest payment and collection periods were in the trade sector (the peaks for DSO and DPO median was less than 10 and 40, respectively). On the other hand, collection periods tend to be longer than payment term at manufacturing companies,

3. Empirical Results (XIV)

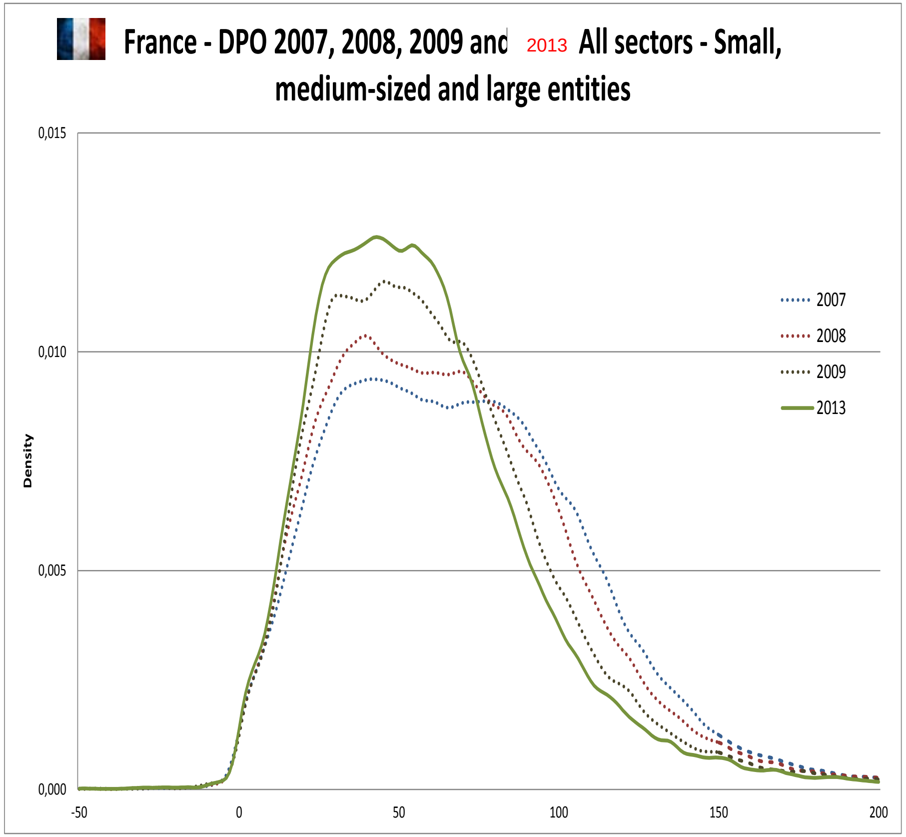


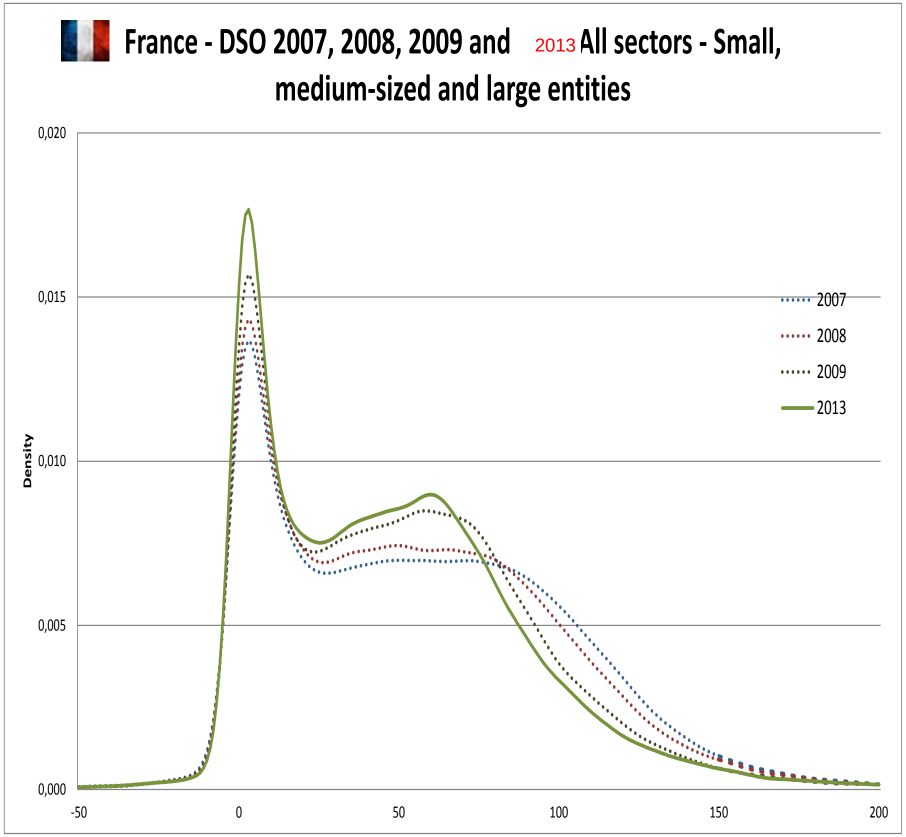


In **Turkey**, like Spanish firms, KDE shows the longest DPO and DSO in the construction sector. However, the highest value of density is way above the Spanish figures, up to 700 days. Although smoother than Spanish figure, the shortest payment and collection period can be seen in trade sector. Collection and payment term difference is also valid for Turkey in terms of manufacturing firms.

3. Empirical Results (XV)

Differences over time: (i) KDE graphs have been set up for the years 2007, 2008, 2009 and the most recent year 2013.





Example for France: The French DSO and DPO have also improved, likely, because of the introduction of the LME law to reduce payment terms.

3. Empirical Results (and XVI)

(ii) using the chi-square test of homogeneity in order to determine if these distributions are similar or different by year.

Chi-square test: DSO over time

Observed data

Sector: Total

Country: FR

Size: Total w/o Micro

		DSO < 0	0 <= DSO < 30	30 <= DSO < 60	60 <= DSO < 90	90 <= DSO < 120	DSO >= 120	# of companies
FR	2012	2,5	32,9	25,9	23,2	9,6	5,9	74424
FR	2013	2,3	33,4	25,5	23,0	9,8	6,1	72824

Observed frequency

		DSO < 0	0 <= DSO < 30	30 <= DSO < 60	60 <= DSO < 90	90 <= DSO < 120	DSO >= 120	
FR	2012	1842	24471	19293	17284	7110	4424	**74424**
FR	2013	1673	24298	18551	16750	7127	4425	**72824**
		3515	**48769**	**37844**	**34034**	**14237**	**8849**	**147248**

Expected frequency

		DSO < 0	0 <= DSO < 30	30 <= DSO < 60	60 <= DSO < 90	90 <= DSO < 120	DSO >= 120	
FR	2012	1777	24649	19128	17202	7196	4473	**74424**
FR	2013	1738	24120	18716	16832	7041	4376	**72824**
		3515	**48769**	**37844**	**34034**	**14237**	**8849**	

Calculations

2,41	1,29	1,43	0,39	1,02	0,53	**Chi statistic**
2,46	1,32	1,46	0,40	1,05	0,54	**14,30**

$Chi^{2}_{0,05}(5)$= **11,07** **p-value** **0,01**

Null hypothesis: The DSO distributions for Total sector and all sizes (FR) in 2012 and 2013 are similar.

The test compares whether frequency counts are distributed identically across different samples (2012 and 2013).

The example of resolution of **chi-square test** for the DSO ratio for the **French samples**. If the significance level is 5%, then we would conclude that there **is statistically significant difference in the proportion of firms** by the six categories of DSO between 2012 and 2013.

OUTLINE

1. Motivation
2. Data Sources and Methodology
3. Empirical Results
4. Conclusions

4. Conclusions

- The study examines the importance of **trade credits** in the countries of FSA WG.

- The **collection and payment periods** of trade credit are assessed, obtained from accounting data, by means of two key financial ratios:
  - Days sales Outstanding (DSO)
  - Days Payables Outstanding (DPO).

- The results reveal **differences** in DSO and DPO between **countries and sectors**.

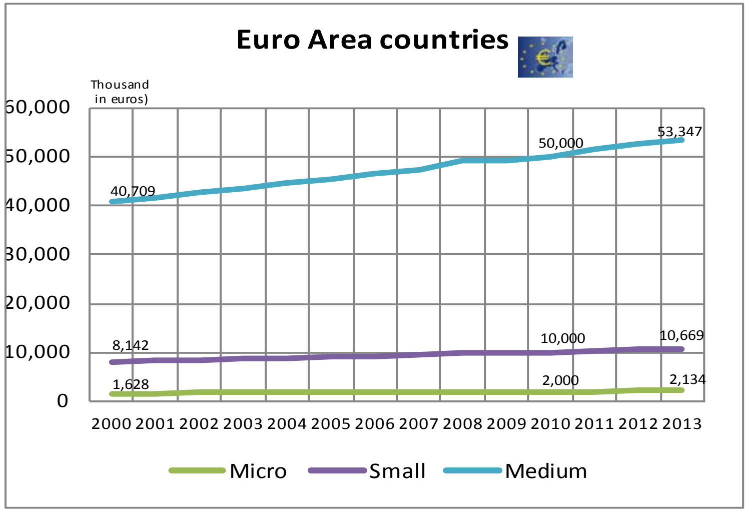
- Identifying **heterogeneous trends** in the evolution of DSO and DPO in the aftermath of the 2008-2009 financial crisis.

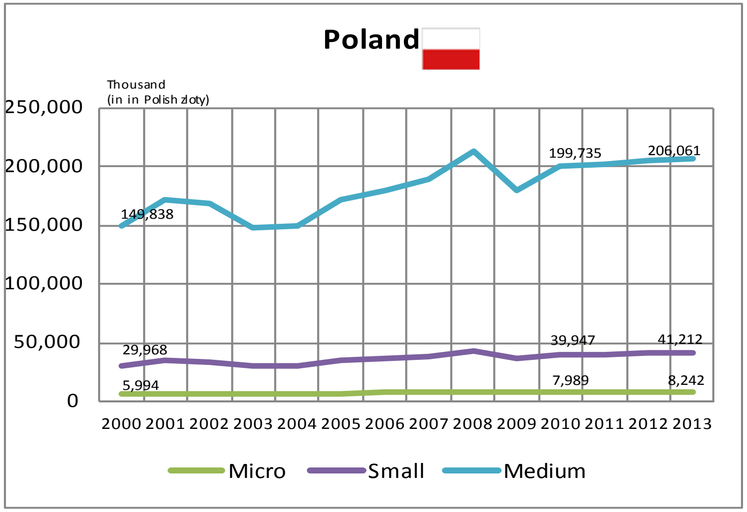
- Future plan → To set up this study on DSO and DPO as **a permanent ECCBSO database of collection and payment periods**
  - Weighted average
  - KDE
  - Statistics test of homogeneity (by year, by country, etc.)

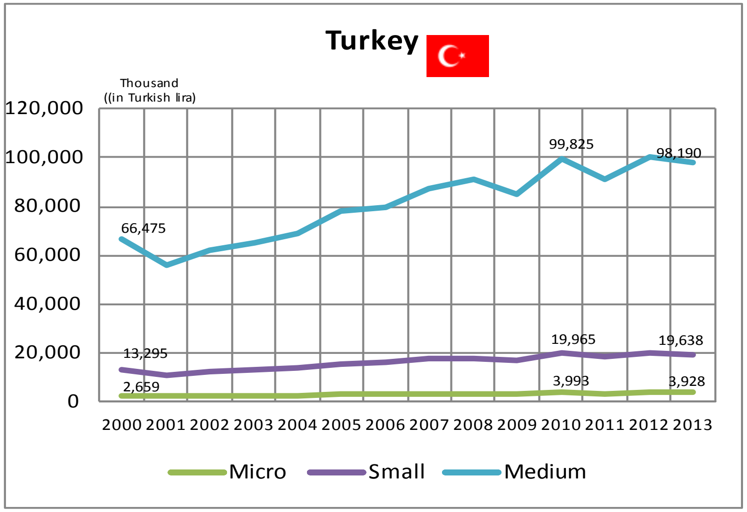
THANK YOU FOR YOUR ATTENTION.

QUESTIONS?

ANNEX (I): DEFLATED CUT-OFF POINTS FOR TURNOVER







ANNEX (II): CORRELATION COEFFICIENTS DSO VS DPO AT FIRM LEVEL

Correlation Coefficients DSO vs DPO in 2012

Sector	Size	Belgium[1]	Germany	Spain
1 Manufacturing	1 Micro	0,28	0,23	0,83
1 Manufacturing	2 Small	0,31	0,19	0,28
1 Manufacturing	3 Medium	0,27	0,14	0,15
1 Manufacturing	4 Large	0,35	0,07	0,15
1 Manufacturing	Total w/o Micro	0,30	0,16	0,21
2 Construction	1 Micro	0,14	0,26	0,00[Δ]
2 Construction	2 Small	0,26	0,27	0,10
2 Construction	3 Medium	0,33	0,22	0,66
2 Construction	4 Large	0,27	0,11[Δ]	-0,08[Δ]
2 Construction	Total w/o Micro	0,30	0,25	0,12
3 Trade	1 Micro	0,14	0,28	0,01
3 Trade	2 Small	0,36	0,29	0,38
3 Trade	3 Medium	0,37	0,10	0,50
3 Trade	4 Large	0,42	0,04	0,88
3 Trade	Total w/o Micro	0,37	0,20	0,44

Subsectors Trade

Sector	Size	Belgium[1]	Germany	Spain
Motor Vehicle Trade	1 Micro	0,20	0,30	0,01[Δ]
Motor Vehicle Trade	2 Small	0,33	0,27	0,47
Motor Vehicle Trade	3 Medium	0,33	0,30	0,59
Motor Vehicle Trade	4 Large	0,39	-0,02[Δ]	0,07[Δ]
Motor Vehicle Trade	Total w/o Micro	0,34	0,24	0,49
Retail Trade	1 Micro	0,12	0,20	0,03
Retail Trade	2 Small	0,27	0,30	0,33
Retail Trade	3 Medium	0,27	-0,20	0,16
Retail Trade	4 Large	0,27	0,06[Δ]	0,02[Δ]
Retail Trade	Total w/o Micro	0,26	0,12	0,31
Wholesale Trade	1 Micro	0,14	0,33	0,01[Δ]
Wholesale Trade	2 Small	0,39	0,32	0,38
Wholesale Trade	3 Medium	0,39	0,27	0,59
Wholesale Trade	4 Large	0,44	0,12	0,07[Δ]
Wholesale Trade	Total w/o Micro	0,41	0,28	0,47

(1) Correlation coefficients relate to year 2013.
(Δ) Correlation coefficients are not significantly different from 0 at the 95% threshold.

First results about correlations at firm level, confirm the positive relation between DSO and DPO.

(*working in progress*)

Irving Fisher Committee on
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BANK FOR INTERNATIONAL SETTLEMENTS

IFC-ECCBSO-CBRT Conference on *"Uses of Central Balance Sheet Data Offices' information"*

Co-organised by the IFC, the European Committee of Central Balance Sheet Data Offices (ECCBSO) and the Central Bank of the Republic of Turkey (CBRT)

Özdere-İzmir, Turkey, 26 September 2016

Exports, real exchange rates and external exposures: empirical evidence from Turkish manufacturing firms[1]

Nazlı Karamollaoğlu, MEF University, and Cihan Yalçın, CBRT

[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.

Exports, Real Exchange Rates and External Exposures: Empirical Evidence from Turkish Manufacturing Firms

Nazlı Toraganlı[a] Cihan Yalçın[b]

Abstract

Turkish manufacturing firms are highly exposed to foreign currency (FX) denominated costs in the forms of liability dollarization and high imported input content in domestic production. This might limit the competitiveness effects of currency depreciation on exports. We attempt to uncover the relationship between the real exchange rates and exports of manufacturing firms in Turkey by taking into account FX exposures and various firm characteristics. We use a large panel of manufacturing firms to carry out an empirical analysis for the period 2002-2010. We document that a real depreciation of the Turkish lira has a positive impact on export volumes and its impact is muted for firms operating in sectors that use imported inputs intensively. That is, the cost of production channel seems to be effective in export performance of firms. In addition, we estimate that exports are less sensitive to real exchange rates for firms having moderate or low FX debt-to-export ratios (naturally hedged) and those are large and mature. Contrary to macro evidence, firm level findings suggest that a depreciation of the lira seems to favour the external competitiveness of firms in general while for naturally hedged, large, mature, and high import intensity firms, the sensitivity is estimated to be smaller.

Contents

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[b] Senior Economist at CBRT Structural Economic Research Department

The views expressed in this paper are those of the author(s) and do not necessarily represent the official views of the Central Bank of the Republic of Turkey.

Exports, Real Exchange Rates and External Exposures: Empirical Evidence from Turkish Manufacturing Firms[1]

1. Introduction

Recent empirical trade literature has extensively studied the role of accessing to finance in promoting exports while it has so far paid little attention to the possible effects of foreign currency (FX) exposures (including imported inputs and FX denominated debt as form of finance) on financial positions of firms in examining the impact of exchange rates on exporting behaviour. A depreciation of the real exchange rate results in cheaper exported goods and services, but also makes the imported input expensive creating a cost disadvantage (for example, see Campa and Goldberg, 1997, Hummels et al., 2001, Greenaway et al. 2010). Ahmed et al. (2015) find evidence that the elasticity of exports to the real exchange rate has been declining mainly due to the vertical integration in global value chains which increase the usage of imported inputs all around the world. Similarly, a depreciation of the local currency reduces the net worth of firms that experience severe currency mismatch, restricting the availability of export financing and causing a loss of competitive advantage. In other words, for firms with large foreign exchange denominated debt (a type of external finance), a shock to capital inflows or sudden stops may lead to a rise in exchange rate volatility and have strong implications for their financial positions thus their real activities (Calvo and Reinhart, 2002; Calvo et al., 2004). In this context, an empirical analysis on Turkish firms would represent an ideal natural experiment for testing the muting effects of currency depreciations on exports due to high imported input content of domestic production, extensive currency mismatch with limited hedging instruments and volatile exchange rates.

This paper builds on the literature focusing on the effects of exchange rate variations on firms' exports' by taking into account the role of financial constraints and FX exposures. We particularly incorporate FX denominated costs into the analysis. The analysis done, referencing the related literature, involves empirical tests that use firm specific variables such as the liability dollarization ratio, labour productivity, real sales, leverage ratio, collateral ratio; industry based variables such as industry-specific real exchange rates and imported input intensity as well as macro variables that reflect domestic and foreign demand and macro volatility. In this context, we intent to control how exchange rate elasticity of exports react to firms heterogeneity in terms of imported inputs intensity, the degree of currency mismatch, size, and age.

Our findings suggest that a real depreciation of the Turkish lira has a positive impact on exports of firms. This positive impact is muted for firms operating in sectors that use imported inputs intensively. Similarly, exports of firms with moderate or low FX debt-exports ratios, so called "naturally-hedged", are less sensitive to real exchange rates as expected. In addition, estimations show that the exports of mature and large firms are estimated to be less sensitive to the variations in real exchange rates.

The rest of the paper is organized as follows. Section II presents economic developments and FX exposure structure in Turkey. Section III describes the firm-level data and variables. Section IV contains the empirical analysis of the links between

[1] This version of the paper is largely adapted from CBRT Working Papers No: 24/16.

export patterns and exchange rates considering various firms characteristics. Section V concludes.

2. A Short Evaluation on Foreign Exchange Exposures in Turkey

High current account deficit (or low domestic savings) has been a major obstacle for achieving high and sustainable growth in Turkey. Heavy dependence on imported inputs and foreign savings raises the sensitivity of the economic activity and prices to fluctuations in capital flows and international commodity prices. In this environment, exchange rates appear to be one of the key variables reflecting the conditions of the economy. In addition to unfavourable external position of the economy mentioned above, relatively high and unstable inflation rates were one of the underlying factors behind volatile exchange rates putting economic agents in a position where their pricing and investment decisions are more complicated.

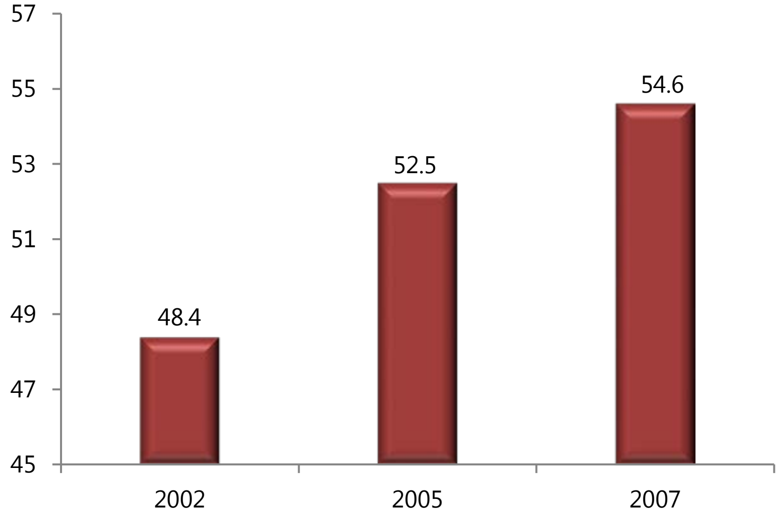
To overcome the uncertainty due to unstable macro environment and volatility in exchange rates and international risk appetite, economic agents in Turkey tend to hold large amounts of FX liabilities and assets and they adopted a widespread FX indexed domestic pricing behaviour especially during 1990s. In other words, economic transactions were highly dollarized. Although there has been a decline in both liability and asset dollarization in 2000s as a consequence of improvement in underlying fundamentals, dollarization and FX indexed pricing have gained momentum again in recent years.

Before going into details of the empirical model, we will present several factors, which have affected the sensitivity of the Turkish economy to the exchange rates through increasing its FX exposure. Firstly, Turkish economy was transformed in a way that it has started to use more imported inputs in the production activity especially in 2000s. Secondly, in addition to growing import bill, fixed investments were largely financed by growing capital inflows which was not only supported Turkish lira especially before the great recession in 2008, but also increased the fragility of the economy to external shocks. Lastly, although there has been a decline in the extent of liability dollarization, the FX indexed pricing in the domestic economy has not lost its importance (Hülagü and Yalçın, 2014). We provide brief discussions on the first two factors below, respectively.

Turkish economy is characterized by a large trade deficit. Although various initiations were taken to encourage exports and reduce the reliance on imported inputs in the production, they failed to stop the widening the external deficit. In fact, trade deficit has deteriorated further in recent years resulting from increasing trend in imports also due to the increasing imported input content of domestic production especially after 2001 (Chart 1). Intermediate goods imports which has been always larger than exports of goods, reached as much as 22 percent of GDP in 2014. Insufficient domestic production in parallel to the strong economic performance during post-2001 crisis period was one of the major reasons of this increasing trend (Saygılı et al., 2010).

During this period, the finance costs and the price of capital goods went down, capital inflows accelerated and the Turkish lira appreciated significantly. Firms tended to allocate more resources to capital intensive production activities such as automotive, machinery and equipment, basic metal, metal products etc. which relied relatively more on imported intermediate and capital (machinery and equipment) inputs. Unavailability of domestic production, the need for high quality and uninterrupted supply to ensure technology transfer, and the possibility of cheaper supply due to domestic currency appreciation and competitive prices in the trading partners (e.g. China) were other major factors contributing to the increasing trend in imported inputs.

Chart 1. The Share of Imported Intermediate Inputs in Total Cost of Production (%)



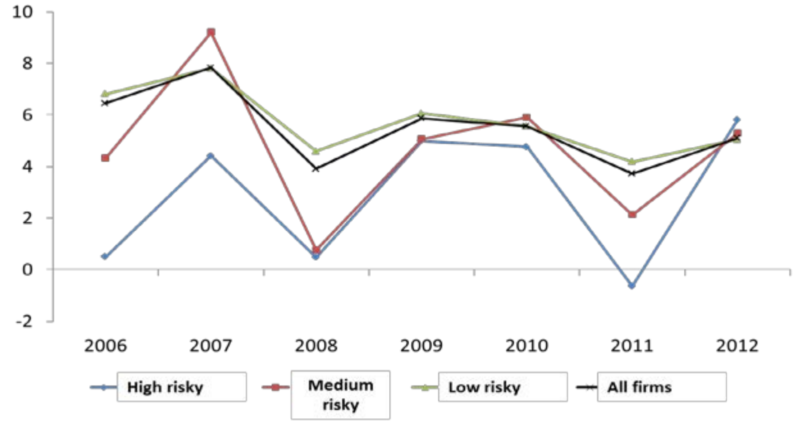
Source: Saygılı, Cihan, Yalçın and Hamsici (2010)

Turkish financial system do not produce sufficient Turkish lira denominated resources with reasonably long maturity to finance financially constrained domestic agents. The most important reasons for this are the relatively low domestic financial savings mostly characterized by short maturity structure. Banks are the primary financial institutions and have to borrow from abroad in order to extend credits with longer maturity. These credits are provided mostly in terms of FX in order to avoid the currency risk. Non-financial firms also borrow heavily from abroad directly. In other words, the growing imports bill and investments are largely financed by FX denominated debt. As a result, the FX liabilities of non-financial firms reached to 35 percent of GDP in 2014 from 14 percent in 2002 and short net FX position of these firms have increased from 3 percent of GDP to 22 percent in the same period.

The liability dollarization ratio, calculated as the share of FX debt in total debt, of non-financial firms in Turkey can be interpreted as high when compared internationally as well (Özmen and Yalçın, 2007). According to IMF (2015), Turkey has the third highest FX-denominated debt to GDP ratio as of 2014 after Chile and Poland. Firm level data show that liability dollarization ratio decreased from 85 percent in 2001 to 65 percent in 2010 in parallel to the declining inflation, structural reforms, and the newly adopted flexible exchange rate system (Alp and Yalçın, 2015). Short-term liability dollarization ratio has been on a declining trend as well. From 76 percent in 1996, it decreased to 50 percent in 2001, and with the positive impact of the reduced uncertainty during the post-2001 period it further shrank to 25 percent in 2010. This situation may increase the fragility of non-financial companies to external shocks such that in the case of a sudden stop foreign funding remains limited and credit to the real sector freezes. However, in spite of risk involved in FX debt, they undermine the extent of financial constraints and contribute to the enhancement of domestic economic activity in an environment where domestic financial system fail to produce enough domestic currency denominated funds mainly due to low domestic savings and short maturity of financial savings.[2]

In addition to imported inputs, it is also important to note that financial expenditures in terms of FX is an important cost item for non-financial firms particularly in times of currency depreciations as FX denominated debt in terms of the domestic currency increases. Chart 2 shows that net profit margins of firms with poor natural hedging (risky firms) melt down significantly when Turkish lira depreciated sharply during the post-2008 financial crisis period. On the other hand, firms that are able to match the currency composition of their debt with their income streams, so called low-risk firms, seem to be affected from currency depreciations to a lesser extent. Any change in the pace of capital inflows and the price of international commodity prices has strong implications for the real exchange rates and thus domestic economy. The Turkish lira has usually exhibited a very volatile pattern over the time given heavy reliance on foreign capital and imported inputs. Given the volatility in the exchange rate and economy's strong reliance on imported inputs, empirical evidence for Turkey documents very strong exchange rate and import price pass through to domestic prices in international standards. Consequently, the export performance has been also affected by strong exchange rate and import price pass-through to domestic prices prevailing in the Turkish economy, which deteriorates firms' relative competitiveness in external markets.

Chart 2. Profit Margins of Non-financial Firms (Percent)



Source: Hülagü and Yalçın (2014)

3. Data and Variables

The firm level data used in this study is based on two sources: i) The Central Bank of the Republic of Turkey (CBRT) Company Accounts and ii) Risk Center Database of Banks' Association of Turkey. The CBRT Company Accounts Database is the most comprehensive database regarding financial data of non-financial firms in Turkey. It

2 Note that although there has been a decline in the extent of liability dollarization, the FX indexed pricing in the domestic economy has not lost its importance. FX-indexed pricing behaviour prevailing in the domestic sector in some sectors has a positive impact on lowering currency risk (Hülagü and Yalçın, 2014).

includes information on balance sheet and income statement items, economic activity classified according to industry or sector, establishment date, number of employees, provinces operated in, and the legal status. Risk Center Database provides information on firm-level foreign and local currency denominated debts and their maturities. We merge two datasets by using firm identifiers, which enables us to incorporate information from balance sheet, income statements, and FX denominated debts items into the same analysis.

One of the drawbacks of the CBRT data is that it does not meet sampling standards as it covers mainly large firms. The database also covers only the participating firms those submit their financial statements regularly to the commercial banks. Any firm whose data of last three years is not available is kept out of the analysis. However, firms included in the dataset are of great weight in total activities, which renders the representative power of this analysis high. The dataset also includes substantial portion of small and medium-sized enterprises in addition to large firms (about two third of the sample) operating in Turkey. About half of the firms in the dataset operate in the manufacturing industry and these firms cover a significant portion of aggregate economic activity. Based on 2010 data, these firms hold about 77 percent of manufacturing sales, over 95 percent of manufacturing exports and about half of manufacturing FX-denominated debts. Firms in the database account for 35 percent of total manufacturing employment.

We use various firm specific, sectoral and macro variables in our analysis. As often used in the literature we utilize logarithms of real sales and logarithms of labour productivity (the ratio real sales to employment) to control for firms' size and productivity, respectively. To control financial conditions, following variables are used in the analysis: (i) leverage ratio, defined as the firm's ratio of total liabilities to total assets, (ii) collateral ratio, defined as real tangible assets over total assets to control capital intensity of firms and (iii) liability dollarization ratio, defined as the ratio of FX liabilities to total liabilities. The first two indicators have been extensively used in the literature dealing with financial constraints and all these variables reveal the degree of the firms' financial health (Greenaway et al., 2007).

FX liabilities is a central variable when examining the impact of exchange rate variations on firm-level exports particularly in the context of developing countries as most of them suffer from high liability dollarization (IMF, 2015). This situation is often referred as "original sin", following Eichengreen et al. (2005) measuring the inability of an economy to borrow internationally in its own currency. In this situation, "currency mismatch" creates a potential source of vulnerability if firm's debt is in the form of FX while the income and assets are mostly denominated in domestic currency. Therefore when evaluating the risks associated with liability dollarization of companies, FX revenues (if any FX denominated revenue exists) should also be considered. Since there is no available data that reflecting the overall FX exposure of Turkish companies' balance sheets, liability dollarization is analysed by taking into account the export revenues of companies. In other words, export revenues are considered as a "natural hedge" for companies that has FX denominated cash loans. If the liability dollarization of a company is high whereas its export revenue is low (or no export revenue), then the financial fragility of those kinds of companies are considered as high due to currency mismatch. In order to measure the degree of currency mismatch, we adopt Echeverry et al. (2003) methodology. Accordingly, we identify each firm as belonging to one of the three zones in the foreign debt-exports space: hell, heaven, and hedge. Firms are classified as hedged if the magnitude of their exports is similar to the magnitude of their foreign denominated liabilities. We construct our measure for currency mismatch by taking the ratio of foreign exchange denominated debt to exports and set upper and lower bound as FX Debt =0.15 Exports and FX Debt =3.2 Exports, representing the upper and lower 25th percentile of the distribution, respectively.

At sectoral level, we construct export-weighted real effective exchange rates. The trade weights of each industry are constructed using the methodology described in Goldberg (2004). The trade shares are averaged (within an industry) across the pre-sample time period (1996-2000), therefore the variation in exchange rate over time comes only from changes in the real exchange rate changes and not from fluctuations in partners' trade shares. A rise in this index represents an appreciation of the domestic currency.

At macro level, we use domestic GDP with constant prices to reflect domestic demand that may be considered a substitute for external markets. For the external demand, we used the weighted average of OECD countries' GDPs (constant prices), where bilateral trade flows as shares in total trade of Turkey are used as weights and data are from IMF. In addition, we use Chicago Board of Exchange (CBOE) Volatility Index (VIX index) as measure of macro volatility.

To mitigate the impact of outliers on the regression results, we drop 0.1 percentile of firms both ends of the distributions of labour productivity, leverage ratio and collateral ratio. We also excluded companies that have missing values and that possess inconsistent values. Subsequently, we end up with about 24 thousand firm-year observations consisting of 4227 firms belonging to 22 manufacturing industries over the period 2002-2010. We deflate all the nominal values using the sectoral-level producer price indices (PPI) obtained from the Turkish Statistical Institute.

We categorize firms into small, medium, and large according to their employment levels. Firms below 50 average employees during the period are grouped as small firms, firms between 50 and 250 average employees are labelled as medium-sized firms and the rest of firms with more than 250 employees are considered as large firms. We also define young firms as belonging to the lowest 25 percentile of the age distribution, and mature firms as those belonging to the highest 25th percentile.

Basic statistics shows that larger and mature firms tend to be more productive and have higher sales. With regard to currency mismatch categorization, firms under the hell category tend have lower export shares, higher real sales, and liability dollarization and leverage ratios. They also hold higher tangible assets. These firms are highly dollarized and are mostly selling in the domestic market evidenced by considerable lower export shares. Firms in the heaven region are relatively smaller in terms of both employment and real sales, have lower dollarization and leverage ratios. In terms of exporting, they in general export more than firms in the hell region but still considerable lower than firms in the hedged area. Firms in the hedged region have high export shares and they are slightly older than their counterparts in the heaven and hell regions.

Consistent with the empirical literature exporters on average have higher employment and labour productivity than non-exporters (see, for example, Bernard and Jensen, 1999, for the US; and Greenaway and Kneller, 2004, for the UK). Firms operating in sectors that use lower imported inputs have higher dollarization rate, export shares, employment, and lower productivity. On the other hand, there is no significant variation in collateral ratios, leverage ratios, real sales, and real export values between firms operating in sectors which have low and high-imported input intensities.

4. Model and Estimation Results

In our empirical specifications described below, we test the relative importance of different above-mentioned channels through which exchange rate variations may affect exports. These channels are often classified as competitiveness, the cost of production and the balance sheets. We start empirical tests with baseline specification and then extent the empirical model by introducing interaction terms representing firm characteristics.

4.1. Baseline Specification

We construct an econometric model to investigate the determinants of export volume of manufacturing firms (intensive margin). Our baseline model is standard where the logarithm of firm level export volumes are explained by sectoral logarithm (log) of real exchange rates (both level and change), VIX index as a measure of macro volatility, domestic output and foreign demand as well as firm specific variables. That is, we utilize variables that allow us to control for macro, sectoral, and firm level dynamics. More specifically, we use the following baseline specification to quantify the impact of exchange rate movements on firm level exports.

$$ln(X_{it}) = \alpha_1 \ln(X_{it-1}) + \alpha_2 \ln(RER_{jt}) + \alpha_3 VOL_t + \alpha_4 Z_{it} + \alpha_5 ln(GDP_t^D) + \alpha_6 ln(GDP_t^F) + \tau\mu_i \quad (1)$$

where i indexes firms, t shows time (years), j is the industry to which firm i belongs to, X_{it} is firm level real exports, $ln(RER_{jt})$ stands for log of industry-specific pre-period trade weighted real exchange rates (a rise in this index represents a real appreciation of the domestic currency); VOL_t is time varying VIX index; Z_{it} is a vector of firm-specific variables including labour productivity, log of real sales, liability dollarization ratio, collateral ratio, leverage ratio; $ln(GDP_t^D)$ and $ln(GDP_t^F)$ are logs of domestic income and export weighted foreign income, respectively; μ_i shows non-time-varying firm-specific idiosyncrasies and ε_{it} is the error term of the regression.

In order to cope with potential endogeneity problem and controlling dynamic aspect of exports, we use a dynamic panel framework where difference GMM estimations are carried out. The difference GMM estimation introduces the lag(s) of dependent variable to control for potential dynamic effects and uses the lags of dependent and explanatory variables as instruments to tackle potential endogeneity problem. Estimation results for the baseline specification are presented in Table 1.

We use the first lag of dependent variable as a regressor to control for the inertia in real exports and use its third lag as instrument variable in all GMM regressions. In addition, we treat liability dollarization ratio, labour productivity (change and its level), and log of real sales as predetermined variables given their endogenous relationships with employment and real sales and we use their up to three lagged values as the GMM-type instruments. Similarly, depending on specification used macro variables and sectoral real exchange rates (change and its level) are employed as standard differenced instruments. We report the Sargan test of over-identification to test for the validity of our instruments. Estimations results are from the one-step GMM procedure while the Sargan and autocorrelation tests, which are obtained from the two-step procedure. Second order autocorrelation tests (*arm2*) do not reject the hypothesis of no serial correlation in the error terms for almost all regressions. Similarly, the Sargan tests do not reject the hypothesis of the validity of over-identifying restrictions almost in all regressions suggesting that instruments are valid.

The GMM estimation enables us to test the inertia in exports or its dynamic aspect. The coefficients of lag dependent variable are estimated to be positive and statistically significant across all specifications suggesting that real export variable has an inertia and its coefficient is estimated around 0.25, i.e. a ten percent rise in the previous year's exports adds about 2.5 percent to current real exports.

For the sake of robustness, we report alternative specifications using the levels and changes in logs of real exchange rates and labour productivity. Estimation results suggest that real appreciation of domestic currency has a negative impact on exports as expected. The real exchange rate elasticity of exports is estimated to be around 3 percent in all specifications of the baseline model. The, the coefficients of the real exchange rate do not change significantly when change in the log of real exchange rate ($\Delta ln(RER_{jt})$) is used instead of the level

We estimate that firm size ($ln(lrsale_{it})$) has positive impact on exports. The coefficients of size variable are significant and larger than unity in specifications where the log of labour productivity is used as regressors. This finding is consistent with literature (Bernard and Jensen, 1999; Wagner, 2001; Greenaway and Kneller; 2004), exporting activity incurs a sunk-cost and this cost is less important for larger firms thus they are expected to enter the export markets more easily. We also use the log of labour productivity, $ln(LP_{it})$, as explanatory variable. The coefficients of this variable are estimated to be positive and significant in the specification without size variable. When size variable is introduced coefficients turns to be insignificant. In order to address the potential multi-collinearity between size and labour productivity, we report the findings with both level and change in log of labour productivity. We estimate positive and significant coefficients for change in log of labour productivity ($\Delta ln(LP_{it})$) suggesting that a ten percentage point rise in labour productivity lead to a rise in export around 3-5 percent. These results are in line with the empirical evidence and theoretical predictions documenting that more productive firms tend to export more than less productive firms (Melitz, 2003).

Liability dollarization ratio ($Dolratio_{it}$) is used to control for several factors: (i) access to foreign finance which is evidently to be cheap and mutes financial constraints, (ii) an instrument of hedging mechanism (iii) the extent of FX-denominated liability exposure or currency mismatch. The first two channels may suggest a positive coefficient for this variable while the last channel suggests a negative coefficient especially when domestic currency depreciates to a large extent. Cheap FX-denominated debt with better terms compared to domestic currency denominated debt is apparently supportive for exports. The estimation results usually suggest a positive and significant association between liability dollarization ratio and export volume. The last channel as an element of production cost and balance sheet effects, suggests that large share of FX debt may not be supportive for exports in case of currency depreciation. We will test these channels in the next section.

