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Measuring interlinkages between non-financial firms, banks and institutional investors: How securities common identifiers can help?[1]

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

Measuring interlinkages between non-financial firms, banks and institutional investors: How securities common identifiers can help?[1]

Jose Maria Serena[2]

Abstract

We describe how to construct a dataset measuring financial interlinkages between non-financial companies and their creditors through their exposures to debt securities. We exploit that securities have common identifiers: using them, we first identify firms' liability exposures to these securities, and then creditors' exposures. These two steps fully define bilateral exposures. To illustrate the advantages of the bilateral exposures at the firm-level, we construct a small-scale dataset and depict recent leverage and profitability trends by firms with different types of creditors.

Keywords: firm-level data, matching datasets, securities common identifiers

JEL classification : C80, C81, F36, G15

Contents

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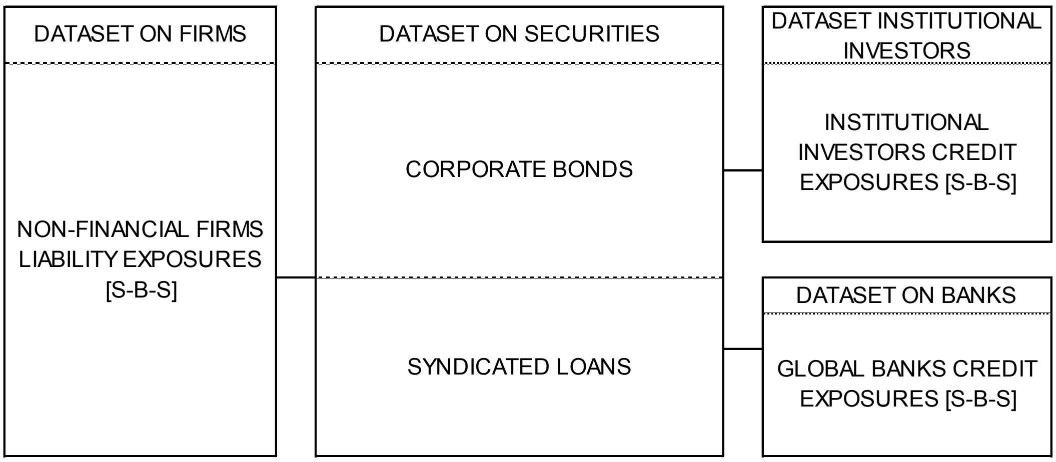
1. Introduction

Due to interlinkages between institutions, significant financial risks can remain hidden in firm-level metrics. Despite many data collection initiatives, information on interlinkages is scarce and constitutes a data gap.

In this paper, we describe how to construct a dataset of bilateral exposures between firms and their creditors, and this way partially overcoming this data gap. Our strategy consists in identifying firms' liability-side, and creditors' asset-side exposures to securities. Since securities (corporate bonds and syndicated loans) have common identifiers –ISINs or Bloomberg FIGI-, researchers can combine a securities dataset with the relevant pieces of information: a firm-level dataset containing liabilities on a security-by-security basis; and datasets on investors' holdings on securities, on a security-by-security basis. As described in Graph 1, combining all three datasets, we obtain the interlinkages between non-financial firms and their creditors (banks and institutional investors).

Measuring financial interlinkages: exposures to securities

Graph 1



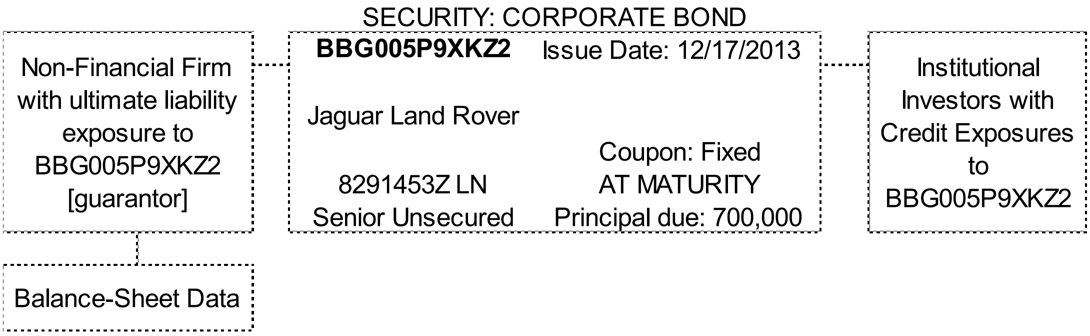
Source: own elaboration

The dataset is constructed in two steps. First, after defining a set of securities, we match them with a firm-level dataset containing their liabilities on a security-by-security basis. We focus on the ultimate risk-bearing entity: we consider that the company guaranteeing the security (not the issuer, nor the parent company) has the ultimate liability exposure. Second, and separately, we match securities with a security-by-security basis dataset on investors' holdings of bonds, and a similar dataset on parties involved in syndicated loans. To measure credit exposures, we focus on direct (immediate) exposures, thus treating creditors on a solo basis.

This method overcomes the drawbacks of the standard approach to compute bilateral exposures, which consists in using firm-level qualitative identifiers from a securities dataset (for instance, the "borrowers' name" in the syndicated loan dataset) and to match the latter with a firm-level dataset. The standard approach has drawbacks since qualitative identifiers often differ slightly across datasets; accordingly researchers need to decide if minor differences in firms' names reflect writing conventions, or are meaningful (ie, refer to different entities). Overall, matching using qualitative identifiers involves substantial judgment. In contrast, securities common identifiers are alphanumeric codes. Consequently, our procedure can be used on a large-scale and easily replicated. On top of this, the standard approach cannot be used to input information on the creditors; as a consequence researchers can only use the information available on the securities database, which is typically rather poor and often inexistent.

Exposures to corporate bond BBG005P9XKZ2

Graph 2



Source: Bloomberg, own elaboration.

We illustrate how the method works with an example in Graph 2, where we depict the interlinkages between a firm and its creditors defined by exposures to the corporate bond with Bloomberg FIGI BBG005P9XKZ2. This security is a senior unsecured plain-vanilla bond, issued the 12/17/2013; it pays a fixed coupon, and the principal is payed at maturity. The indenture of the corporate bond BBG005P9XKZ2 states that it was issued by Jaguar Land Rover –assigned an equity ticker 8291453Z LN-, who also has the legal obligation to repay it. Next, we find out which institutional investors hold the bond, and thus have credit exposures to BBG005P9XKZ2. Upon successful completion of these two steps, the financial interlinkages between a non-financial firm (ie, Jaguar Land-Rover) and their creditors (ie, institutional investors holding the bond) are neatly determined.

We argue that datasets constructed using this method provide important insights into system-wide risks in global financial markets, since they exhibit bilateral, firm-level exposures. To illustrate the type of insights we can get, we prepare a small-scale dataset measuring the interlinkages of the top 100 non-financial companies in the world financial markets. Then we depict differences in profitability and leverage for firms with different creditors. For the subset of companies with outstanding loans, we compare those with loans arranged by a G-SIFI with a capital surcharge>2%, versus the rest. For the subset of firms with outstanding bonds, we compare those in which Blackrock is the top holder of at least a bond, versus the others.

A final word on our purpose: in this paper we seek to emphasize a method to match datasets, and not to stress the sources of information we have used. Our method consists in placing securities at the center of the stage: we show that by exploiting securities common identifiers, researchers can jump from one database to another. We emphasize that researchers can use any dataset containing securities identifiers. The method can be applied generally, and works independently of the sources of information[3].

The rest of the article is structured as follows. Section 2 summarizes previous research and statistical initiatives matching datasets. Section 3 discusses our methodology, step-by-step. Section 4 illustrates the advantages of having a dataset on financial interlinkages using a small-scale dataset. Section 5 presents the main conclusions.

2. Matching datasets: An overview of previous methodologies

Measuring financial interlinkages between firms and their creditors requires matching datasets. To combine datasets, researchers need identifiers simultaneously present in the different sets of information. So far, firms' Legal Economic Identifiers –LEIs- are not fully available. Consequently, the standard approach to measure interlinkages consists in combining a firm-level and a securities dataset using firm qualitative-identifiers. Firm qualitative-identifiers are, for instance, firm name, or the parent-company name.

For instance, Ferreira and Matos (2012, 2015) match a large sample of syndicated loans with their borrowers (ie, non-financial firms' data) to investigate lending relationships. They obtain syndicated loans from DealScan, while non-financial firms' data is obtained from Datastream/Worldscope. To merge the data they focus on the Borrower-Parent field in DealScan, which they use to identify the firm's country and ticker and subsequently obtain the firm-level information. But, as they describe, this strategy sometimes fails and they need to resort to manual matching.