We use the leverage ratio ($Leverage_{it}$) and collateral ratio ($Collateral_{it}$) as explanatory variables in order to control the financial health or capital of firms. Estimations suggest no statistically significant link between leverage ratio and exports. We estimate often insignificant coefficients for collateral ratio except in one specification (Table 1 in column 3) where we have negative and significant coefficient, implying that as the share of tangible assets rises, firm's exports declines. Data shows that exports of firms in the lowest 25 percentile in terms of collateral ratio grew faster than exports of firms in the 75 percentile. Contrary to this findings, empirical literature document that industries with more tangible assets enjoy easier access to outside capital because firms can pledge more collateral (Braun, 2003; Claessens and Laeven, 2003; Manova,2015). Literature also documents that export starters have a significant ex-ante financial advantage, compared to non-exporters (Bellone et al. 2010; Muuls, 2012). That is, firm capital is more vital for the new exporter starters. However, even though better financial health has been associated with increasing export market participation (the extensive margin of trade) it does not necessarily increases intensive margin (Berman and Hericourt, 2010; Muuls, 2008) which is in line with the existence of large sunk costs which have to be paid to access the export market for the first time. Manova (2013) and Hur et al. (2006) find that in economies with higher levels of financial development, exports of vulnerable industries with fewer tangible assets grow faster. Therefore our finding on the impact of tangibility on intensive margin do not contradict fully with the empirical findings given the fact that recent improvement in conditions of accessing to credits by Turkish exporters and new incentives supporting exports might have increased the export performance of firms with lower collateral ratios.

For the macro variables, we use time varying VIX index as a regressor. In line with expectation and contrary to findings in fixed effect estimations, coefficients of this variable are estimated to be negative and significant in specifications where the log change of labour productivity while they are mostly negative and significant in the extended model estimations. In addition, we use $ln(GDP_t^F)$ to control for foreign demand and we estimate positive as expected but not always significant coefficients for this variable. We also use domestic demand, $ln(GDP_t^D)$ to control for potential substitution between domestic sales and exports. We estimate negative and significant coefficients for this variable, implying a substitution between domestic sales and exports. Anecdotal evidence for Turkish manufacturing suggests that firms substitute exports for domestic sales in the periods of weak domestic activity. This evidence is supported by Şahinbeyoğlu and Ulaşan (1999) that estimate a negative association between exports and domestic income. Parallel with our findings, empirical studies carried out for EU countries suggest a strong substitution between domestic sales and exports in the short run especially when domestic demand is weak (Bobeica, Esteves, Rua and Staehr, 2015), and economies are highly diversified in exporting or activities are less concentrated (Esteves and Prades, 2016).

Baseline Specification: Estimations with Difference GMM Model Table 1

	(1)	(2)	(3)	(4)
lrexp$_{i,t-1}$	0.198***	0.254***	0.230***	0.254***
	(0.0328)	(0.0387)	(0.0346)	(0.0374)
ln(RER$_{jt}$)	-0.319**	-0.276*	-	-
	(0.154)	(0.164)		
Δ(ln(RER$_{jt}$))	-	-	-0.340***	-0.230***
			(0.0714)	(0.0733)
ln(LP$_{it}$)	0.160	-	-0.202	-
	(0.163)		(0.186)	
Δ(ln(LP$_{it}$))	-	0.530***	-	0.338**
		(0.135)		(0.152)
ln(lrsale$_{it}$)	1.088***	0.824***	1.117***	0.878***
	(0.127)	(0.148)	(0.130)	(0.142)
Dolratio$_{it}$	0.424**	0.323	0.525***	0.412**
	(0.189)	(0.215)	(0.193)	(0.208)
Collateral$_{it}$	-1.026	0.361	-2.155**	-0.501
	(0.973)	(1.251)	(1.021)	(1.219)
Leverage$_{it}$	0.218	0.739	0.260	0.584
	(0.502)	(0.650)	(0.517)	(0.630)
$ln(GDP_t^F)$	1.489	3.735***	0.501	2.360
	(1.160)	(1.414)	(1.222)	(1.450)
$ln(GDP_t^D)$	-1.488**	-2.620***	-1.294**	-2.173***
	(0.608)	(0.722)	(0.607)	(0.710)
VIX$_t$	-0.004	-0.007**	-0.003	-0.006**
	(0.003)	(0.003)	(0.003)	(0.003)
Constant	2.918	9.579***	7.618***	9.304***
	(2.701)	(2.853)	(2.887)	(2.700)
Observations	20,969	20,908	20,969	20,908
Number of firms	3,855	3,847	3,855	3,847
Sargan (P-value)	0.0172	0.553	0.399	0.670
arm2 (p-value)	0.0704	0.954	0.313	0.672
arm1 (p-value)	0	0	0	0

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

4.2. The Extended Specification

We extend the baseline specification by introducing dummy variables interacted with industry-specific real exchange rate (both level and change) to examine the sensitivity of exports to sectoral real exchange rates across various firm characteristics. We construct dummy variables reflecting the imported input intensity, the degree of currency mismatch, the firm size, and the firm age. We interact these dummy variables with the real exchange rate to test how the sensitivity of real exports to the real exchange rate alters across these characteristics. The model that includes the interaction terms mentioned above (the extended specification) is given in equation (2) below and is estimated by using the difference GMM estimation technique.

$$\ln(X_{it}) = \alpha_1 \ln(X_{it-1}) + \alpha_2 \Delta\ln(RER_{jt}) + \alpha_3 VOL_t + \alpha_4 Z_{it} + \alpha_5 \ln(GDP_t^D) + \alpha_6 \ln(GDP_t^F) + \alpha_7 (FCD \times \Delta\ln(RER_{jt})) + \tau\mu_i + \varepsilon_{it} \quad (2)$$

where *FCD* is a dummy variable reflecting firm characteristics and sets equal to "1" for firms that have specific characteristics mentioned above and "0" otherwise. We report and discuss findings concerning these interaction terms and provide details on how these dummies are constructed under the relevant sub-sections below, respectively.

4.2.1. Imported Inputs

Campa and Goldberg (1997) and Greenaway, Kneller and Zhang (2010) find evidence that the impact of real exchange rate on exports is muted to some extent by the usage of imported intermediate inputs in the domestic production. We follow similar path to test the impact of real exchange rate on firm level export volume in Turkey. Evidence suggests that domestic manufacturing production is highly exposed to imported inputs in Turkey. Saygılı et al (2010) estimated that about 55 percent of total intermediate inputs are made up of imported inputs and it has been rising over the period of our study. In addition, there is widespread foreign exchange denominated pricing in domestic economy including in housing, manufacturing, tourism sectors and especially commodities, leading to high exchange rate pass through to CPI inflation. Based on this background, the competitive impact of currency depreciation on export volume in Turkey might be muted by the degree of foreign exchange exposures through the cost of production channel.

We construct a dummy variable based on sectoral imported inputs intensity following Saygılı et al. (2010) which reports sectoral imported input intensity ratio based on 2002 Input-Output Table. We define the sector in which firms are classified as high imported input intensity if this ratio is larger than 0.29 (IM_j is equal to "1", otherwise it is "0") which is the median ratio of the imported input intensities for two digit manufacturing industries in our analysis. We test the cost of production channel by using the interaction term between the real exchange rate variable and imported intensity dummy (IM_j) as regressor. We expect the coefficient of interaction terms between the sectoral exchange rate variable and the imported input intensity dummy to be positive. That is, the exports of manufacturing firms with high imported inputs in their production are expected to be less sensitive to real exchange rate (the sum of interaction term and the log real exchange rate is smaller in absolute term). In other words, a depreciation of the domestic currency is expected to raise production costs of companies that rely on imported inputs and thus reduces the sensitivity of exports to the real exchange rate.

Table 2 provides the estimation results in which interaction terms of the level and change in the log of real exchange rate with IM_j are used as explanatory variable, respectively. In line with expectations, estimations show that the coefficients of these interaction terms are positive but it is statistically significant only for the interaction term with the log of real exchange rate. This suggests that exports of firms belonging to sectors with high imported inputs intensity are less sensitive to level real exchange rate. That is, imported inputs as an item of production cost may mute the impact of the competitiveness channel of the real exchange rate, i.e. the sums of coefficients of interaction terms and real exchange rate variables are smaller in absolute value.

4.2.2. Currency Mismatch: Firms in Hell, Heaven or Hedged Regions

We extend our analysis by introducing a better firm-level proxy for currency mismatch, calculated by taking the period averages of the ratio of FX-denominated debt to exports ($MISMATCH_i$). The numerator represents liabilities while the denominator represents revenues thus larger $MISMATCH_i$ implies higher degree of currency mismatch. Although the ideal way of calculating a proxy for the currency mismatch is to consider also FX-denominated assets and FX indexed domestic sales, due to lack of data we use only exports in the denominator of the ratio. We think this proxy is biased upward as the denominator may be larger than the actual export figures. We use the period average of $MISMATCH_i$ and classify firms into three groups and named them "heaven", "hedged" and "hell" inspired by Echeverry et al. (2003). The first group is reflected by a dummy that represents firms in the lower 25 percentile of average $MISMATCH_i$, "heaven". The second group is made up of firms in the upper 25 percentile of average $MISMATCH_i$, "hell". The last group represents the rest of the firms, "hedged". We use interaction terms of these three dummies with levels and change in log real exchange rate and run regression for the model given in equation (2).

Extended Specification with Imported Inputs: Estimations with Difference GMM Model

Table 2

	(1)	(2)
$lrexp_{i,t-1}$	0.252***	0.253***
	(0.0386)	(0.0375)
$ln(RER_{jt})$	-0.392**	-
	(0.185)	
$\Delta(ln(RER_{jt}))$	-	-0.270***
		(0.104)
$ln(RER_{jt})*IM_j$	0.344*	-
	(0.202)	
$\Delta(ln(RER_{jt}))*IM_j$	-	0.0989
		(0.147)
$\Delta(ln(LP_{it}))$	0.531***	0.330**
	(0.135)	(0.158)
$ln(lrsale_{it})$	0.829***	0.882***
	(0.147)	(0.143)
$Dolratio_{it}$	0.297	0.410**
	(0.215)	(0.208)
$Collateral_{it}$	0.317	-0.530
	(1.245)	(1.218)
$Leverage_{it}$	0.717	0.577
	(0.648)	(0.628)
$ln(GDP_t^F)$	3.664***	2.305
	(1.406)	(1.457)
$ln(GDP_t^D)$	-2.598***	-2.145***
	(0.720)	(0.714)
VIX_t	-0.007**	-0.006**
	(0.003)	(0.003)
Constant	9.571***	9.204***
	(2.854)	(2.722)
Observations	20,908	20,908
Number of firms	3,847	3,847
Sargan (P-value)	0.534	0.666
arm2 (p-value)	0.955	0.670
arm1 (p-value)	0	0

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

We expect the export sensitivity of hedged firms to the real exchange rate be small i.e. the coefficient of the interaction term of hedged firms is expected to be positive. We expect an insignificant coefficient for the interaction term for the firms belonging to the heaven region as the mismatch is not a problem for these firms and thus the impact through cost of production and balance sheets channels are muted. However, it is not straightforward to guess the expected sign of the coefficient for interaction term for the firms belonging to the hell region. Counteracting channels may determine the sign of this coefficient. A depreciation of the domestic currency may hit the firms' overall economic activity negatively including exports through cost of production and balance sheet channels when currency mismatch exists to a great extent. Therefore, we may expect a positive sign for the coefficient of the interaction term. On the contrary, we may expect a negative sign for the coefficient of the interaction term when the competitiveness channel dominates.

Findings from estimations are often in line with these expectations (Table 3). We estimate insignificant coefficients for the interaction terms with heaven firms dummy. That is, the exports of these firms are unlikely to be sensitive to real exchange rates. On the other side of the distribution, however, we estimate significant and negative signs for the interaction terms of firms in the hell region. In this case, firms seem to be more sensitive to the real exchange rate fluctuations. This finding is interesting as it suggests that exports of firms with high currency mismatch are more sensitive to real exchange rates thus a depreciation of domestic currency is favourable for the exports of these firms. Contrary to our expectation, the cost of production and the balance sheets channels seem to be not binding when domestic currency depreciates implying that competitiveness channel dominates. This finding supports the idea that firms with high FX debt relative to their exports are somehow able to sustain their export performance with a depreciation of the domestic currency. We discover that these firms seem to be largely domestic oriented (14 percent export share, compared to 40 and 26 percent for firms in the hedged and heaven regions, respectively) and they have relatively lower imported inputs which may be a potential explanation for the strong sensitivity of their exports to the real exchange rates.

We estimate a positive and significant coefficient for the interaction terms with hedged firms dummy. These firms, by definition, may be treated as candidates for naturally hedged ones whose activities including exports are expected to be less sensitive to the variations in the real exchange rate. This suggests that the sensitivity of the exports to real exchange rate is muted, i.e. the cost of production channel limits the impact of competitiveness channel to some extent. These results are in line with findings in Bleakley and Cowan (2008), and confirm that firms tend to match the currency composition of their liabilities with their ex-ante sensitivity of revenues to the real exchange rate.

4.2.3. Size and Age

We interact firm size and age dummy variables with the change and level of log of real exchange rate and report regression results in Table 4 and Table 5, respectively. We expect to estimate a positive signs for the coefficients of interaction terms with large and old dummies and negative signs for small, medium, and young dummies. The latter group of firms is expected to be financially constrained and is not mature enough both in terms of size and age to manage the currency mismatch which makes their exports sensitive to the real exchange rate fluctuations. Estimations results are generally in line with expectations. We estimate generally positive and only significant coefficients for the interaction terms with log of real exchange rate for large and old dummies while generally negative and only significant coefficients for the interaction term with log of real exchange rate for medium and young dummies. The coefficient of interaction terms with small dummy is estimated to be generally insignificant. In short, estimations show that the exports of large and old groups are generally less sensitive to the real exchange rate.

Extended Specification with Natural Hedge Position: Estimations with Difference GMM Model

Table 3

	(1)	(2)	(3)	(4)	(5)	(6)
$lrexp_{i,t-1}$	0.256***	0.253***	0.273***	0.260***	0.272***	0.261***
	(0.0392)	(0.0374)	(0.0386)	(0.0380)	(0.0381)	(0.0374)
$ln(RER_{jt})$	-0.274	-	-0.680***		-0.0747	-
	(0.167)		(0.201)		(0.173)	
$\Delta(ln(RER_{jt}))$	-	-0.245***	-	-0.450***	-	-0.107
		(0.0799)		(0.101)		(0.0846)
$ln(RER_{jt})*HEAVEN_i$	0.00248	-	-	-	-	-
	(0.231)					
$\Delta ln(RER_{jt})*HEAVEN_i$	-	0.0742	-	-	-	-
		(0.164)				
$ln(RER_{jt})*HEDGED_i$	-	-	0.639***	-	-	-
			(0.185)			
$\Delta ln(RER_{jt})*HEDGED_i$	-	-	-	0.384***	-	-
				(0.132)		
$ln(RER_{jt})*HELL_i$	-	-	-	-	-0.845***	-
					(0.234)	
$\Delta ln(RER_{jt})*HELL_i$	-	-	-	-	-	-0.552***
						(0.156)
$\Delta(ln(LP_{it}))$	0.526***	0.326**	0.556***	0.417***	0.518***	0.345**
	(0.135)	(0.153)	(0.136)	(0.161)	(0.136)	(0.153)
$ln(lrsale_{it})$	0.824***	0.883***	0.812***	0.854***	0.837***	0.872***
	(0.149)	(0.143)	(0.149)	(0.144)	(0.150)	(0.143)
$Dolratio_{it}$	0.297	0.415**	0.386*	0.446**	0.209	0.408**
	(0.209)	(0.204)	(0.221)	(0.211)	(0.210)	(0.208)
$Collateral_{it}$	0.468	-0.548	0.353	-0.523	0.548	-0.528
	(1.258)	(1.214)	(1.269)	(1.236)	(1.273)	(1.221)
$Leverage_{it}$	0.803	0.557	0.779	0.546	0.841	0.558
	(0.659)	(0.624)	(0.656)	(0.639)	(0.663)	(0.631)
$ln(GDP_t^F)$	3.765***	2.313	3.872***	2.579*	3.793***	2.418*
	(1.422)	(1.452)	(1.427)	(1.471)	(1.428)	(1.453)
$ln(GDP_t^D)$	-2.632***	-2.152***	-2.692***	-2.290***	-2.675***	-2.211***
	(0.725)	(0.710)	(0.729)	(0.721)	(0.726)	(0.711)
VIX_t	-0.007**	-0.007**	-0.008**	-0.006**	-0.008**	-0.006**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Constant	9.493***	9.252***	9.751***	9.908***	9.380***	9.476***
	(2.850)	(2.688)	(2.890)	(2.750)	(2.863)	(2.710)
Observations	20,908	20,908	20,908	20,908	20,908	20,908
Number of firms	3,847	3,847	3,847	3,847	3,847	3,847
Sargan (P-value)	0.538	0.670	0.575	0.676	0.362	0.679
arm2 (p-value)	0.969	0.645	0.846	0.752	0.988	0.592
arm1 (p-value)	0	0	0	0	0	0

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Extended Specification with Size: Estimations with Difference GMM Model

Table 4

	(1)	(2)	(3)	(4)	(5)	(6)
$lrexp_{i,t-1}$	0.265***	0.254***	0.255***	0.253***	0.259***	0.254***
	(0.0398)	(0.0376)	(0.0388)	(0.0375)	(0.0392)	(0.0373)
$ln(RER_{jt})$	-0.449**	-	-0.127	-	-0.219	-
	(0.179)		(0.183)		(0.170)	
$\Delta(ln(RER_{jt}))$	-	-0.260***	-	-0.132	-	-0.268***
		(0.0825)		(0.0968)		(0.0802)
$ln(RER_{jt})*LARGE_i$	0.576***	-	-	-	-	-
	(0.203)					
$\Delta(ln(RER_{jt}))*LARGE_i$	-	0.111	-	-	-	-
		(0.139)				
$ln(RER_{jt})*MED_i$	-	-	-0.300*	-	-	-
			(0.175)			
$\Delta(ln(RER_{jt}))*MED_i$	-	-	-	-0.194	-	-
				(0.123)		
$ln(RER_{jt})*SMALL_i$	-	-	-	-	-0.281	-
					(0.226)	
$\Delta(ln(RER_{jt}))*SMALL_i$	-	-	-	-	-	0.170
						(0.155)
$\Delta(ln(LP_{it}))$	0.558***	0.354**	0.530***	0.340**	0.545***	0.315**
	(0.138)	(0.154)	(0.135)	(0.152)	(0.137)	(0.153)
$ln(lrsale_{it})$	0.824***	0.877***	0.826***	0.880***	0.820***	0.882***
	(0.149)	(0.143)	(0.148)	(0.143)	(0.149)	(0.142)
$Dolratio_{it}$	0.321	0.417**	0.322	0.425**	0.323	0.403*
	(0.217)	(0.211)	(0.215)	(0.209)	(0.216)	(0.208)
$Collateral_{it}$	0.541	-0.522	0.385	-0.574	0.444	-0.460
	(1.278)	(1.238)	(1.252)	(1.227)	(1.264)	(1.216)
$Leverage_{it}$	0.840	0.560	0.752	0.547	0.785	0.613
	(0.666)	(0.640)	(0.652)	(0.634)	(0.658)	(0.627)
$ln(GDP_t^F)$	3.862***	2.392*	3.735***	2.322	3.814***	2.310
	(1.437)	(1.452)	(1.415)	(1.451)	(1.428)	(1.447)
$ln(GDP_t^D)$	-2.689***	-2.194***	-2.619***	-2.157***	-2.662***	-2.143***
	(0.734)	(0.710)	(0.723)	(0.710)	(0.729)	(0.708)
VIX_t	-0.007**	-0.006**	-0.007**	-0.006**	-0.007**	-0.006**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Constant	9.546***	9.410***	9.527***	9.327***	9.648***	9.107***
	(2.882)	(2.719)	(2.855)	(2.701)	(2.870)	(2.702)
Observations	20,908	20,908	20,908	20,908	20,908	20,908
Number of firms	3,847	3,847	3,847	3,847	3,847	3,847
Sargan (P-value)	0.609	0.657	0.563	0.665	0.579	0.676
arm2 (p-value)	0.821	0.705	0.947	0.668	0.900	0.624
arm1 (p-value)	0	0	0	0	0	0

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Extended Specification with Age: Estimations with Difference GMM Model

Table 5

	(1)	(2)	(3)	(4)
$lrexp_{i,t-1}$	0.257***	0.253***	0.257***	0.251***
	(0.0389)	(0.0375)	(0.0387)	(0.0373)
$ln(RER_{jt})$	-0.407**	-	-0.191	-
	(0.177)		(0.169)	
$D(ln(RER_{jt}))$	-	-0.272***	-	-0.189**
		(0.0876)		(0.0808)
$ln(RER_{jt})*OLD_i$	0.411**	-	-	-
	(0.189)			
$Dln(RER_{jt})*OLD_i$		0.144	-	-
	-	(0.133)		
$ln(RER_{jt})*YOUNG_i$		-	-0.449*	-
	-		(0.217)	
$Dln(RER_{jt})*YOUNG_i$		-	-	-0.202
				(0.153)
$D(ln(LP_{it}))$	0.533***	0.344**	0.531***	0.341**
	(0.135)	(0.152)	(0.135)	(0.153)
$ln(lrsale_{it})$	0.823***	0.878***	0.831***	0.876***
	(0.148)	(0.143)	(0.148)	(0.143)
$Dolratio_{it}$	0.310	0.417**	0.314	0.435**
	(0.215)	(0.209)	(0.215)	(0.207)
$Collateral_{it}$	0.414	-0.549	0.365	-0.646
	(1.255)	(1.228)	(1.251)	(1.209)
$Leverage_{it}$	0.802	0.563	0.795	0.531
	(0.655)	(0.632)	(0.650)	(0.626)
log_GDP_Partners	3.758***	2.369	3.722***	2.377
	(1.418)	(1.450)	(1.417)	(1.453)
log_GDP	-2.618***	-2.181***	-2.602***	-2.190***
	(0.724)	(0.710)	(0.724)	(0.712)
VIX_t	-0.007**	-0.006**	-0.007**	-0.006**
	(0.003)	(0.003)	(0.003)	(0.003)
Constant	9.487***	9.390***	9.422***	9.553***
	(2.857)	(2.702)	(2.864)	(2.714)
Observations	20,908	20,908	20,908	20,908
Number of id	3,847	3,847	3,847	3,847
Sargan (P-value)	0.575	0.664	0.578	0.651
arm2 (p-value)	0.946	0.675	0.950	0.646
arm1 (p-value)	0	0	0	0

*Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1*

5. Conclusions and Assessments

Empirical studies that use macro data often fail to find a relationship between real exchange rate and manufacturing exports in Turkey. This finding may be justified with a large content of costs in the forms of foreign exchange including extensive imported inputs and high liability dollarization. In other words, foreign exchange denominated cost items are made up of a significant portion of manufacturing production. Given the cost structure of domestic manufacturing production, the competitive impact of the exchange rate depreciation may be balanced or muted by the cost of production and the balance sheets channels. In this study we use large panel of manufacturing firms to investigate the impact of the variations in exchange rate on exports for the period 2002-2010. We attempt to uncover the relationship between the real exchange rates and exports of manufacturing firms in Turkey by taking account FX exposures and various firm characteristics. Our main contribution is to strike attention to the role of FX exposures and currency mismatch in examining export performance of firms operating in manufacturing industry.

We document that a real depreciation of the Turkish lira has a positive impact on exports and this impact is muted for manufacturing firms operating in sectors that use imported inputs intensively. That is, the cost of production channel seems to be effective in export performance of firms. We also find that exports of firms with moderate FX debt-to-export ratios, so called "naturally hedged firms", are less sensitive to real exchange rates as expected. That is, our findings suggest that degree of currency mismatch appears an important determinant for firm level exports in addition to other commonly used firm specific financial health measures in the literature. Our estimations also show that the exports of medium, small, and young firm groups are generally more sensitive to the real exchange rates while the exports of mature and large firms are estimated to be less sensitive. Contrary to macro evidence, firm level findings suggest that a depreciation of Turkish lira seems to favour the external competitiveness of firms in general while for naturally hedged, large, mature and high import intensity firms, the sensitivity is estimated to be smaller.

These findings are consistent with fact that small and medium sized-young firms in Turkey are more concerned with the level of the exchange rate than large-mature firms which are somehow naturally hedged and hold a large amount of FX debt with longer maturity. The latter group of firms expects lower volatility rather than the level for the exchange rate. Similarly, the former group of firms that uses Turkish lira denominated financing intensively is concerned with high domestic interest rate which creates a financing burden for them.

Liability dollarization in itself is an anomaly for an economy, which may threaten the financial stability. Turkish manufacturing firms are highly dollarized in terms of their liabilities, which may lead to a currency mismatch and thus potentially deteriorate their financial positions in case of large depreciations. However, as also documented by Alp and Yalçın (2015), having access to foreign exchange funds with longer maturity undermines the extent of financial constraints and thus support firms' activity. That is, a strong association is estimated among liability dollarization ratio, and sales, employment and exports of firms. In addition, we estimate that the competitiveness channel dominates the negative outcomes of balance sheet and the cost of production channels in case of currency depreciation for firms, which experience currency mismatch. This finding suggests that the corporate sector has potential to deal with the negative impact of depreciation of the domestic currency.

The data used in this study is confined with balance sheets and income statements of firms. There is extensive foreign exchange indexed pricing in Turkey, which has important implications for the impact of real exchange rate depreciation on firms activity and their financial positions. To better measure the extent of currency mismatch and assess the impact of exchange rate on export, foreign exchange indexed pricing and foreign exchange denominated assets of firms should be incorporated into the analysis. This is a starting point for future research.

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IFC-ECCBSO-CBRT Conference on *"Uses of Central Balance Sheet Data Offices' information"*

Co-organised by the IFC, the European Committee of Central Balance Sheet Data Offices (ECCBSO) and the Central Bank of the Republic of Turkey (CBRT)

Özdere-İzmir, Turkey, 26 September 2016

Exports, real exchange rates and external exposures: empirical evidence from Turkish manufacturing firms[1]

Nazlı Karamollaoğlu, MEF University, and Cihan Yalçın, CBRT

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

TÜRKİYE CUMHURİYET
MERKEZ BANKASI

Exports, Real Exchange Rates and External Exposures: Empirical Evidence from Turkish Manufacturing Firms

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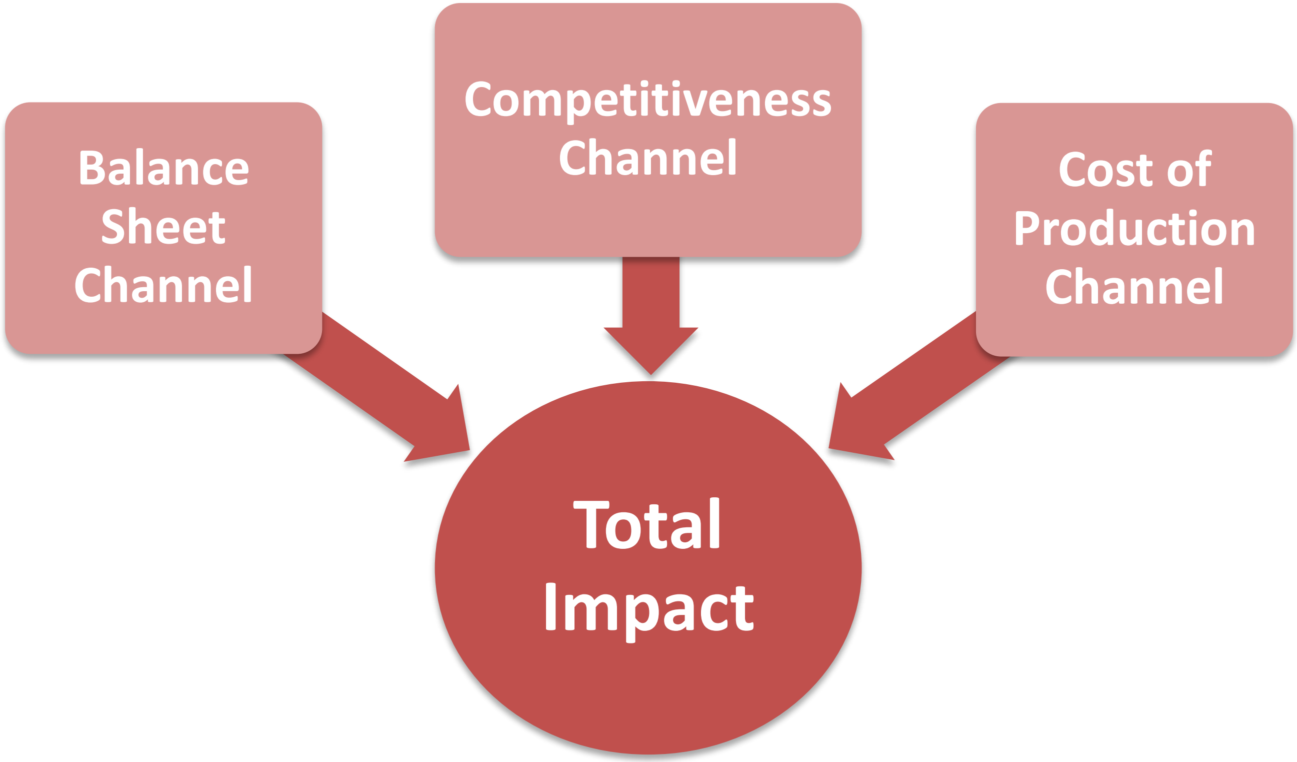
IFC / ECCBSO / CBRT Conference on
“Uses of Central Balance Sheet Data Offices’ information”, İzmir, September 26th, 2016

Motivation

- A policy question: Do exports respond to real exchange rate changes?
- Studies using macro data report insignificant results (Exchange rate disconnect puzzle) Dekle et al. 2008
- Firm level evidence suggests a significant response. Fitzgerald and Haller (2008), Dekle and Ryoo (2007), Tybout and Roberts (1997)
- The empirical trade literature has so far paid little attention to the possible effects of foreign exchange exposures, except few studies such as Campa and Goldberg (1997) and Greenaway et al. (2010) and recently Ahmed et al. (2015)
- Turkish manufacturaing firms that are highly exposed to FX denominated costs provides an opportunity to test the role of FX exposures in the response of exports to real exchange rates

Exchange rates and exports



	Balance Sheet	Competitiveness	Cost of Production
Depreciation	(-)	(+)	(-)

Contribution of the paper

- Adds to the literature on the impact of currency variations on firms' exports in the context of a developing country.
- Investigate the impact of exchange rates on firms' exports controlling for
  - Foreign exchange exposures in the forms of imported inputs (sectoral), liability dollarization or FX debt-exports ratio
  - Productivity
  - Firm-level financial ratios including collateral and leverage
  - Macro variables: volatility, domestic and external demand

Main findings

- A real depreciation of TRY has a positive impact on the intensive margins of exports.
- This impact is lower for firms operating in sectors that use imported inputs intensively
- For “naturally hedged" firms, the sensitivity of exports to exchange rate variations is estimated to be weaker.
- The exports of SMEs and young firms seem to be more sensitive to the exchange rate variations

Literature

New-new trade theory (Melitz, 2003) suggests significant barriers to engaging in exporting activity (sunk costs).

Sunk costs "form of investment that need to be financed".

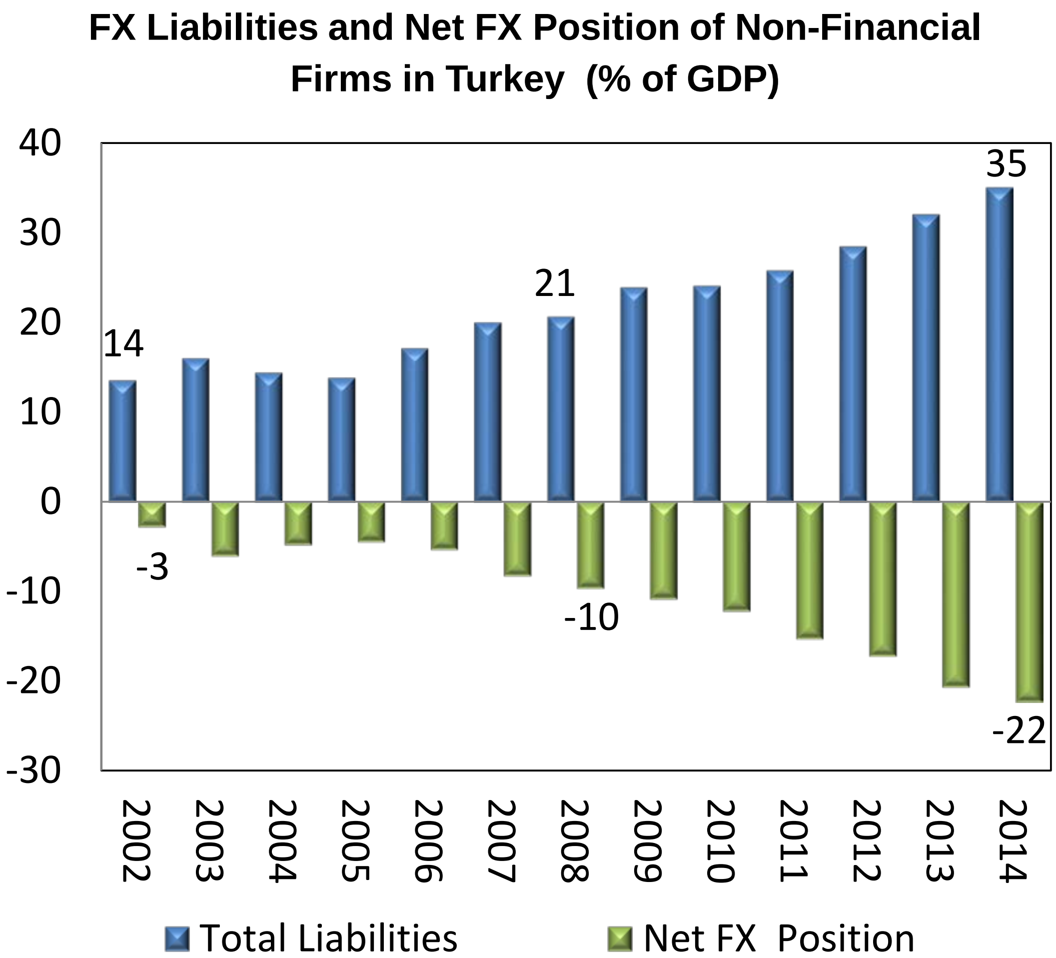
- Financial constraints is an important determinant of exporting decision at firm-level (Greenaway, 2007; Minetti and Zhu,2011; Muuls; 2015)
- Disconnection between productivity and exporting when financial constraints dominate (Berman and Hericourt, 2010; Liu and Li, 2015)

Few studies incorporating the exchange rates and FX exposure dimensions in the analysis of financial constraints and exports.

FX exposures of non-financial firms in Turkey

- Low domestic savings
- Limited local currency denominated funds and the need for FX denominated funds
- High FX denominated debt of non-financial firms: more than half of total debts in their balance sheets
- Large currency mismatches of non-financial firms. The net foreign exchange position of non-financial firms in Turkey reached to 187 billion USD as of February 2016, representing roughly 25% of GDP.

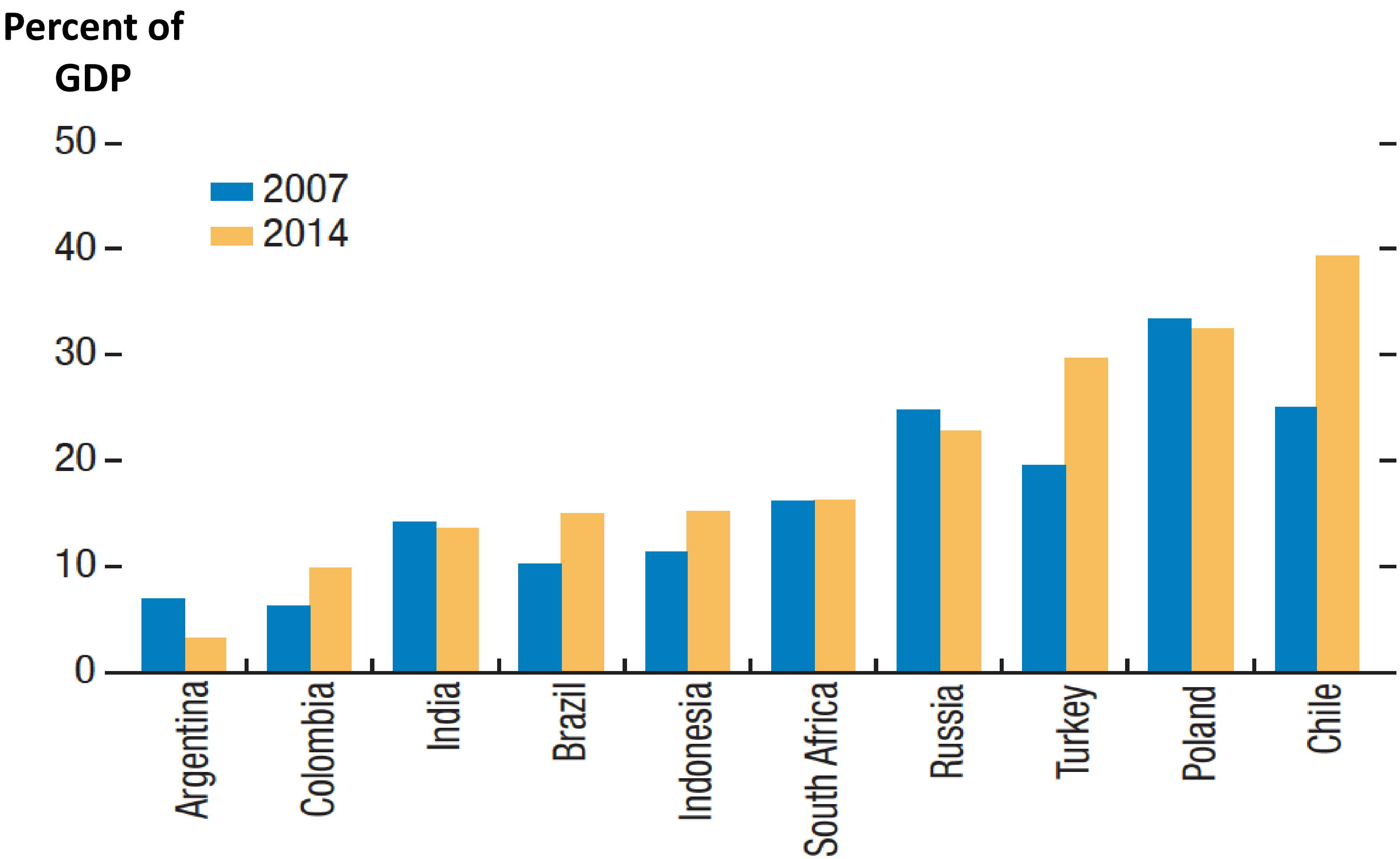
FX exposures of non-financial firms in Turkey



Source: Central Bank of Turkey

- FX liabilities of non-financial firms reached to 35 percent of GDP in 2014 from 14 percent in 2002 and short net foreign exchange (FX) position of these firms have increased from 3 percent of GDP to 22 percent in the same period.