Similarly Ongena et al. (2015) construct a bank-firm level data for a sample of Eastern European countries combining bank-level information from Bankscope and firm-level data from Amadeus. They use the 2010 vintage of Kompass to identify lending relationship between banks and firms. In this case, they cannot match datasets using the name, since writing conventions differ in the two datasets. In this way they complement borrowers' names with information on website, email address and/or telephone number. If information on the borrower of the security coincides in all these dimensions (name, website, email address, telephone number) with the equivalent information on the firm-level dataset, they assume both entities are the same and subsequently merge the datasets. The main problem with this procedure is that it involves judgment: coincidence in the chosen fields does not ensure that the two entities are equivalent. Moreover, the information on lenders is often poor or unavailable.

Overall, matching datasets using firm-level qualitative identifiers has drawbacks. As this method involves judgement, it is difficult to conduct the procedure on a large

[3] Datasets provided by private vendors (eg, Thomson Reuters, Bloomberg, S&P IQ, Worldscope) have important pieces of information, which often contain similar information; separately central banks micro-level datasets (for instance, the ECB SHS, CBDH) contain relevant information. In our specific case, we have used Bloomberg. Similarly, in this paper, we use the FIGI (Bloomberg Global Identifier) as our security identifier, but alternatively we could have used the ISIN.

scale, regularly update the dataset, or replicate other researchers' work. On the other hand, it is not possible to use firm-level qualitative identifiers to input creditors' information, since datasets on securities-by-securities holdings rarely contain the name of the issuer or its parent company.

For this reason, we propose exploiting the fact that securities –corporate bonds and syndicated loans- have common identifiers[4]. Upon issuance, securities receive two distinct identifiers: the ISIN (International Securities Identification Number), and the FIGI (Financial Instrument Global Identifier). The ISIN is the International Securities Identification Number, which is an alphanumeric twelve-digit code assigned to securities such as bonds, shares, options, derivatives, futures, and syndicated loans. The ISIN has global reach and encompasses national coding schemes such as CUSIP (which identifies US and Canadian securities), or SEDOL (similar for the UK Stock Exchange). The FIGI is the Financial Instrument Global Identifier previously known as the Bloomberg Global Identifier), also a twelve-character alphanumeric identifier. It was introduced by Bloomberg in 2014, and it is assigned to instruments of all asset classes[5].

Securities identifiers are readily available in securities datasets. Thus we are able to combine the securities dataset with any other containing them -we can jump from one dataset to another-.

Our proposal to make use of common identifiers to combine datasets is aligned with ongoing statistical initiatives using micro data. So far common identifiers have been used in work focusing on firm-bank linkages in a specific country, which might combine up to three central banks' datasets using in-house identifiers: credit register, bank balance sheets and income statements, and firm balance-sheets and income statements[6].

Some recent research has also used common identifiers to match securities datasets with other pieces of information on a cross-country setup. Bruno and Shin (2016) match a firm-level and a securities dataset using the ultimate parent CUSIP as firm-identifier (that is, the CUSIP or the equity security listed by the firm). This CUSIP is available in the securities dataset they are using (SDC Platinum New Issues Database from Thomson Reuters), so they do not need to resort to qualitative firm-identifiers. Fuertes and Serena (2015) match a firm-level and a securities dataset using securities common identifiers. None of these papers, however, combines the securities dataset with information on creditors. On the other hand, some research has combined securities holding (creditors) data with bond-level datasets, but not with borrowers' information. Barbu et al. (2016) use securities common identifiers to combine the Bundesbank Investment Funds Statistics with the ESCB Centralised Securities Database. Becker and Ivanisha (2015) combine data on institutional

4 Syndicated loans are treated as a debt-security, since can be traded in secondary markets; accordingly since 2004 they receive an ISIN; Bloomberg also identifies them as well by a FIGI.

5 While there is some debate between advocates of each of them, for our practical purposes both are equally useful. Their advantage is that each security has a sole financial identifier. It is straightforward to identify corporate bonds and syndicated loans either by their ISIN or their FIGI.

6 For instance De Jonghe et al. (2016) merge firm-bank level credit data to investigate credit reallocation, using data from the National Bank of Belgium (NBB). Baskaya et al. (2016, 2017) use data from the Central Bank of Turkey (CBRT) to construct a similar bank-firm dataset, combining also the three dimensions. Carabin et al. (2015) merge firms' data with loans and corporate bonds issued in both domestic and international markets, for the case of Mexico.

investors' holdings of corporate bonds, with securities data, and information on yields.

Overall, the use of common identifiers is taking off. They are also at the heart of existing, large-scale, security-by-security databases, such as the Central Securities Database of (CSDB) (Cornejo and Huertas (2016), Cornejo et al. (2017)). In this paper, we propose to extend their use to shed light on interlinkages between firms, banks, and institutional investors.

3. Matching process: Step-by-step

The matching process proceeds sequentially. As a preliminary step we define a group of securities (corporate bonds and syndicated loans). Each security is uniquely identified by an ISIN code, and a FIGI identifier. We separately identify the liability and the asset-side exposures to these securities. These two matching processes are fully independent, and upon completion, they define the financial interlinkages between non-financial companies and their creditors.

The identification of the liability-side exposures consists in two steps, which we illustrate in Graph 3 using as an example three corporate bonds issued by companies of the Tata Motors Ltd. conglomerate.

First, to measure firms 'exposures to securities we need to identify the ultimate risk-bearing entity (Tissot, 2016) in a firm-level dataset with a security-by-security breakdown. Such datasets shall list the securities (and the corresponding ISIN/FIGI) to which a firm is, in certain way, exposed. There are different ways of defining exposures: at the issuance level -securities issued by a given firm-; at the guarantor level -securities guaranteed by a company-; at the parent company level -securities issued by a company and all its subsidiaries-. In box 1 we briefly describe the structure of these datasets.

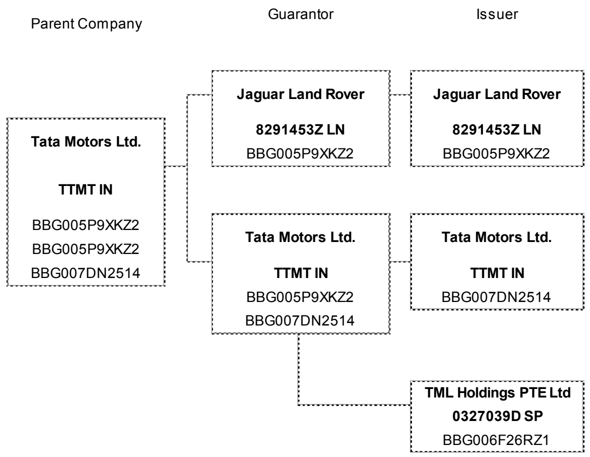
We posit that the ultimate risk-bearing entity is the company guaranteeing the security. This choice matters, as we describe in our example below –Graph 5-. Each of the three bonds has been issued by a different entity (Jaguar Land Rover, Tata Motors Ltd, and TML Holdings PTE Ltd). However, there are only two guarantors, since the corporate bond issued by TML Holdings PTE Ltd -with FIGI BBG006F26RZ1- receives a guarantee from Tata Motors Ltd. As previously described, the three bonds have been issued by companies of the same conglomerate, since Tata Motors Ltd fully owns both Jaguar Land Rover and TML Holdings PTE Ltd.

In the second step, we recover the financial information for each of these guarantors, and match this firm-level dataset with the securities dataset using the FIGI of each instrument (see Panel B). We input firms' financial information using firms' equity tickers as firm-identifiers. It is noteworthy that the financial metrics of Jaguar Land Rover and Tata Motors Ltd. exhibit important differences: the latter has higher leverage ratios, and lower profitability, although as expected it is a much larger company. This underscores the fact that choosing between the issuer, the guarantor, and the parent company matters.