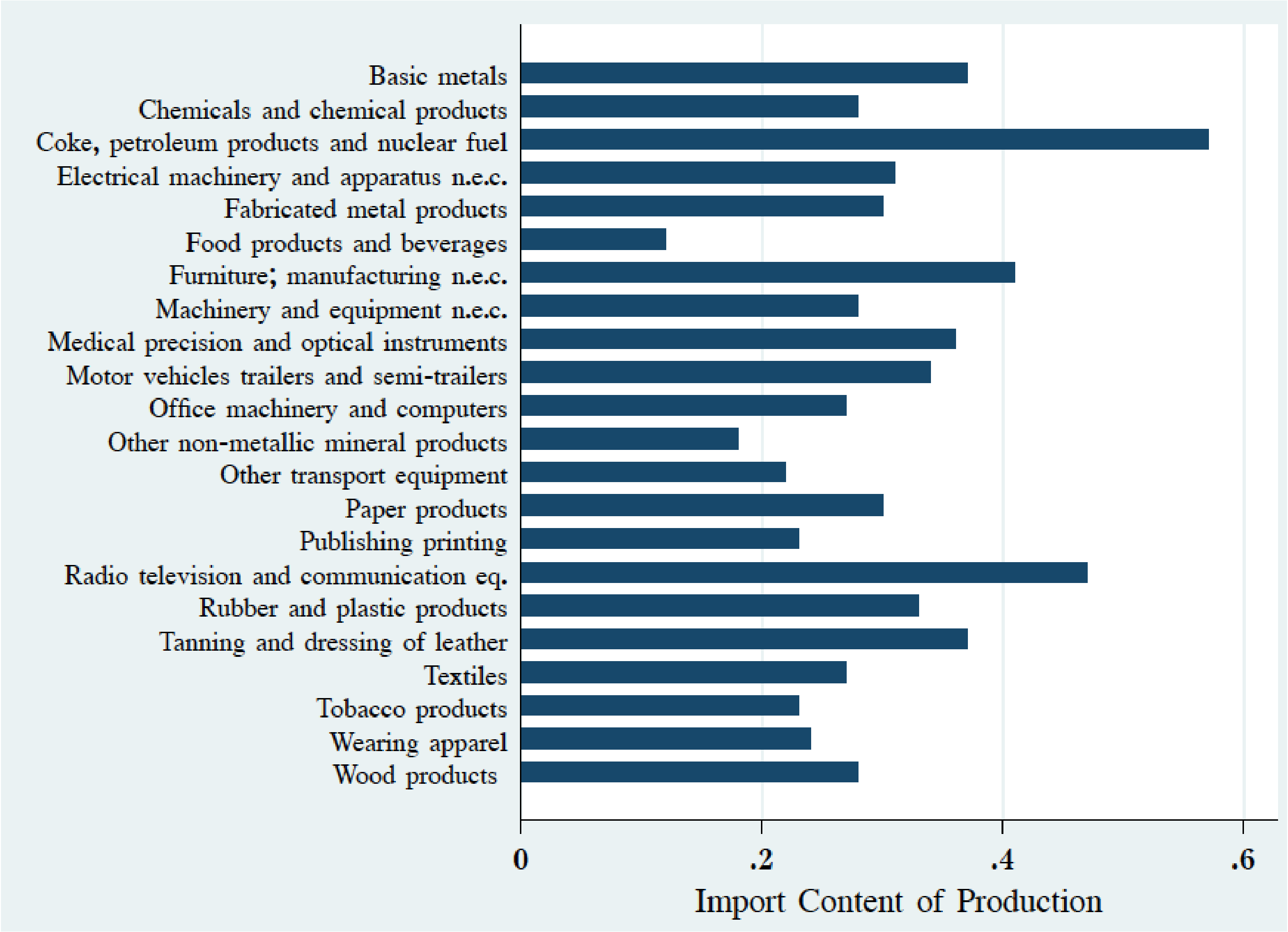
Foreign currency debt of non-financial firms and households



Sources: IMG Global Financial Stability Report. Note: Foreign Currency Debt comprises domestic loans, international loans and international bonds.

Imported input content of production

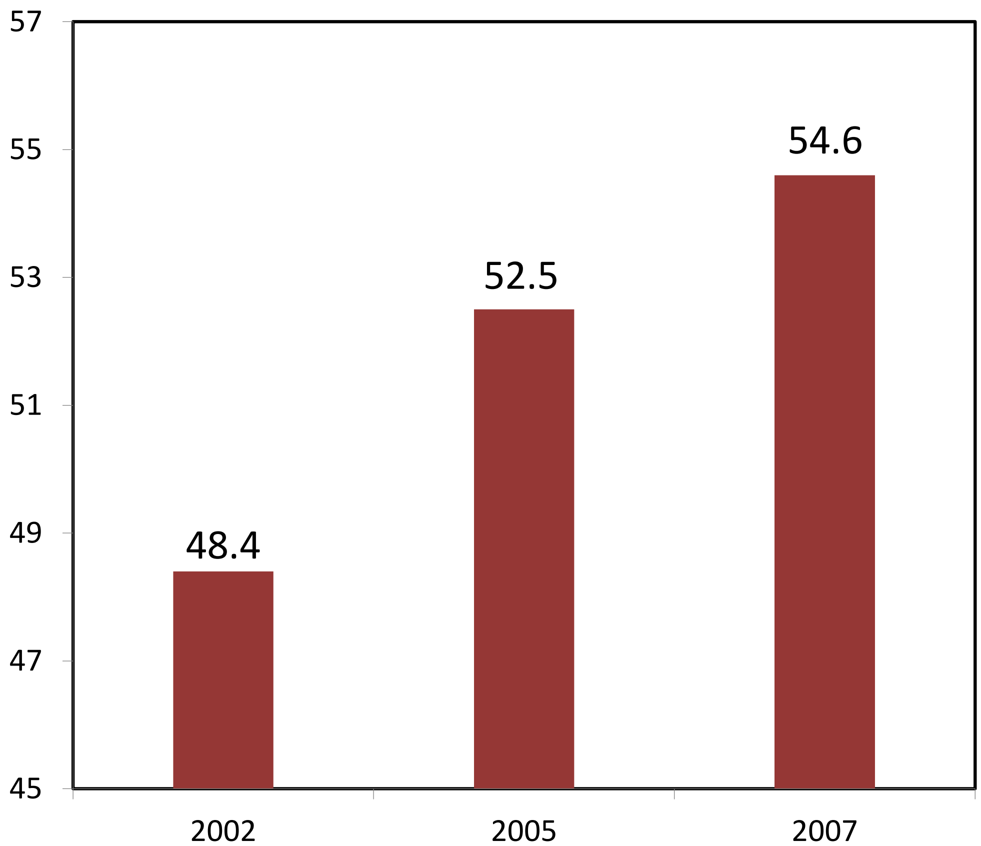
Shares of import in the production value based on 2002 input output tables



Source: Saygili et al. (2010)

Import content of production

The Share of Imported Intermediate Inputs in Total Cost of Production (Percent)

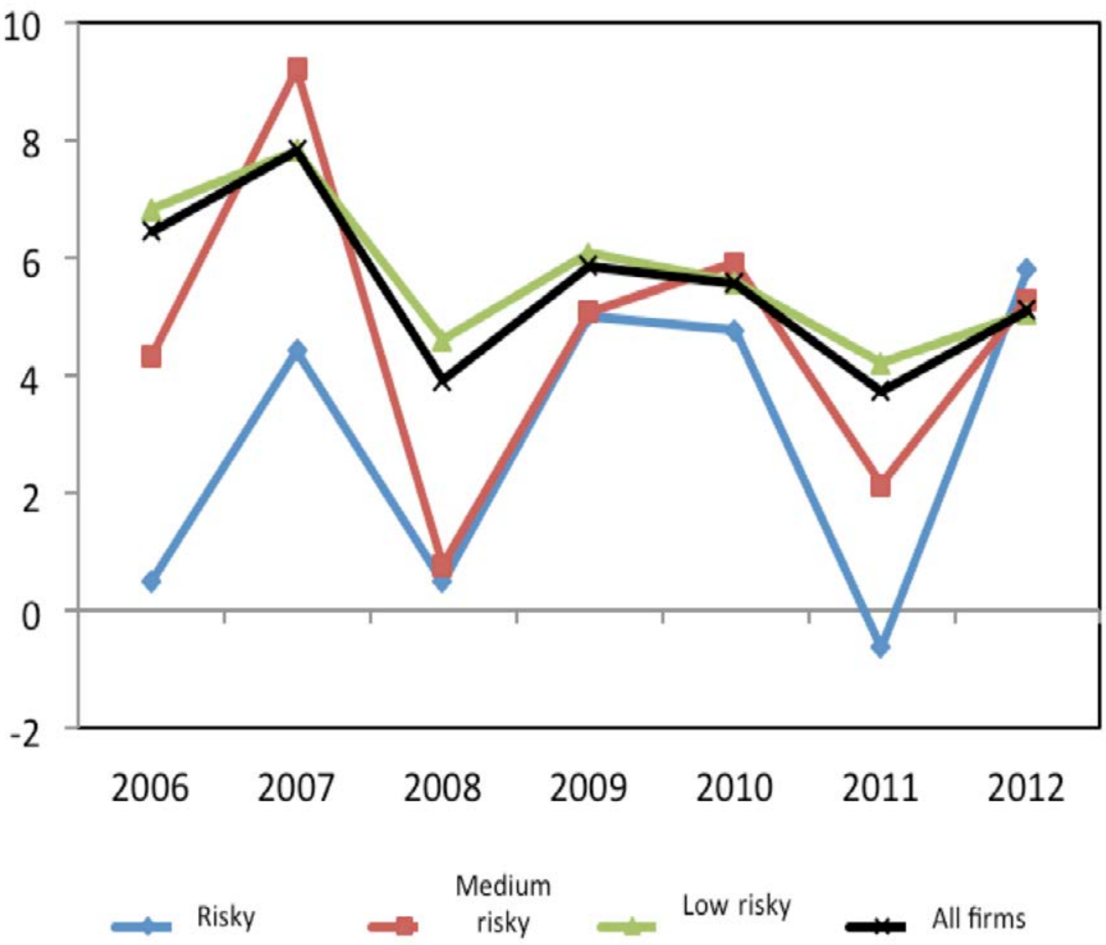


Source: Saygılı, Cihan, Yalçın and Hamsici (2010)

- Turkish economy is characterized by a large trade deficit.
- Trade deficit has deteriorated further in recent years resulting from increasing trend in imports which have grown rapidly due to the increasing imported input content of domestic production especially after 2001
- Intermediate goods imports which has been always larger than exports of goods, reached 22 percent of GDP in 2014.

Foreign exchange exposures and profit margins

Profit margins of non-financial firms (%)



- Net profit margins of firms with poor natural hedging (risky firms) melt down significantly when Turkish lira depreciated sharply during the post-2008 financial crisis period.
- Firms that are able to match the currency composition of their debt with their income streams, so called low-risk firms, seem to be affected from currency depreciations to a lesser extent.

Source: Hülagü and Yalçın (2014)

The data

- Central Bank of Turkey - Company Sector Database
- Banks's Association of Turkey - Risk Center Database
- Annual data for the period 2002-2010
- 3860 firms belonging to 21 industries (over 90% of total manufacturing exports)
- All the real values are deflated using the sectoral-level PPI
- Industry specific exchange rates
- Weighted average of OECD countries's GDPs (constant prices)
- Domestic GDP
- We classify firms according to sectoral imported input intensity, dollarization ratio, currency mismatch (FX-denominated debt-exports ratio) size, age

Descriptive statistics - Size and Age

	N	Mean	Min	Max
Log of Labour Productivity				
Small	5755	11.60	5.00	17.00
Medium	12126	11.63	7.00	18.60
Large	6164	11.74	7.00	19.30
Log of Real sales				
Small	5755	15.12	8.00	19.60
Medium	12126	16.50	11.00	23.60
Large	6164	18.19	12.00	23.80
Log of Real Exports				
Small	5755	12.78	0.00	18.60
Medium	12126	14.31	1.00	23.20
Large	6164	16.27	3.00	22.00
Export Share (Exports/ Total sales)				
Small	5755	0.27	0.00	1
Medium	12126	0.30	0.00	1
Large	6164	0.35	0.00	1
Employment				
Small	5755	32	3	50
Medium	12126	125	50	249
Large	6164	751	249	17482

	N	Mean	Min	Max
Log of Labour Productivity				
Young	6979	11.58	4.74	19.00
Medium age	11144	11.60	7.93	17.00
Mature	5824	11.83	6.94	19.00
Log of Real sales				
Young	6979	16.22	8.18	21.00
Medium age	11144	16.52	8.35	24.00
Mature	5824	17.23	10.25	24.00
Log of Real Exports				
Young	6979	13.93	0.22	20.00
Medium age	11144	14.43	1.10	22.00
Mature	5824	15.11	1.47	23.00
Export Share (Exports/ Total sales)				
Young	6979	0.30	0.00	1
Medium age	11144	0.33	0.00	1
Mature	5824	0.28	0.00	1
Employment				
Young	6979	169	3	4105
Medium age	11144	223	4	4527
Mature	5824	455	5	17482

- Labor productivities increase with size and age. Sales increase with age.
- Exports shares incrase with size. Mature firms have lower export shares.

Descriptive statistics - Size and Age

	N	Mean	Min	Max		N	Mean	Min	Max
Age					**Age**				
Small	5733	21.11	3	110	*Young*	6979	13.65	3	17
Medium	12068	24.16	3	134	*Medium age*	11144	23.27	17	30
Large	6146	28.27	4	122	*Mature*	5824	39.79	30	134
Dollarization Ratio					**Dollarization Ratio**				
Small	5755	0.38	0	1	*Young*	6979	0.51	0	1
Medium	12126	0.52	0	1	*Medium age*	11144	0.52	0	1
Large	6164	0.61	0	1	*Mature*	5824	0.50	0	1
Leverage Ratio					**Leverage Ratio**				
Small	5755	0.6	0	3.20	*Young*	6979	0.61	0	5.00
Medium	12126	0.58	0	5.10	*Medium age*	11144	0.57	0	5.00
Large	6164	0.54	0	3.40	*Mature*	5824	0.54	0	4.00
Collateral Ratio					**Collateral Ratio**				
Small	5755	0.25	0	1	*Young*	6979	0.28	0	1
Medium	12126	0.28	0	1	*Medium age*	11144	0.28	0	1
Large	6164	0.32	0	1	*Mature*	5824	0.3	0	1

- On average, larger firms are older, highly dollarized and have low leverage and high collaterial ratios.
- Young firms are more leveraged and dollarized compared to mature firms.

Descriptive statistics - Export status

	N	Mean	Min	Max
Log of Labour Productivity				
Non-exporter	2934	11.46	5.03	16.86
Low - Exporter	2014	11.78	7.75	16.64
Med. - Exporter	14236	11.68	4.74	16.93
High - Exporter	7795	11.56	6.84	19.29
Log of Real sales				
Non-exporter	2934	14.96	5.25	20.46
Low - Exporter	2014	16.45	12.19	22.41
Med. - Exporter	14236	16.6	8.18	23.82
High - Exporter	7795	16.64	10.2	23.6
Employment				
Non-exporter	2934	64	1	1852
Low - Exporter	2014	221	3	10726
Med. - Exporter	14236	250	3	17482
High - Exporter	7795	299	5	5245
Age				
Non-exporter	2906	21	5	77
Low - Exporter	2002	23	4	134
Med. - Exporter	14173	25	3	122
High - Exporter	7772	24	3	110

	N	Mean	Min	Max
Dollarization Ratio				
Non-exporter	2934	0.09	0	1
Low - Exporter	2014	0.28	0	1
Med. - Exporter	14236	0.46	0	1
High - Exporter	7795	0.66	0	1
Leverage Ratio				
Non-exporter	2934	0.59	0	3.81
Low - Exporter	2014	0.54	0	1.92
Med. - Exporter	14236	0.57	0	4.67
High - Exporter	7795	0.59	0	5.13
Collateral Ratio				
Non-exporter	2934	0.28	0	0.99
Low - Exporter	2014	0.3	0	0.97
Med. - Exporter	14236	0.28	0	0.97
High - Exporter	7795	0.28	0	0.99

- Exporters on average have higher employment, labor productivity and real sales than non-exporters.
- Exporters have higher dollarization rate than non-exporters.

Descriptive statistics – Imported inputs intensity

	N	Mean	Median	Sd	Min	Max
Log of Labour Productivity						
High III	9485	11.74	11.64	0.96	6.94	19.29
Low III	14560	11.59	11.5	0.93	4.74	16.34
Log of Real sales						
High III	9485	16.64	16.54	1.66	8.35	23.82
Low III	14560	16.58	16.56	1.46	8.18	22.41
Employment						
High III	9485	247.58	109.43	551.77	3	6796
Low III	14560	273.35	125	657.14	3	17482
Age						
High III	9464	25.42	24	11.04	3	110
Low III	14483	23.87	22	11.07	3	134
Dollarization Ratio						
High III	9485	0.46	0.49	0.4	0	1
Low III	14560	0.54	0.72	0.41	0	1
Leverage Ratio						
High III	9485	0.56	0.57	0.25	0	3.5
Low III	14560	0.58	0.58	0.27	0	5.13
Collateral Ratio						
High III	9485	0.28	0.26	0.18	0	0.97
Low III	14560	0.28	0.26	0.19	0	0.99

- Firms operating in sectors that use higher imported inputs have higher productivity and lower dollarization rate, export shares and employment,
- Significant variations in collateral ratios, leverage ratios, real sales, and real export values between low and high-imported input intensities sectors

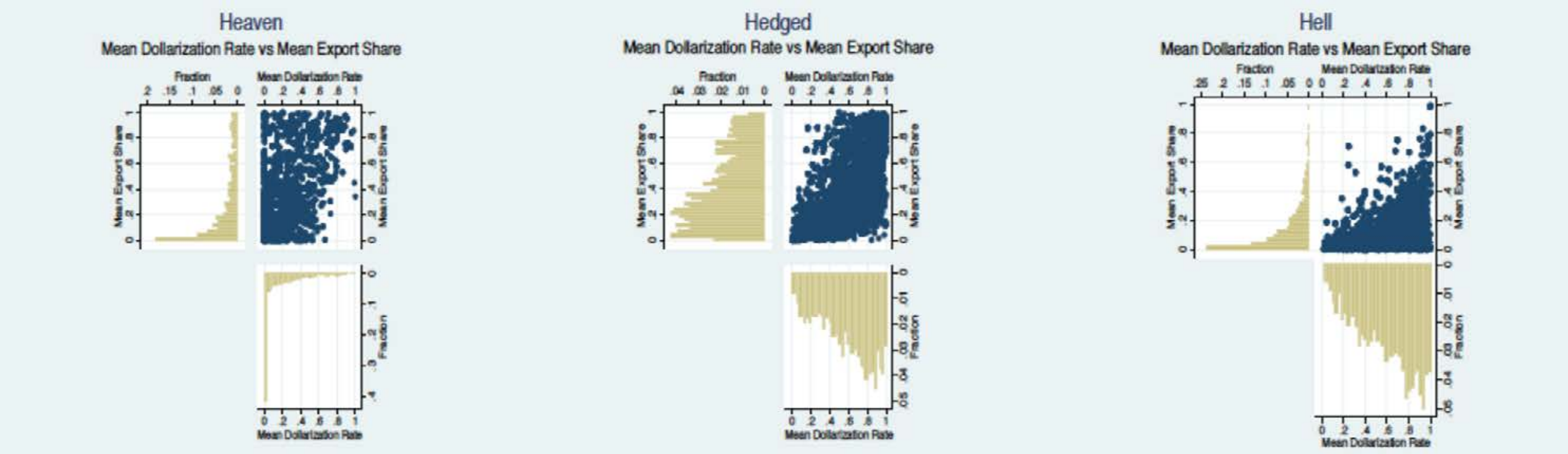
Descriptive statistics – Currency mismatch

	N	Mean	Min	Max
Log of Labour Productivity				
Hell	5863	11.71	4.74	16.93
Hedged	13561	11.69	7.06	19.29
Heaven	4621	11.47	8.21	16.17
Log of Real sales				
Hell	5863	16.79	8.18	22.62
Hedged	13561	16.74	10.63	23.6
Heaven	4621	15.97	8.35	23.82
Employment				
Hell	5863	252	5	5556
Hedged	13561	284	3	7967
Heaven	4621	217	3	17482
Age				
Hell	5830	23.67	3	122
Hedged	13521	24.96	4	93
Heaven	4596	24.12	3	134

	N	Mean	Min	Max
Dollarization Ratio				
Hell	5863	0.63	0	1
Hedged	13561	0.6	0	1
Heaven	4621	0.09	0	1
Leverage Ratio				
Hell	5863	0.61	0	3.39
Hedged	13561	0.58	0	5.13
Heaven	4621	0.51	0	3.83
Collateral Ratio				
Hell	5863	0.33	0	1
Hedged	13561	0.27	0	1
Heaven	4621	0.26	0	1
Log of Real Exports				
Hell	5863	13.37	1.1	21.88
Hedged	13561	15.24	1.32	23.24
Heaven	4621	13.48	0.22	22.00
Export Share (Exports/ Total sales)				
Hell	5863	0.14	0	1
Hedged	13561	0.4	0	1
Heaven	4621	0.26	0	1

- Firms under the hell category tend have lower export shares, higher tangible assets, and liability dollarization and leverage ratios.
- Firms in the heaven region, are relatively smaller in terms of both employment and real sales, have lower dollarization and leverage ratios. In terms of exporting, they in general export more than firms in the hell region but still considerable lower than firms in the hedged area.
- Firms in the hedged region have high export shares and they are slightly older than their counterparts in the heaven and hell regions.

FX denominated debt-export ratios



- Firms in heaven have an export share distribution skewed to the left ranging between 0 and 1
- The distribution of the dollarization ratio suggest that they tend to not carry foreign exchange denominated debt

- Firms belonging to the hedge region carry out both export and substantial amount of foreign currency debt.
- Firms in hedged region possess both high export share and liability dollarization ratio.

- Firms in the hell region are characterized by low export shares and high dollarization rates.

Statistics summary

- Labor productivities increase with size and age. Sales increase with age.
- Exports shares incrase with size. Mature firms have lower export shares.
- Larger firms are older, highly dollarized and have low leverage and high collateral ratios.
- Young firms are more leveraged and dollarized compared to mature firms.
- Exporters on average have higher labor productivity, real sales than non-exporters.
- Exporters have higher dollarization rate than non-exporters.
- Firms operating in sectors that use higher imported inputs have higher productivity and lower dollarization ratio, export shares and employment
- Firms under the hell category tend have lower export shares, higher tangible assets, and liability dollarization and leverage ratios.
- Firms in the heaven region, are relatively smaller in terms of both employment and real sales, have lower dollarization and leverage ratios.
- Firms in the hedged region have high export shares and they are slightly older than their counterparts in the heaven and hell regions.

Empirical model

➢ The baseline specification

$$\ln(X_{it}) = \alpha_1 \ln(RER_{jt}) + \alpha_2 VOL_t + \alpha_3 Z_{it} + \alpha_7 ln(GDP_t^D) \quad + \alpha_8 ln(GDP_t^F) \ + \ \tau\mu_i + \varepsilon_{it}$$

➢ The extended specification

$$\ln(X_{it}) = \alpha_1 \ln(RER_{jt}) + \alpha_2 VOL_t + \alpha_3 Z_{it} + \alpha_7 GDP_t^D + \alpha_8 GDP_t^F + \boldsymbol{\alpha_9 (FCD \times ln\ (RER_{jt}))} + \tau\mu_i + \varepsilon_{it}$$

- ***Z*** consists of firm specific variables: the log of labor productivity, log of real sales, liability dollarization ratio, leverage ratio, collateral ratio.
- We use levels and changes of log of exchange rates and labor productivity alternatively
- ***FCD*** are firm-specific dummies and interacted with real exchange rate to control for;
  - ➢ Sectoral import intensity
  - ➢ Liability dollarization
  - ➢ Natural hedging position
  - ➢ Size and age age

Estimation method

- Differenced GMM to consider dynamic aspects and control for potential endogeniety
- Liability dollarization ratio, log of labor productivity (change and its level), and log of real sales are treated as endogenous variables
- Using up to three lagged values of these variables and dependent variable (log of real exports) as the GMM-type instruments
- Macro variables and sectoral real exchange rates (change and its level) are employed as standard differenced instruments
- Second order autocorrelation tests (arm2) do not reject the hypothesis of no serial correlation in the error terms for almost all regressions.
- The Sargan tests do not reject the hypothesis of the validity of over-identifying restrictions almost in all regressions suggesting that instruments are valid
- Estimation period of 2002-2010 when flexible exhange rate regime was effective

Findings-1

- Real exports has an inertia and the coefficient of its lag is estimated in the range of 0.20-0.25 in all specifications.
- ***The exhange rate elasticity of exports*** is estimated around 3 percent, a ten percent depreciation of the exhange rate is estimated to increase exports about 3 percent.
- The coefficient of the change in labor productivity is estimated to be positive and significant
- Sales seem to affect exports positively.

	(1)	(2)	(3)	(4)
$lrexp_{i,t-1}$	0.198***	0.254***	0.230***	0.254***
$\ln(RER_{jt})$	-0.319**	-0.276*		
$\Delta(\ln(RER_{jt}))$			-0.340***	-0.230***
$\ln(LP_{it})$	0.160		-0.202	
$\Delta(\ln(LP_{it}))$		0.530***		0.338**
$\ln(lrsale_{it})$	1.088***	0.824***	1.117***	0.878***

Findings-2

- Liability dollarization is estimated to support exports significantly, probably due to its role of undermining financial constraints.
- Firms with low tangible total assets ratios are estimated to have high export performance in general while the coeffcient of leverage ratio is insignificant in all specifications.
- Exchange rate volatility seem to curb export even though its coefficents is not significant in most cases.
- External demand seems to not support firm exports.

	(1)	(2)	(3)	(4)
$Dolratio_{it}$	0.424**	0.323	0.525***	0.412**
$Collateral_{it}$	-1.026	0.361	-2.155**	-0.501
$Leverage_{it}$	0.218	0.739	0.260	0.584
$\ln(GDP_t^F)$	1.489	3.735***	0.501	2.360
$\ln(GDP_t^D)$	-1.488**	-2.620***	-1.294**	-2.173***
VOL_t	-0.004	-0.007**	-0.003	-0.006**

Findings-3

- The exports of firms operating in sectors with high import intensitiy is estimated to be less sensitive to the change in real exchange rates
- The exports of firms with high FX debt-export ratio (hell) are more sensitive to real exchange rates.
- The exports of firms with moderate FX debt-export ratio (hedged) are less sensitive to real exchange rate.

	Import Intensity		Heaven		Naturally Hedged		Hell	
$\ln(RER_{jt})$	-0.392**		-0.274		-0.680***		-0.075	
$\Delta(\ln(RER_{jt}))$		-0.270***		-0.245***		-0.450***		-0.107
$\ln(RER_{jt})*IM_j$	0.344*							
$D(\ln(RER_{jt}))*IM_j$		0.099						
$\ln(RER_{jt})*HEAVEN_i$			0.003					
$\Delta\ln(RER_{jt})*HEAVEN_i$				0.074				
$\ln(RER_{jt})*HEDGED_i$					0.639***			
$\Delta\ln(RER_{jt})*HEDGED_i$						0.384***		
$\ln(RER_{jt})*HELLi$							-0.845***	
$\Delta\ln(RER_{jt})*HELL_i$								-0.552***

Findings-4

- Exports of medium, small and young firm groups are generally more sensitive to the real exchange rates.
- Large and mature firms are generally hedged against exchange rate fluactuations.
- Political economy outcome: unlike SMEs and young firms, they did not react to persistent currency appreciations in 2000s.

	Large		SMEs		Old		Young	
$ln(RER_{jt})$	-0.449**		-0.127		-0.407**		-0.191	
$\Delta(ln(RER_{jt}))$		-0.260***		-0.132		-0.272***		-0.189**
$ln(RER_{jt})*LARGE_i$	0.576***							
$\Delta ln(RER_{jt})*LARGE_i$		0.111						
$ln(RER_{jt})*SMEs_i$			-0.300*					
$\Delta ln(RER_{jt})*SMEs_i$				-0.194				
$ln(RER_{jt})*OLD_i$					0.411**			
$\Delta ln(RER_{jt})*OLD_i$						0.144		
$ln(RER_{jt})*YOUNG_i$							-0.449*	
$\Delta ln(RER_{jt})*YOUNG_i$								-0.202

Concluding remarks

- Contrary to macro evidence, analysis based on firms data suggests that exports of Turkish manufacturing firms are sensitive to real exchange rates.
- This sensitivity is smaller for firms operating in sectors with high import content, and those are naturally hedged, large and mature.
- The exports of firms with high currency mismatch are more sensitive to the change in real exchange rates. It seems competitiveness channel dominates the cost of production and the balance sheets channels.
- Evidence implies that liability dollarization undermines financial constraints and thus supports exports even though it might have negative impact on firms’ profitibility in cases of large depreciation due to currency mismatch.

Thank you for listening..

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Foreign ownership and performance: evidence from a panel of Italian firms[1]

Chiara Bentivogli and Litterio Mirenda,
Bank of Italy

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

Foreign ownership and performance: Evidence from a panel of Italian firms

by Chiara Bentivogli* and Litterio Mirenda†

Abstract

The paper studies the impact of foreign ownership on a firm's economic performance. We use a unique panel dataset to test the foreign ownership premium by comparing our sample of firms based in Italy and owned by a foreign subject with a sample of purely domestic firms that, in order to have a proper counterfactual, were selected using propensity score matching. Our difference-in-differences results show the existence of a premium for the size, profitability and financial soundness of the foreign-owned companies. The premium increases with time, is concentrated in the service sector, and disappears if the foreign investor is based in a fiscal haven.

JEL Classification: F23, F61

Keywords: Multinational enterprise; ownership; foreign direct investment, firm performance.

Contents

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1. Introduction[1]

Foreign direct investment (FDI) plays an important role in the world economy. In 2014 FDI stock reached a volume of more than US$ 26 trillion, rising from an average of US$14 trillion in the three years before the financial crisis; employment of foreign affiliates reached 75 million (Unctad, 2015).

The size and pervasiveness of FDI in the world motivate the analysis of the effects of FDI on national economies and, in particular, the performance comparison of foreign-controlled firms *vis-à-vis* domestic-owned ones in order to assess the existence of systematic differences due specifically to foreign acquisition. The topic is of interest for economic policy, as it could give analytical support to the implementation of policies to attract or discourage foreign investment.

Two main streams of theoretical literature dealing with different performances of foreign-controlled firms can be identified:

1. the first one is related to the general hypothesis of the existence of advantages for multinational companies (MNEs) over purely domestic firms (Hymer, 1960; Dunning, 1988). In a context of within-sector firm heterogeneity in productivity, only the more productive companies engage in FDI, given that entry into a foreign market involves high fixed costs (Helpman *et al.*, 2004). This, in turn, implies that improvement in the performance of a foreign-owned firm depends on the transfer of proprietary assets from its MNE parent company (ex-post forward linkages). According to this stream of literature, foreign investors are indeed able to transfer superior technology and organizational practices to potential local subsidiaries (Barba Navaretti and Venables, 2004), thus generating a foreign ownership premium (FOP);

2. the second one derives from the market for corporate control literature; this stream highlights the importance of the ex-ante selection bias as the key factor that explains the different performance of foreign-controlled firms. According to Manne (1965) well-performing foreign firms choose underperforming companies for their acquisitions, (negative selection) in order to remove inefficient managers and fully exploit the firm's potential. Negative selection could also emerge from high information asymmetries about the quality of the acquired local company. It could also be the case that, on the contrary, international acquisition only happens to the (ex-ante) best domestic firms, so that their superior performance is partially due to the selection process (positive selection).[2] Guadalupe *et al.* (2012) explain se-

[1] The views expressed in the articles are those of the authors and do not necessarily correspond to those of the Bank of Italy. We would like to thank Alessandro Borin, Ines Buono, Andrea Carboni, Sauro Mocetti, Valeria Pellegrini and two anonymous referees for their useful suggestions and comments.

[2] Negative and positive selection are also mentioned in the literature as, respectively, 'lemon-grabbing' and 'cherry-picking' effects.

lection in terms of complementarities between foreign and domestic firms' characteristics. As an example they cite the introduction of a new product into a foreign market through the acquisition of a domestic firm, which will be more valuable the greater the marketing abilities of the acquired firm.

The empirical tests of these two strands of literature on foreign acquisition use very different strategies. While the positive/negative/complementary selection hypotheses require a test on the ex-ante differences (in terms of economic performance and structural features) between the foreign acquired firms and the purely domestic ones, the foreign ownership premium (FOP) hypothesis entails the identification of the causal effect of foreign acquisition on the ex-post performance of the foreign-owned firm. However, the two theories discussed are not mutually exclusive but rather coexist. This implies that FOP testing requires controlling for the endogeneity of the selection process, in order to disentangle the differences in performance due to ex-ante factors from those due to the acquisition itself.

Empirical studies have investigated the selection process with mixed conclusions. Many authors find evidence of positive selection. Looking at the Spanish case, Guadalupe *et al.* (2012) find evidence of foreign acquisition of the most productive firms within industries; Blonigen *et al.* (2012) find a higher probability of foreign acquisition of domestic companies with higher productivity levels some years before the acquisition. Weche Gelübcke (2013) finds that German manufacturing firms with above average productivity are more likely to become targets for foreign takeovers. At the same time, Weche Gelübcke shows that the exact opposite is true regarding profitability, as very low performing firms are MNEs' favourite targets. Evidence of negative selection due to information asymmetries is less common. One example is the analysis of Gioia and Thomsen (2004) which identifies negative selection for Danish companies acquired by MNEs in the nineties.[3] However, a major limitation of these studies is that, in general, positive or negative selection is analysed without considering the element of price in driving the acquisition decision together with performance characteristics. Indeed, the price could make an acquisition a good deal or a bad deal depending on the associated firm's 'quality'.

Most of the empirical studies on foreign ownership premium converge on the its existence, mainly in productivity and wages. Arnold and Javorcik (2009) find that a set of performance variables for Indonesia, including wages and productivity, increase under foreign ownership. Guadalupe *et al.* (2012) find that, after controlling for selection, acquired firms increase their process innovation. Girma and Gorg (2007) find positive wage effects for UK companies after an acquisition by a US MNE. Criscuolo and Martin (2009) find that US- owned plants have a significant productivity advantage in the United Kingdom, in relation to both British MNEs and

3 For Italian firms, Mattevi (2014) finds positive selection: before the acquisition, foreign-controlled firms are bigger and more export-oriented than domestic firms. Crinò and Onida (2007) find positive selection only in manufacturing firms in the Italian region of Lombardy. Castellani and Zanfei (2004) do not find positive selection for a sample of Italian manufacturing firms in the years 1997-2000.

other foreign- owned plants. Bandick *et al.* (2014) find FOP for foreign-controlled firms' R&D in Sweden.[4]

This paper belongs to the FOP vein of literature: we test the existence of a causal relationship between foreign acquisition and the economic performance of the acquired Italian firms. Following previous works, we select an identification strategy that allows us to control for the endogeneity of the selection process. Our contribution to this strand of literature is mainly the database that we use and the variables chosen as performance indicators:

1. we update previous empirical work by building and exploiting a matched firm-shareholder panel containing information on firms' balance sheets and on the shareholders; the dataset is obtained from the administrative register and includes almost all the Italian limited companies for seven years (from 2007 to 2013). Previous works mainly use small samples often focused on a single industry (e.g. Guadalupe *et al.* (2012) use a panel of manufacturing firms, Girma and Gorg (2007) focus on electronics and food and Piscitello and Rabbiosi (2005) work on manufacturing). Moreover, this is the first empirical FOP analysis of the Italian economy for the period that covers most of the recent economic crisis. Studying FDI during the most recent crisis is interesting, since foreign acquisition has been an important part of firms' toolboxes for reacting to the crisis. On the other hand, the crisis should not distort the results of the analysis because our empirical strategy (see below) controls for the heterogeneous effects of the crisis on the firms in our sample;

2. we test FOP on selected balance sheet indicators in order to investigate the effect of FDI on three different features of a firm's performance: size, profitability and financial soundness. These characteristics are of interest for policy purposes as they complement the analysis on FOP based on productivity and wages, given that productivity and wage premiums have been extensively studied up to now.[5] Indeed, size is an important source of competitive advantage for several reasons, the most important of which is the exploitation of economies of scale. Secondly, profitability is the ultimate indicator of a firm's success and the main engine of an entrepreneur's activity. Lastly, financial soundness is often disregarded by the literature, yet it is crucial to ensure a steady growth for a firm and to insulate it from market volatility. Specifically, we consider net sales as a proxy for size, return on equity and cash flow on assets as measures of profitability, and financial debt on assets together with a comprehensive credit risk indicator to identify financial soundness.

In order to evaluate FOP, our empirical strategy is to apply a difference-in-differences (DID) methodology considering foreign participation as the 'treatment'. This allows us to control for all observable and unobservable time-invariant variables that influence the acquisition decision and the outcome. As the literature on

4 For Italy, Piscitello and Rabbiosi (2005) find FOP on labour productivity in the nineties, while Benfratello and Sembenelli (2006) exclude it.

5 See the survey of the literature on FOP discussed above.

the selection process points out, we are still left with the problem of non-random sample selection. We approach this problem by combining DID with propensity score matching (PSM), which restricts the control sample to firms with similar observable pre-acquisition characteristics. These firms are used as a counterfactual, i.e. they proxy how the foreign owned firms would have behaved had they not been acquired by foreign firms.

PSM and DID have been widely used in the FOP literature, but as far as we know they have been applied to other performance variables, or to test the effects of an internationalization strategy on investing firms. Among others, the abovementioned Girma and Gorg (2007) use PSM and DID to test FOP on wages, Arnold and Javorcik (2009) on productivity, investment, employment, and wages, Guadalupe *et al.* (2012) on productivity, and Bandick *et al.* (2014) on R&D intensity after acquisition. Borin and Mancini (2015) use the PSM-DID strategy to test the foreign direct investment effect on investor performance. Despite the use of the same empirical strategy, a one-to-one comparison of our results with those on productivity and wages is hampered by the different information content of our outcome variables. Nonetheless, we believe that our findings can strengthen the general result for FOP in terms of the sign of the causal effect.