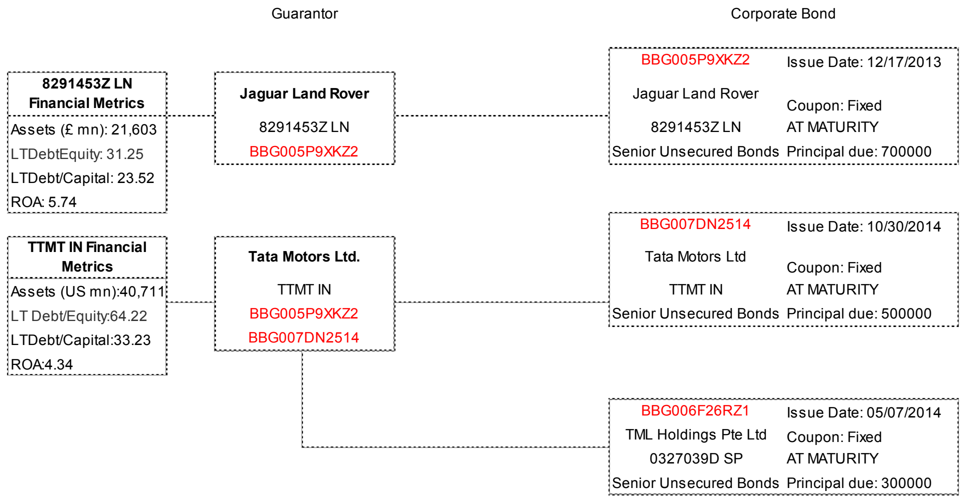
Identifying liability-side exposures to securities

Graph 3

Panel A. Issuance structure in the firm-level dataset with security-by-security breakdown



Panel B. Matching firm-level (guarantor) with securities dataset



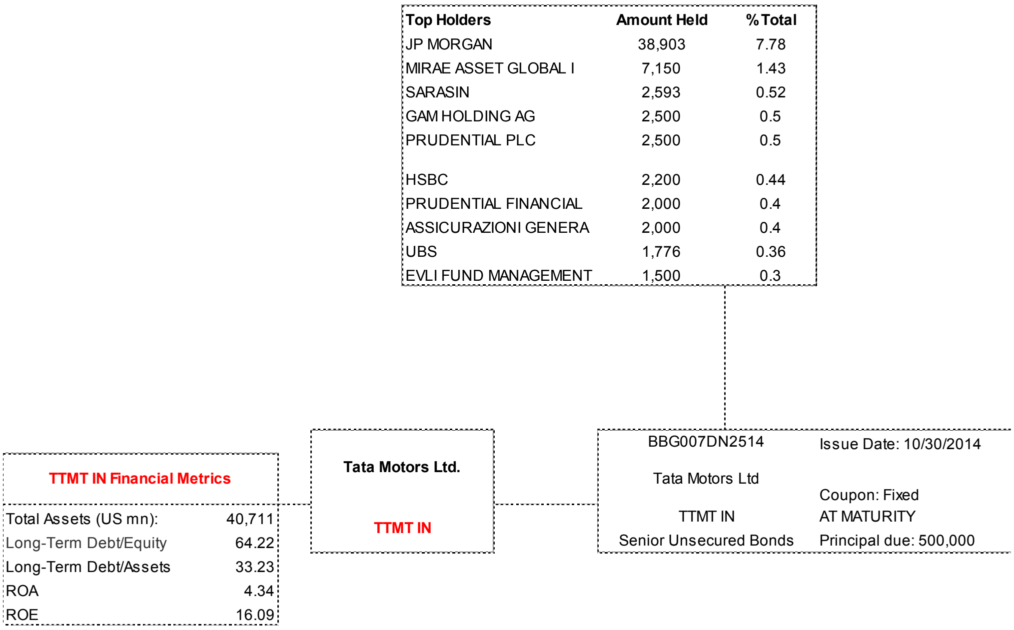
Source: Bloomberg, own elaboration

Next we identify the asset-side exposures to these securities, combining the current dataset with information on creditors. Here we need to pin down different pieces of information: on the one hand a dataset on bondholders on a security-by-security basis; on the other, a dataset on global banks' syndicated loans, also at the deal level. These datasets can be matched as long as they contain the relevant common identifier of the security (ISIN/FIGI).

Following up with our example, we detail investors' exposures to the corporate bond BBG007DN2514, inputting information on bondholders on a security-by-security basis. Researchers can obtain this information from different sources. In this exercise, we input it from Bloomberg (holdings as of April 2017). We report in Graph 4 the top 10 holders of the bond: JP Morgan holds 7.78% of the total, while the remaining holders have smaller fractions.

Identifying asset-side exposures: holders of corporate bond BBG007DN2514

Graph 4



Source: Bloomberg, own elaboration.

Similarly, in Graph 5 we input the initial exposures to the syndicated loan BBG00BVH29V7, and specific aspects of the deal. ANZ Banking Group act as the book runner. Many institutions took part in the deal, and ANZ Banking Group and Bank of Tokyo-Mitsubishi acquired the largest participations.

Overall, by completing these two steps, we have defined the firm-level interlinkages between firms and their creditors. We know, for instance, that the Korean Development Bank took a stake of 8% in a syndicated loan to Tata Motors Ltd in 03/11/2016, and in the last filings this company reported a ROA of 4,3%.

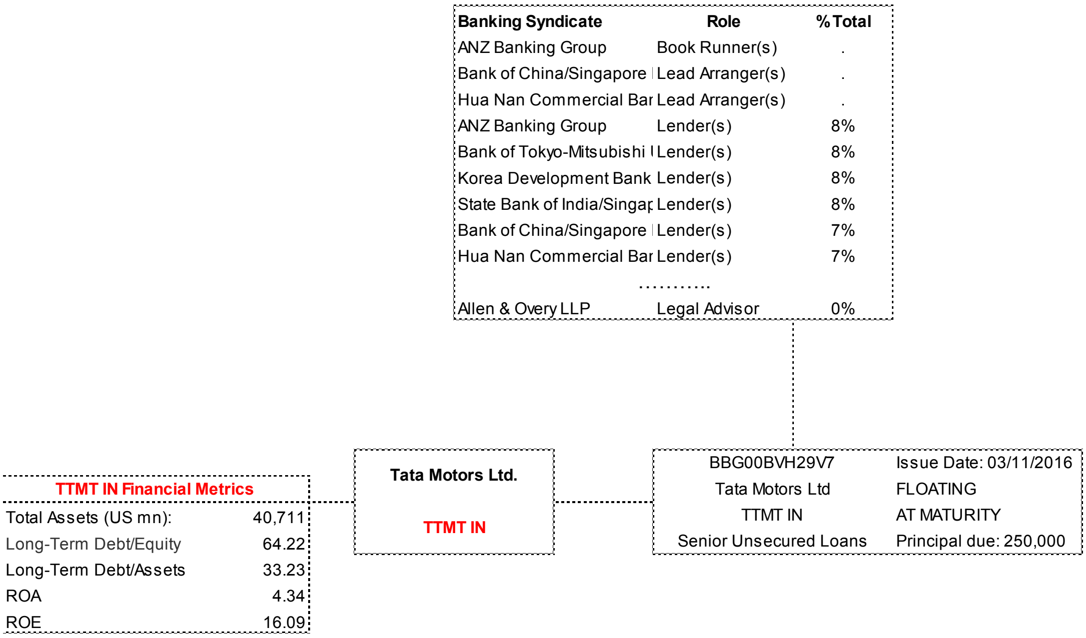
Using this methodology, we can construct a cross-country, firm-level dataset on bilateral interlinkages between firms and their creditors.

Our exercise still has several limitations, since we measure asset-side exposures on an immediate basis. Ultimate exposures can be substantially different due to derivatives transactions. Moreover, in the syndicated loan data, we have used reports the original parties, and not transactions in the secondary market. Finally, in the bondholders' data we have used only includes current holdings, but we do not have information on historical information.

It is important to stress that these limitations have to do with the specific data we have used, and not with the method. Researchers could compute ultimate exposures using derivatives transactions. They could also track syndicated loans transactions in the secondary market. Finally, they could input historical data on bondholders' exposures.

Identifying asset-side exposures: banking syndicate of loan BBG00BVH29VY

Graph 5



GraphFootnote

Source: Bloomberg, own elaboration.

4. Reaping the gains: bilateral exposures at the firm-level

In this section, we briefly illustrate the type of highly granular analyses that researchers can conduct with a dataset depicting firms' financial metrics by type of creditor. The main advantage is that it contains bilateral exposures at a firm-level.

For illustration purposes, we construct a small-scale dataset covering the top 100 firms in world financial markets, excluding non-financial firms and Chinese companies. Table 1 shows the summary statistics. The dataset covers 73 firms, most of which are based in the United States. They guarantee 2,454 securities, of which 2,352 are corporate bonds, and 102 are syndicated loans (we disregard municipal securities). We briefly summarize the number of creditors in the last two columns.

We exploit the fact that the dataset contains bilateral exposures at a firm-level, and we depict differences in profitability (Graph 7) and leverage (Graph 8) for firms with different creditors. This exercise is just for illustrative purposes, and we do not comment on the patterns below; we acknowledge that the sample is small and perhaps these patterns do not hold in a larger dataset.

Matched firm-securities-creditors dataset. Summary statistics[1]

Table 1

	Number of firms	Number of securities			Number of holders	
		Total	Bond	Loans	Parties in syndicated loan	Bond holders
Total	73	2,454	2,352	102	343	1098
United States	49	2,042	1,964	78	221	1020
Europe	15	326	309	17	154	431
Rest of the world	9	86	79	7	55	100

[1] Sample: Top 100 firms in the Bloomberg World global index, excluding financial companies, and Chinese firms. Municipal securities not included.