Looking at our results, our difference-in-differences matching estimates indicate that acquisition leads to better company results: several indicators of firms' performance improve after FDI, and the effect increases over time. Moreover, the effect of FDI on performance is significant only in services and disappears if the foreign investor is based in a fiscal haven.

The rest of the article is organized as follows: Section 2 describes the dataset and presents some preliminary statistics. Section 3 outlines the empirical strategy, while Section 4 focuses on econometric results and presents some robustness tests. Section 5 concludes.

2. Data description

We combine two different panels of data. The first one is the Infocamere database, which is taken from Italian official business registers managed by the association of Italian Chambers of Commerce. It contains exhaustive, current and historical vital statistics on firms and their ownership structure (domestic and foreign shareholders, participation shares and so on) covering about 1.12 million unlisted limited companies for 2010. Given its coverage, the Bank of Italy uses it to feed a register of foreign-owned firms, and to extract the sample for Direct Reporting (a survey used to compile the balance of payments statistics on FDI) from it. The second dataset is Cerved, a company accounts data system provided by the Cerved Group, which collects companies' balance sheets and indicators. The Cerved database covers a very large portion of Italian limited companies (about 965,000 balance sheets for 2010) providing detailed company balance sheet data.

In order to build our panel we extract a seven-year subset (from 2007 to 2013, the latest available year) from the Infocamere dataset and do some cleaning when the country of investor is missing and for other problems related to the administrative nature of the data. Then from the Infocamere subset we identify a group of firms with the following characteristics: 1) companies subject to foreign direct investment for the first time in 2010;[6] 2) the FDI gives a foreign investor a control share (≥ 50%); 3) companies remain under foreign control in the three years following 2010. This group of firms represents our 'treated' group (780 firms in 2010). We then merge this group with the Cerved database in order to attribute to each firm its annual balance sheet information for the whole period (2007-2013). Finally, we get a seven-year panel of 4,987 observations in which treated companies are observed for three years (from 2007 to 2009) before the treatment and for four years (from 2010 to 2013) after the treatment.

As far as purely domestic firms are concerned, we extract them from the Cerved database, with the constraint that they had no foreign investor for the whole period 2007-13 (checked with Infocamere).[7] This panel amounts to 2,903,794 observations.

Graph 1 plots the distribution by the size classes and industry groups of the two samples of data in 2009, one year before the foreign acquisition. It provides some evidence of a concentration of treated firms in the groups of a greater size, while 74% of the untreated firms have yearly net sales of at most € 2 million. Moreover, foreign acquisition is oriented towards specific sectors, i.e. consumer services, metalworking and firm services.

Graph a1 in the Appendix provides some evidence on the pre-acquisition difference between the two samples. We consider the following group of performance variables: i) net sales, a size variable; ii) ROE, return on equity, a profitability indicator; iii) value added to labour cost, which measures firms' competitiveness in terms of labour cost; iv) financial debt on assets, a measure of the financial structure and, indirectly, of financial soundness. We also consider some variables that proxy the structural characteristics of companies: i) knowledge intensity (intangible assets/total assets), a measure of the level of knowledge capital (e.g., brands, trademarks and patents) employed in the business; ii) vertical integration (value added/net sales), an indicator that proxies the number of stages of the production process performed within the confines of the firm, in relation to those carried out ex-

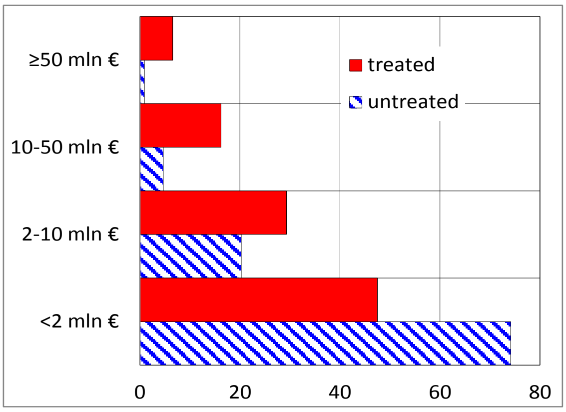
[6] The choice of 2010 allows us to have enough data before and after FDI.

[7] We apply some filters to Cerved data in order to select active, "comparable" companies. Financial (including holdings) and real estate companies have been excluded from the analysis.

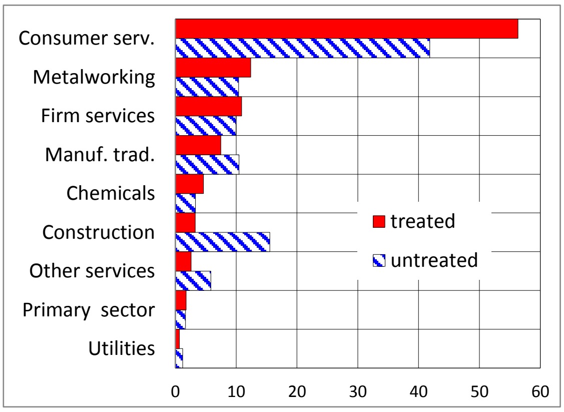
ternally; iii) age.[8] These variables, together with other controls, have been used in the probit model of the PSM procedure (see section 3).

Distribution by size and industry of treated firms and those that stay purely domestic (2009; percentages)
Graph 1

size (net sales)



industries



Source: Infocamere and Cerved.

In order to smooth the tails of the distribution and to eliminate some extreme outliers, we winsorize ROE at the 1% and 99% levels. Nevertheless, after winsorization, ROE still presents very long tails (with a mean of -1.2, and values ranging from -600 to 167); this feature is due to the high sensitivity of the ratio as equity reaches low levels, following for instance a sequence of negative economic results. Therefore, in order to handle the indicator more easily, we do some smoothing with a percentile filter for the ROE by replacing each data point with its percentile rank.

In Graph a1, in the left-hand column, pre-acquisition means (2007-09) of these variables for foreign-controlled (dotted lines) and purely domestic firms are compared. A mixed picture emerges: the former are older and have a greater size and a smaller financial debt on assets ratio, but lower profitability. Thus the graphic evidence of ex-ante characteristics does not confirm that positive selection is present in all the performance variables.

3. The strategy

We combine two different techniques: a difference-indifference (DID) estimation and a propensity score matching (PSM). The first one allows us to handle endogeneity related to time-invariant unobserved effects. The credibility of the DID estimator crucially relies on the assumption that in absence of the treatment, the average outcomes for treated and controls would have followed parallel trends over time. In order to address this concern and to select a more appropriate control sample we adopt a propensity score matching methodology that pairs each treated

8 See Table a1 for a complete description of the variables.

firm with 'similar' control units. This approach should strengthen the parallel paths hypothesis, allowing us to control for time-variant pre-treatment observables. The validity of PSM also rests on the conditional independence assumption (CIA). CIA holds when, conditional on the observed covariates used in the PSM, assignment to treatment is independent of the outcome. Unfortunately, this assumption is not directly testable, but we can assume it if we believe that we have included all the relevant variables in the PSM. We discussed the variable choice in chapter 2, and from this viewpoint we are confident about our selection of variables. Other tests on the quality of matching are presented in paragraph 4.1.

In the PSM we match FDI firms (treated) with non-FDI firms (controls). Specifically, we adopt nearest-neighbour matching, selecting the non-FDI firms with a (predicted) probability of being treated that is closest to that of the FDI firms. For each treated unit, we match the ten nearest neighbours, allowing a given non-FDI firm to be matched to more than one FDI firm.

We choose those presented in the previous paragraph as covariates; they represent performance and structural firm characteristics that we believe best fit the acquisition process. In our choice of covariates we follow the suggestions of the literature reviewed in the introduction: we choose performance variables that allow us to control for bias due to positive (or negative) selection. We also add a set of covariates for firms' characteristics that could drive the acquisition choice when it aims at exploiting some complementarities between a foreign and a domestic firm (Guadalupe *et al.*, 2012).[9]

We also add controls for sector effects (a full set of dummies for the groups of industries presented in graph 1), and per capita GDP of the area where the firm is located. In order to smooth the value of the pre-acquisition covariates chosen to find appropriate controls, we consider 2007-09 averages. The probit model of foreign acquisition can be represented as follows:

$$p_i = \Pr(D_i = 1|X_i) = \Phi(X_i{}'\beta + \varepsilon_i) \qquad (1)$$

where D_i is a binary variable describing treatment status: D=1 if the firm i becomes an MNE, and D=0 otherwise; X_i is a vector of observable characteristics in the three years before the acquisition, and Φ is a standard normal cumulative distribution function. Then we calculate the predicted probability of switching (propensity score) from domestic to foreign-controlled and we create a sample where for each foreign-controlled (treated) firm there are ten purely domestic firms (matched counterfactual) having a very similar ex-ante probability of becoming foreign-owned.

9 For example, a firm with a good distribution network and high production costs may search for a partner with low production costs due to long production experience. In this case, structural variables like age (high) and intangible assets (low) may be relevant for the selection.

The last step of our strategy is to compare treated firms and controls after the acquisition of the treated ones using difference-in-differences (DID). We consider 2010-2013 as post-acquisition time.[10]

For each performance variable, we estimate an equation including year, firm fixed effects and a set of time-variant controls on the geographical area and industry of the firm, to take account of possible different trends among sectors or geographical areas. Panel data help to control for the unobservable non-random elements of the acquisition decision that are constant over time. The baseline estimated equation is:

$$\text{performance}_{it} = \alpha + \beta \,{*}\text{FDI}_i{*}\text{post}_t + \text{year FE} + \text{firm FE} + \text{sector}_i{*}\text{trend}_t + \text{area}_i{*}\text{trend}_t + u_{it} \qquad (2)$$

where

i = firm; t = time

FDI = 1 for i = foreign- acquired and 0 otherwise

post = 1 for t ≥ 2010 and 0 otherwise

sector = firm's sector (see table a1)

area = firm's geographical location (see table a1)

trend = 1,2,3... for the time span considered in the equation

A different approach for dealing with the potential endogeneity of the ownership variable is to use instrumental variables (Benfratello and Sembenelli, 2006, among others). The papers that use this methodology focus on productivity (TFP) as an outcome variable, and this allows them to exploit structural functional forms (a Cobb-Douglas production function) in the analysis. Since our examination extends to a large set of economic performance indicators, there is much less a priori theoretical ground for the assumptions on the form of the estimating equations, and therefore DID is our preferred choice.

4. Results

4.1 Propensity score matching

As a first step for propensity score matching, we estimate the probability of being foreign- acquired using a probit model. Table 1 presents the results of the probit model in equation (1).

All the covariates are significant at 1%, supporting the assumption that size, profitability, the financial situation and the structural indicators chosen influence the acquisition decision.

[10] The choice to consider 2010 as the post-acquisition year is somewhat arbitrary; however, as our analysis also considers the FOP effects for each year after the acquisition (see table 5), we believe that this choice should not affect the results..

Probit model: probability of being acquired in 2010 using 2007-09 variables		Table 1
Variables	Coefficients	Standard error
log(net sales)	0.169 ***	0.009
vadded labour	-0.037 ***	0.009
ROE rank	-0.003 ***	0.001
fdebt asset	-0.170 ***	0.064
intangible assets	-0.423 ***	0.157
vertical integration	0.320 ***	0.067
age	-0.009 ***	0.001
GDP	0.000 ***	0.000
chemicals	0.155 *	0.094
construction	-0.260 ***	0.094
traditional manuf.	0.020	0.084
metalworking	0.087	0.080
primary sector	0.405 ***	0.118
firm services	0.155 *	0.081
consumer serv.	0.262 ***	0.074
utilities	-0.166	0.160
constant	-5.489 ***	0.134

*** $p<0.01$, ** $p<0.05$, * $p<0.1$. Number of observations: 392,254. The first eight variables are 2007-09 means. See Table a1 for a complete description of the variables.

PSM provides a robust and reliable control sample for estimating the foreign acquisition effect if the pre-acquisition variables are balanced between the acquired and the non-acquired groups. The balancing property implies that the control group produced by PSM has a distribution of covariates very similar to that in the treated group. Table 2 shows the mean values of treated firms and controls both in the full sample and in the post-PSM sample, and the results of a simple t-test on the mean value differences of the performance variables of the two groups of firms.

The third column shows that, before matching, size (net sales) and age are significantly larger for treated firms than for the rest of the sample, while the value added/labour ratio and profitability are lower. At the same time, there is no ex-ante important difference in the financial structure and in the importance of intangible assets. After matching, the differences in means are significantly reduced: the hypothesis that the difference in covariate means of treated firms and controls is null cannot be rejected. At the bottom of the table we also report the growth rates of the outcome variables, both for treated firms and controls in the pre-treatment period. After matching, the t-test shows that the assumption of similar mean growth rates cannot be rejected, supporting the common trend assumption required by DID methodology.

Comparisons between full sample, treated firms and controls; means for 2007-09								Table 2
Variables	Full sample				Propensity score matching sample			
	Mean		Difference in means		Mean		% Bias	Difference in means
	Treated	Control			Treated	Control		
log(net sales)	8.01	6.89	1.12	***	8.01	8.08	-4.5	-0.07
vadded labour	1.64	2.14	-0.50	***	1.64	1.72	-3,4	-0.08
ROE rank	46.45	51.01	-4.57	***	46.45	46.73	-1.1	-0.28
fdebt asset	0.22	0.22	-0.01		0.22	0.22	-2.7	-0.01
intangible assets	0.04	0.04	0.00		0.04	0.04	2.5	0.00
vertical integration	0.29	0.31	-0.03	***	0.29	0.28	-1.4	0.00
age	14.60	13.19	1.41	***	14.60	14.45	-1.3	0.15
GDP	32,282	27,3311	4,951	***	32,282	32,151	2.3	131
chemicals	0.05	0.03	0.02		0.05	0.05	0.7	0.00
construction	0.03	0.04	-0.01		0.03	0.04	-2.6	-0.01
traditional manuf.	0.08	0.11	-0.03		0.08	0.07	0.9	0.00
metalworking	0.13	0.11	0.02		0.13	0.12	1.1	0.00
primary sector	0.02	0.01	0.00		0.02	0.02	-3.1	0.00
firm services	0.11	0.10	0.01		0.11	0.10	1.5	0.00
consumer serv.	0.56	0.41	0.14		0.56	0.55	0.8	0.00
utilities	0.01	0.01	0.00		0.01	0.01	-1.3	0.00
	2007-09 % Growth rates of performance variables							
net sales	-5.92	-11.93	-6,01	**	-5.92	-3.35		-2.57
ROE rank	-11.25	-5.98	-5,27	***	-11.25	-9.03		-2.22
cash asset rank	-4.94	-1.45	-3.49	***	-4.94	-3.55		-1.39
fdebt asset	-0.49	11.71	12,2	**	-0.49	9.18		-9.67
score	8.28	5.02	-3,26	***	8.28	8.51		-0.23

Firms are observed in the three years before acquisition. Differences in means are accompanied by a t-test to document significant differences between the treated firms and the matched control subset; the standardized bias is defined as the difference of sample means in the treated and matched control subsample as a percentage of the square root of the average of sample variances in both groups. *** p<0.01, ** p<0.05, * p<0.1.

The balancing property is confirmed by the size of the standardized bias (at most 4.5% for net sales) as suggested by Rosenbaum and Rubin (1985). For each covariate it is defined as the difference of sample means in the treated and matched subsamples as a percentage of the square root of the average of sample variances in both groups.

Even though there is no clear threshold for establishing the success of the matching procedure, a standardized bias of around 5% or less is considered acceptable (Caliendo and Kopeinig, 2008). The balancing property is supported by the result of the Hotelling T2 test of the joint significance of differences in means (see Table a2).

Lastly, we verified "common support", which is the overlap between values of X for the comparison groups (treated and controls), confirming our a priori assumption that the large sample from which controls are selected would ensure it.[11]

4.2 Difference-in-differences

As mentioned in the introduction, our analysis focuses on a set of selected balance sheet indicators, which allow us to investigate the effect of FDI on three different features of firm performance: size, profitability, and financial soundness. Specifically, we considered net sales as a proxy for size, ROE and cash flow on assets as measures of profitability, and financial debt on assets together with a score (a comprehensive credit risk indicator obtained by linear discriminant analysis with lower values indicating safer firms) as measures of financial soundness.[12] Both ROE and cash flow on assets are measured as a percentile rank. For the last two variables we expect a negative sign of the coefficients, while we expect positive signs for all the other variables.

Before implementing a difference-in-differences estimate, as a robustness check, we test the DID common trend assumption using pre-treatment data (2007-09).[13] The test is carried out by estimating two placebo experiments that artificially move the acquisition year from 2010 to 2008 (the first one) and to 2009 (the second one, Waldinger, 2012). The estimated equations have the following structure:

$$\text{performance}_{it} = \alpha + \beta * \text{FDI}_i * \text{placebo}_t + \text{year FE} + \text{firm FE} + \text{sector}_i * \text{trend}_t + \text{area}_i * \text{trend}_t + u_{it} \quad (3)$$

where

i = firm; t = time (2007, 2008, 2009)

FDI = 1 for i = foreign-acquired and 0 for the matched controls

placebo = 1 for $t \geq 2008$ in the first placebo test and 0 otherwise

placebo = 1 for t = 2009 in the second placebo test and 0 otherwise

sector, area, trend as defined in equation (2)

The results reported in Table 3 shows that the β coefficients in the regressions (3) are not significant, excluding the existence of an ex-ante divergent trend of future treated firms compared to the matched controls.

11 We used the Stata routine psmatch2 to implement the matching and to verify the common support assumption.

12 See Table a1 for a description of the variables.

13 The common trend assumption is that, in the absence of the acquisition, treated firms and controls would have followed the same trend.

Placebo tests for common trend (1)					Table 3
Variables	log (net sales)	ROE rank	cash asset rank	fdebt asset	score
			first regression: moving acquisition to 2008		
FDI*placebo$_{2008,2009}$	**-0.030**	**-1.117**	**-0.182**	**-0.006**	**-0.028**
	(0.018)	(1.285)	(0.541)	(0.008)	(0.055)
constant	**8.190*** **	**57.970*** **	**8.341*** **	**0.198*** **	**4.427*** **
	(0.009)	(0.571)	(0.236)	(0.003)	(0.025)
firm FE	Y	Y	Y	Y	Y
year FE	Y	Y	Y	Y	Y
sector/area trend	Y	Y	Y	Y	Y
obs.	20,227	19,233	20,227	20,227	20,227
			second regression: moving acquisition to 2009		
FDI*placebo$_{2009}$	**-0.016**	**-2.139**	**-0.876**	**0.003**	**0.005**
	(0.020)	(1.346)	(0.593)	(0.007)	(0.057)
constant	**8.193*** **	**57.73*** **	**8.177*** **	**0.200*** **	**4.435*** **
	(0.009)	(0.637)	(0.262)	(0.004)	(0.027)
firm FE	Y	Y	Y	Y	Y
year FE	Y	Y	Y	Y	Y
sector/area trend	Y	Y	Y	Y	Y
obs.	20,227	19,233	20,227	20,227	20,227

(1) Robust standard errors (clustered by firm) in parentheses. ***significance at 1%; ** at 5%; * at 10%.

We performed four different exercises using difference-in-differences. The first one is the baseline and simply tests the effect on the five performance variables of being foreign-owned. The second one tests FOP on FDI versus non-FDI for each year after acquisition, in order to check the timing of the effect of foreign acquisition on performance. The third exercise examines the possible differences in FOP between manufacturing and services. The last one (discussed in the section dedicated to the robustness checks) looks for differential FOP effects depending on the country of origin of the controlling firm (advanced countries versus tax havens).

Table 4 shows the results of the first exercise: a DID regression based on equation (2). As expected, the foreign ownership premium is significant; the signs for all the performance indicators are consistent with the expected ones.

After acquisition, net sales improve by 7%; profitability increases by 1.8 positions in terms of ROE and 1.7 positions in terms of cash flow on assets (in a ranking of 1 to 100); the level of indebtedness decreases by 2.8 percentage points; the score (a measure increasing in level of riskiness) improves by 0.1 on a scale of 1 to 10.

Difference-in-differences: FDI versus non-FDI (1)					Table 4
Variables	log (net sales)	ROE rank	cash asset rank	fdebt asset	score
FDI*post	**0.070*** **	**1.800***	**1.691***	**-0.028*** **	**-0.102** **
	(0.026)	(0.988)	(0.929)	(0.007)	(0.049)
constant	**8.237*** **	**55.360*** **	**53.64*** **	**0.206*** **	**4.552*** **
	(0.013)	(0.601)	(0.532)	(0.004)	(0.028)
firm FE	Y	Y	Y	Y	Y
year FE	Y	Y	Y	Y	Y
sector/area trend	Y	Y	Y	Y	Y
obs.	44,231	41,375	44,231	44,231	44,231

(1) Firm controls include sector trends and geographical area trends. Robust standard errors (clustered by firm) in parentheses. ***significance at 1%; ** at 5%; * at 10%.

Table 5 shows the results of the second exercise: a DID regression based on the following equation:

$$\begin{aligned} performance_{it} = \alpha + \beta_1\, FDI_i{*}Y2010 + \beta_2\, FDI_i{*}Y2011 + \beta_3\, FDI_i{*}Y2012 + \\ \beta_4\, FDI_i{*}Y2013 + \text{year FE} + \text{firm FE} + \\ sector_i{*}trend_t + area_i{*}trend_t + u_{it} \end{aligned} \tag{4}$$

where

i = firm; t= time

FDI = 1 for i = foreign-acquired and 0 otherwise

Y2010 = 1 for t = 2010 and 0 otherwise

Y2011 = 1 for t = 2011 and 0 otherwise

Y2012 = 1 for t = 2012 and 0 otherwise

Y2013 = 1 for t = 2013 and 0 otherwise

sector, area, trend as defined in equation (2)

The effect of foreign ownership increases over time for all variables. For net sales, the greater effects emerge three years after the acquisition. Improvement in profitability is less steady: coefficients for the ROE rank and for cash flow on the assets rank are at their highest in 2013, but they are not significant in 2010 and 2012. This effect is expected to a certain extent as these variables depend on a large range of company variables: sales, cost structure and financial equilibrium; a certain delay is necessary in order to transmit the improvement of these variables to profits. The financial indicator coefficient is always significant, stays negative and increases in absolute value year after year. Lastly, the score variable, which can be considered as a comprehensive indicator of economic and financial performance, grows in magnitude and is significant from the third year onwards.

Difference-in-differences: FDI versus non-FDI each year after acquisition (1)					Table 5
Variables	log (net sales)	ROE rank	cash asset rank	fdebt asset	score
FDI * Y2010	**0.047****	**-0.456**	**0.186**	**-0.019*****	**-0.010**
	(0.023)	(1.158)	(1.012)	(0.007)	(0.051)
FDI * Y2011	**0.072****	**2.163***	**2.241***	**-0.023*****	**-0.052**
	0.028	(1.311)	(1.159)	(0.008)	(0.056)
FDI * Y2012	**0.070****	**1.388**	**1.902**	**-0.037*****	**-0.182*****
	(0.034)	(1.378)	(1.257)	(0.009)	(0.066)
FDI * Y2013	**0.100*****	**4.995*****	**2.867****	**-0.038*****	**-0.202*****
	(0.037)	(1.450)	(1.372)	(0.009)	(0.071)
constant	**8.240*****	**55.640*****	**53.740*****	**0.206*****	**4.543*****
	(0.012)	(0.598)	(0.528)	(0.004)	(0.028)
firm FE	Y	Y	Y	Y	Y
year FE	Y	Y	Y	Y	Y
sector/area trend	Y	Y	Y	Y	Y
obs.	44,231	41,375	44,231	44,231	44,231

(1) Firm controls include sector trends and geographical area trends. Robust standard errors (clustered by firm) in parentheses. ***significance at 1%; ** at 5%; * at 10%.

Table 6 shows the impact of the foreign ownership premium across broad industry groups. The DID regression is based on the following equation which presents triple interaction terms; second-order non-collinear factors have been considered too:[14]

$$performance_{it} = \alpha + \beta_1\, FDI_i{*}manufacturing_i{*}post_t + \beta_2\, FDI_i{*}services_i{*}\, post_t + \beta_3\, FDI_i{*}other_i{*}post_t + \beta_4\, manufacturing_i{*}post_t + \beta_5\, services_i{*}\, post_t + \beta_6\, other_i{*}\, post_t + year\ FE + firm\ FE + sector_i{*}trend_t + area_i{*}trend_t + u_{it} \quad (5)$$

where

i = firm; t= time

FDI = 1 for i = foreign-acquired and 0 otherwise

post = 1 for t ≥ 2010 and 0 otherwise

manufacturing = 1 for manufacturing and 0 otherwise

services = 1 for services and 0 otherwise

[14] The second-order interactions: $FDI_i{*}manufacturing_i$, $FDI_i{*}services_i$ and $FDI_i{*}other_i$ are time-invariant dummies absorbed by a firm's fixed effects; the interaction $FDI_i{*}post_t$ can be obtained as the sum of the three dummies: $FDI_i{*}manufacturing_i{*}post_t$, β_2 $FDI_i{*}services_i{*}post_t$ and β_3 $FDI_i{*}other_i{*}post_t$, given that the three broad industry groups are exhaustive.

other = 1 for firms in the residual sectors (primary and construction) and 0 otherwise[15]

sector, area, trend as defined in equation (2)

The β_1, β_2 and β_3 coefficients, which interest us, show that the impact of foreign ownership is not homogeneous across broad groups of industries, being significant in services but not in manufacturing. A possible explanation for this phenomenon could depend on the greater exposure of manufacturing industries to international market discipline that induces greater efficiency. On the other hand, many service branches are regulated and have some forms of barriers to entry that limit efficiency achievements. Therefore foreign acquisition should improve performance more for service sector firms than for manufacturing entities that possibly tend to be nearer to the efficiency frontier. The results are confirmed if we reapply the PSM + DID procedure as defined in equations (1) and (2) separately from the subsample of manufacturing and from the subsample of service firms; the figures are shown in Tables a3 and a4 in the appendix. Obviously, this approach does not allow us to make a meaningful comparison of the estimations, but it helps us to refine the matching procedure for the purpose of testing the treatment effect separately within each broad industry.

Difference-in-differences: FDI in manufacturing versus FDI in services (1) — Table 6

Variables	log (net sales)	ROE rank	cash asset rank	fdebt asset	score
FDI * manufacturing * post	**0.040**	**1.064**	**0.682**	**-0.013**	**-0.092**
	(0.050)	(1.762)	(1.743)	(0.014)	(0.105)
FDI * services * post	**0.076****	**2.009**	**2.156***	**-0.032*****	**-0.112***
	(0.032)	(1.224)	(1.115)	(0.008)	(0.056)
FDI * other * post	**0.157**	**2.806**	**0.136**	**-0.069*****	**0.030**
	(0.137)	(4.522)	(4.585)	(0.031)	(0.202)
constant	**8.239*****	**55.620*****	**53.91*****	**0.207*****	**4.519*****
	(0.017)	(0.785)	(0.700)	(0.005)	(0.036)
firm FE	Y	Y	Y	Y	Y
year FE	Y	Y	Y	Y	Y
sector/area trend	Y	Y	Y	Y	Y
manufacturing * post	Y	Y	Y	Y	Y
services * post	Y	Y	Y	Y	Y
other * post	Y	Y	Y	Y	Y
obs.	44,231	41,375	44,231	44,231	44,231

(1) Firm controls include sector trends and geographical area trends. Robust standard errors (clustered by firm) in parentheses. ***significance at 1%; ** at 5%; * at 10%.

[15] They represent 3.75% of the treated sample; see Table a1 for sector definitions.

4.3 Further robustness checks

As a further check on the existence and the strength of the foreign ownership premium, we test it by grouping treated firms into classes, according to the country of origin of the acquisition. In fact at micro level our dataset shows a significant share of foreign investors located in countries that provide fiscal or legal benefits. Anecdotal evidence indicates that in many cases the ultimate control subject of these entities is domestic, and the 'foreign investor' is only a shell company created in a fiscal haven just for fiscal or legal reasons. Consequently, this kind of business does not imply any true acquisition: thus in this case we do not expect any foreign ownership premium.

Unfortunately, we cannot test our assumption directly on 'vested foreign investors' because our dataset does not allow us to detect the ultimate investor. In any case, even if the assumption on tax havens is true only in part, we can use it to test the robustness of FOP. Assuming the existence of 'vested foreign investors' implies that a fraction of our treated sample has not really been treated; this fraction is concentrated among the firms controlled by foreign owners located in tax havens. By interacting the treatment variable with a dummy for tax havens, we are in fact carrying out a falsification test on FOP as, in this case, the treatment is mostly a false treatment and then we expect the absence of a premium.

We create three dummy variables: the first one assumes value 1 if the company is treated and the country of origin of the participation is an 'advanced' one (0 otherwise); the second assumes value 1 if the company is treated and the country of origin of participation can be considered a tax haven (0 otherwise); the third one assumes value 1 if the company is treated and the participation comes from a country not considered before (0 otherwise; this group represents 2.93% of the treated sample). The sum of the three dummies gives exactly the treatment variable (FDI). The regression takes the following form:

$$\begin{aligned} performance_{it} = \alpha + \beta_1\, advanced_i{*}post_t + \beta_2\, havens_i{*}post_t +\\ \beta_3\, other_i{*}post_t + year\ FE + firm\ FE +\\ sector_i{*}trend_t + area_i{*}trend_t + u_{it} \end{aligned} \tag{6}$$

where

i = firm; t = time

post = 1 for $t \geq 2010$ and 0 otherwise

advanced = 1 for i = foreign-acquired from an advanced country and 0 otherwise

havens = 1 for i = foreign-acquired from a tax haven and 0 otherwise[16]

other = 1 for i = foreign-acquired from other countries and 0 otherwise

sector, area, trend as defined in equation (2)

16 See Table a1 for details.

The results of the regression (table 7) show that FOP is not significant for any performance variable when the acquisition comes from a tax haven. On the contrary, controlling entities from advanced countries produce real and financial improvements in the acquired firms.

The findings discussed so far are based on a selection of variables for PSM that include performance and structural firm characteristics that we believe best fit the acquisition process and influence the outcome. This follows a general trend of the literature, which suggests including variables correlated with both the treatment and the outcome. However, the set of performance variables used is slightly different from that considered as the outcome in the DID estimation.

Difference-in-differences: FDI from advanced countries/from tax havens (1) — Table 7

Variables	log (net sales)	ROE rank	cash asset rank	fdebt asset	score
advanced*post	**0.101*** **	**1.952***	**2.070***	**-0.030*** **	**-0.154*** **
	(0.027)	(1.152)	(1.111)	(0.008)	(0.057)
havens*post	**0.017**	**1.871**	**1.141**	**-0.020**	**0.023**
	(0.068)	(1.926)	(1.715)	(0.014)	(0.096)
other*post	**-0.031**	**-0.005**	**-1.373**	**-0.039**	**0.128**
	(0.288)	(5.105)	(3-313)	(0.0340)	(0.205)
constant	**8.237*** **	**55.37*** **	**53.64*** **	**0.206*** **	**4.551*** **
	(0.013)	(0.602)	(0.533)	(0.004)	(0.028)
firm FE	Y	Y	Y	Y	Y
year FE	Y	Y	Y	Y	Y
sector/area trend	Y	Y	Y	Y	Y
obs.	44,231	41,375	44,231	44,231	44,231

(1) Firm controls include sector trends and geographical area trends. Robust standard errors (clustered by firm) in parentheses. ***significance at 1%; ** at 5%; * at 10%.

Even if there is no common point of view in the literature about the requirement of coincidence between covariates in PSM and outcomes in DID, we propose an alternative estimation of our baseline as a robustness test, using all the outcome variables considered in the DID estimation as covariates for PSM. Thus we re-estimate equation (1) using an alternative Xi vector of observables that includes the 2007-2009 means of our five performance indicators (log net sales, ROE rank, cash asset rank, fdebt asset and score) plus controls for sector effects, and then our baseline equation (2) using the new control sample obtained. Table 8 shows results consistent with the previous ones.

5. Conclusions

The main stream of theoretical literature on foreign acquisition emphasizes the superior technical and managerial skills that multinationals transfer to acquired firms. This process, in turn, generates a foreign ownership premium (FOP) that materializes through the improvement of the acquired firm's performance.

In order to test this theoretical argument empirically it is necessary to rule out the possibility that the different performances of foreign-acquired firms, compared with purely domestic ones, is simply due to an ex-ante selection bias.

Using PSM combined with a difference-in-differences methodology to control for the possible ex-ante selection bias, we find that the performance of domestic firms improves after FDI. In order to identify the covariates to control for, we exploited the literature on selection processes. These variables are, in turn, the ones relevant for MNEs' investment choices.

A foreign ownership premium is present in all three characteristics considered for a firm's performance: size, profitability, and financial soundness. The effects increase over time, indicating that the transmission of knowledge and organizational and managerial changes is a slow process.

The effect of FDI on performance is only significant for service firms; this sector is generally more sheltered from international market discipline, leaving greater room for performance improvement than for industrial firms.

Lastly, FOP is not significant for any performance variable when the FDI comes from a tax haven. Assuming the existence of a significant number of 'vested foreign investors' concentrated in tax havens, we consider this result a falsification test: only 'true' acquisitions generate FOP, while shell companies with parent companies located in tax havens do not actually affect performance.

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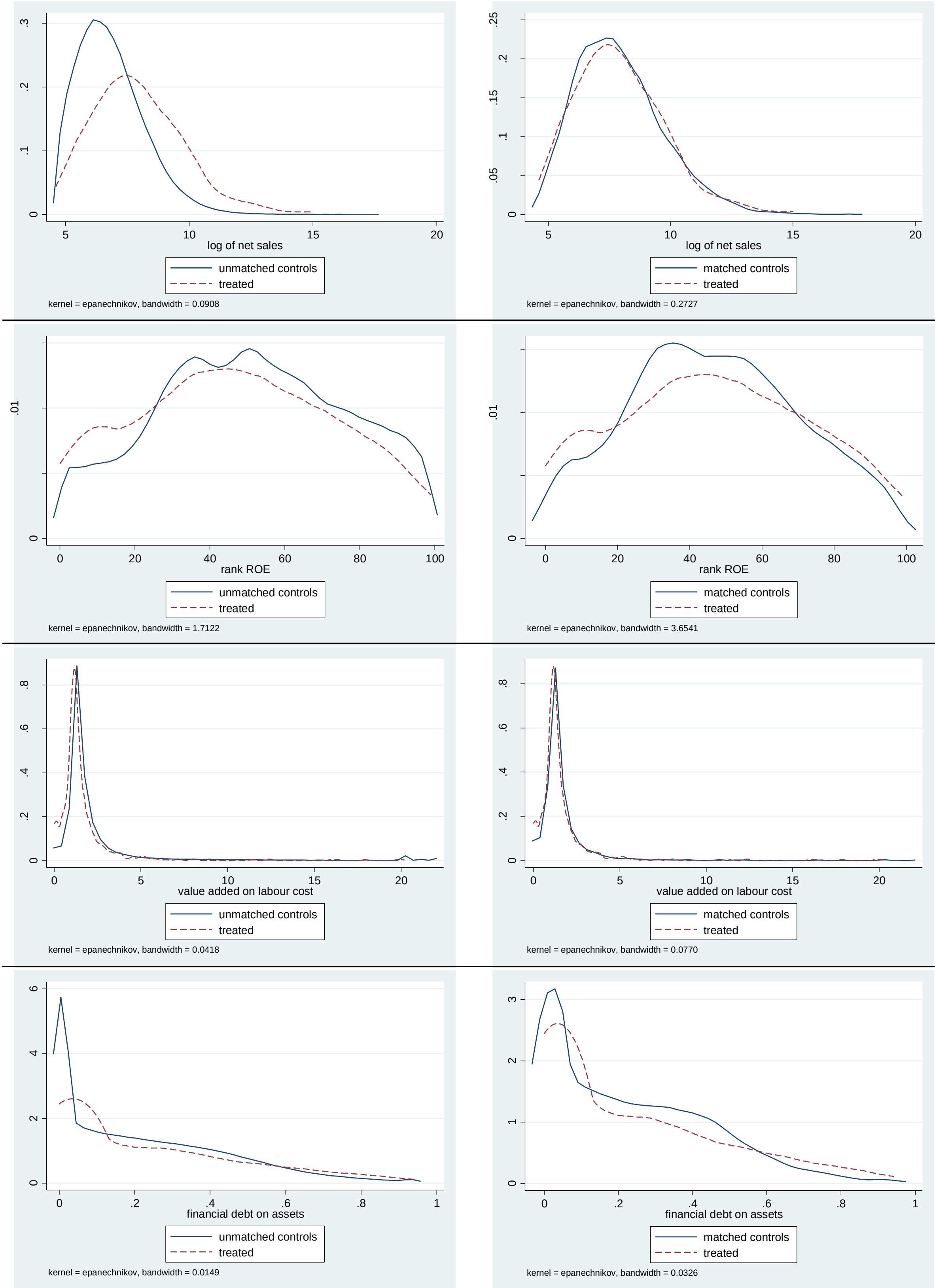
Appendix

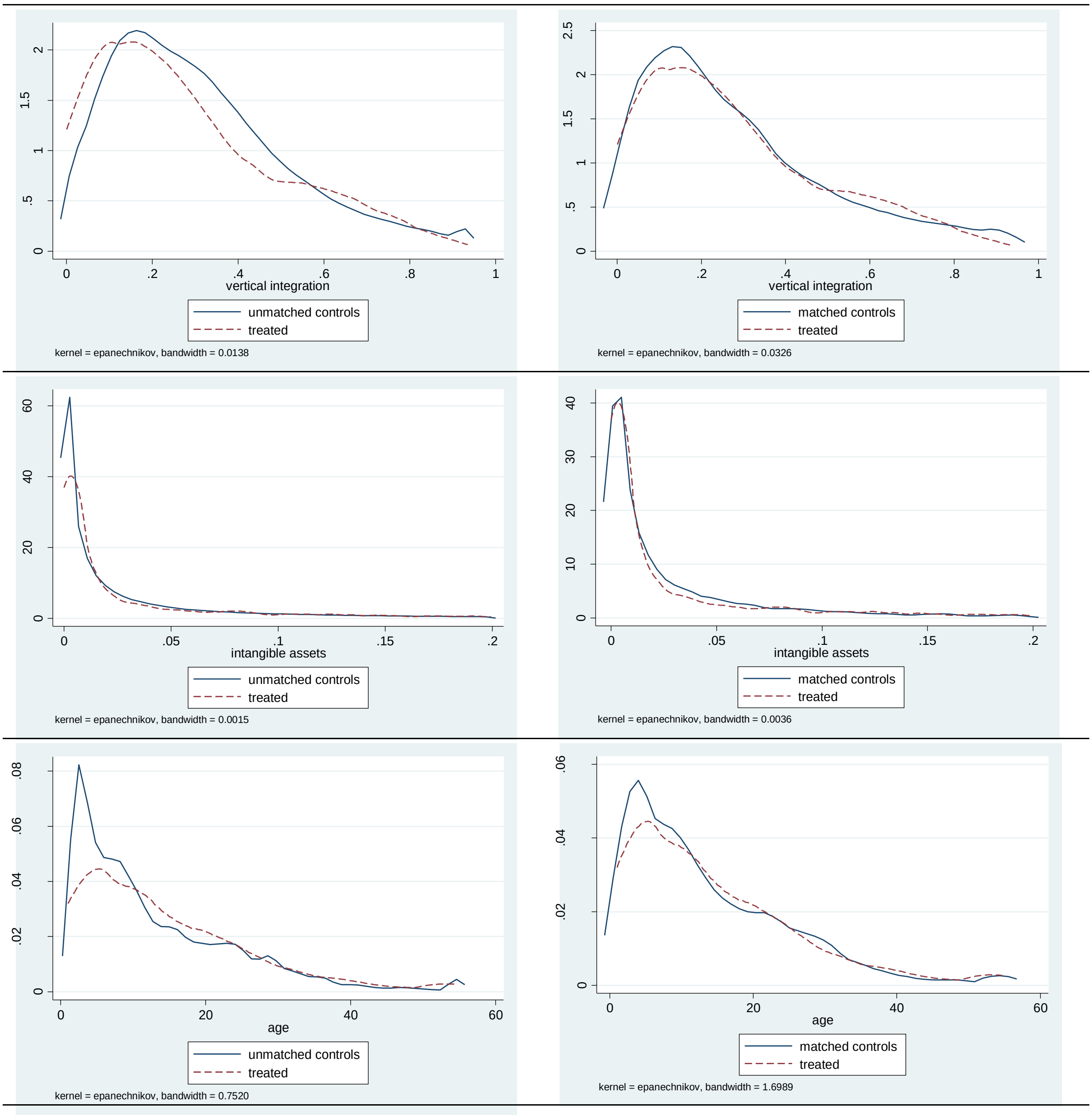
Variables description		Table a1

<table>
<tr><th>Variable name</th><th colspan="2">Description [source]</th></tr>
<tr><td>FDI</td><td colspan="2">Dummy equal to 1 if the firm is foreign-owned for the first time in 2010 (treated) and 0 if is not foreign-owned from 2007 to 2013 [Infocamere]</td></tr>
<tr><td>log (net sales)</td><td colspan="2">Log of net sales [Cerved]</td></tr>
<tr><td>ROE rank</td><td colspan="2">Return on equity (rank centiles) [Cerved]</td></tr>
<tr><td>vadded labour</td><td colspan="2">Value added to labour cost [Cerved]</td></tr>
<tr><td>fdebt asset</td><td colspan="2">Financial debt on assets [Cerved]</td></tr>
<tr><td>intangible assets</td><td colspan="2">Intangible assets/total assets [Cerved]</td></tr>
<tr><td>vertical integration</td><td colspan="2">Value added/net sales [Cerved]</td></tr>
<tr><td>age</td><td colspan="2">Firm’s age [Cerved]</td></tr>
<tr><td>score</td><td colspan="2">Z-score; it is a measure of credit risk obtained by linear discriminant analysis; value range is 1 to 10, with lower values indicating safer firms and higher values risky firms [Cerved]</td></tr>
<tr><td>cash asset rank</td><td colspan="2">Cash flow on assets (rank centiles) [Cerved]</td></tr>
<tr><td>GDP</td><td colspan="2">Per-capita GDP in the province where the firm is located</td></tr>
<tr><td rowspan="2">sector (1..9)</td><td colspan="2">2-digits NACE Rev. 2 classification:</td></tr>
<tr><td>1 Other serv. = 84-99
2 Chemicals = 19-23
3 Construction = 41-43
4 Traditional manuf.= 10-18, 31-33
5 Metalworking = 24-30</td><td>6 Primary sector = 01-09
7 Firm services = 69-82
8 Consumer serv. = 45-63
9 Utilities = 35-39</td></tr>
<tr><td>area</td><td>1 North West
2 North East</td><td>3 Centre
4 South</td></tr>
<tr><td>manufacturing, services</td><td colspan="2">manufacturing= sectors 2, 4, 5, 9
services= sectors 1, 7, 8
other= sectors 3, 6</td></tr>
<tr><td>country type
(countries selected are those included in the dataset)</td><td>Advanced = Austria, Belgium, Bulgaria, Canada, Czech Republic, Cyprus, Croatia, Denmark, Finland, France, Germany, Japan, Gibraltar, Greece, Ireland, Israel, Lithuania, Malta, Norway, Netherlands, Poland, Portugal, United Kingdom, Romania, Singapore, Spain, United States, Sweden, Hungary</td><td>Tax havens = Liechtenstein, Luxembourg, Panama, San Marino, Switzerland</td></tr>
</table>

Kernel density estimates of covariates distribution, averages 2007-09 - pre and post-matching Graph a1

pre-matching post-matching





Propensity score matching: Hotelling T-squared test (1)	Table a2
Sample	Hotelling P-value
treated vs unmatched	0.000
treated vs matched	0.979

(1) H_0: difference between covariates means jointly null.