Sources: own elaboration.

With this caveat in mind, in the upper left-hand panel we compare differences in financial metrics between firms with, and without outstanding securities, as well as the overall mean. In the upper right-hand panel, we compare firms that are loan issuers, which those that are bond issuers. These panels exploit the information of the firm-level dataset with securities-by-securities breakdown; we can thus identify which firms have outstanding securities, and their type. We do not want to overstress the patterns. However, it seems that firms without securities are less profitable; despite this, they exhibit, perhaps surprisingly, a similar rising leverage trend.

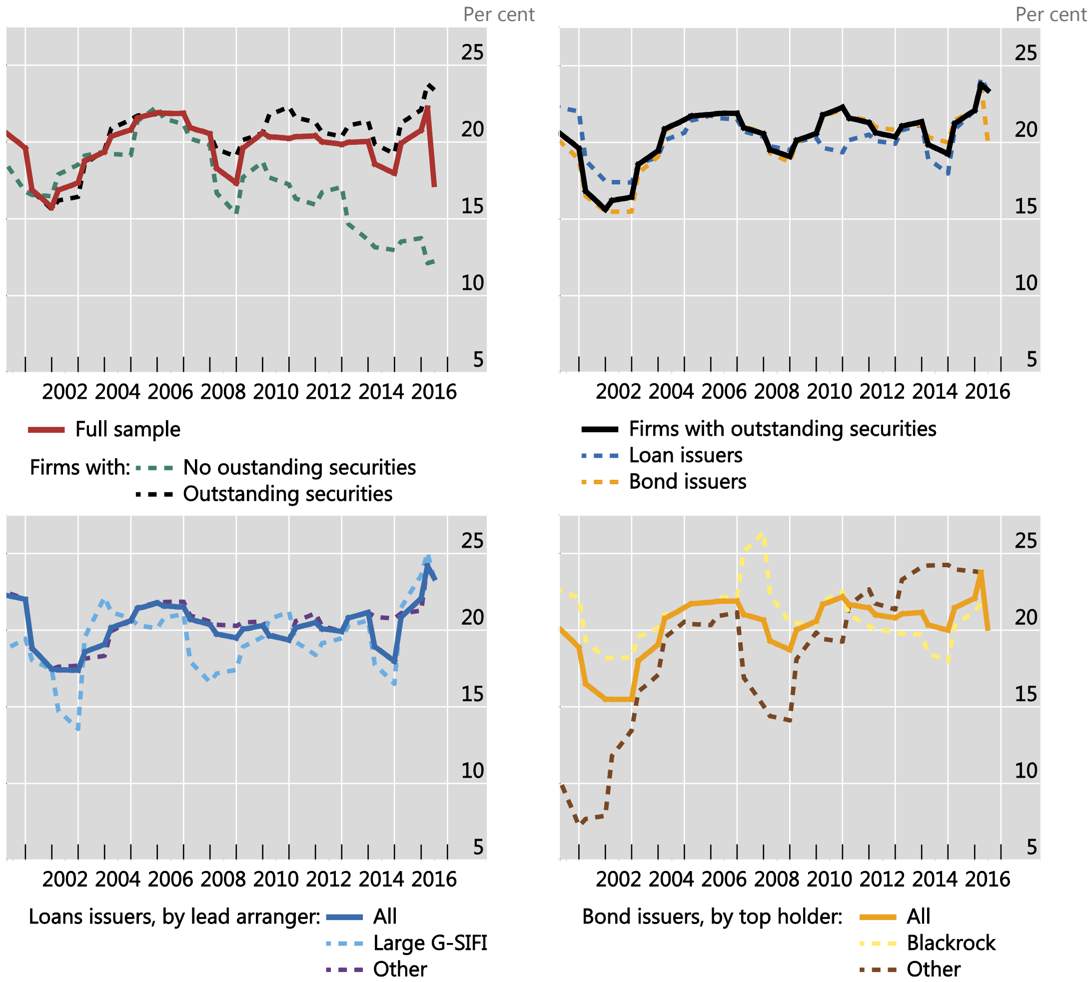
Next we exploit the bilateral exposures at a firm level. In the bottom left-hand panel we focus on the subset of companies with outstanding loans. For each loan we know the full list of members of the banking syndicate, as well as their type of involvement (ie, main lender, lender, legal advisor, and so on). To illustrate the power of a dataset on firm-level bilateral exposures, we compare firms that borrowed from a large global bank, with the rest. We consider that a firm borrowed from a large global bank when a G-SIFI with a capital surcharge>2% acted as lead arranger. We can carry out this exercise because the dataset contains information on the members of the banking syndicate that took part in each deal.

There are theoretical reasons why the financial metrics of these two groups of companies might exhibit non-random differences. On the one hand, large banks are likely to exhibit a major ex-post involvement in firms' decisions. This can lend to differences in their payout, expenditures, and borrowing and investment policies. On the other hand, large banks have a higher ability to oversee companies, so ex-ante might select different deals (for instance, more "complex" borrowers). Comparing firms' financial metrics can shed light on interesting questions: are financial metrics trends different for firms with loans vis-à-vis large banks? Are they more erratic, or systematically below, or above, their peers metrics? The differences in our sample are not remarkable, but it would be interesting to investigate this pattern in a dataset covering a much larger number of companies.

Non-financial firms' ROE

Median values, by type of financial interlinkage

Graph 6

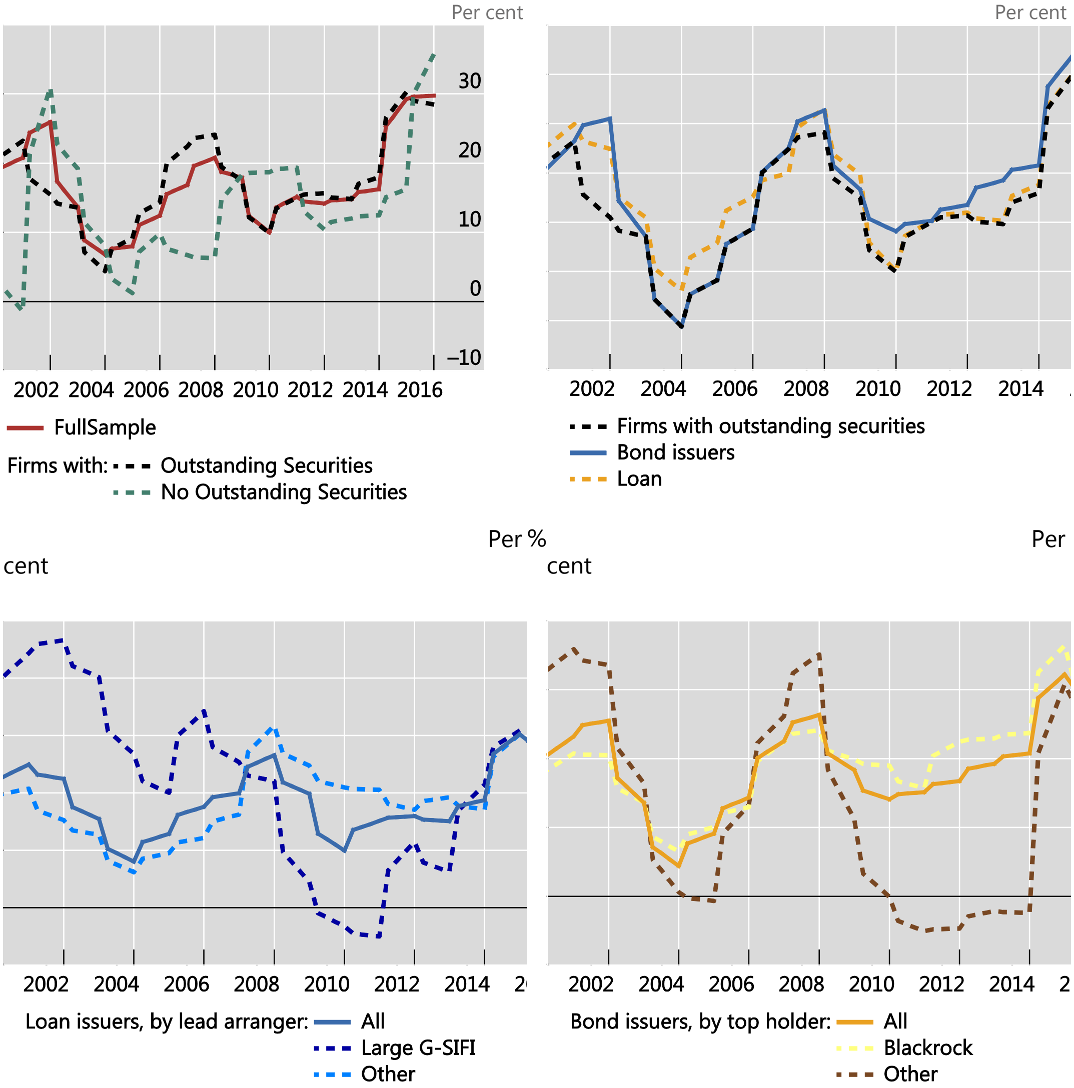


Source: Bloomberg, own elaboration.

Finally, in the bottom right-hand panel we focus on companies with at least an outstanding bond. For each bond we know the list of the ten largest holders. Consequently, we can compare if firms with bonds vis-à-vis different bondholders exhibit different metrics. We define a group with the subset of firms with at least an outstanding bond in which Blackrock is the top holder; the control group contains the remaining firms. We assume the major top holder has more power and interest in monitoring the company. Thus the very same arguments sketched above could explain differences in metrics between these two groups of firms (ie, Blackrock is a large company, and thus can exert a higher influence on firms, or select different deals). While we do not want to overstretch the results, the financial metrics of the firms with bilateral exposures to Blackrock seem less erratic.

Non-financial firms' leverage

Median values, by type of financial interlinkage — Graph 7



Source: own elaboration, Bloomberg.

5. Conclusions

Datasets on interlinkages between firms and their creditors are important to assess macroprudential risks. The process to construct such datasets is complex and requires combining different data in sources.

In this paper we propose a method to construct it. It consists in matching datasets using the securities identifiers. First, combining a securities dataset with a firm-level database with a security-by-security liability breakdown. Next merging the resulting dataset with information on bondholders on a security-by-security basis; and with information on the parties involved in syndicated lending.

To highlight the importance of measuring bilateral linkages, we construct a small-scale dataset. We compare differences in financial metrics for firms with different creditors. It is possible to use this procedure to construct a large-scale, cross-country, firm-level dataset on bilateral exposures.

References

Avdjiev,S., B, McCauley, and H. Shin, (2015), "Breaking free of the triple coincidence in international finance", Econ Policy (2016) 31 (87): 409-451

Barbu, A., C. Fricke, and E. Moench (2017), "Reach for Yield in Investment Funds", mimeo

Baskaya, Y.S., J. di Giovani, S. Kalemli-Ozcan, ad M. Fatih Ulu (2016), "International Spillovers and Local Credit Cycles", mimeo

Baskaya, Y.S., J. di Giovani, and S. Kalemli-Ozcan (2017), "Capital Flows and the International Credit Channel", mimeo

Bronzini, R. and A. D'Ignazio (2012), "Bank internationalisation and firm exports: evidence from matched firm-bank data", EFIGE Working Paper No. 59 August 2012

Carvalho, D., M.A. Ferreira, and P. Matos (2015), "Lending Relationships and the Effect of Bank Distress: Evidence from the 2007-2009 Financial Crisis", Journal of Financial and Quantitative Analysis Vol. 50 No. 6 Dec. 2015

CIEPR (2015), "Corporate Debt in Emerging Economies: A Threat to Financial Stability", Brooking Institutions

Clerc, L., A. Giovannini, S. Langfield, T. Peltonen, R. Portes, and M. Scheicher (2016), "Indirect contagion: the policy problem", ESRB Occasional Paper Series No.9 January 2016

Cornejo, A., J. Huerga, F. Mayerlen, J. Micheler (2017),"Unique identifiers in micro-data Management –the Centralised Securities Database (CSDB) experience", in "IFC Bulletin No.43 -Statistical implications of the new financial landscape"

Cornejo, A. and J. Huerga, (2016)," The Centralised Securities Database (CSDB) - Standardised micro data for financial stability purposes", in "IFC Bulletin No.41 - Combining micro and macro statistical data for financial stability analysis. Experiences, opportunities and challenges"

De Jonghe, O., H. Dewachter, K. Mulier, S. Ongena, and G. Schepens (2017), "Some borrowers are more equal than other: Bank funding shocks and credit reallocation", mimeo

Carabin, M., De la Garza, M., and O. Moreno (2015), "The effect of global liquidity on corporate financing in Mexico", mimeo

Ferreira, M. and P. Matos (2012), "Universal Banks and Corporate Control: Evidence from the Global Syndicated Loan Market" Review Financial Studies

McCauley, B,, P. McGuire, P., and V. Suskho (2015a), "Dollar credit to emerging market economies", BIS Quarterly Review December 2015

McCauley, B,, P. McGuire, P., and V. Suskho (2015b) "US monetary policy, leverage and offshore dollar credit" Economic Policy, vol 30, no 82, April 2015, pp 187-229.

Ongena, S., J.L. Peydro, and N. van Horen (2015), "Shocks Abroad, Pain at Home? Bank Firm Level Evidence on the International Transmission of Financial Shocks" IMF Economic Review November 2015

Tarashev, N., S. Avdjiev, and B, Cohen (2016), "International capital flows and financial vulnerabilities in emerging market economies: analysis and data gaps", Note submitted to the G20 International Financial Architecture Working Group

Tissot, B. (2016), "Globalisation and financial stability risks: is the residence based approach of the national accounts old-fashioned?", BIS Working Papers ° 587 October 2016

Box A

Liability breakdown at the firm-level

A firm-level database with a security-by-security liability breakdown lists all the securities guaranteed by a company. Securities shall be identified with their corresponding common identifier (ISIN/FIGI). Security-by-security breakdown are available in some firm-level datasets. We illustrate the structure of this dataset in Table A, using as example TTMT IN. In this specific example, we have obtained the information from S&P Capital IQ.

List of the latest eight securities guaranteed by TTMT IN (1)

Offer Date	Maturity Date	Issuer	Coupon	Offering Amount ($mm)	Outstanding Amount ($mm)	Coupon Type
Jun-22-2017	Jun-22-2022	Tata Motors Ltd	7.5	77.38	77.37	Fixed
Jan-25-2017	Jan-25-2020	Tata Motors Finance Ltd	-	22.04	23.21	Zero
Jan-10-2017	Jan-10-2020	Tata Motors Finance Ltd	-	36.63	38.68	Zero
Jan-10-2017	Apr-15-2020	Tata Motors Finance Ltd	-	25.64	27.08	Zero
Jan-10-2017	Mar-26-2020	Tata Motors Finance Ltd	-	25.64	27.08	Zero
Oct-30-2014	Apr-30-2020	Tata Motors Ltd	4.625	500.0	500.0	Fixed
Oct-30-2014	Oct-30-2024	Tata Motors Ltd	5.75	250.0	250.0	Fixed
May-07-2014	May-07-2021	TML Holdings Pte. Ltd.	5.75	300.0	300.0	Fixed

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MEASURING INTERLINKAGES BETWEEN NON-FINANCIAL FIRMS, BANKS AND INSTITUTIONAL INVESTORS. HOW SECURITIES COMMON IDENTIFIERS CAN HELP?