Difference-in-differences: FDI versus non-FDI - manufacturing (1)					Table a3
Variables	log (net sales)	ROE rank	cash asset rank	fdebt asset	score
FDI*post	**0.018**	**1.771**	**0.626**	**-0.013**	**-0.068**
	(0.049)	(1.742)	(1.737)	(0.014)	(0.103)
constant	**8.892*** **	**54.010*** **	**55,440*** **	**0.241*** **	**4.400*** **
	(0.022)	(1.005)	(0.969)	(0.009)	(0.060)
firm FE	Y	Y	Y	Y	Y
year FE	Y	Y	Y	Y	Y
sector/area trend	Y	Y	Y	Y	Y
obs.	11,920	11,334	11,920	11,920	11,920

(1) Firm controls include sector trends and geographical area trends. Robust standard errors (clustered by firm) in parentheses. ***significance at 1%; ** at 5%; * at 10%.

Difference-in-differences: FDI versus non-FDI services (1)					Table a4
Variables	log (net sales)	ROE rank	cash asset rank	fdebt asset	score
FDI*post	**0.076***	**2.517*** **	**2,624***	**-0.031*** **	**-0.159***
	(0.032)	(1.241)	(1.135)	(0.008)	(0.057)
constant	**8.060*** **	**55.980*** **	**53.550*** **	**0.182*** **	**4.564*** **
	(0.016)	(0.759)	(0.648)	(0.005)	(0.032)
firm FE	Y	Y	Y	Y	Y
year FE	Y	Y	Y	Y	Y
sector/area trend	Y	Y	Y	Y	Y
obs.	30,472	28,263	30,472	30,472	30,472

(1) Firm controls include sector trends and geographical area trends. Robust standard errors (clustered by firm) in parentheses. ***significance at 1%; ** at 5%; * at 10%.

Irving Fisher Committee on
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BANK FOR INTERNATIONAL SETTLEMENTS

IFC-ECCBSO-CBRT Conference on *"Uses of Central Balance Sheet Data Offices' information"*

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Özdere-İzmir, Turkey, 26 September 2016

Foreign ownership and performance: evidence from a panel of Italian firms[1]

Chiara Bentivogli and Litterio Mirenda,

Bank of Italy

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

BANCA D'ITALIA

EUROSISTEMA

Foreign ownership and performance

evidence from a panel of Italian firms

Chiara Bentivogli and Litterio Mirenda

The opinions expressed in this paper are the authors' own and do not reflect the view of the Bank of Italy

Abstract

The paper studies the impact of the foreign ownership on the firm's economic performance. We use a unique panel dataset to test foreign ownership premium by comparing our sample of firms based in Italy and participated by a foreign subject with a sample of purely domestic firms that, in order to have a proper counterfactual, have been selected through a propensity score matching. Our difference-in-differences results show the existence of a premium for size, profitability and financial soundness of the foreign-participated companies. The premium increases with time, it is concentrated in service sector, and disappears if the foreign investor is based in a fiscal haven.

- **JEL Classification**: F23, F61
- **Keywords**: Multinational enterprise; Ownership; Foreign direct investment, Firm performance.

Agenda

- Why we do investigate foreign ownership premium? Its existence could justify policies to attract FDIs

- How:

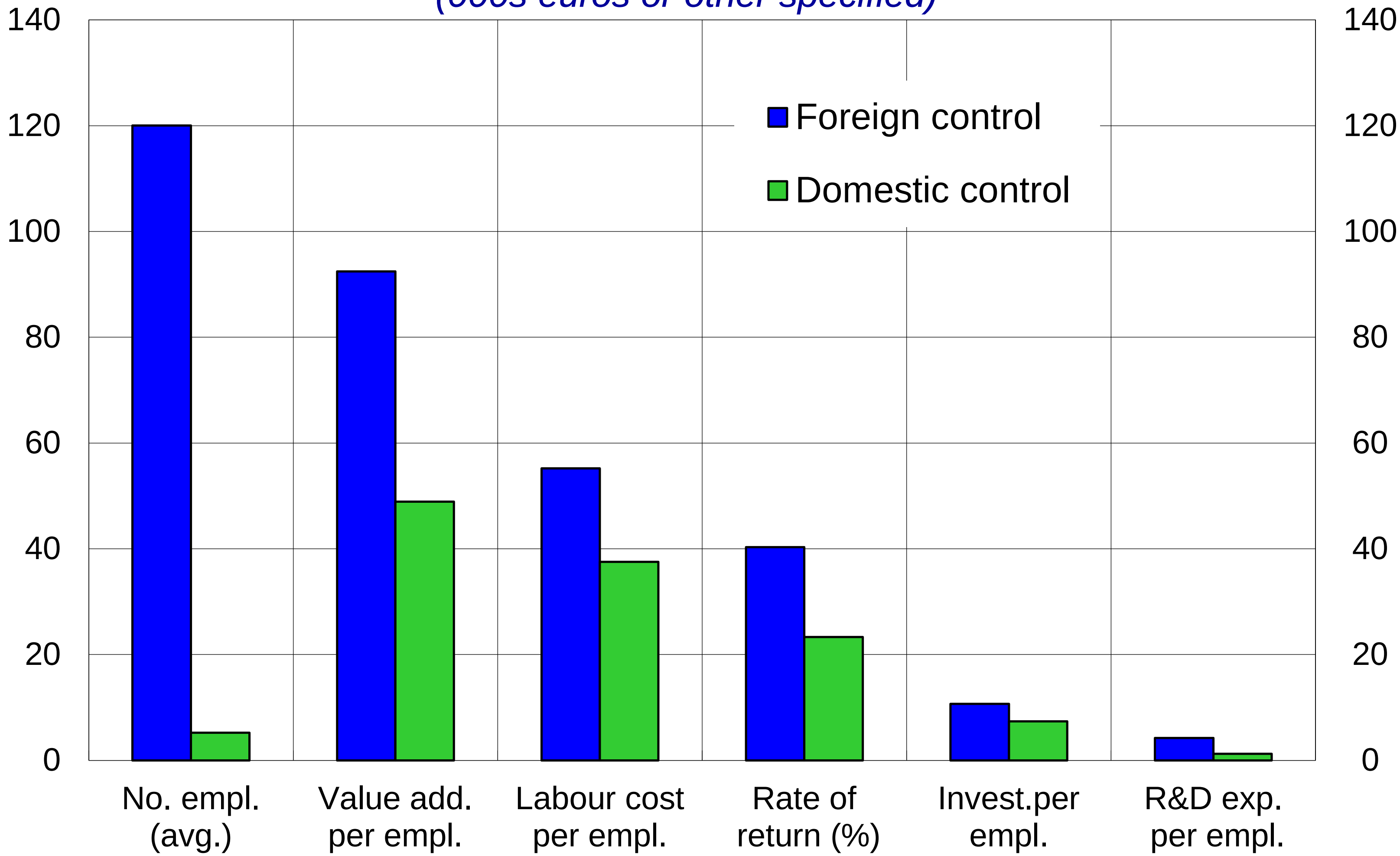
✓ Introduction: foreign ownership premium (FOP) facts & theory

✓ Empirical strategy: counterfactual,controls,DIFF-IN-DIFF

✓ Results: we find foreign ownership premium

data show better performance of foreign owned firms vis-à-vis domestic firms

(000s euros or other specified)



Source: Istat, FATS. Year 2012, industry, Italy.

Why? Ex-ante vs ex-post

- ✓ Ex-post: Forward linkages:

  MNE parent company transfers superior technology and organizational practices to its affiliate, thus improving performance (Hymer, Dunning) → FOP

- ✓ Ex-ante: selection bias:

  - Well-performing foreign firms choose to acquire underperforming companies (negative selection; Manne);

  - Only best firms are acquired (positive selection; Guadalupe)

Literature on FOP

Mixed results:

- Guadalupe et al. (2012), Arnold and Javorcik (2009), Girma and Gorg (2007), Piscitello and Rabbiosi (205) find FOP
- Benfratello & Sembenelli (2006) do not find FOP on productivity
- Crinò & Onida (2008) find small FOP only in manufacturing

Previous literature	This paper
Cross sections	Panel
Small samples	Large sample
Productivity and wages	Balance sheet indicators

Endogeneity:

We would like to estimate β in

→ performance= α + β FDI + controls + u

But as firms are chosen non randomly by foreign investors:

→ FDI = α + β performance + controls + u

Endogeneity - our strategy (PSM-DID)

- Need a counterfactual: How would the firm have performed had the FDI not taken place?
- The control sample: firms with similar observable characteristics selected using propensity score matching (PSM)
- Panel data to control for time invariant unobservables
- DID est.

$$\textbf{performance}_{it} = \alpha + \beta \,\textbf{*FDI}_i\textbf{*post}_t + \textbf{time FE} + \textbf{firm FE} + \textbf{+sector}_i\textbf{*trend}_t + \textbf{area}_i\textbf{*trend}_t + \textbf{u}_{it}$$

Data selection

Treated

- Using 'Infocamere' data on shareholdings, we extract the subset of new FDI in 2010 (same database used to extract the sample for Bank of Italy's Direct Reporting survey (BOP FDI)
- Dataset has been cleaned (missing country of investor, inconsistent data, etc..); only control (share ≥ 50%) shareholding has been considered

Control

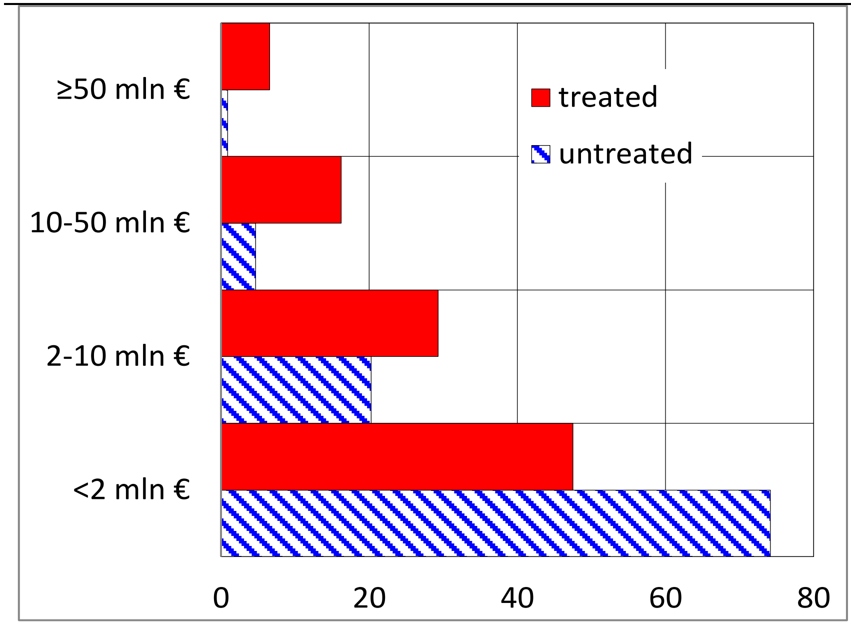
- Selection of the control sample → from the 2010 Cerved database (965,000 companies)

Final panel (2007-2013) ~ 44,000 obs.

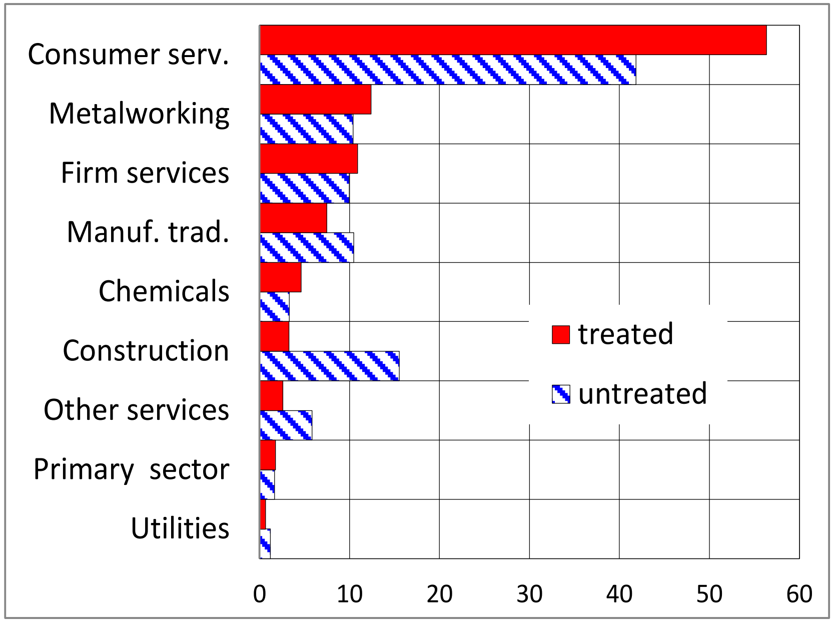
Treated firms concentrate on larger size – specific industries

Distribution by size and industry of treated firms and those that stay purely domestic (2009; %)

size (net sales)



industries



PSM one-to-ten nearest neighbour matching (probit)

- covariates in probit = performance variables + structural vars **relevant for FDI**

Size (net sales)

profitability (ROE)

financial soundness (financial debt/assets)

competitiveness (value added/labour cost)

Knowledge intensity (intangible assets/total assets)

Vertical integration (value added/net sales)

Age; per-capita GDP; industry controls

PSM: Probit model: probability of being acquired in 2010 using 2007-09 variables (means)

Variables	Coefficients	Standard error
log(net sales)	0.169***	0.009
vadded labour	-0.037***	0.009
rank ROE	-0.003***	0.001
fdebt asset	-0.170***	0.064
intangible assets	-0.423***	0.157
vertical integration	0.320***	0.067
age	-0.009***	0.001
GDP	0.000***	0.000

+ industry controls

*(1) ***significance at 1%; ** at 5%; * at 10%.*

PSM: evidence on balancing: T-test on difference in covariates means (means 2007-09)

Variables	Full sample				PSM sample			
	Mean		Diff. in means		Mean		% Bias	Diff.in means
	Treated	Control			Treated	Control		
log(net sales)	8.01	6.89	1.12	***	8.01	8.08	-4.5	-0.07
vadded labour	1.64	2.14	-0.50	***	1.64	1.72	-3,4	-0.08
rank ROE	46.45	51.01	-4.57	***	46.45	46.73	-1.1	-0.28
fdebt asset	0.22	0.22	-0.01		0.22	0.22	-2.7	-0.01
Int. assets	0.04	0.04	0.00		0.04	0.04	2.5	0.00
Vert.integrat.	0.29	0.31	-0.03	***	0.29	0.28	-1.4	0.00
age	14.60	13.19	1.41	***	14.60	14.45	-1.3	0.15

+ p.c. GDP + industry controls

Do not reject H_0: means T&M are equal

DID: step 1 -> placebo test for common trend using pre-treatment data (t= 2007,2008,2009)

$$performance_{it} = \alpha + \beta * FDI_{i*} placebo_t + year\ FE + firm\ FE + sector_i * trend_t + area_i * trend_t + u_{it}$$

Variables	log (net sales)	rank ROE	rank cash asset	fdebt asset	score
	first regression: moving acquisition to 2008 ($placebo_t$=1 for t=2008,2009)				
FDI*placebo$_{2008,2009}$	**-0.030**	**-1.117**	**-0.182**	**-0.006**	**-0.028**
	(0.018)	(1.285)	(0.541)	(0.008)	(0.055)
constant	**8.190***	**57.970***	**8.341***	**0.198***	**4.427***
	(0.009)	(0.571)	(0.236)	(0.003)	(0.025)
	second regression: moving acquisition to 2009 ($placebo_t$=1 for t=2009)				
FDI*placebo$_{2009}$	**-0.016**	**-2.139**	**-0.876**	**0.003**	**0.005**
	(0.020)	(1.346)	(0.593)	(0.007)	(0.057)
constant	**8.193***	**57.73***	**8.177***	**0.200***	**4.435***
	(0.009)	(0.637)	(0.262)	(0.004)	(0.027)

+ firm FE,year FE, sector/area trend

*(1) Robust std errors (clustered by firm) in parentheses. ***significance at 1%; ** at 5%; * at 10%.*

(1) DID: FDI/non-FDI

Variables	log (net sales)	rank ROE	rank cash asset	fdebt asset	score
FDI*post	**0.070*** **	**1.800***	**1.691***	**-0.028*** **	**-0.102** **
	(0.026)	(0.988)	(0.929)	(0.007)	(0.049)
constant	**8.237*** **	**55.360*** **	**53.64*** **	**0.206*** **	**4.552*** **
	(0.013)	(0.601)	(0.532)	(0.004)	(0.028)
firm FE	Y	Y	Y	Y	Y
year FE	Y	Y	Y	Y	Y
sector/area trend	Y	Y	Y	Y	Y
obs.	44,231	41,375	44,231	44,231	44,231

*(1) Robust standard errors (clustered by firm) in parentheses. ***significance at 1%; ** at 5%; * at 10%.*

(2) DID: FDI/non-FDI in each year after acquisition

Variables	log (net sales)	rank ROE	rank cash asset	fdebt asset	score
FDI * Y2010	**0.047****	**-0.456**	**0.186**	**-0.019*****	**-0.010**
	(0.023)	(1.158)	(1.012)	(0.007)	(0.051)
FDI * Y2011	**0.072****	**2.163***	**2.241***	**-0.023*****	**-0.052**
	0.028	(1.311)	(1.159)	(0.008)	(0.056)
FDI * Y2012	**0.070****	**1.388**	**1.902**	**-0.037*****	**-0.182*****
	(0.034)	(1.378)	(1.257)	(0.009)	(0.066)
FDI * Y2013	**0.100*****	**4.995*****	**2.867****	**-0.038*****	**-0.202*****
	(0.037)	(1.450)	(1.372)	(0.009)	(0.071)
constant	**8.240*****	**55.640*****	**53.740*****	**0.206*****	**4.543*****
	(0.012)	(0.598)	(0.528)	(0.004)	(0.028)
firm FE, year FE, sect/area trend	Y	Y	Y	Y	Y
obs.	44,231	41,375	44,231	44,231	44,231

*(1) Robust standard errors (clustered by firm) in parentheses. ***significance at 1%; ** at 5%; * at 10%.*

(3) DID: FDI manufacturing/FDI services

Variables	log (net sales)	Rank ROE	rank cash asset	fdebt asset	score
FDI * manufacturing	**0.040**	**1.064**	**0.682**	**-0.013**	**-0.092**
	(0.050)	(1.762)	(1.743)	(0.014)	(0.105)
FDI * services	**0.076****	**2.009**	**2.156***	**-0.032*****	**-0.112***
	(0.032)	(1.224)	(1.115)	(0.008)	(0.056)
FDI * other	**0.157**	**2.806**	**0.136**	**-0.069*****	**0.030**
	(0.137)	(4.522)	(4.585)	(0.031)	(0.202)
constant	**8.239*****	**55.620*****	**53.91*****	**0.207*****	**4.519*****
	(0.017)	(0.785)	(0.700)	(0.005)	(0.036)
firm FE, year FE, sector/area trend	Y	Y	Y	Y	Y
manufacturing*post, services*post, other*post	Y	Y	Y	Y	Y
obs.	44,231	41,375	44,231	44,231	44,231

*(1) Robust standard errors (clustered by firm) in parentheses. ***significance at 1%; ** at 5%; * at 10%.*

(4) FDI from advanced countries/from tax havens

Variables	log (net sales)	Rank ROE	rank cash asset	fdebt asset	score
FDI * advanced	**0.101*** **	**1.952***	**2.070***	**-0.030*** **	**-0.154*** **
	(0.027)	(1.152)	(1.111)	(0.008)	(0.057)
FDI * havens	**0.017**	**1.871**	**1.141**	**-0.020**	**0.023**
	(0.068)	(1.926)	(1.715)	(0.014)	(0.096)
FDI * other	**-0.031**	**-0.005**	**-1.373**	**-0.039**	**0.128**
	(0.288)	(5.105)	(3-313)	(0.0340)	(0.205)
constant	**8.237*** **	**55.37*** **	**53.64*** **	**0.206*** **	**4.551*** **
	(0.013)	(0.602)	(0.533)	(0.004)	(0.028)
firm FE, year FE, sector/area trend	Y	Y	Y	Y	Y
obs.	44,231	41,375	44,231	44,231	44,231

*(1) Robust standard errors (clustered by firm) in parentheses. ***significance at 1%; ** at 5%; * at 10%.*

Conclusions

- We find that performance of Italian firms improves after FDI
- The effect on performance increases with time
- The effect of FDI on performance is significant only for service firms (in manufacturing international markets discipline)
- FOP is stronger when FDI comes from advanced countries (know how transmission…)
- Only «true» acquisitions generate FOP (chinese boxes with parent companies in tax havens unaffect performance)

Thanks for your attention

IFC-ECCBSO-CBRT Conference on *"Uses of Central Balance Sheet Data Offices' information"*

Co-organised by the IFC, the European Committee of Central Balance Sheet Data Offices (ECCBSO) and the Central Bank of the Republic of Turkey (CBRT)

Özdere-İzmir, Turkey, 26 September 2016

Employment growth and uncertainty: evidence from Turkey[1]

Aslıhan Atabek Demirhan and Burcu Gürcihan Yüncüler, CBRT

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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.

Employment Growth and Uncertainty: Evidence from Turkey

Aslıhan Atabek Demirhan

H. Burcu Gürcihan Yüncüler

Abstract

Using a unique matched data set of firm balance sheets and business tendency survey, we investigate the relation between employment growth and uncertainty. Company Account is an annual comprehensive dataset that contains balance sheets, income statements and firm specific information. Monthly tendency survey enables to track firms' short-term assessments in the manufacturing industry about the recent past, current situation and their expectations regarding the future course of business conditions. Using assessments of current situation and future expectations firm level uncertainties are constructed. Alternative firm-level uncertainty measures for domestic sales, foreign sales and production are employed in the analysis. Our estimation results reveal negative impact of uncertainty on employment growth. One standard deviation increase in foreign demand uncertainty is found to reduce employment growth at around 1 percentage points. We also observe that exporters, small firms and credit constrained firms are more responsive to uncertainty.

Keywords: uncertainty, firm-level, employment growth, qualitative survey data, Turkey

JEL classification: D8, C81, E24, E32

Contents

Introduction

Recent theoretical and empirical economic literature on the effects of uncertainty unveils the important role of uncertainty on the real economy. Theoretical literature focuses on two main channels to disclose the impact of uncertainty on economic activity. The first channel is through possible wait-and-see strategy of the economic actors in order to avoid a false move. According to Bloom (2009) under higher uncertainty, firms prefer to postpone their investment and hiring decisions. Existence of hiring and firing costs gives a particular reason for uncertainty to affect employment (Bloom, Bond and Van Reenen, 2007). The second channel is through the risk premia. Higher uncertainty exacerbates information asymmetry between lenders and borrowers which in turn might give rise to an increase in borrowing costs. Accordingly higher borrowing costs exert additional binding constraint for the economic activity.

Empirically the impact of uncertainty on real economy has been investigated using both aggregate time series data and panel data at country, industry or firm level. Previously conducted studies reveal that uncertainty has adverse impact on investment, firm entry decisions, capital to labour ratio, output, employment and welfare (see for example Dixit, 1989; Ghosal, 1991; Carruth et al., 2000; Rosenberg, 2002; Bloom et al., 2007). Moreover, it is observed that uncertainty may differentially affect employment in small and large firms (Ghosal and Loungani, 1996, 2000; Lensink, 2005). When we turn attention to the Turkish economy, despite the fact that firms and households are exposed to high level of uncertainty, literature on measuring the impact of uncertainty is fairly limited. Most of the existing studies use aggregate measures of uncertainty which may miss the variation at the micro level. Using firm level data, Demir (2009) investigates the impact of exchange rate volatility on employment growth and identifies an adverse impact. Cengiz (2009) utilizing aggregate macro data shows that higher exchange rate risk is associated with higher unemployment and informality in the labour market. Using business tendency survey, Arslan et al. (2013) shows that uncertainty has a negative impact on economic activity.

In the empirical literature several indicators have been used to measure uncertainty at the firm level. One of these is the stock market volatility (Bloom, 2009). Alternative measures are obtained from survey data. Guiso and Parigi (1998) and Lensink (2005) use survey data that includes information on the probability attached to beliefs about possible future outcomes by entrepreneurs. Forecast errors derived from business tendency surveys are used as a proxy for uncertainty at the aggregate level by Bachmann, Elster and Sims (2010) and at the firm level by Arslan et al. (2013).

In this paper we investigate the impact of uncertainty on employment growth by using a unique matched data set of firm balance sheets and business tendency survey. Analysis is carried out using annual data for the period 2007-2014. Using higher frequency survey data, uncertainty is measured at the firm level. In particular we construct expectation errors of firms by comparing their survey responses about expectations and realizations on their sales and production volumes. Average of the squared errors within a year constitutes the firm level measure of uncertainty.

Our paper contributes to the literature in two ways. Firstly, to our knowledge, this is the first study that merge data sets of firm balance sheets and business tendency survey for the purpose of investigating the impact of uncertainty. Second, there are limited numbers of micro-level studies on the effects of uncertainty on employment growth and to our knowledge there is none for the Turkish economy.

The structure of the paper is as follows: In the next section data, variables and empirical analysis are given. Third section is devoted to the model and empirical findings and in the last section conclusion is presented.

Data and Variables

In order to investigate empirically the impact of different type of uncertainties on employment growth of the firms, we employ panel estimation methods for 2007-2014 periods. The data used in the analysis come from two different sources; Central Bank of the Republic of Turkey Business Tendency Survey (BTS) and Company Accounts (CA). BTS is a monthly survey that includes firms' evaluation of current, past and future trends of production, volume of sales orders, level of employment, stocks of finished goods, selling prices, unit cost, capacity utilization rate, producer price inflation rate, interest rates on loans and general course of business conditions. CA dataset covers information on balance sheets, income statements and firm data—such as employment, establishment date, company town, and legal status.

These two data sets are merged using the firm's identification codes. BTS is used for the construction of firm-level uncertainty measures and CA is used for deriving firm specific variables such as employment, total assets and net sales. Firms that do not change answers for the whole observation period which correspond to 227 firms are excluded from our analysis.

Uncertainty Measures

Although theoretically the impact of uncertainty on economic activity can be conceptualized, empirical identification of this relation is neither easy nor obvious. Primarily, measurement of uncertainty is the main challenge for the empirical studies. Uncertainty can be measured along several dimensions (such as demand, supply, price, cost etc.), in different ways (as unconditional variance, forecast errors or survey measures) and at different aggregation levels (such as aggregate economy, industry or firm-level). Bloom et al. (2012) use the variance and dispersions of several variables at establishment, firm, and industry levels to measure uncertainty. Some studies, such as Leahy and Whited (1996) and Bloom (2009), use stock market volatility as a measure of uncertainty. Another widely used uncertainty measure is the variance of forecasters' expectations (Bachmann et al., 2013). Baker et al. (2013) use the frequency of policy related news to form a proxy of policy uncertainty, which they found to be related to real activity, such as investment and output. Demir (2009) uses exchange rate volatility.

Here in this study using BTS, firm-level uncertainty measures related with production, domestic orders and export orders are calculated. BTS is monthly survey that aims to produce indicators that will show the short-term tendencies in the manufacturing industry. It covers manufacturing firms with more than 20 employees. Each month firms are asked to evaluate current, past and future trends of production, volume of sales orders, level of employment, stocks of finished goods, selling prices, unit cost and capacity utilization rate, producer price inflation rate, interest rates on loans and general course of business conditions. Using over the last 3 months and next 3 months questions related with production, domestic orders and export orders, three different firm level uncertainties are calculated (Table 1).

BTS questions used for uncertainty measure construction	Table 1
Production uncertainty	
BTS Q1. How has your production developed over the past 3 months? It has... (increased, remained same, decreased)	
BTS Q5. How do you expect your production to develop over the next 3 months? It will... (will increase, remain same, decrease)	
Domestic demand uncertainty	
BTS Q20. How have your domestic orders developed over the past 3 months? They have ... (increased, remained same, decreased)	
BTS Q21. How do you expect your domestic orders to develop over the next 3 months? They will... (increase, remain same, decrease)	
Foreign demand uncertainty	
BTS Q18. How have your export orders developed over the past 3 months? They have ... (increased, remained same, decreased)	
BTS Q12. How do you expect your export orders to develop over the next 3 months? They will... (increase, remain same, decrease)	

Firm-level uncertainty measures are calculated as the mean of the squared forecast errors according to the following formula:

$$\mathrm{unc}_{iT}^{k} = \frac{1}{n_{iT}} \sum_{t \in T} (\text{Developments over the last 3 months}_{it}^{k} - \text{Expectations over the next 3 months}_{it-3}^{k})^2$$

unc_{iT}^{k} is the k type uncertainty for firm i in year T (t represents quarters within a year) where k stands for production, domestic demand and foreign demand uncertainty; n stands for the number of forecast errors observed within a year. Expectation errors take values from -2 to 2 (Table 2).

Expectation errors	Table 2
	Development over the last 3 months(t)

		Increased	Remained unchanged	Decreased
Expectations over the next 3 months (t-3)	Increase	0	1	2
	Remain unchanged	-1	0	1
	Decrease	-2	-1	0

Other Firm Specific Variables

CA data set provides detailed firm-level information for comprehensive number of firms for a fairly long time period. Since 1989, balance sheets, income statements and firm specific information such as employment, establishment date, company town and legal status have been collected from financial and non-financial firms on an annual basis. Unique identification numbers given to each firm allow matching across the years to form a panel data set. The data has been compiling by economic sectors, classified according to four-digit level of NACE (Nomenclature Générale des Activités Economique dans les Communautes Européennes) Rev 2.

From CA data set the following firm specific variables are derived:

- Total assets variable is used as an indicator for firm size.
- Growth in total net sales variable is considered as a performance indicator for firms.
- Employment

Descriptive Analysis

Firms that are present in both data sets are matched as mentioned before. Those firms that are present in both data sets constitute our sample. As it can be seen from Table 3, on average there are 1500 firms for the 2007-2014 period.

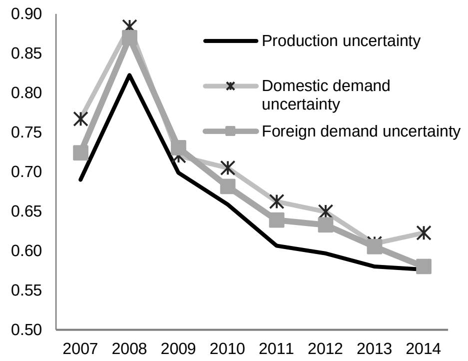
Descriptive Statistics for the Matched Sample — Table 3

	2007	2008	2009	2010	2011	2012	2013	2014
# of observations (Matched)	1056	1346	1372	1563	1721	1776	1663	1448
Average employment	480	405	383	383	378	385	376	399
Real net sales (2010=100)	119	107	100	100	104	104	113	117
Export share in total sales (%)	29	29	29	28	28	27	27	26

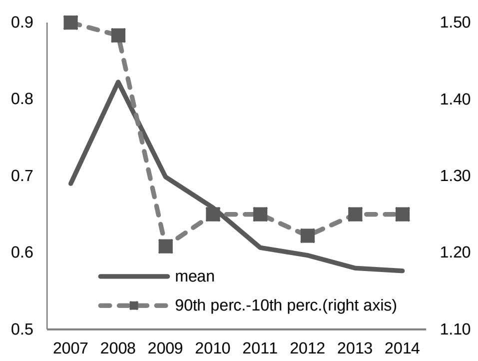
Using BTS responses of the firms that are present in the matched sample, production, domestic demand and foreign demand uncertainty measures are constructed. Summary of the uncertainty measures are given in the following figures and Table 4.

Figure 1. Uncertainty Measures Over Time (Mean)

Figure 2. Production Uncertainty



Source: Authors calculations



Source: Authors calculations

From the calculated measures, it is observed that uncertainty increased amid the crisis as expected and declined thereafter. Among different type of uncertainties, demand uncertainty seems to be higher relative to production uncertainty. From Figure 2, we can say that uncertainty dispersion widens from time to time.

Calculated uncertainty measures by specification take a value between 0 and 4. Mean and standard deviation of the measures are close to 0.6. And for 90 percent of the time, they take a value below 1.5.

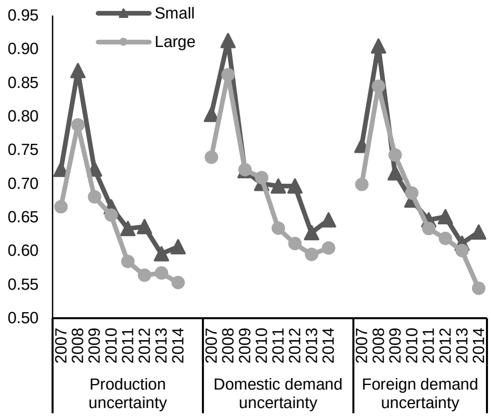
Summary Of The Calculated Uncertainty Measures

Table 4

		2007	2008	2009	2010	2011	2012	2013	2014	Total
Production uncertainty	mean	0.69	0.82	0.70	0.66	0.61	0.60	0.58	0.58	0.65
	st. dev.	0.59	0.73	0.54	0.56	0.52	0.50	0.56	0.56	0.57
	p90-p10	1.50	1.48	1.21	1.25	1.25	1.22	1.25	1.25	1.33
Domestic demand uncertainty	mean	0.77	0.88	0.72	0.70	0.66	0.65	0.61	0.62	0.69
	st. dev.	0.65	0.80	0.56	0.59	0.58	0.54	0.57	0.57	0.61
	p90-p10	1.67	1.72	1.26	1.33	1.38	1.33	1.30	1.33	1.42
Foreign demand uncertainty	mean	0.72	0.87	0.73	0.68	0.64	0.63	0.61	0.58	0.68
	st. dev.	0.64	0.79	0.57	0.58	0.59	0.54	0.57	0.56	0.61
	p90-p10	1.50	1.58	1.32	1.36	1.36	1.27	1.25	1.25	1.40

When uncertainty evaluation across different type of firms is considered, heterogeneity in the perception of uncertainty becomes obvious. Uncertainty encountered by small firms is higher for each type especially with respect to domestic and foreign demand (Figure 3). Domestic demand uncertainty is higher for firms with low export levels and firms with higher export level are subject to higher foreign demand uncertainty (Figure 4).