Jose Maria Serena Garralda*

Irving Fisher Committee Secretariat

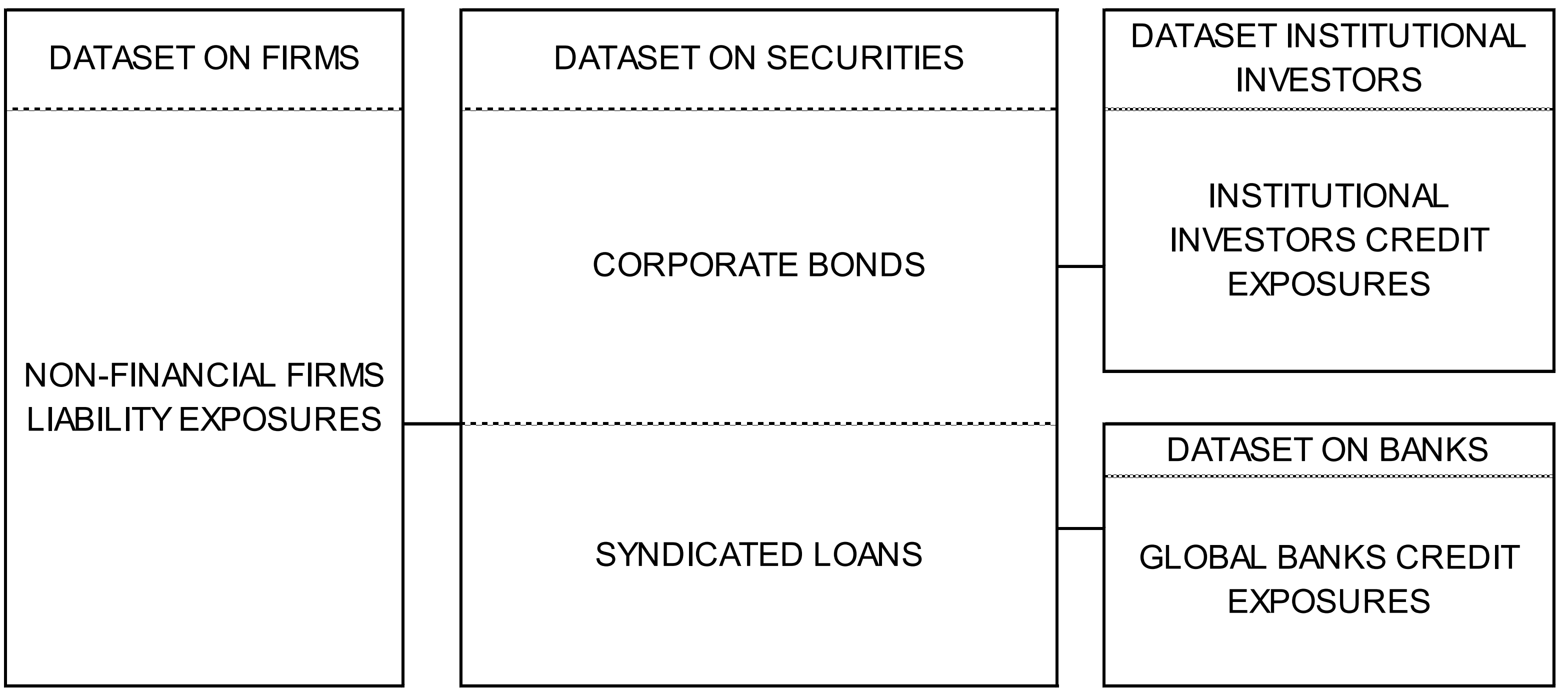
Bank for International Settlements

Joint work with Kaushik Jayaram (BIS)

The views expressed are those of the author and do not necessarily reflect those of the BIS or the IFC.

INTRODUCTION

- Macroprudential policy has two dimensions: the cyclical, and the system-wide. Financial interlinkages between firms and their creditors (banks and institutional investors) are an important aspect of the latter. But firm-level measurement is highly challenging.



INTRODUCTION

- This paper: addresses measurement problems and proposes a matching method which directly identifies institutions' credit and liability exposures using securities common identifiers (ISIN-FIGI).

SECURITY: CORPORATE BOND

Non-Financial Firm with ultimate liability exposure to BBG005P9XKZ2 [guarantor]

BBG005P9XKZ2 Issue Date: 12/17/2013

Jaguar Land Rover

8291453Z LN
Senior Unsecured

Coupon: Fixed
AT MATURITY
Principal due: 700,000

Institutional Investors with Credit Exposures to BBG005P9XKZ2

Balance-Sheet Data

- Resulting datasets will enhance our understanding of system-wide risks. To illustrate this we construct a small-scale dataset and depict firms' profitability trends for companies with different interlinkages.

OUTLINE

1. Introduction
2. Securities common identifiers: their role
3. Matching process: step-by-step
4. The gains: ROE trends by financial interlinkages
5. Conclusions

SECURITIES COMMON IDENTIFIERS: THEIR ROLE

- **Old approach:** match firm and securities-level datasets using qualitative firm-level information; imprecise, and cannot be used to match creditors 'data.

Non-Financial Firm

~~Firm LEI~~
Firm Name
Firm Parent Name

SECURITY: CORPORATE BOND

~~Issuer LEI~~	Issue Date: 12/17/2013
Issuer Name	Coupon: Fixed
Issuer Parent Name	AT MATURITY
Senior Unsecured	Principal due: 700,000

Balance-Sheet Data

"Matching process is rather cumbersome as only a small portion of the firms can be matched directly by name (as writing conventions differ between the two databases). (…)" Ongena, Peydro, and van Horen (2015), *IMF Economic Review*

SECURITIES COMMON IDENTIFIERS: THEIR ROLE

- **New approach:** exploit that securities [corporate bonds and syndicated loans] have common identifiers:
  - ISIN: corporate bonds, shares, options, derivatives, futures, and syndicated loans.
  - FIGI [Bloomberg]: twelve-character alphanumeric identifier, introduced in 2014 assigned to instruments of all asset classes.
- Then answer these two questions…
  - Which firms have liability exposure to these securities – identified by their ISIN/FIGI-?
  - Which investors (banks and institutional investors) have asset-side exposures to them?
- …using equity tickers as firm-identifiers (Bruno and Shin (2017), Fuertes and Serena (2016)); since LEIs are not well-defined.

SECURITIES COMMON IDENTIFIERS: SOME INTERESTING REFERENCES

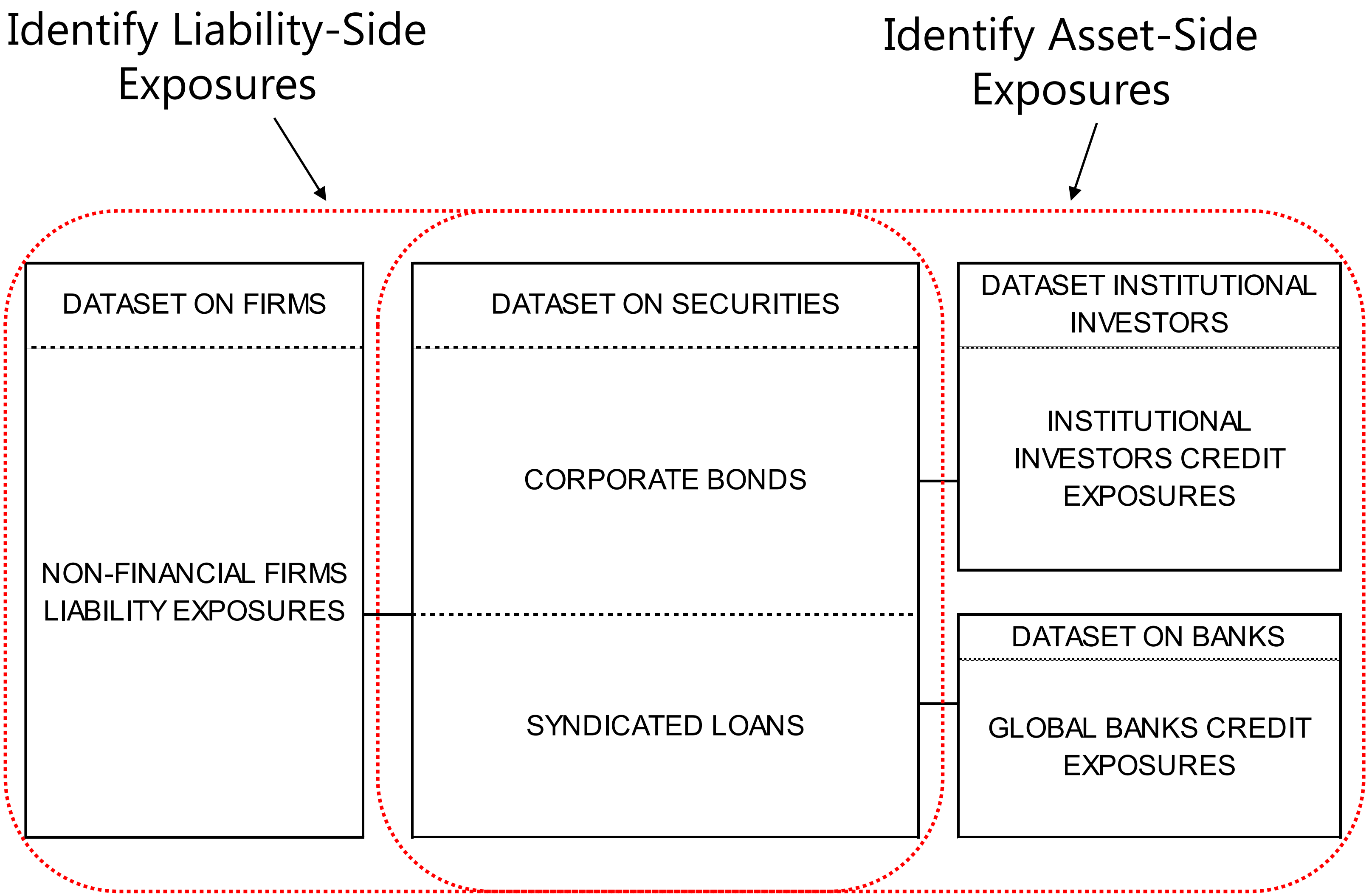
- Barbu, A., C. Fricke, and E. Moench, “Reach for Yield in Investment Funds”, *mimeo*