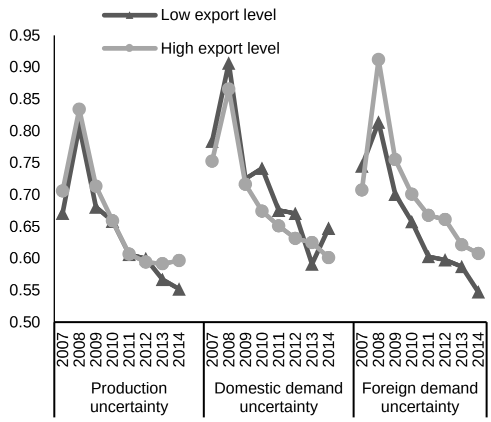
Figure 3. Uncertainty Measures Across Size Groups



Source: Authors calculations

Note: Small (large) refers to firms with total assets below (above) the median.

Figure 4. Uncertainty Measures According To Export Intensity

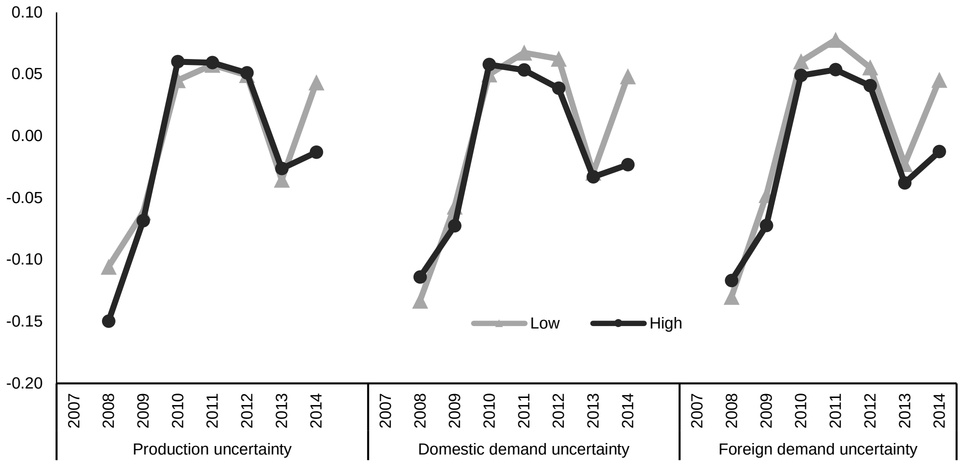


Source: Authors calculations

Note: Low (high) refers to firms with export below (above) the median.

Our main interest is to figure out the impact of uncertainty on employment growth. In order to visualize this relationship in Figure 5, average employment growth according to uncertainty levels are given. As expressed by the simple graph relating average employment growth to the uncertainty measures, there seems to be an evidence of a negative relationship between employment growth and uncertainty. In order to make close exanimation of this relation empirical model is employed in the next section.

Figure 5. Employment growth (log difference) according to uncertainty levels



Source: Authors calculations

Note: Low (high) refers to the level below (above) the median.

Empirical Model and Results

Based on theoretical arguments, negative relationship between uncertainty and employment growth is expected. To test validity of this argument for the case of Turkey, the following empirical model is estimated:

$$\Delta emp_{iT} = \alpha_i + \beta unc^{k}_{iT} + \delta Z_{iT} + \gamma T_T + \varepsilon_{iT}$$

where Δemp_{iT} stands for employment growth (log difference) of firm i at year T, unc^{k}_{iT} is the firm-level uncertainty of type k (k=production, domestic demand and foreign demand), Z_{iT} contains firm-specific control variables such as size proxied by total assets, log difference of real sales to control for economic activity. T_T denotes time dummies, α_i firm-specific unobserved heterogeneity and ε_{iT} is the error term. The estimated models are given in Table 5.

Results suggest that for the overall sample, among the uncertainty measures that we use only foreign demand uncertainty has a statistically significant adverse impact on employment growth. This is consistent with the earlier finding for the Turkish economy that point out the adverse impact of exchange rate volatility (Demir, 2009; Cengiz, 2009). Accordingly one standard deviation increase in foreign demand uncertainty reduces employment growth by around 1 (1.5*0.6) percentage points.

Model Estimation Results

Table 5

Dependent variable: log difference of employment
Model: FE

	k=		
Variables	Production uncertainty	Domestic demand uncertainty	Foreign demand uncertainty
Unc^{k}_{iT}	0.000	-0.009	-0.015*
	(0.010)	(0.009)	(0.009)
Unc^{k}_{iT-1}	-0.006	0.008	-0.012
	(0.008)	(0.009)	(0.008)
Controls	√	√	√
Time dummies	√	√	√
R^2	0.056	0.057	0.062
# of Observations	8,116	7,781	7,309
# of Firms	2,028	1,965	1,848

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

In order to observe differentiated responses of different group of firms with respect to exporter status, size and credit availability, we re-estimate the model given above with the interaction terms. The corresponding estimation results are given in the following tables.

Model Estimation Result With Exporter Status Interaction Term

Table 6

Type of interaction: Dummy=1 if export share in sales is above the median, 0 otherwise
Dependent variable: log difference of employment
Model: FE

	k=		
Variables	Production uncertainty	Domestic demand uncertainty	Foreign demand uncertainty
Unc^{k}_{iT}	0.027*	-0.001	0.001
	(0.015)	(0.012)	(0.014)
Unc^{k}_{iT-1}	0.001	0.009	0.006

	(0.013)	(0.014)	(0.014)
Unc^k_{iT}xDummy	-0.046**	-0.015	-0.028
	(0.020)	(0.017)	(0.019)
Unc^k_{iT-1}xDummy	-0.013	-0.002	-0.031*
	(0.016)	(0.017)	(0.019)
R^2	0.058	0.057	0.064
# of Observations	8,116	7,781	7,309
# of Firms	2,028	1,965	1,848

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All estimations include control variables, time dummies and the interaction dummy.

Although production uncertainty has no significant impact on average, it does matter for firms that have higher export share. Differentiated response of exporters is also significantly higher with respect to foreign demand uncertainty (Table 6). For the group of exporters one standard deviation increase in production and foreign demand uncertainty reduces employment growth by 2.8 and 1.9 percentage points respectively. Furthermore, small and credit constrained firms are adversely affected by production and domestic demand uncertainty (Table 7 and Table 8). Size of the firm is determined by the size of its assets. Credit condition of the firm is measured as the ratio of total bank credit to total amount of external resources used. This measure takes a value between 0 and 1, as it approaches to 0 credit conditions worsen for the firm, in other word firm becomes more credit constrained.

Model Estimation Result With Size Dummy Interaction Term

Table 7

Type of interaction: Dummy=1 if firm's assets are less than the median, 0 otherwise
Dependent variable: log difference of employment
Model: FE

	k=		
Variables	Production uncertainty	Domestic demand uncertainty	Foreign demand uncertainty
Unc^k_{iT}	-0.001	0.003	-0.026**
	(0.012)	(0.012)	(0.012)
Unc^k_{iT-1}	0.001	0.005	-0.003
	(0.011)	(0.012)	(0.011)
Unc^k_{iT}xDummy	0.005	-0.030*	0.025
	(0.022)	(0.018)	(0.020)
Unc^k_{iT-1}xDummy	-0.018	0.003	-0.023
	(0.017)	(0.018)	(0.018)
R^2	0.057	0.058	0.064
# of	8,116	7,781	7,309
# of Firms	2,028	1,965	1,848

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All estimations include control variables, time dummies and the interaction dummy.

Model Estimation Result With Credit Conditions Dummy Interaction Term

Table 8

Type of interaction: Dummy=1 if firm is more credit constrained than the median firm, 0 otherwise
Dependent variable: log difference of employment
Model: FE

	k=		
Variables	Production uncertainty	Domestic demand	Foreign demand
Unc^{k}_{iT}	0.019	-0.017	-0.015
	(0.014)	(0.013)	(0.013)
Unc^{k}_{iT-1}	-0.004	0.022*	-0.010
	(0.012)	(0.012)	(0.011)
Unc^{k}_{iT}xDummy	-0.037*	0.016	-0.001
	(0.019)	(0.018)	(0.018)
Unc^{k}_{iT-1}xDummy	-0.004	-0.029*	-0.004
	(0.015)	(0.016)	(0.015)
R^2	0.057	0.058	0.064
# of	8,116	7,781	7,309
# of Firms	2,028	1,965	1,848

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All estimations include control variables, time dummies and the interaction dummy

Conclusion

In this paper we estimate the impact of uncertainty on employment growth using a matched firm level data set of sector balance sheets and business tendency survey. The analysis is annual and covers the period 2007-2014. Availability of business tendency survey results at monthly frequency facilitates the computation of uncertainty measures at the firm level. Deriving from forecast error approach uncertainty measure is based on the differences between realizations and expectations of production and demand for the specified time period. In the literature there are few papers that measure the impact of uncertainty on employment growth at the firm level and to our knowledge this is the first paper that uses a matched sample of firm balance sheets and business tendency survey for this purpose.

Our results suggest that overall only foreign demand uncertainty has statistically significant adverse impact on employment growth. This is consistent with the earlier findings for the Turkish economy that point out the adverse impact of exchange rate volatility. Accordingly one standard deviation increase in foreign demand uncertainty reduces employment growth by around 1 percentage points. Although production uncertainty does not have a significant impact for the overall sample, looking at different groups, exporters, small firms and credit constrained firms are found to be negatively affected by production uncertainty. Moreover, exporters are affected more severely by foreign demand uncertainty. Finally, small and financially constrained firms are also affected by domestic demand uncertainty.

As an extension of this line of research it would be beneficial to look at the asymmetric effects of uncertainty along the business cycle.

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IFC-ECCBSO-CBRT Conference on *"Uses of Central Balance Sheet Data Offices' information"*

Co-organised by the IFC, the European Committee of Central Balance Sheet Data Offices (ECCBSO) and the Central Bank of the Republic of Turkey (CBRT)

Özdere-İzmir, Turkey, 26 September 2016

Employment growth and uncertainty: evidence from Turkey[1]

Aslıhan Atabek Demirhan and Burcu Gürcihan Yüncüler, CBRT

[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.

Employment Growth and Uncertainty: Evidence from Turkey

Aslıhan Atabek Demirhan
H. Burcu Gürcihan Yüncüler

IFC / ECCBSO / CBRT Conference on
“Uses of Central Balance Sheet Data Offices’ Information”

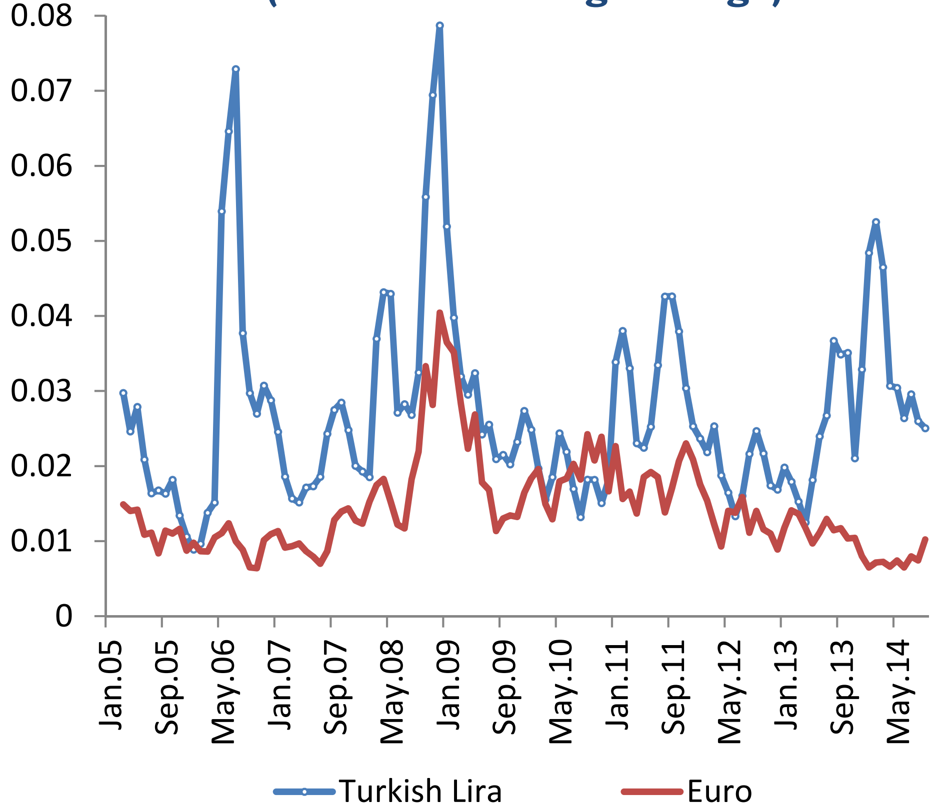
26 September 2016

Outline

- **Motivation**
- **Literature in brief**
- **Data**
- **Analysis**
  - Uncertainty measures
  - Estimation strategy
- **Results**
  - Relevance of exporter status and firm size on employment growth - uncertainty relationship

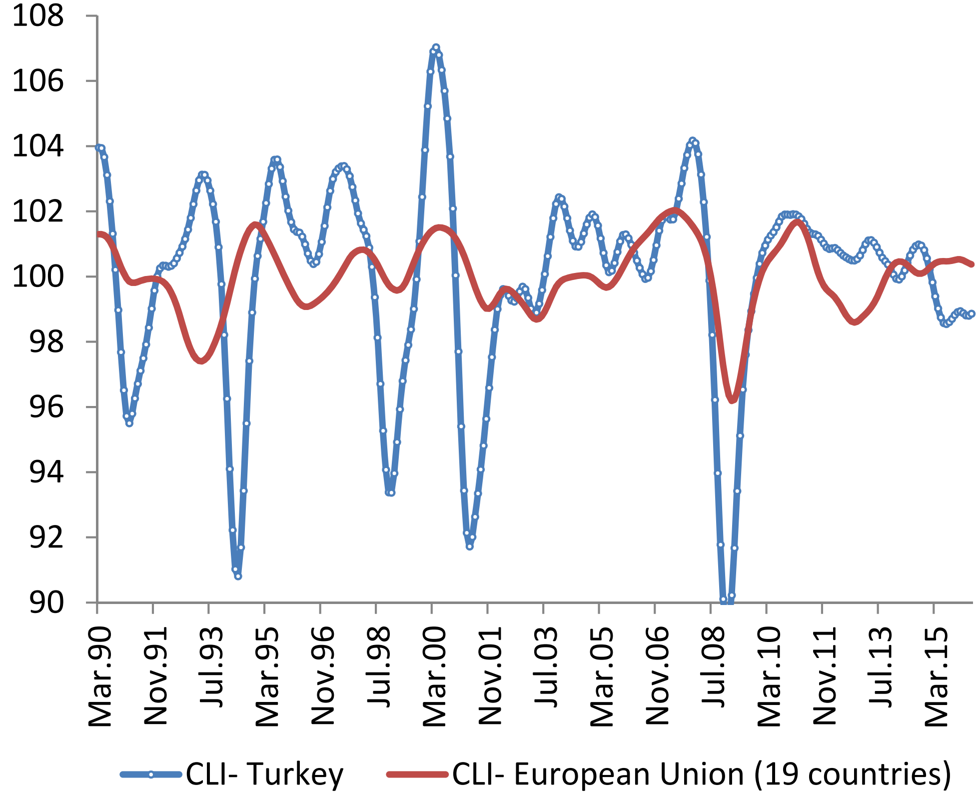
Firms in Turkey are exposed to high level of uncertainty…

Exchange rate volatility of the US dollar
(3 month moving average)



Source: Bloomberg

Composite Leading Indicators (CLI)



Source: OECD

Motivation

- **For the Turkish case, literature on measuring the impact of uncertainty is limited.**

- **Most of the literature uses aggregate measures of uncertainty. However uncertainty measured at the macro level misses the variation at the micro level.**

- **We pursue firm level analysis of uncertainty and employment dynamics using uncertainty measured at the firm level.**

- **Uncertainty affects firms' decisions via alternative channels**
  - **Theoretical explanations:**
    - **sunk cost component of expenditures adversely affects initiatives (McDonald and Siegal,1986 ; Dixit and Pindyck,1994);**
    - **greater uncertainty exacerbates information asymmetry between lenders and borrowers (small firms are affected more) (Greenwald and Stiglitz,1990);**
    - **risk-aversion**
- **Why would uncertainty affect employment in particular?**
  - **Existence of hiring and firing costs (Bloom, Bond and Van Reenen, 2007)**

Literature

- Empirically the impact of uncertainty is measured using both aggregate time series data and panel data at country, industry or firm level.

- Some results from empirical studies:

  - uncertainty have adverse impact on investment, firm entry decisions, capital to labor ratio, output, employment, welfare
  - Uncertainty may differentially affect small and large firms (Ghosal and Loungani (1996, 2000), Lensink (2005))

- Literature on the Turkish economy:

  - Using firm level data Demir (2009) finds adverse impact of exchange rate volatility on employment growth
  - Using Business Tendency Survey, Arslan (2013) shows that one st. dev. increase in aggregate uncertainty is followed by a 0.5 p.p. decline in year-on-year change of industrial production on impact.

- **Measuring Uncertainty**

  – **Uncertainty along several dimensions**
    - Demand : production, sales
    - Price and cost: fuel price growth, energy prices, output prices
    - Project-related technical factors
    - Macro policies and macro economic trends: expectations about credits, overall state of the economy (GDP, industrial production, stock prices, inflation, interest rates)

  – **Measured in different ways**
    - Unconditional variance (e.g. standard deviation of stock price)
    - Forecast errors (based on survey results or regression framework)
    - Survey measures (directly using questions on the perception of uncertainty)

- **Measuring Uncertainty**

  - **Aggregation at different levels**
    - **Industry (e.g. industry specific price as in Ghosal (2008))**
    - **Firm (e.g. sales as in Lensink (2005))**
    - **Macro level (e.g. industrial production as in Ghosal and Ye (2015))**

	CBRT Company Accounts (CA)	CBRT Business Tendency Survey (BTS)
Frequency Period Coverage	Annual 1990-2014 Financial and non-financial companies	Monthly January 2007- August 2016 Manufacturing firms (with 20 or more employees)
Purpose	Monitor the sectoral developments via the use of individual data from the financial statements of real sector enterprises	To produce indicators that will show the short-term tendencies in the manufacturing industry
Classification	NACE Rev.2	NACE Rev.2
Scope	Balance sheet, income statement, firm-specific information—such as employment, establishment date, company town, and legal status	Current, past and future trends of production, volume of sales orders, level of employment, stocks of finished goods, selling prices, unit cost and capacity utilization rate, producer price inflation rate, interest rates on loans and general course of business conditions.

Data and Variables

	2007	2008	2009	2010	2011	2012	2013	2014
# of Observations (CA, Manufacturing)	1299	1669	1732	2101	2406	2426	2546	2473
# of Observations (Matched)	1056	1346	1372	1563	1721	1776	1663	1448
Firms by size (share, %)								
Employment ≤50	2	4	5	5	4	4	6	6
50< Employment ≤250	42	52	52	53	55	54	53	52
Employment>250	55	44	43	42	41	42	41	42
Firms by export status (share, %)								
Exporter	92	90	90	91	89	89	89	87
Share of exports within total sales (%,median)	24	25	24	23	23	22	21	20

- Firms that are present in both data sets are matched.

Data and Variables

- **From CA dataset**

  - **Profitability** (defined as operating profits per net sales)
  - **Total assets**
  - **Total sales and exports**
  - **Credit constraints** (ratio of short-term bank loans to total liabilities)
  - **Employment**
  - **Region dummies** (according to NUTS 2) and **Sector dummies** (according to NACE Rev. 2)

Data and Variables

- **From BTS dataset: Firm-level uncertainty measures are calculated using BTS**

  - **Production uncertainty**

  BTS Q1. How has your production developed over the past 3 months? It has… (increased, remained same, decreased)

  BTS Q5. How do you expect your production to develop over the next 3 months? It will… (will increase, remain same, decrease)

  - **Domestic demand uncertainty**

  BTS Q20. How have your domestic orders developed over the past 3 months? They have … (increased, remained same, decreased)

  BTS Q21. How do you expect your domestic orders to develop over the next 3 months? They will… (increase, remain same, decrease)

  - **Foreign demand uncertainty**

  BTS Q18. How have your export orders developed over the past 3 months? They have … (increased, remained same, decreased)

  BTS Q12. How do you expect your export orders to develop over the next 3 months? They will… (increase, remain same, decrease)

Firm-level uncertainty measures are calculated according to the following formula:

$$unc_{iT}^{k} = \sum_{t \in T} (Developments\ over\ the\ last\ 3\ months_{it}^{k} - Expectations\ over\ the\ next\ 3\ months_{it-3}^{k})^2$$

unc_{iT}^{k} *is the k type uncertainty for firm i in year T (t represents quarters within a year).*

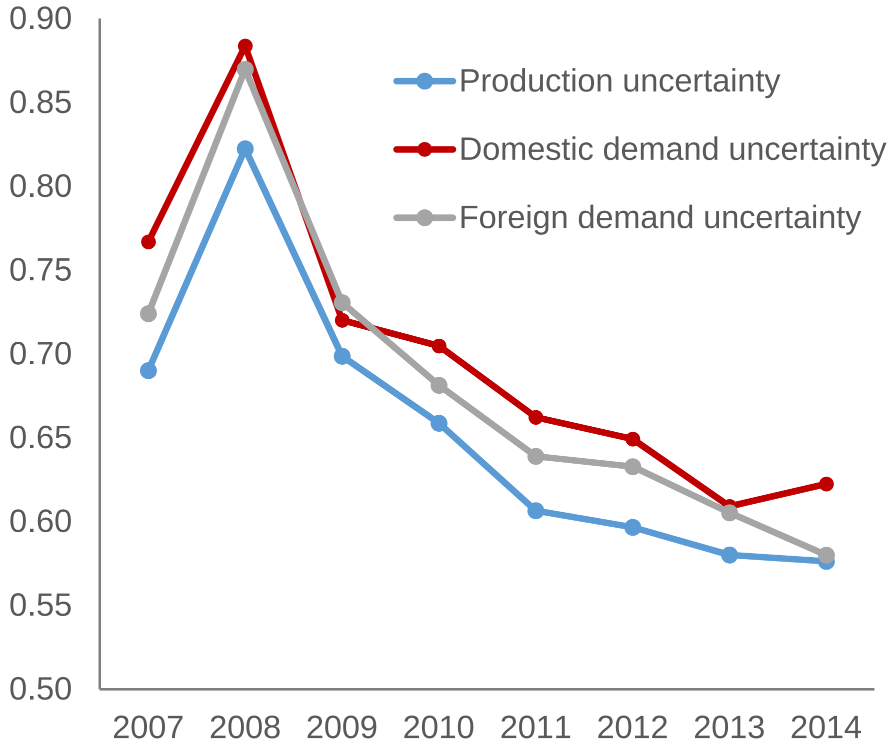
Using over the last and next 3 months questions related with production, domestic orders and export orders, three different firm level uncertainties are calculated.

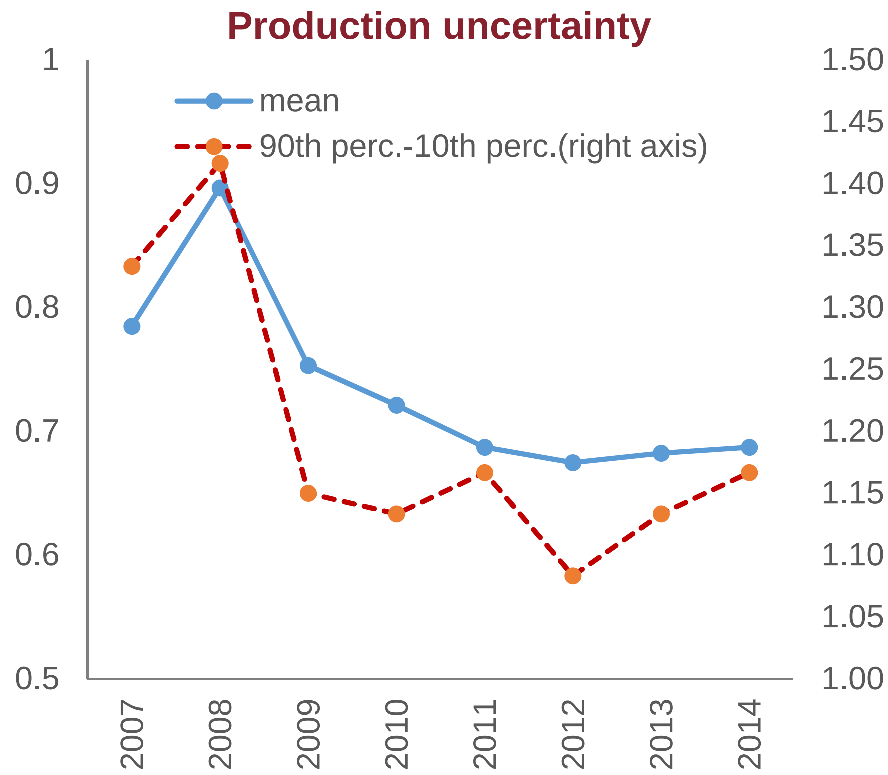
-Production uncertainty - Domestic demand uncertainty

-Foreign demand uncertainty

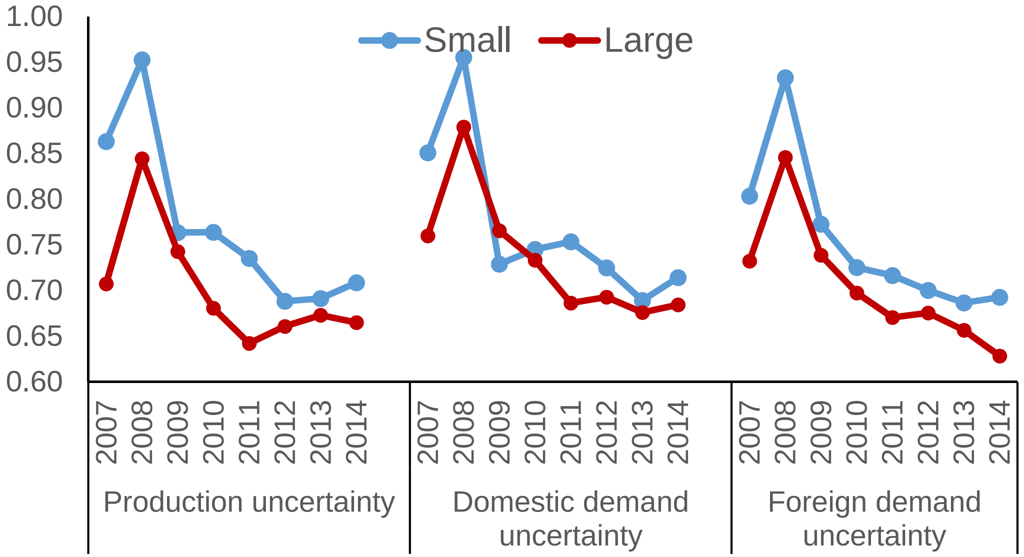
Summary Statistics: Firm Level Uncertainty Measures

- **Uncertainty measures increase during the crisis and decrease thereafter.**
- **Demand uncertainty seems to be higher relative to production uncertainty.**
- **Uncertainty dispersion widens from time to time**

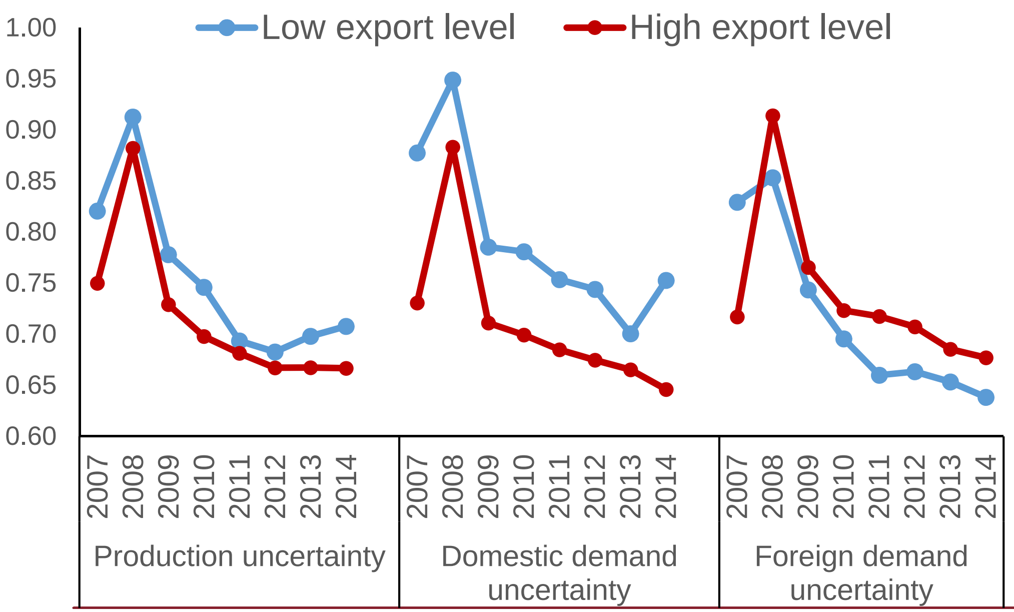




Summary Statistics: Firm Level Uncertainty Measures

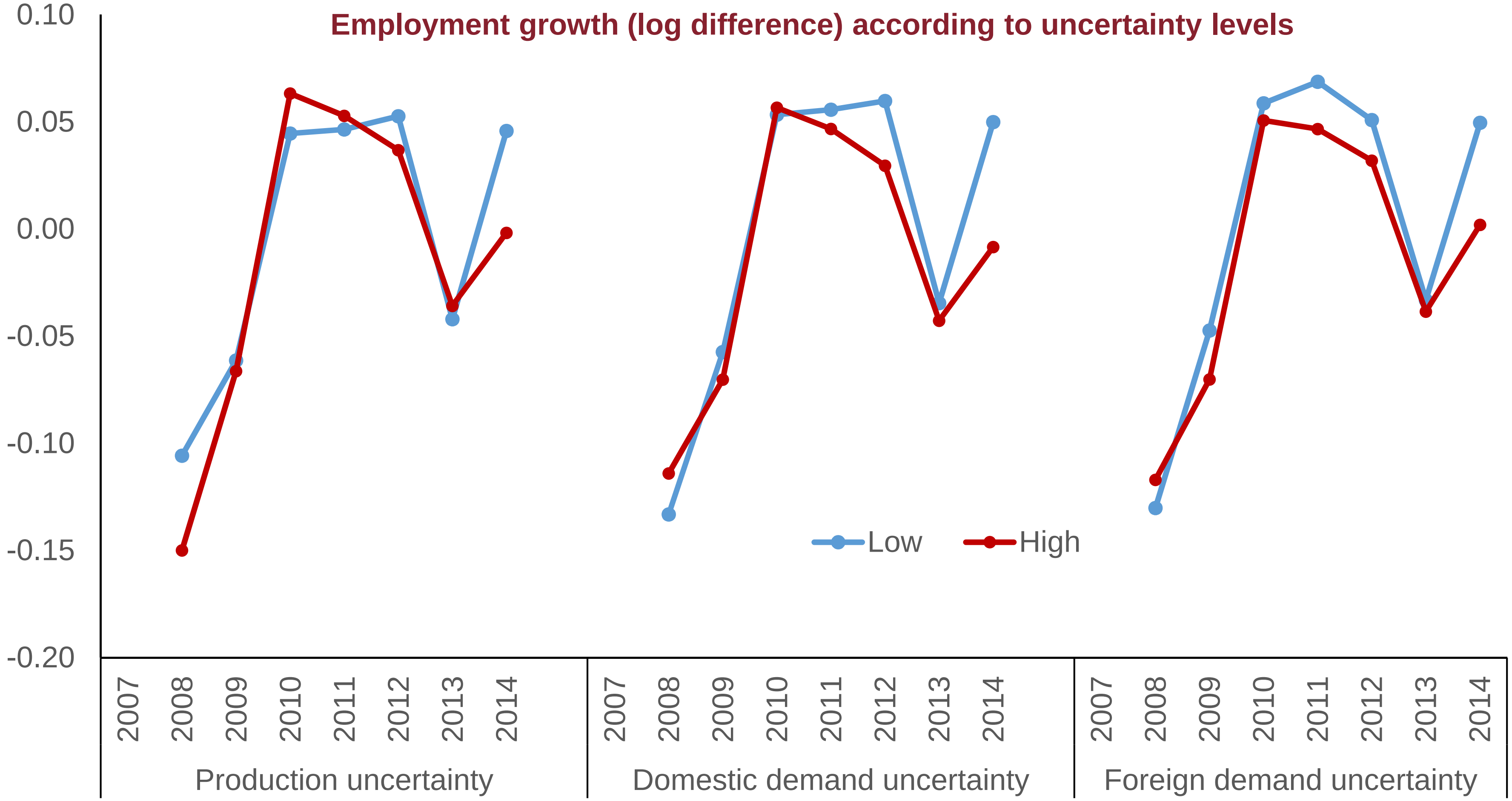


Note: Small (large) refers to firms with total assets below (above) the median.



- **Uncertainty encountered by small firms is higher.**
- **Production uncertainty is higher for firms with low export levels.**
- **Exporters are subject to higher foreign demand uncertainty.**

Summary Statistics: Employment Growth and Uncertainty



- **Without any controls, employment growth is lower for groups facing relatively higher uncertainty.**

$$\Delta emp_{it} = \alpha_i + \beta unc_{it}^{k} + \delta Z_{it} + \gamma T_t + \varepsilon_{it}$$

- where Δemp_{it} stands for employment growth (log difference) of firm i at year t,
- unc_{it}^{k} is the firm-level uncertainty of type k (k=production, domestic demand and foreign demand),
- Z_{it} contains firm-specific control variables such as size proxied by total assets, profitability measured as the ratio of operating profits to net sales, log difference of real sales,
- sectoral and regional dummies are also included as control variables. T_t denotes time dummies, α_i firm-specific unobserved heterogeneity and ε_{it} is the error term.

Preliminary Estimation Results

	Random Effect Results			Fixed Effect Results		
	k=			k=		
Variables	Production uncertainty	Domestic demand uncertainty	Foreign demand uncertainty	Production uncertainty	Domestic demand uncertainty	Foreign demand uncertainty
unc^k	-0.0005	-0.008	-0.007	0.0005	-0.010	**-0.016***
	(0.007)	(0.007)	(0.007)	(0.010)	(0.010)	(0.009)
$unc^k_{(-1)}$	**-0.012***	-0.002	**-0.011***	-0.006	0.008	-0.012
	(0.007)	(0.007)	(0.006)	(0.008)	(0.009)	(0.008)
Controls	√	√	√	√	√	√
Time dummies	√	√	√	√	√	√
Region dummies	√	√	√	X	X	X
R^2						
within	0.054	0.054	0.061	0.056	0.057	0.063
between	0.208	0.190	0.186	0.055	0.043	0.062
overall	0.084	0.083	0.090	0.042	0.037	0.054
Observations	8079	7756	7291	8182	7847	7362
Groups	2004	1944	1832	2056	1993	1872

In order to measure response of different group of firms. We use interaction terms;

Type of interaction: Dummy=1 if export share in sales is above the median, 0 otherwise

Dependent variable: log difference of employment
Model: FE

	k=		
	Production uncertainty	Domestic demand uncertainty	Foreign demand uncertainty
Variables			
unc^k	0.024	-0.006	0.001
	(0.016)	(0.014)	(0.015)
unc^k_{-1}	-0.004	0.011	0.014
	(0.013)	(0.014)	(0.016)
unc^k * Dummy	**-0.048****	-0.010	-0.028
	(0.021)	(0.019)	(0.020)
unc^k_{-1}* Dummy	-0.005	-0.001	**-0.034***
	(0.017)	(0.018)	(0.019)
Observations	7,279	6,989	6,571
R^2	0.117	0.120	0.136
Number of firms	1,933	1,872	1,769

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All estimations include control variables, time dummies and the interaction dummy.

Preliminary Estimation Results

Type of interaction: Dummy=1 if firm's assets are less than the median, 0 otherwise			
Dependent variable: log difference of employment **Model: FE**			
	k=		
	Production uncertainty	**Domestic demand uncertainty**	**Foreign demand uncertainty**
Variables			
unc^k	0.012	-0.006	-0.015
	(0.012)	(0.012)	(0.013)
unc^k_{-1}	-0.003	0.023*	0.004
	(0.011)	(0.012)	(0.011)
unc^k * Dummy	**-0.035***	-0.013	-0.001
	(0.021)	(0.020)	(0.020)
unc^k_{-1}* Dummy	-0.010	**-0.029***	-0.023
	(0.017)	(0.018)	(0.017)
Observations	7,279	6,989	6,571
R^2	0.115	0.121	0.135
Number of firms	1,933	1,872	1,769

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All estimations include control variables, time dummies and the interaction dummy.

Conclusion

Our preliminary estimation results reveal that:

- **Uncertainty has negative impact on employment growth of Turkish manufacturing firms.**

- **Foreign demand uncertainty has the highest negative impact on employment growth.**

- **Employment growth in more export oriented firms is adversely affected from uncertainty about production and foreign sales.**

- **Employment growth of small firms is adversely affected by uncertainty in production and domestic sales.**

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IFC-ECCBSO-CBRT Conference on *"Uses of Central Balance Sheet Data Offices' information"*

Co-organised by the IFC, the European Committee of Central Balance Sheet Data Offices (ECCBSO) and the Central Bank of the Republic of Turkey (CBRT)

Özdere-İzmir, Turkey, 26 September 2016

Looking at aggregate currency mismatches and beyond[1]

Emese Kuruc, Bruno Tissot and Philip Turner,
Bank for International Settlements

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

Looking at aggregate currency mismatches and beyond

Emese Kuruc, Bruno Tissot and Philip Turner (BIS)[1]

Abstract

As a result of major reforms, aggregate currency mismatches in emerging market economies (EMEs) were much reduced in the decade or so before 2010. The lower sovereign credit spreads in international bond markets that resulted made it easier for companies from EMEs to borrow abroad. It also helped EMEs to face the turbulence related to the Great Financial Crisis of 2007-09.

Although they have increased since 2010, aggregate currency mismatches are no longer a problem in most EMEs. But this is almost entirely due to the stronger foreign exchange position of the official sector – higher forex reserves and less foreign currency-denominated government debt. Currency mismatches of the non-official sector are larger and measures reported in this paper provide an indication of their size.