- Bruno, V. and H. Shin (2017), “Global dollar credit and carry trades: a firm-level analysis”, *Review of Financial Studies*, vol 30, no 3, 2017

- Cornejo, A., J. Huerga, F. Mayerlen, J. Micheler (2017),”Unique identifiers in micro-data Management –the Centralised Securities Database (CSDB) experience”, in *“IFC Bulletin No.43 -”*

- Fuertes, A. and J. M. Serena (2016), “How firms borrow in international bond markets: Securities regulation and market segmentation”, *Banco de Espana Working Paper* No. 1603

MATCHING PROCESS: STEP-BY-STEP



LIABILITY-SIDE EXPOSURES
STEP I. DEFINE ISSUANCE STRUCTURE

Parent Company	Guarantor	Issuer	Corporate Bond	
Tata Motors Ltd. **TTMT IN**	**Jaguar Land Rover** **8291453Z LN**	**Jaguar Land Rover** **8291453Z LN**	BBG005P9XKZ2 Jaguar Land Rover 8291453Z LN Senior Unsecured Bonds	Issue Date: 12/17/2013 Coupon: Fixed AT MATURITY Principal due: 700,000
	Tata Motors Ltd. **TTMT IN**	**Tata Motors Ltd.** **TTMT IN**	BBG007DN2514 Tata Motors Ltd TTMT IN Senior Unsecured Bonds	Issue Date: 10/30/2014 Coupon: Fixed AT MATURITY Principal due: 500,000
		TML Holdings PTE Ltd **0327039D SP**	BBG006F26RZ1 TML Holdings Pte Ltd 0327039D SP Senior Unsecured Bonds	Issue Date: 05/07/2014 Coupon: Fixed AT MATURITY Principal due: 300,000

LIABILITY-SIDE EXPOSURES
STEP II. IDENTIFY THE GUARANTOR

Guarantor

Corporate Bond

Jaguar Land Rover

8291453Z LN

BBG005P9XKZ2
Jaguar Land Rover
8291453Z LN
Senior Unsecured Bonds

Issue Date: 12/17/2013
Coupon: Fixed
AT MATURITY
Principal due: 700000

Tata Motors Ltd.

TTMT IN

BBG007DN2514
Tata Motors Ltd
TTMT IN
Senior Unsecured Bonds

Issue Date: 10/30/2014
Coupon: Fixed
AT MATURITY
Principal due: 500000

BBG006F26RZ1
TML Holdings Pte Ltd
0327039D SP
Senior Unsecured Bonds

Issue Date: 05/07/2014
Coupon: Fixed
AT MATURITY
Principal due: 300000

LIABILITY-SIDE EXPOSURES
STEP III. FINANCIAL METRICS OF THE GUARANTOR

Guarantor

Corporate Bond

Financial Metrics
Assets (£m): 21,603
LTDebtEquity: 31.25
LTDebt/Capital: 23.52
ROA: 5.74
ROE: 18.3

Jaguar Land Rover

8291453Z LN

BBG005P9XKZ2
Jaguar Land Rover
8291453Z LN
Senior Unsecured Bonds

Issue Date: 12/17/2013
Coupon: Fixed
AT MATURITY
Principal due: 700000

Financial Metrics
Assets (US mn):40,711
LT Debt/Equity:64.22
LTDebt/Capital:33.23
ROA:4.34
ROE:16.09

Tata Motors Ltd.

TTMT IN

BBG007DN2514
Tata Motors Ltd
TTMT IN
Senior Unsecured Bonds

Issue Date: 10/30/2014
Coupon: Fixed
AT MATURITY
Principal due: 500000

BBG006F26RZ1
TML Holdings Pte Ltd
0327039D SP
Senior Unsecured Bonds

Issue Date: 05/07/2014
Coupon: Fixed
AT MATURITY
Principal due: 300000

ASSET-SIDE EXPOSURES
STEP I. FOR CORPORATE BONDS
[TTMT IN: BBG007DN2514]

Identify the holders of the corporate bond BBG007DN2514

Top Holders	Amount Held	% Total
JP MORGAN	38,903	7.78
MIRAE ASSET GLOBAL I	7,150	1.43
SARASIN	2,593	0.52
GAM HOLDING AG	2,500	0.5
PRUDENTIAL PLC	2,500	0.5
HSBC	2,200	0.44
PRUDENTIAL FINANCIAL	2,000	0.4
ASSICURAZIONI GENERA	2,000	0.4
UBS	1,776	0.36
EVLI FUND MANAGEMENT	1,500	0.3

TTMT IN Financial Metrics	
Total Assets (US mn):	40,711
Long-Term Debt/Equity	64.22
Long-Term Debt/Assets	33.23
ROA	4.34
ROE	16.09

Tata Motors Ltd.

TTMT IN

BBG007DN2514
Tata Motors Ltd
TTMT IN
Senior Unsecured Bonds

Issue Date: 10/30/2014
Coupon: Fixed
AT MATURITY
Principal due: 500,000

ASSET-SIDE EXPOSURES
STEP II. FOR SYNDICATED LOANS
[TTMT IN: BBG00BVH29V7]

Identify the members of the banking syndicate of the loan BBG00BVH29V7

Banking Syndicate	Role	% Total
ANZ Banking Group	Book Runner(s)	.
Bank of China/Singapore I	Lead Arranger(s)	.
Hua Nan Commercial Bar	Lead Arranger(s)	.
ANZ Banking Group	Lender(s)	8%
Bank of Tokyo-Mitsubishi U	Lender(s)	8%
Korea Development Bank	Lender(s)	8%
State Bank of India/Singap	Lender(s)	8%
Bank of China/Singapore I	Lender(s)	7%
Hua Nan Commercial Bar	Lender(s)	7%
	……….	
Allen & Overy LLP	Legal Advisor	0%

TTMT IN Financial Metrics	
Total Assets (US mn):	40,711
Long-Term Debt/Equity	64.22
Long-Term Debt/Assets	33.23
ROA	4.34
ROE	16.09

Tata Motors Ltd.

TTMT IN

BBG00BVH29V7	Issue Date: 03/11/2016
Tata Motors Ltd	FLOATING
TTMT IN	AT MATURITY
Senior Unsecured Loans	Principal due: 250,000

FIRMS'ROE AND FINANCIAL INTERLINKAGES

- Dataset matching top companies worldwide, with all the securities guaranteed, and creditors (bond-holders and parties in syndicated loans) with asset side exposures:

Matched firm-securities-creditors database. Summary statistics

Table 1

	Number of firms[1]	Number of securities guaranteed[2]			Number of creditors[3]	
		Total	Bond	Loans	Parties in syndicated loan	Bond holders
Total	73	2,454	2,352	102	343	1,098
United States	49	2,042	1,964	78	221	1,020
Europe	15	326	309	17	154	431
Rest of the world	9	86	79	7	55	100

[1] Top 100 firms in the Bloomberg World global index, excluding financial companies, and Chinese firms. [2]Municipal securities not included.[3] Number of investors with claims on the firms (parties involved in syndicated loans); investors holding bonds (top 10 holders).

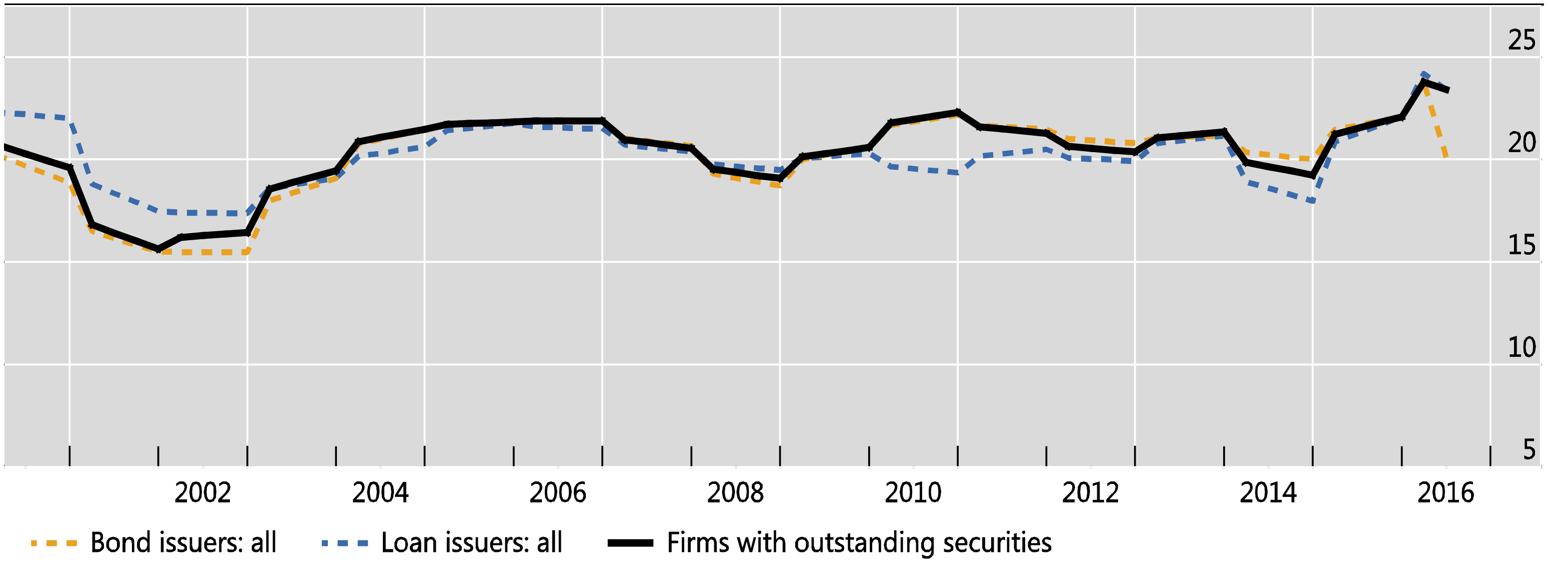
Sources: own elaboration.