In addition, a significant proportion of foreign currency bonds of EME local corporations have been issued by their financing vehicles located abroad. Such borrowing is not captured by residency-based statistics. In several cases, these overseas affiliates of EME local corporations have a rather limited productive and exporting capacity. For this reason, the measures reported here may significantly understate the true size of the recent increase in currency mismatches for EME corporates. This puts a premium on using as a complement information collected at consolidated group level – that is, on a nationality basis.

Keywords: currency mismatch, emerging markets, foreign currency exposure, financial stability.

JEL classification: C18, E00, F31, F34, F60

[1] Paper presented on the occasion of the IFC/ECCBSO/CBRT Conference on "*Uses of Central Balance Sheet Data Offices' information*", organised by the Irving Fisher Committee on Central Bank Statistics (IFC), the European Committee of Central Balance Sheet Data Offices (ECCBSO) and the Central Bank of the Republic of Turkey (CBRT), Özdere-İzmir, 26 September 2016. The views expressed are those of the authors and do not necessarily reflect those of the BIS or the IFC.

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Contents

1. Introduction

Foreign currency mismatches have been traditionally seen as a key source of weakness for emerging market economies (EMEs), often triggering or aggravating financial crises. Some felt that EMEs would never be able to borrow abroad in their own currencies – the "*original sin*" view put forward by Eichengreen et al (2002). Yet a combination of macroeconomic reforms in the EMEs and better economic conditions confounded this initial pessimism. Moreover, in aggregate terms, the situation has greatly improved over the past two decades, and many no longer consider currency mismatches as a problem in most EMEs.

Yet correctly assessing the related financial stability risks posed by foreign currency exposures requires to look beyond aggregate numbers. First, not all countries are in the same position. Second, most of the improvement observed in EMEs has reflected the enhanced balance sheet position of the official sector; the situation of the private sector is less strong. Third, corporates in EMEs have increasingly issued foreign currency debt through their affiliates located abroad. Such affiliates are often located in international financial centres and have no independent exporting capacity. Hence, residency-based statistics may significantly understate the true exposures of the parent companies located in EMEs. These reservations underline the interest in looking at more granular data to better assess the risks posed by foreign currency mismatches.

Section 2 reviews the concept of currency mismatch and highlights the need to effectively monitor exposures to exchange rate movements. Section 3 presents an approach to actually compute indicators for measuring such currency mismatches, and Section 4 analyses the evolution of main emerging regions observed before and after the Great Financial Crisis (GFC). Section 5 shows how the concept of currency mismatch can be useful for assessing the full impact of exchange rates movements for emerging market economies. Section 6 reviews the limitations posed by the residency-based view of economic activity and Section 7 highlights the need for more granular information. Section 8 concludes.

2. Currency mismatch and exposure to exchange rate movements

BIS statistics have always been central to attempts to assess currency exposures. It was Andrew Crockett, then General Manager of the BIS, who suggested in the early 2000s the use of BIS's data on international banks and debt securities to construct measures of currency mismatches. He instigated at the BIS a systematic study by Morris Goldstein and Philip Turner of currency mismatches in emerging economies, and the results were published in Goldstein and Turner (2004).

The concept of currency mismatch is easy to state (even if difficult to measure). A currency mismatch between domestic and foreign currencies arises whenever an entity's financial position is sensitive to changes in the exchange rate.[2] The "stock" aspect of such a currency mismatch is given by the sensitivity of the balance sheet to changes in the exchange rate; meanwhile, the "flow" aspect is given by the sensitivity of the income statement to these changes. The greater such sensitivity, the larger the currency mismatch. Typically, one will focus on the adverse impact of an exchange rate depreciation, since difficulties for EME domestic borrowers arise when they have a short position in foreign currencies – when the local currency depreciates, it is more difficult for those domestic borrowers to repay foreign currency debt, all else equal.

Box 1

External debt and foreign currency exposure

Debt measures can vary depending on the currency denomination and the residence of lenders, and each approach has its own advantages and drawbacks. The Goldstein–Turner concept of foreign currency exposures referred to in this paper differs from the concept of external debt in the national accounts framework because it (i) seeks to include domestic debt denominated in foreign currency and (ii) excludes liabilities to non-residents expressed in local currency. This "total foreign currency-denominated debt approach" is also the one followed by the BIS in computing debt-weighted exchange rate indices (see Berger (2016)).

In contrast, and according to the External Debt Statistics Guide (IMF (2014)), "*gross external debt is the amount, at any given time, of disbursed and outstanding contractual liabilities of residents of a country to non-residents to repay principal, with or without interest, or to pay interest, with or without principal*" (IMF (2014); cf #1.2). Accordingly, "*the net external debt position is equal to gross external debt less gross external assets in debt instruments*" (#7.50). This approach includes external debt denominated in local currency but excludes foreign currency-denominated debt to residents.

A second important point relates to the instruments being considered. Both the Goldstein–Turner foreign currency debt exposures concept and the external debt concept include only debt-like instruments. Equity-like instruments (including FDI) are excluded because they have no obvious foreign currency/local currency characteristics and are, in addition, not subject to similar repayment obligation as for debt-like instruments. This approach is different from the international investment position (IIP) of an economy, which "*is the balance sheet of the stock of external financial assets and liabilities, with the difference being the net asset (or liability) position*" (cf #1.4 and Appendix 4 of the External Debt Statistics Guide). As a result, the broader IIP concept encompasses equity instruments and not just debt instruments (see also Table A4.1 of the Guide for how these various concepts interact). This broader approach is typically followed for assessing the balance sheet of an economy and the valuation effects related to exchange rate movements (Bénétrix et al (2015)).

A last point to note is that the IIP also differs from the country's net worth, which includes non-financial assets – on these System of National Accounts (SNA) concepts, see also European Commission et al (2009).

It follows from this definition that it will generally not be possible to get a reliable picture of a country's aggregate currency mismatch by looking solely at the country's external balance sheet (as is often done by observers). Although they can be linked, *foreign currency exposure* is in fact not the same as *net external debt* (see Box 1). Because there has been much confusion on this point, it is worth clarifying when these two concepts would coincide. There are two necessary – but not sufficient –

[2] Hence, as mentioned by Gagnon (2014), a currency mismatch occurs when "*a household's or a firm's liabilities are denominated in a different currency from that of the future stream of earnings that are to be used to service those liabilities*".

conditions for equivalence between the concept of foreign currency exposure and external debt.[3] The first is that all debt contracts between residents (such as, for example, bond sales) be in local currency – that is, there are no internal contracts in foreign currency. The second condition is that all contracts of residents with non-residents be in foreign currency.[4]

These conditions are rarely met, implying that the concept of foreign currency exposure usually differs markedly from the concept of external debt. Many internal contracts between residents of the same country, especially in emerging regions, are in foreign currency; hence foreign currency exposure can arise despite a balanced external position at country level. Conversely, a significant part of EMEs' external liabilities reflects foreign purchases of their government bonds denominated in local currency. These external debt liabilities do not create foreign currency exposure, and they have indeed increased significantly in many EMEs in recent years with the development of domestic bond markets (CGFS (2007a)).

Moreover, the two conditions referred above are usually not consistent. For instance, if the second condition applies – that is, non-residents are prepared to buy a country's bonds only if denominated in foreign currency (eg dollar) and not in domestic currency – surely, some residents would also have a similar preference and would want to have domestic contracts in foreign currency. In practice, indeed, it is often residents in countries where there is little confidence in the local currency (or in the respect for local contracts) who buy a significant portion of the international bonds issued by their government. So it is quite unlikely to have a situation where both all contracts between residents are in local currency ***and*** all contracts of residents with non-residents are in foreign currency. Hence, there is no reason to suppose that aggregate foreign currency exposure should be equal to net external debt.

3. Measuring currency mismatches

Goldstein and Turner (2004) have developed a measure of aggregate currency mismatches in the economy as a whole.[5] The objective was to quantify the riskiness of foreign currency exposures of countries whose foreign currency debt liabilities exceeded their foreign currency assets. Their measure used data on international

[3] Here we focus only on the exposures/external debt of *resident* entities. As argued below (Section 6), one would also want to look at the exposures of national entities on a *consolidated* basis; this would represent a third factor of differentiation with the net external debt concept, which relies on the residency-based national accounts framework.

[4] They are not sufficient conditions because external assets could be in one foreign currency while external liabilities be in a different foreign currency. In this case, there would still be foreign currency exposures (independently of the given state of the net external debt) that would arise from movements in the cross-rates between foreign currencies. Because leveraged investors who wish to take calculated risks will usually borrow in a "safe", low-interest-rate foreign currency to hold assets in a higher-interest-rate foreign currency, this type of mismatch can be common.

[5] The Goldstein-Turner indicators have since been regularly used in BIS publications; see for instance Jeanneau and Tovar (2006), CGFS (2007a), CGFS (2007b), Mohanty and Turner (2010), Mehrotra et al (2012), Montoro and Rojas-Suarez (2012), Gadanecz and Mehrotra (2013), Devereux and Yetman (2014) as well as Chui et al (2016).

bank lending and bond issuance; on the currency of domestic bond issuance; and on the currency denomination of domestic credit.

An important element was that the Goldstein-Turner measure takes account of internal foreign currency exposures: that is, bank and bond financing in foreign currency from one resident to another. In fact, capturing such lending relationships is essential for financial stability analysis because a sharp currency depreciation can lead borrowers to default on FC debts to other residents. It is therefore important to avoid netting FC exposures that can arise within a country among domestic residents. Moreover, the measure follows the "economy as a whole" principle, ie it includes in the analysis all the resident entities of the country, whether foreign- or domestic-owned. As a result, this also means that these currency mismatch measures do not include entities that are located outside of the country (eg offshore financing vehicles) even if linked to domestic firms or households – a limitation that has become more serious with the increased globalisation of financial markets (as discussed in Section 6 below).

As detailed more fully in Chui et al (2016), an adequate measure of forex debt exposure should combine two distinct components of currency mismatches, the importance of the share of FC-denominated debt and the net foreign debt position.

The **first element** is the foreign currency share of total (ie domestic and external) debt, FC%TD, scaled against the share of exports in GDP, X/Y. The reason is that, ideally, the country should have enough FC revenues to service its FC debt. Hence, the foreign currency share of debt should be viewed in comparison to the share of tradables in GDP – Goldstein and Turner (2004) used total exports of goods and services as a proxy for this tradables share of GDP. The first, simple mismatch ratio is thus:

$$(1) \qquad \frac{\text{FC\%TD}}{\text{X/Y}}$$

The reasoning is that countries with high export/GDP ratios can sustain higher foreign currency shares in total debt. The greater this mismatch ratio is – ie the larger the share of foreign currency debt is compared to the exports share – the more difficult the situation for the country can be: at some point, exports may not generate sufficient earnings to finance foreign currency debt servicing. A number of studies (eg Montoro and Rojas-Suarez (2012)) have highlighted the usefulness of such a simple mismatch indicator for analysing the resilience of economies to an external financial shock.

The **second element** to be considered for assessing FC exposures is the difference between foreign currency debt assets (FCA) and foreign currency liabilities (FCL) as a percentage of GDP. The mismatch ratio is:

$$(2) \qquad \frac{\text{FCA–FCL}}{\text{Y}}$$

When a country has net foreign currency liabilities, its Net Foreign Currency Asset (NFCA) position – that is, assets minus liabilities (ie: FCA-FCL) – is negative. In that situation, any exchange rate depreciation has a negative balance sheet effect; that is, the country's NFCA, expressed in domestic currency, becomes more negative. The larger the net liability position relative to GDP, the greater this balance sheet effect. Of course, it is important to keep in mind the significant uncertainty (and revisions) affecting measures of financial assets and liabilities as well as the difficulty to adequately capture off-balance sheet exposures (cf Box 2).

Box 2

Computation of the Net Foreign Currency Asset position

To start with, the NFCA is calculated as the sum of:

- (i) the net foreign assets of the central banks and other depository corporations (that is, banks; source IMF-IFS);
- plus (ii) non-bank foreign currency cross-border assets with BIS reporting banks (source BIS locational international banking statistics (LBS));
- minus (iii) non-bank foreign currency cross-border liabilities (excluding debt securities) to BIS reporting banks (source BIS LBS); and
- minus (iv) non-bank international debt securities outstanding in foreign currency (source BIS international debt securities statistics (IDS)).

For a general introduction on the BIS statistics underlying these calculations, see BIS (2015) as well as BIS, FSB and IMF (2015). Note that (i) covers the net external positions of the resident banking sector, (ii) and (iii) cover the net assets of the non-bank resident sectors (excluding the debt securities they may have issued and that would be held by BIS reporting banks) vis-à-vis the foreign banking system, and (iv) covers FC debt securities issued by non-bank residents.

Obviously the measures computed are approximations based on a number of simplifications (in addition to the significant uncertainty – and revisions – affecting estimates of financial assets and liabilities)[6]:

- One is that (i) is assumed to be mainly in FC. Admittedly, this is more likely to be the case for EMEs compared to advanced economies (typically, EME external assets would be assumed to be in dollars). But this simplification is likely to significantly understate the extent of cross-currency mismatches.
- Second, most of the instruments covered by (ii) and (iii) are supposed to be debt instruments (excluding debt securities from the liabilities), noting that some limited part of the cross-border assets and liabilities captured by the BIS LBS can be equity instruments; and there may also be some potential double-counting with banks' positions as recorded in (i).
- Third, it is assumed that most international banking activity is captured by BIS reporting banks.
- Lastly, the FC exposures deriving from these reported balance sheet positions do not take into consideration potential hedging operations (see Section 7 below).[7] In particular, while central banks' FC positions comprised in (i) would typically not be assumed to be hedged, unhedged commercial banks' positions could be expected to be small due to supervisory requirements (admittedly, at the bank-consolidated level rather than on a residency basis). As regards non-banks' positions, anecdotal evidence suggests that aggregate country's exposures through derivatives contracts could potentially be large; this is noted by Gagnon (2014), who finds for instance that the economy with the greatest AECM computed using balance-sheet data in emerging Asia

[6] As recognised for instance in #12.27 of the External Debt Statistics Guide: "*the boundaries between debt and equity, and direct, portfolio, and other investment are subject to different interpretations, and also subject to error and mismeasurement*".

[7] The inclusion of derivatives varies across the data sources. As regards the next external debt, "*financial derivatives (…) are not included in the gross external debt position because they are not debt liabilities*" (#2.52). Derivatives are captured in the BIS LBS in general, but not in the subcomponents used here to estimate (ii) and (iii). As regards the IMF-IFS statistics used for (i), the net foreign assets should include financial derivatives. Yet their measurement is prone to uncertainty and variations across countries. Moreover, it is based on the value of the related contracts and will not capture their potential impact on exposures as recognised in the *Monetary and financial statistics manual and compilation guide* (IMF (2016); #6.142): "*analysis of the vulnerability of an economy's external debt position requires data beyond that provided by the IIP framework…*" including "*increasingly, extent to which financial derivatives are used to hedge, or even increase, exposure to risk*".

(Korea) has also the most developed derivatives markets. Yet, while Bénétrix et al (2015) recognise that cross-border currency hedging is difficult to assess, they also argue that it is typically advanced economies that engage in derivatives operations; this suggests that the related uncertainty for EMEs should be relatively modest.[8]

The resulting index for **aggregate 'effective' currency mismatch** (termed AECM) follows from the multiplication of the two mismatch ratios presented above:

(3) $$AECM = \frac{NFCA}{X} \cdot FC\%TD$$

where: FC%TD = Foreign currency share of total debt;

X = Exports of goods and services;

NFCA = Net Foreign Currency Assets.

If foreign currency assets are exactly equal to foreign currency liabilities then AECM is zero – that is, there is no aggregate effective currency mismatch. This would be true even if FC%TD is high, as in a dollarised economy, where debts are largely denominated in dollars. If a country has a net liability position in foreign currency (ie NFCA is negative), AECM will be negative, and the country's net debt position worsens when the currency depreciates. The greater the foreign currency share of total debt, the greater the aggregate impact. Ratio (3) can thus be thought of as a stress test for assessing, in a stylised way, the overall impact of an exchange rate shock on the FC exposure of a country – combining the share of foreign currency in total debt with a measure of the country's net foreign currency position relative to its exports. Using this AECM concept, Gagnon (2014) shows that Asian EME economies have significantly reduced their vulnerability after the Asian financial crisis of 2007/08. Borio and Packer (2004) found that explicit proxies for currency mismatches do matter when explaining sovereign ratings.

Yet using summary indicators as proposed above has three notable caveats. The first is that a *more comprehensive assessment of the macroeconomic consequence of an exchange rate movement* should also take into consideration other factors. An important one is the competitiveness effect from currency depreciation, that is, the associated rise in real exports and fall in real imports. Traditionally, this leads initially to a deterioration of the nominal trade balance, followed in the longer run by an improvement depending on the country's specific lags and circumstances (eg the so-called Marshall–Lerner condition). Another important factor to be considered is that

8 An assumption that seems consistent with the results of the BIS Triennial Central Bank Survey of foreign exchange and OTC derivatives markets in 2016 (http://www.bis.org/publ/rpfx16.htm), which shows that only 10% of global derivatives turnover is in contracts denominated in the currency of an EME. As argued by Upper and Valli (2016), "*derivatives markets for EME currencies and interest rates tend to be much smaller than their advanced economy counterparts* (…). *EME derivatives markets are also limited to a narrower set of instruments* (… and…) *there is reason to believe that residents of and investors in EMEs find it more difficult and more costly to hedge their exposures than their peers in advanced economies*".

the value of equity-like FC instruments and thus of the whole country's financial balance sheet will also be affected by the depreciation.[9]

The second issue relates to the word "*aggregate*": the AECM indicator is computed for an economy as a whole. Yet a specific aggregate may conceal sectoral (as well as intra-sector) differences in terms of net FC assets. For instance, the government may have a positive NFCA but the private sector a negative NFCA. This matters for several reasons. One is that the government would not be expected to cover private sector liabilities, so that netting the asset positions of all the sectors together may mask the real exposures of the private sector – although recent crises have highlighted the important role the government can play in providing implicit or explicit guarantees. From this perspective, consolidating private debts with large forex reserves at the country level could be highly misleading. Another factor is that the creditworthiness of the private sector will depend on its own currency exposures, not just of the country-wide situation. Yet a last factor is that specific market dynamics can be shaped by the private sector's reaction to an external shock; for instance, companies with large dollar debts will buy dollars to cover themselves when they think the dollar will appreciate – thereby putting downward pressure on the local currency, with the risk of creating a vicious circle of currency depreciation.

The third caveat is the difficulty to *capture off balance sheet positions and the related hedging of FC exposures*. The mismatch indicators presented here rely on a number of simplified assumptions (cf Box 2) which can lead to important shortcomings as discussed in Section 7 below. Nevertheless, even if the indicators cannot identify the extent to which the mismatch position has been hedged, this information can be useful for assessing vulnerabilities (CGFS (2007b)).[10]

9 The impact on the country's total net financial worth (ie not just the NFCA that considers only the foreign currency debt instruments) is complex as it depends on the relative currency composition of all external assets and liabilities. Moreover, it is generally acknowledged that the related valuation effects have grown in importance with financial globalisation and the expansion of cross-border portfolio allocation (Lane and Shambaugh (2010)). A well-known example is the US international position and the role of valuation effects related to exchange rate movements due to the idiosyncratic role played by the dollar. US assets are denominated in several currencies (not least because these assets comprise a significant amount of US direct investment in foreign countries), while the vast majority of US liabilities are denominated in dollars, reflecting the primary role played by the dollar in international markets as well as the safe haven status of the US economy. As a result, when the dollar weakens vis-a-vis other major currencies, the value in dollars of US assets goes up, and the US IIP position improves, everything else being equal (Heath (2007)). This net effect should increase relative to GDP in parallel with the rise in the stocks of assets and liabilities associated with financial globalisation.

10 For instance, the detection of large potential mismatches can be useful for monitoring whether and how hedging does in fact take place. Moreover, financial hedging can be costly, esp. for EME SMEs, or imperfect, raising other types of fragility (see also Chui et al (2014)). In particular, Gagnon (2014) notes that a solution to a currency mismatch may be creating a maturity mismatch to the extent that the balance-sheet positions have typically a longer maturity than corresponding derivatives positions; this is particularly problematic since maturity mismatches are often more difficult to identify – for an analysis of the interactions between FX and maturity risks in banks' balance sheets and the role played by the short maturity of FX swaps used for hedging positions, see in particular McGuire and von Peter (2009). Furthermore, when a crisis occurs, the financial position of the providers of hedges may also be impaired. A last point to note is that Borio and Packer (2004) found that adding measures of hedging possibilities do not bring much information when looking at the power of currency mismatch indicators for explaining sovereign ratings.

4. Evolution of currency mismatches in EMEs before and after the GFC

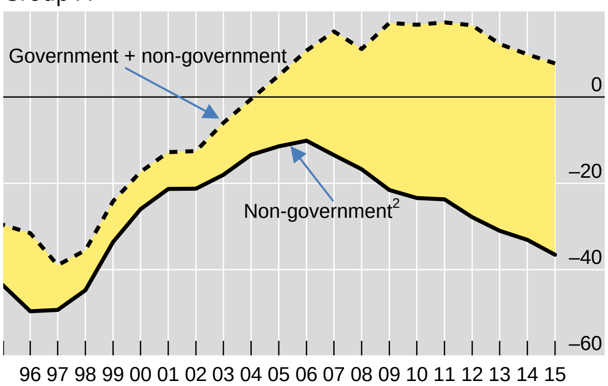
In what follows, we shall focus on the developments in aggregate net foreign currency assets as a percentage of exports (ie the NFCA/X ratio in (3)), leaving aside the influence of the FC share of debt.[11] The evolution observed since the mid-1990s is summarised in the dotted line of Graph 1. For a number of very large countries (eg China, India, Korea and Russia), shown in Panel B, the aggregate NFCA position is very strong, largely because of large official foreign exchange reserves: it increased markedly in the 2000s, and has roughly stabilised since 2010 at 120% of exports. In contrast, the position for the medium-sized EMEs, shown in Panel A, is less strong: their aggregate NFCA/X has in fact fallen since 2010 (although it is still somewhat positive).

Net foreign currency assets as a percentage of exports[1]

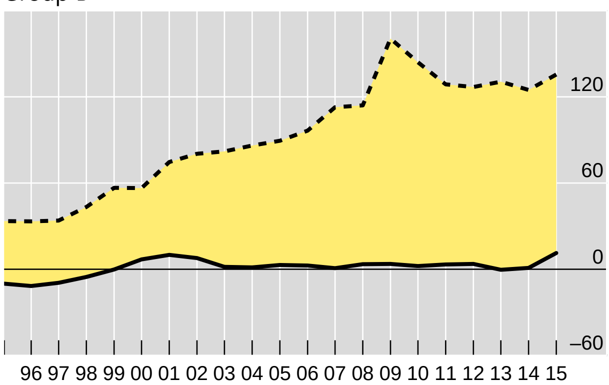
In percentages

Graph 1

Group A[3]



Group B[4]



[1] For net foreign currency assets, outstanding positions at year-end. Calculated with aggregates of the economies listed in footnotes 3-4. [2] Excluding the central bank and general government assets/liabilities where these can be identified. [3] Brazil, Chile, Colombia, the Czech Republic, Hungary, Indonesia, Malaysia, Mexico, Peru, the Philippines, Poland, South Africa, Thailand and Turkey. [4] China, Chinese Taipei, India, Korea and Russia.

Source: M Chui, E Kuruc and P Turner (2016).

Another key feature is that the decline in EMEs' currency mismatches revealed by these aggregate measures in the past few decades – especially from the 1990s to the 2000s – reflects to a significant extent changes in the ***official sector***'s[12] currency

[11] The reason of the simplified approach followed here (ie to focus only on the NFCA/X ratio instead of the more complete AECM in equation (3)) is that as a first approximation FC%TD is a *stock* variable that will change only progressively over time even if the FC composition of new debt issuance (the *flows* variable) varies. See Chui et al (2016) for the comprehensive data on recent developments in FC%TD and thereby on the AECM ratio, which shows a (relative) stabilization of the FC share of total debt in most EMEs since the early 2000s at least.

[12] The official sector being defined here as the sum of the government sector and the central bank (which in the SNA belongs to the financial corporate sector).

exposures, due to two main developments. One is that governments have reduced their foreign currency liabilities by shifting from bond issuance in dollars to local issuance, almost entirely in domestic currency.[13] A second is that EMEs' central banks have accumulated large foreign exchange reserves. The net result is that many official sectors in emerging regions now have a large net foreign currency asset position – so that any depreciation in the domestic currency actually improves aggregate countries' balance sheets.

In contrast, and not least reflecting the improved credit standing of many EME governments, EME companies have found it easier to borrow abroad. Several BIS papers have been pointing out for some time that the scale of EME companies' foreign currency borrowing rose substantially in the past decade – the "second phase of global liquidity (Shin (2013)). Recent BIS statistical work has therefore attempted to decompose aggregate currency mismatch measures into official sector and non-official sector mismatches (Chui et al (2016)). One difficulty is that the international data sources that can be used for this purpose do not provide full official sector/private sector breakdowns.

Nevertheless, two big components can be identified for EMEs: the central bank's foreign exchange reserves and the international foreign currency bonds issued by the government. Moreover, information is also available on the sectoral breakdown for the foreign currency claims of non-bank residents reported in the BIS LBS (cf BIS (2013)). The result of these estimates is the non-government sub-component of the NFCA/X ratio as shown in the continuous line of Graph 1. In particular, the left panel shows that in most medium-sized EMEs FC debt liabilities far exceed FC assets for the non-government sector (which mainly consists of non-financial corporations). By end-2015, net foreign currency liabilities of these countries have risen to 37% of exports. This suggests that the destabilising impact of the FC exposures recorded in some EMEs could be much larger than what aggregate country numbers tend to show.

5. Assessing the impact of exchange rates movements

As analysed above, the private sector's FC exposure plays a key role in determining forex market reactions. In case of significant currency mismatches, the balance sheets of EME firms worsen when the currency depreciates. In that case, depreciation can have a contractionary effect, counterbalancing the "traditional" stimulative effect through net exports. Attention has in particular focused on how exchange rate shifts can affect macroeconomic outcomes through the so-called "risk-taking channel", which works through changes in balance sheets and financial risk-taking (Bruno and Shin (2015)). A depreciation tends to weaken the balance sheets of entities that have net foreign currency liabilities. This in turn can weigh on internal demand directly (eg corporate spending) as well as indirectly, with the worsening of credit conditions: negative balance sheet effects reduce local lenders' risk-taking capacity, curtailing the provision of credit to the domestic economy.

[13] See CGFS (2007a) and the statistics compiled afterwards by the BIS, available for central government debt securities markets on http://www.bis.org/statistics/c2.pdf (Table C2).

Long-run elasticity of GDP growth with respect to real effective (REER) and debt-weighted (DWER) exchange rates

Table 1

	EMEs			Advanced economies		
	Short-run	Long-run	Ratio: short-run to long-run	Short-run	Long-run	Ratio: short-run to long-run
REER	–0.103***	–0.1217***	0.85	–0.058	–0.104***	0.56
DWER	0.1322***	0.105***	1.26	0.026	0.032	[1]
R-squared[2]		0.92			0.32	

***/**/* denotes results significant at the 1/5/10% level.

[1] Neither elasticity is statistically significant at 10%. [2] The higher R-squared for EMEs is a reflection of the higher explanatory power of the lagged dependent variable compared with advanced economies.

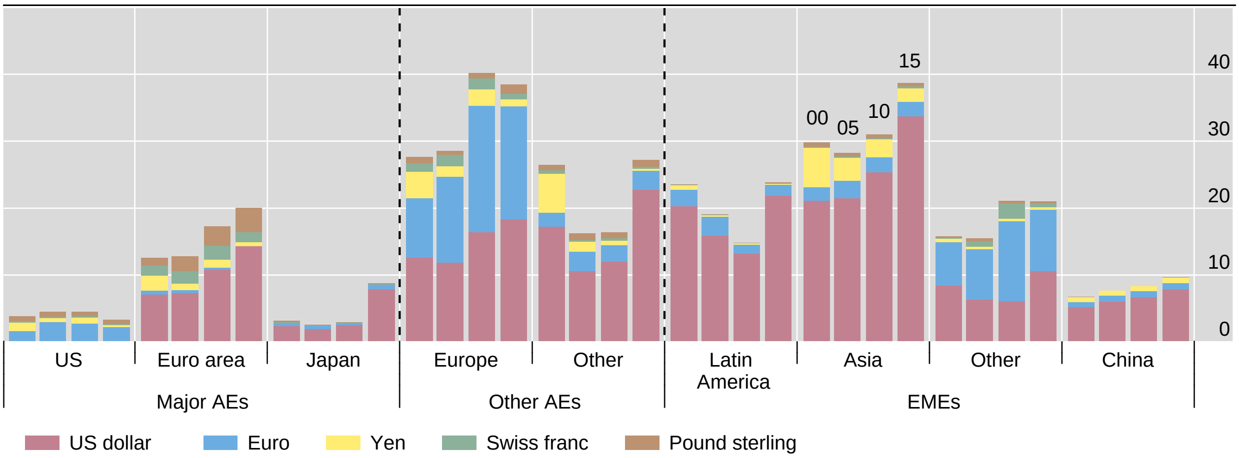
Source: BIS (2016).

Indeed, empirical evidence (BIS (2016)) tends to suggest the existence of a significant effect of exchange rate movements through the risk-taking channel for EMEs (while the effect is much smaller and not significant for advanced economies).[14] For the group of EMEs as a whole, BIS calculations indicate that the financial channel overshoots in the initial phase and has a larger short-run impact than the trade channel (whose effect builds with time). This implies that the contractionary effects of any currency depreciation via the financial channel dominate the expansionary effects of the trade channel in the short run; in the longer run, a depreciation seems to provide only a small boost to GDP (Table 1).

The US dollar is the dominant global funding currency[1]

Ratio of total foreign currency debt[2] to GDP for 2000, 2005, 2010 and 2015; in per cent

Graph 2



[1] Simple average across regions. End-of-year ratios. [2] Total foreign currency debt of non-bank residents of the respective economies.

Sources: BIS debt securities statistics and locational banking statistics; national data; BIS calculations (BIS (2016)).

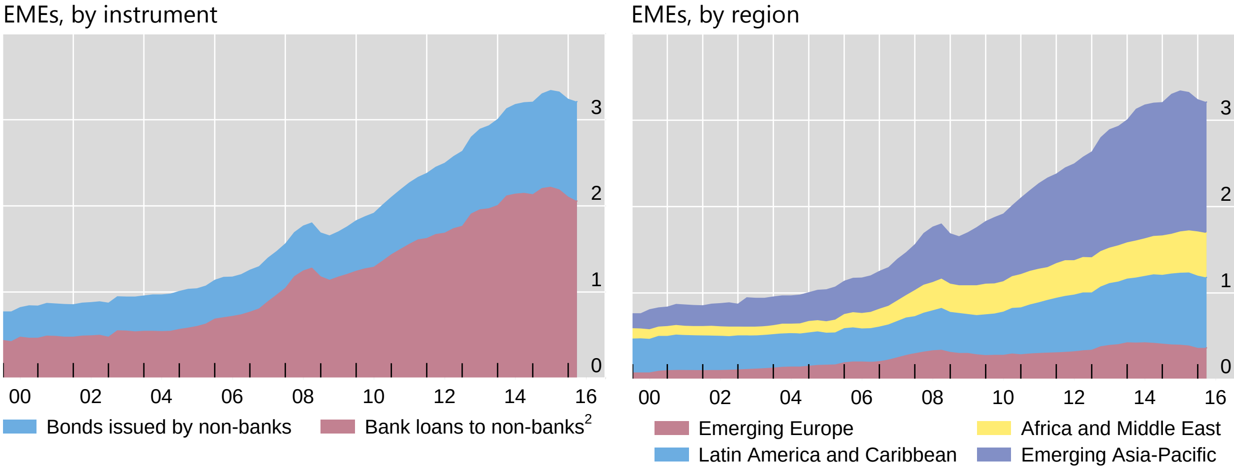
[14] An analysis confirmed by Kearns and Patel (2016), whose estimates try in addition to take into consideration country heterogeneity.

Moreover, much more of EMEs debt than EMEs trade is denominated in dollars. The dominant role of the US dollar as the global funding currency (Graph 2) implies that the possibility of contractionary depreciation can arise not only when the dollar appreciates relative to EMEs currencies, but also when it appreciates relative to the currencies of the major export markets of these EMEs, notably the euro (depending on the evolution of the related export prices).

These effects are likely to have increased in recent decades with the greater financial integration observed at the global level. For instance, the influence of a major international funding currency such as the dollar on global financial conditions, especially for EME borrowers, has been reflected in the substantial growth registered in the stock of US dollar-denominated debt of non-banks outside the United States (McCauley et al (2015)). Graph 3 shows its expansion to \$9.7 trillion at end-2015, with \$3.3 trillion of this to EMEs, a doubling since 2009.

US dollar-denominated credit to non-banks outside the United States[1]

Amounts outstanding, in trillions of US dollars — Graph 3



Further information on the BIS global liquidity indicators is available at www.bis.org/statistics/gli.htm.

[1] Non-banks comprise non-bank financial entities, non-financial corporations, governments, households and international organisations. [2] Loans by LBS-reporting banks to non-bank borrowers, including non-bank financial entities, comprise cross-border plus local loans. For countries that are not LBS-reporting countries, local loans in USD are estimated as follows: for China, local loans in foreign currencies are from national data and are assumed to be composed of 80% USD; for other non-reporting countries, local loans to non-banks are set equal to LBS-reporting banks' cross-border loans to banks in the country (denominated in USD), on the assumption that these funds are onlent to non-banks.

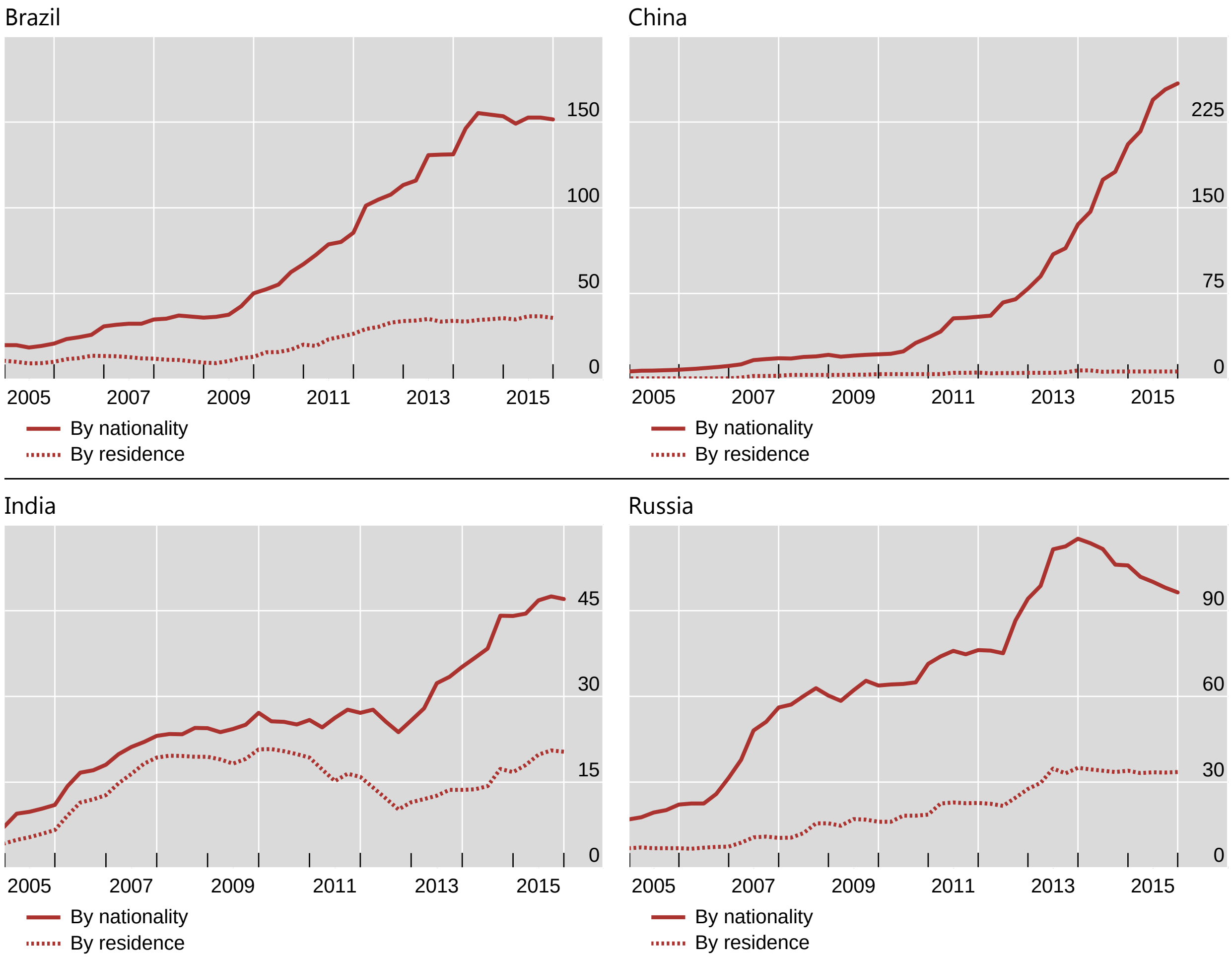
Sources: Datastream; BIS debt securities statistics and locational banking statistics (LBS).

6. The limitations posed by the residency-based view of economic activity

The story does not end here. The international bond statistics used in the Goldstein and Turner measures of currency mismatches were compiled on a residency basis – that is, issuance by entities located in the country. Since 2010, however, local EMEs corporations have increasingly relied on bond issuance by their overseas subsidiaries – including financing vehicles established in financial centres offshore. Such issuance can be better captured by statistics based on the nationality of the issuer (Gruić and Wooldridge (2015)). Nationality-based measures are better measures of the true risk exposures of corporate borrowers. It is the consolidated balance sheet of an international firm that can better capture its vulnerabilities, and that determines how the firm will react to macroeconomic or financial shocks (Tissot (2016a)).

International debt securities issued by non-financial companies outstanding in foreign currencies, by residency and by nationality[1]

Outstanding amounts, in billions of US dollars — Graph 4



[1] Issuer sector is immediate borrower basis by residence and ultimate borrower basis by nationality.

Sources: BIS international debt securities statistics.

Graph 4 shows how the gap between the debt issued on a residency and on a nationality basis has widened in recent years. The difference between international bonds outstanding in foreign currency on a residency basis and that on a nationality basis is largest for China ($260 billion on a nationality basis compared with $7 billion on a residency basis at end-2014), Brazil ($150 billion compared with $36 billion), India ($47 billion compared with $20 billion) and Russia ($96 billion compared with $34 billion).

Should the mismatch measure described above be adapted by replacing international bond issuance on a residency basis by that on a nationality basis? The answer is "perhaps, but not necessarily".

On the one hand, if a group has a foreign affiliate designed as purely a financing vehicle (motivated by tax, regulatory or jurisdictional considerations), such an affiliate would not generate new foreign currency sales. That is, the FC exposure of this affiliate would be high – it has foreign currency debts but is not generating additional foreign currency earnings. In such a case, the measures reported here would *understate* the true size of currency mismatches ultimately covered by the parent company. As argued by Avdjiev et al (2016), the "triple coincidence" of GDP area, decision-making unit and currency area can thus be highly misleading when assessing financial vulnerabilities.

On the other hand, EMEs' overseas affiliates may have their own productive capacity and can therefore generate revenues in foreign currencies. But the currency mismatch indicators presented above take into consideration a residency-based foreign trade measure, ie exports, which does not include the sales of foreign affiliates in the SNA framework. In that case, the indicators would overstate the mismatches, all else equal.

But one additional complication is that the residency-based measures of a country's exports also include the exports of the affiliates of foreign companies that are located in the country. These export revenues are therefore taken into consideration (with a positive impact) when constructing the country mismatch indicators presented above, while they may in fact lead to understate the true exposures of the domestic corporates of this country. All in all, the above factors suggest that it would be worth to compile complementary measures of currency mismatches, based on a residency and a nationality basis, to have a more complete picture.

7. The need for more granular information

Given the limitations analysed above, drawing a correct assessment of currency risk exposures would require mobilising more granular, microeconomic data on the balance sheets of specific companies. This calls for information at the consolidated group-level (eg nationality-based information). Indeed, after the GFC public authorities realised the need to enhance the availability of financial statistics to specifically address these issues (Borio (2013)). In particular, the International Monetary Fund (IMF) and the Financial Stability Board (FSB) launched in 2009 a Data Gaps Initiative (DGI-I) endorsed by the G-20 which comprised a recommendation to recognise the data deficiencies related to cross-border exposures. These included, for instance, the implicit guarantees provided by resident corporates to offshore entities set up to raise finance abroad, or the corporate exposures to exchange rate derivative products booked outside domestic jurisdictions (IMF and FSB (2009)).[15]

[15] Specifically, the DGI Recommendation #13 asked for a "*more comprehensive approach (… to…) identify such cross-border exposures*" and to "*address the methodological and practical issues of handling the concept of consolidation and the definition of corporate groups*". The organisations members of the

The second phase of the DGI (DGI-II) launched in 2016 in order to implement "*the regular collection and dissemination of comparable, timely, integrated, high quality, and standardized statistics for policy use*" also includes a Recommendation #14 specifically targeted to cross-border exposures, with a focus on non-financial corporations (Heath and Goksu (2016)). International organisations are invited to improve the consistency and dissemination of data on non-bank corporations' cross-border exposures, including those through foreign affiliates and intra-group funding, in order to better analyse the risks and vulnerabilities arising from such exposures including foreign currency mismatches. This work should draw on existing data collections by the BIS (which are precisely the sources mobilised for constructing the indicators presented above) and the IMF, and on the development of the OECD framework for Foreign Direct Investment (FDI). The development of an improved "infrastructure" for consolidating granular data for corporate positions and related exposures was in addition recommended (IMF and FSB (2015)).

Even with such international initiatives underway, however, it will be some time before comprehensive currency mismatch indicators can be made available. In the meantime, there is also room for better mobilising available micro data that provide information on corporate balance sheets.

Indeed, aggregate information can be usefully complemented by data drawn from financial statements, which are already publicly disclosed and available for listed corporates from commercial sources. Of particular interest are the databases combining funding information with firm-level financial data, for which one can derive leverage metrics and indicators of currency mismatch and funding risks (cf Graph 5 derived from Chui et al (2014)). Yet corporate-level accounting data raise significant issues not least in terms of international consistency as well as the difficulty to report information on currency exposures especially through hedging – noting that the reporting of hedging practices and uses of derivatives has still to be more standardised across accounting standards eg GAAPs/IFRS, and that complex accounting rules may lead to limited disclosure, esp. by (middle-sized) non-financial corporations (for a discussion of these issues, see Inter-Agency Group on Economic and Financial Statistics (2015)).

Moreover, corporate-level information is less available for non-listed companies, although they arguably represent only a smaller part of cross-border business and FX funding activities in EMEs. Certainly, other sources of granular balance sheet information (eg supervisory dataset) can be mobilised – cf Hulagu and Yalcin (2016), for a large panel of Turkish exporters, as well as IFC (2016a) and Tissot (2016b) more generally. As highlighted during the September 2016 IFC-ECCBSO-CBRT Conference on the *Uses of Central Balance Sheet Data Offices' information*, one could also develop and make use of the data collected by central balance sheet offices and credit registers. Other potential sources of useful micro information comprise derivatives exchanges, dealers networks and clearing houses providing registry services (eg to assess customers' derivatives exposures). The international community is indeed increasing its efforts to make a better use of the data collected by Trade Repositories and Central Clearing Counterparties in the aftermath of the Great Financial Crisis. Lastly, some ad hoc surveys can be helpful, such as the one organised by the Reserve

Inter-Agency Group on Economic and Financial Statistics (IAG) were thus invited to "*investigate the issue of monitoring and measuring cross-border, including foreign exchange derivative, exposures of nonfinancial, and financial, corporations with the intention of promoting reporting guidance and the dissemination of data*".

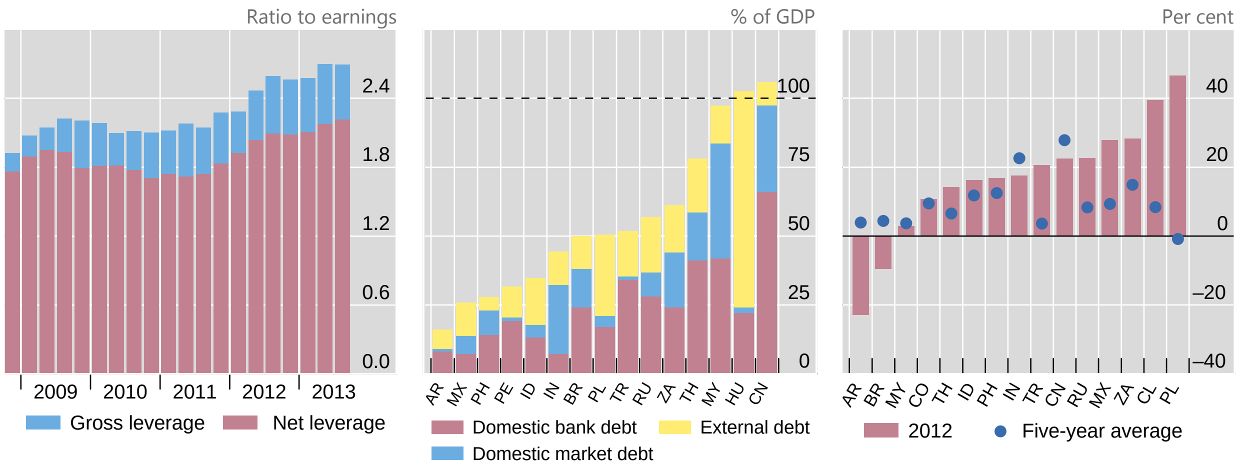
Bank of Australia on FX exposures and derivatives positions to monitor country's external position and banks' FX hedging (Rush et al (2013)). Such domestic surveys may be useful in particular to assess the respective role of natural hedges provided by FX revenues and financial hedging, as well as to identify specific patterns and exposures (eg unhedged currency funding such as carry trades; complex funding sources, structures and/or instruments; particular derivatives hedging techniques and counterparties).

Using financial statements to compute firm-level metrics[16]

Graph 5

EME corporate balance sheets: selected metrics

Leverage ratio of EME corporations[1] | Corporate sector debt in 2013[2] | Annual growth rates of interest expenses



AR = Argentina; BR = Brazil; CL = Chile; CN = China; CO = Colombia; HU = Hungary; ID = Indonesia; IN = India; MX = Mexico; MY = Malaysia; PE = Peru; PH = Philippines; PL = Poland; RU =Russia; TH = Thailand; TR = Turkey; ZA = South Africa.

[1] Firm-level data from S&P Capital IQ for 900 companies in seven EMEs; simple average across countries; gross leverage = total debt/earnings; net leverage = (total debt – cash)/earnings. [2] External debt includes liabilities from affiliates, direct investments and other sources.

Sources: IMF, *Global Financial Stability Report*, April 2014; Morgan Stanley; BIS calculations.

Such data may not be sufficient to capture derivatives activity at the global, consolidated group level (ie with non-resident counterparties) as well as the full range of (untested) guarantees between the parent company and its offshore subsidiaries. Legal and confidentiality issues also constrain the wider use of such information. From this perspective, there is a need for promoting more (granular) data-sharing especially between national authorities. This was highlighted in the IFC Report on data-sharing (IFC (2015)) and is in line with the #20 recommendation of the second phase of the DGI that calls for the "*Promotion of Data Sharing by G-20 economies*". However, a recent survey of central banks shows that external sharing of micro data between central banks and other authorities remains limited (IFC (2016b)).

[16] Derived from Chui et al (2014).

8. Conclusion

The BIS's international banking and financial statistics can be very useful for assessing currency exposures, which is a key issue for EMEs. They allow computing summary indicators of currency mismatches, for the economy as a whole as well as for specific sectors.

These indicators show a significant decline in aggregate currency mismatches from the late 1990s to around 2010. But this reflected a reduction in the official sector's foreign currency exposures. Currency mismatches of EME corporates have increased in many medium-sized EMEs. The balance sheets of entities with net foreign currency liabilities would weaken significantly following currency depreciation. This can constrain corporate investment and so weigh on EMEs economic performance.

In addition, EMEs corporations have increasingly relied on bond issuance by their overseas subsidiaries, implying that residency-based indicators probably understate the true size of their fragilities. Addressing these issues in order to improve the assessment of currency risk exposures could benefit from accessing more granular, microeconomic data on corporates' balance sheets. Fortunately, a number of international statistical initiatives have been launched that should facilitate this endeavour.

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IFC-ECCBSO-CBRT Conference on *"Uses of Central Balance Sheet Data Offices' information"*

Co-organised by the IFC, the European Committee of Central Balance Sheet Data Offices (ECCBSO) and the Central Bank of the Republic of Turkey (CBRT)

Özdere-İzmir, Turkey, 26 September 2016

Looking at aggregate currency mismatches and beyond[1]

Emese Kuruc, Bruno Tissot and Philip Turner,

Bank for International Settlements

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

Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

Looking at aggregate currency mismatches and beyond

by Emese Kuruc, Bruno Tissot and Philip Turner (BIS)

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IFC / ECCBSO / CBRT Conference on "Uses of Central Balance Sheet Data Offices' information"

Özdere-İzmir, 26 September 2016

The concept of currency mismatch

- Mismatch between domestic and foreign currencies
- Arises when exchange rate changes impact the financial position of an entity:
  - "stock" aspect: impact on its balance sheet
  - "flow" aspect: impact on its income statement
- The greater the degree of sensitivity to exchange rate changes, the greater the extent of the currency mismatch
- International banking and financial data are central to measure such mismatches

Aggregate currency mismatch versus external debt

- Foreign Currency (FC) exposure differs from external debt:
  - FC internal contracts between residents (esp. if low confidence in the local currency or local contracts); cf dollarized economy where debts are largely denominated in $
  - Contracts of residents with non-residents in domestic currency

- Role of leveraged investors eg «carry trades»
  - Borrow in a "safe", low-interest-rate FC
  - Hold assets in a higher-interest-rate FC
  - Common type of mismatch due to FC cross-rates

Measuring currency mismatch for the economy

- Look at FC Exposures
  - Foreign currency liabilities and assets
  - Including internal FC exposures (from one resident to another)

- Economy "as a whole": all residents
  - Include foreign and domestic-owned entities
  - But does not include entities abroad controlled by domestic residents

Two distinct elements of a currency mismatch…

1. **FC share of total debt relative to GDP export share: FC%TD / (X/Y)**
   - Earnings from exports can finance higher FC interest payments
   - Problem if larger FC debt than FC earnings

2. **Net Foreign Currency Asset (NFCA) position – ie assets minus liabilities – in % of GDP: (FCA–FCL) / Y**
   - Depreciation has a negative balance sheet effect (net worth falls)
   - Working in the opposite direction is the positive competitiveness effect (with lags)

… combined in one country indicator

- **Index for aggregate “effective” currency mismatch:**

  AECM = (NFCA/X) * (FC%TD)

  - Multiply the 2 indicators ie FC%TD/(X/Y) and (FCA–FCL)/Y
  - AECM = 0 if FC assets equal FC liabilities (no effective mismatch, even in a dollarized economy)
  - AECM ≤ 0 if the country has a net FC liability position

- Stress test for an exchange rate shock: the impact reflects the combination of the country’s FC debt share and its net FC position

Recent developments in net FC positions

- Some large countries (China, India, Korea and Russia) have a strong aggregate NFCA position

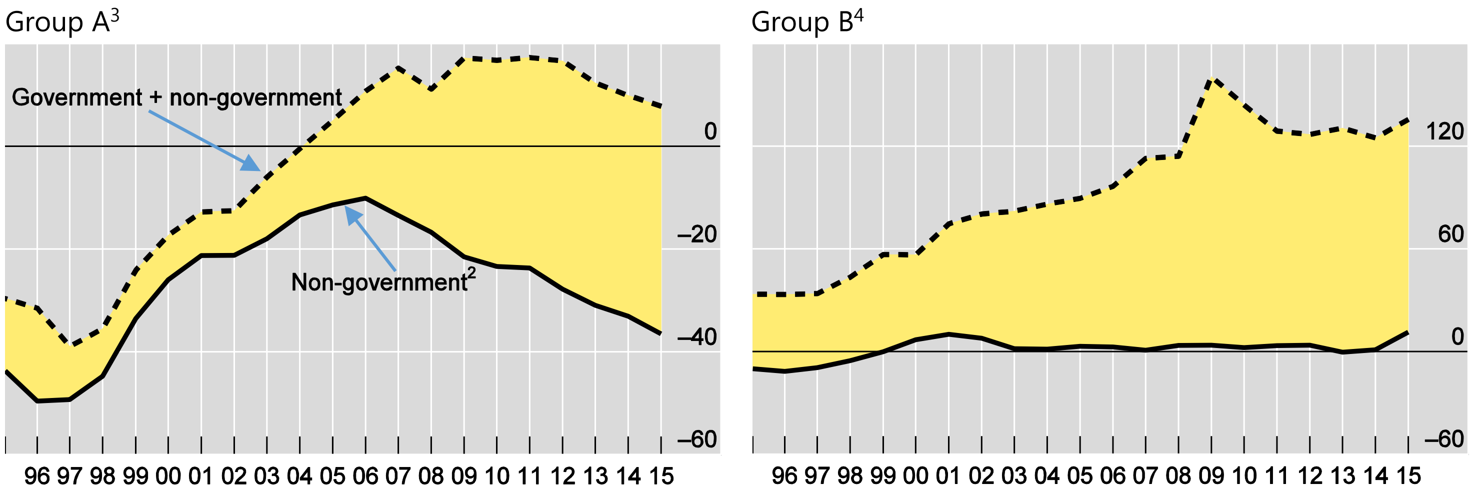
►*see Group B*

- Position of medium-sized EMEs is weaker esp. since 2010

►*see Group A*

Net foreign currency assets as a percentage of exports[1]

In percentages — Graph 1



[1] For net foreign currency assets, outstanding positions of year-end. Calculated with aggregates of the economies listed in footnotes 3-4. [2] Excluding the central bank and general government assets/liabilities where these can be identified separately. [3] Brazil, Chile, Colombia, the Czech Republic, Hungary, Indonesia, Malaysia, Mexico, Peru, the Philippines, Poland, South Africa, Thailand and Turkey. [4] China, Chinese Taipei, India, Korea and Russia.

Source: M Chui, E Kuruc and P Turner (2016): "A new dimension to currency mismatches in the emerging markets - non-financial companies", *BIS Working Paper,* no 550, March 2016.

The need to go beyond national aggregates

- A positive aggregate NFCA may conceal large liabilities in some sectors
- This matters for several reasons:
  - Government will not / may not **guarantee** private sector debts
  - The **creditworthiness** of the private sector will depend on its own FC exposures (not just of the country's ones)
  - Private sector's **reactions** to an external shock can lead to specific market dynamics (different from what is observed "traditionally" when most of the FC mismatch is related to the government financial position)
  - Eg companies with $ debts buy $ if it is expected to appreciate, or increase the hedging of their $ debts, pushing the $ further up

Recent EMEs improvements were indeed driven by the official sector…

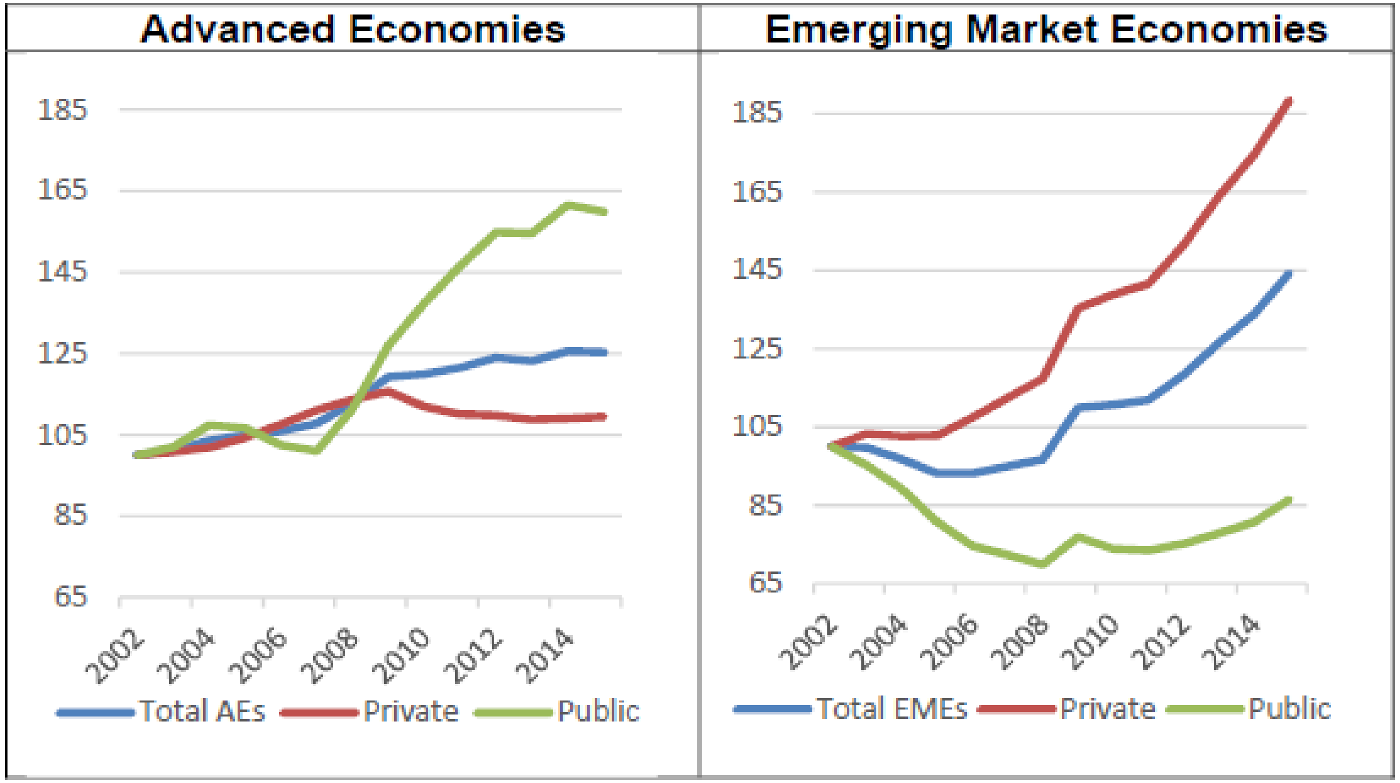
- Overall decline of EMEs' aggregate measures of FC mismatches since the 1990s

- Mostly due to lower official sectors' FC exposures
  - Less government $ bonds
  - More local issuance in domestic currency
  - Central banks' accumulation of FX reserves

- Many EMEs now have a large FC asset position for their official sectors

… but EMEs' private debt has been up…

Chart 2: Private and public debt patterns before and after the Great Financial Crisis

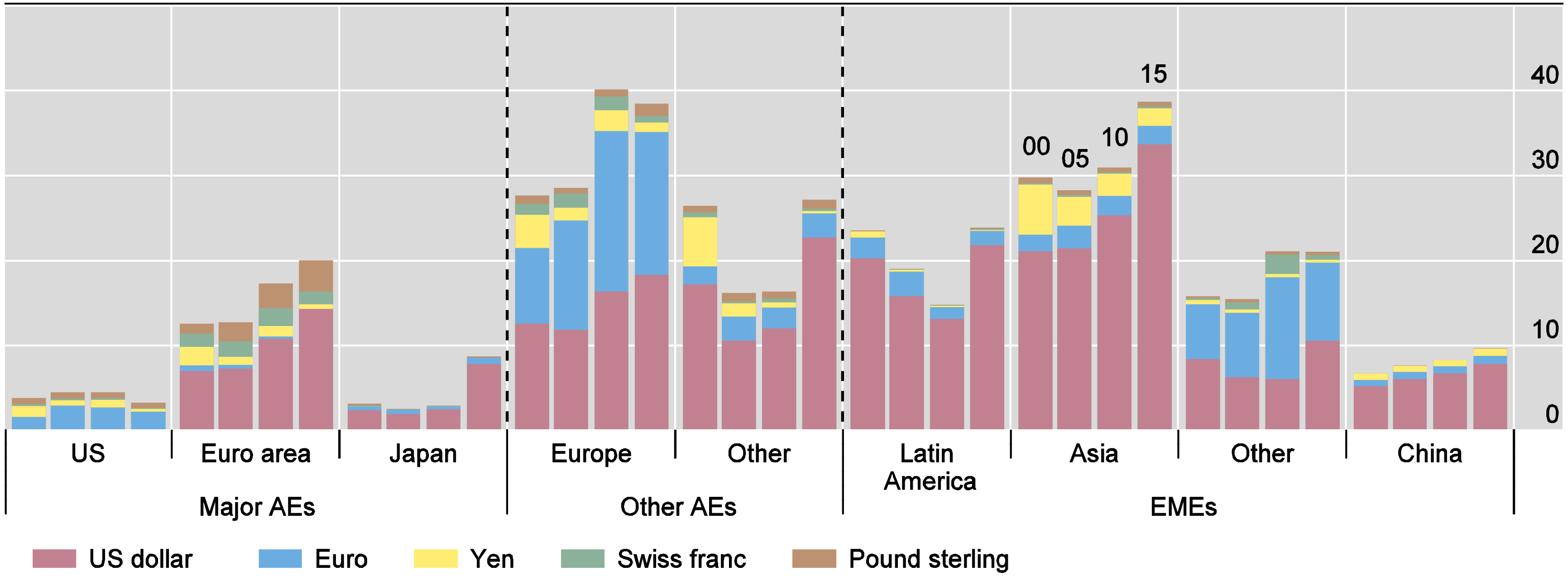


Notes: Evolution of total, private (non-financial sector) and public debt in % of GDP in Advanced and Emerging economies, 2002-2016 (2002=100); regional aggregates using PPP weights; market values, except EMEs' public debt in nominal terms.
Source: BIS; author's calculations.

… with the US Dollar the dominant funding currency…

Graph 3: The US dollar is the dominant global funding currency[1]

Ratio of total foreign currency debt[2] to GDP for 2000, 2005, 2010 and 2015; in per cent

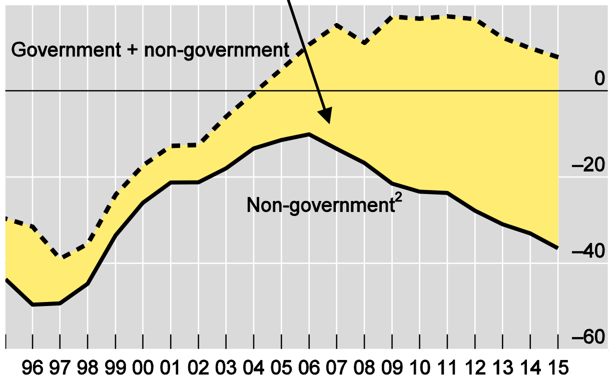


[1] Simple average across regions. End-of-year ratios. [2] Total foreign currency debt of non-bank residents of the respective economies.

Sources: BIS debt securities statistics and locational banking statistics; national data; BIS calculations.

… and significant corporate exposures in a number of EMEs

- Improved credit standing of many EME governments has facilitated foreign borrowing for corporates
- FC corporate debts far exceed FC assets in most medium-sized EMEs (esp. for non-financial firms): see for Group B countries in Graph 1



- Net FC liabilities of these countries have risen to 37% of exports by end-2015

The role of currency mismatches in case of an exchange rate shock

- The balance sheets of EMEs firms with large FC mismatches worsen when the currency depreciates
- With currency mismatches, depreciation of the local currency can be contractionary:
  - Firms with weaker balance sheets cut spending
  - (bank and non-bank) lenders risk-taking capacity is reduced
  - Domestic credit is constrained
- Much more of EME debt than EME trade is in $: contractionary depreciation can also happen when the $ rises relative to the currencies of EMEs export markets (notably the euro)

Exchange rate movements and the financial channel

- *BIS 2016 Annual Report suggests that the stimulative effect of exchange rate depreciation through the trade channel can be counterbalanced, at least in the short run, by the negative impact of the financial channel*

Long-run elasticity of GDP growth with respect to real effective (REER) and debt-weighted (DWER) exchange rates

	EMEs			Advanced economies		
	Short-run	Long-run	Ratio: short-run to long-run	Short-run	Long-run	Ratio: short-run to long-run
REER	–0.103***	–0.1217***	0.85	–0.058	–0.104***	0.56
	(0.017)	(0.040)		(0.034)	(0.044)	
DWER	0.1322***	0.105***	1.26	0.026	0.032	.[1]
	(0.025)	(0.033)		(0.027)	(0.033)	
Observations	1055			1072		
R-squared[2]	0.92			0.32		

Robust standard errors (clustered by country) in parentheses; ***/**/* denotes results significant at the 1/5/10% level.

[1] Neither elasticity is statistically significant at 10%. [2] The higher R-squared for EMEs is a reflection of the higher explanatory power of the lagged dependent variable compared with advanced economies.

Residency-based data may underestimate the risk of FC mismatches…

- Measures of currency mismatches are compiled on a residence basis – that is, issuance by entities located in the country
- EME corporations have increasingly relied on bond issuance by their overseas subsidiaries – including financing vehicles established in financial centres offshore
- Such issuance is captured by statistics based on the nationality of the issuer, a better measures of the true risk exposures of the consolidated balance sheet of an international firm
- When a foreign affiliate is just a financing vehicle, residency-based measures understate the true size of the FC mismatch

… especially at the present juncture…

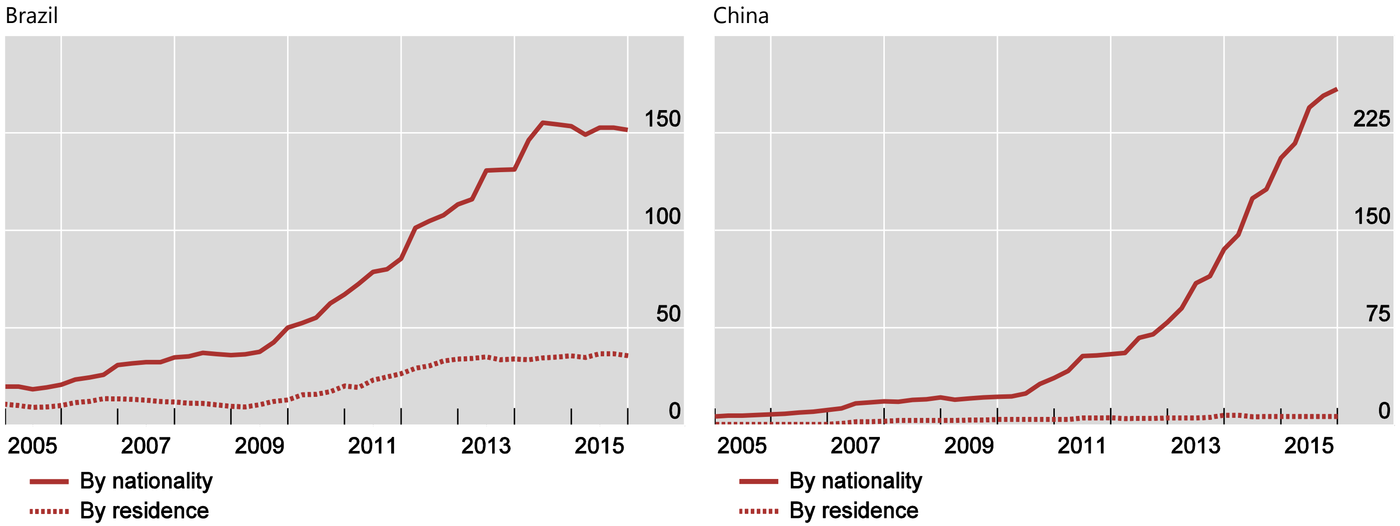
- The difference between international bonds outstanding in foreign currency on a residence basis and that on a nationality basis is high for several EMEs

►*eg China: $260 billion versus $7 billion at end-2014*

- The gap between the residence and the nationality bases has widened in recent years

International debt securities issued by non-financial companies outstanding in foreign currencies, by residence and by nationality

Outstanding amounts, in billions of US dollars — Graph 4



[1] Issuer sector is immediate borrower basis by residence and ultimate borrower basis by nationality. [2] Sum of Indonesia, Korea, Malaysia, the Philippines and Thailand.

Sources: BIS international debt securities statistics.

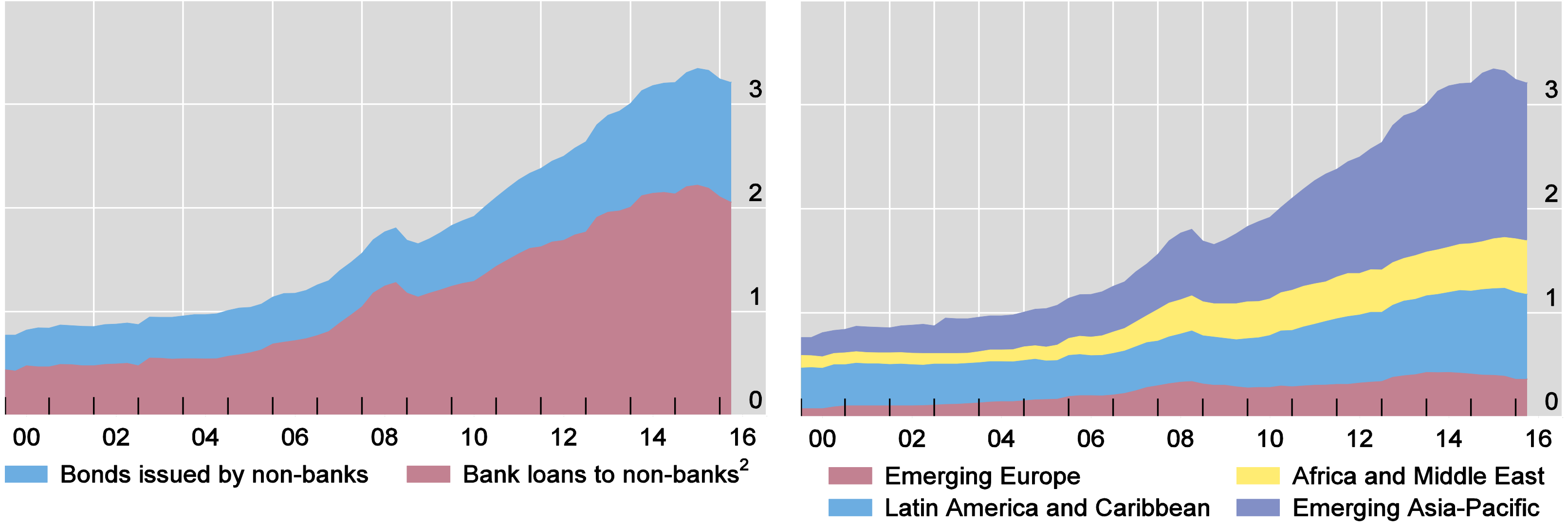
… in a context of ample USD global liquidity

Graph 5: US dollar-denominated credit to non-banks outside the United States[1]

Amounts outstanding, in trillions of US dollars

EMEs, by instrument

EMEs, by region



Further information on the BIS global liquidity indicators is available at www.bis.org/statistics/gli.htm.

[1] Non-banks comprise non-bank financial entities, non-financial corporations, governments, households and international organisations. [2] Loans by LBS-reporting banks to non-bank borrowers, including non-bank financial entities, comprise cross-border plus local loans. For countries that are not LBS-reporting countries, local loans in USD are estimated as follows: for China, local loans in foreign currencies are from national data and are assumed to be composed of 80% USD; for other non-reporting countries, local loans to non-banks are set equal to LBS-reporting banks' cross-border loans to banks in the country (denominated in USD), on the assumption that these funds are onlent to non-banks.

Sources: Datastream; BIS debt securities statistics and locational banking statistics (LBS).

There is a need for more (granular) analysis…

- Complexity reinforced by the fact that foreign trade measure is also a residence-based estimate of exports
- Microeconomic data on the exposures of specific companies is needed to better understand factors such as:
  - Role of affiliates
  - Transfer of risks (eg guarantees)
  - Financial hedging operations
  - Natural hedges (eg export revenues)

… as highlighted by the G20 Data Gaps Initiative (Recommendation # 14)

- Initial guidance on conceptual issues related to nationality and consolidation
- Measures for monitoring corporations' exposures, both on- & off-balance sheet positions and intra-group funding
- Use existing data collections
  - BIS (eg banking, debt securities)
  - IMF (intra-group funding)
  - OECD (multi-national enterprises (MNEs)
  - Role of the Legal Entity Identifier (LEI) for foreign subsidiaries identification

Granular financial statements data can be mobilised

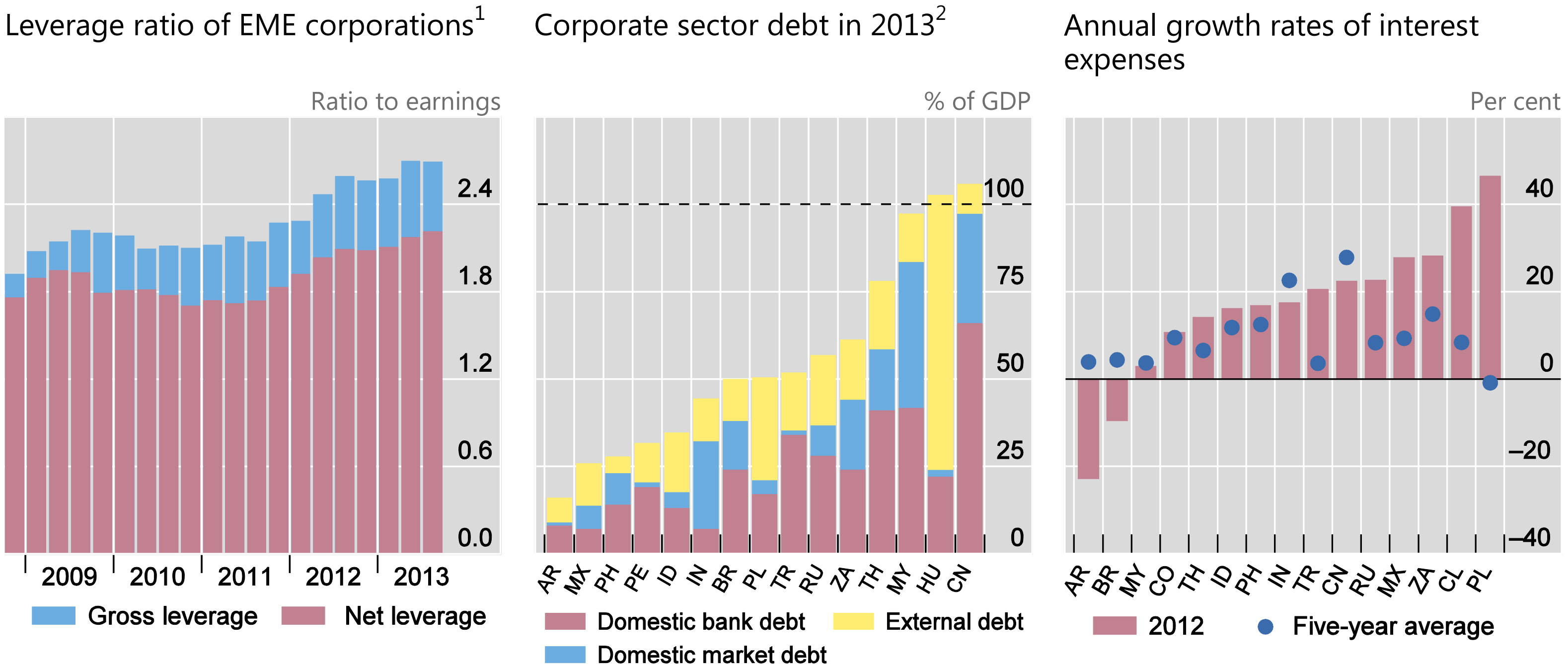
- Granular data on financial statements
  - Listed corporates: commercial sources, public disclosures
  - Represent the bulk of cross-border business and FX funding
  - Interest for databases combining funding information with firm-level financial data (eg Worldscope, Capital IQ, Thomson Reuters)

- See *Risks related to EME corporate balance sheets: the role of leverage and currency mismatch*, M Chui, I Fender & V Sushko, BIS Quarterly Review, September 2014

- Issues of interest:
  - Domestic funding: interest rate and rollover risks
  - Currency mismatches

Using granular data on corporate balance sheets

EME corporate balance sheets: selected metrics



AR = Argentina; BR = Brazil; CL = Chile; CN = China; CO = Colombia; HU = Hungary; ID = Indonesia; IN = India; MX = Mexico; MY = Malaysia; PE = Peru; PH = Philippines; PL = Poland; RU =Russia; TH = Thailand; TR = Turkey; ZA = South Africa.

[1] Firm-level data from S&P Capital IQ for 900 companies in seven EMEs; simple average across countries; gross leverage = total debt/earnings; net leverage = (total debt – cash)/earnings. [2] External debt includes liabilities from affiliates, direct investments and other sources.

Sources: IMF, *Global Financial Stability Report*, April 2014; Morgan Stanley; BIS calculations.

Source: "Risks related to EME corporate balance sheets: the role of leverage and currency mismatch", M Chui, I Fender & V Sushko, BIS Quarterly Review, September 2014