FIRMS'ROE AND FINANCIAL INTERLINKAGES
MATCHING FIRM-LEVEL AND SECURITIES-LEVEL DATA

Return-on-equity: only firms with outstanding securities

In per cent

Graph 3

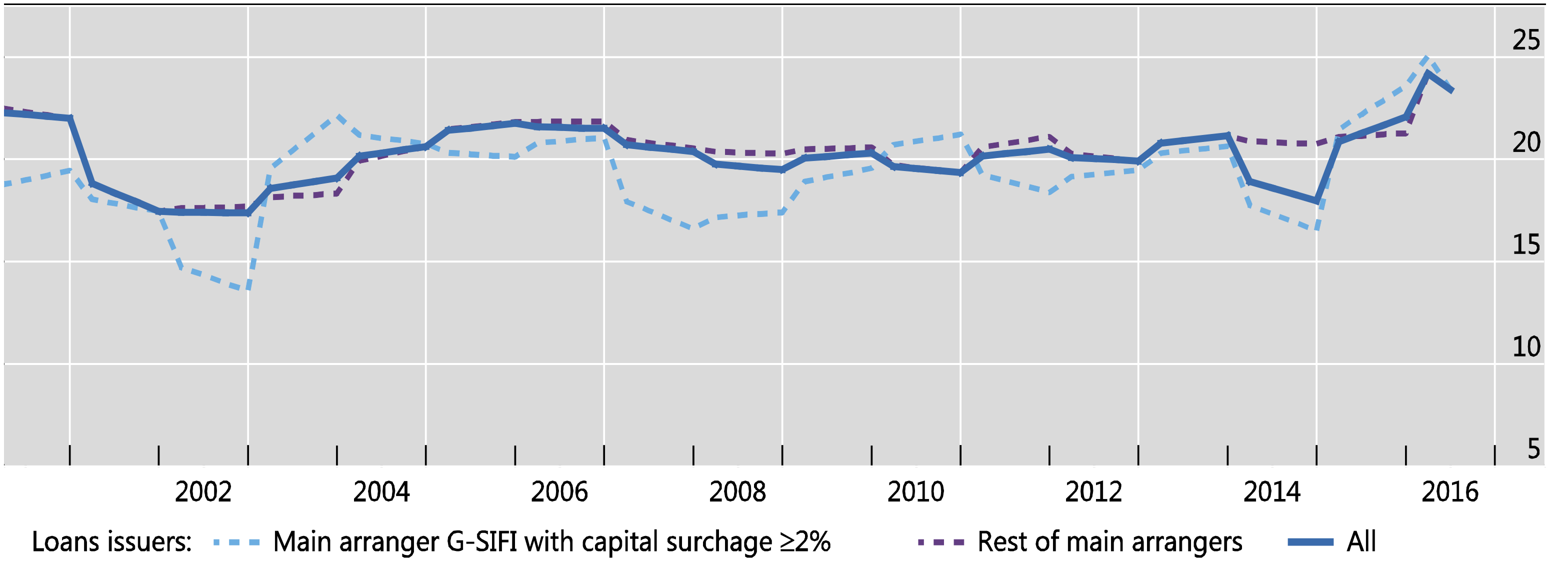


Source: Bloomberg.

FIRMS'ROE AND FINANCIAL INTERLINKAGES INPUTTING ALSO BANKING SYNDICATED DATA

Return-on-equity: only firms with outstanding loans

In per cent Graph 4



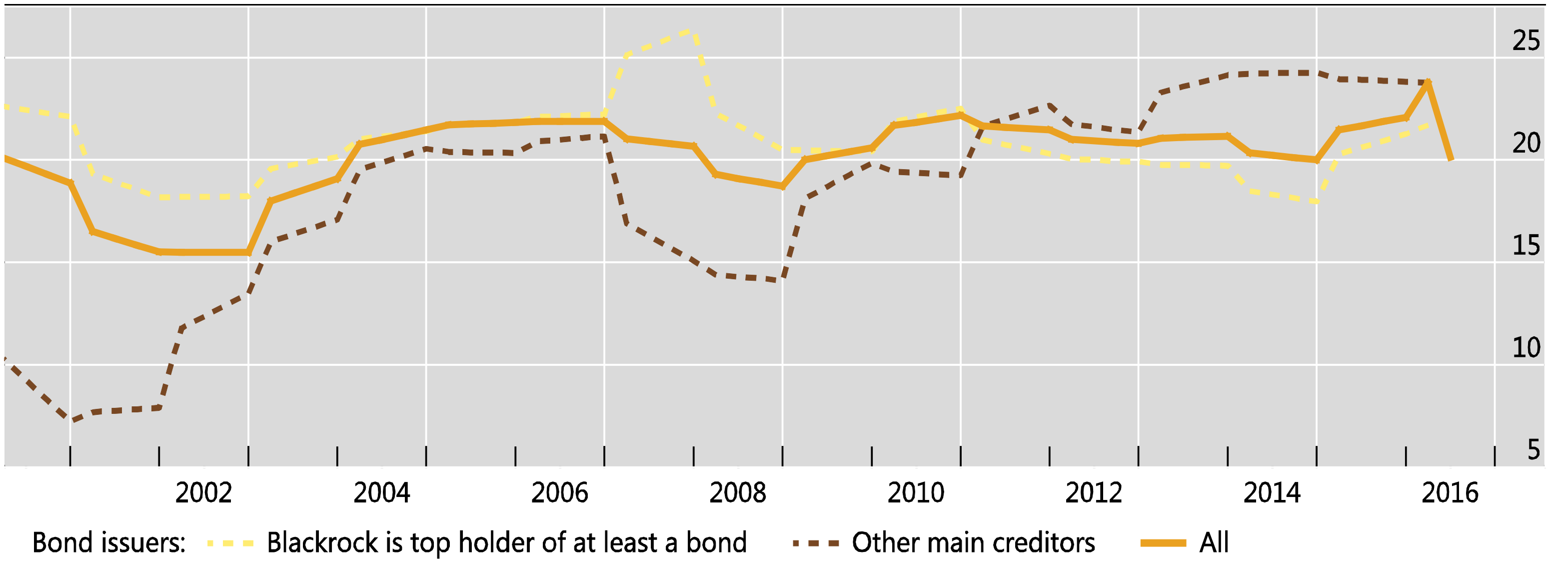
Source: Bloomberg.

FIRMS'ROE AND FINANCIAL INTERLINKAGES INPUTTING ALSO BOND-HOLDERS DATA

Return-on-equity: only firms with outstanding corporate bonds

In per cent

Graph 5



Source: Bloomberg.

CONCLUSION

- In this paper we use securities identifiers to construct a dataset on financial interlinkages between firms and their creditors (banks and institutional investors). This way we overcome the problems of matching datasets with qualitative information.

- Resulting datasets allow understanding system-wide risks arising from interconnectedness. We illustrate the type of gains with a small-scale exercise.

- Our final objective is to construct a global, cross-country, firm-level dataset on interlinkages -work-ahead!

THANK YOU FOR YOUR ATTENTION

REFERENCES. MATCHING SYNDICATED LOANS WITH FIRM-LEVEL DATA

- Ferreira, M. and P. Matos (2012), “Universal Banks and Corporate Control: Evidence from the Global Syndicated Loan Market” *Review Financial Studies*

- Ongena, S., J.L. Peydro, and N. van Horen (2015), “Shocks Abroad, Pain at Home? Bank Firm Level Evidence on the International Transmission of Financial Shocks” *IMF Economic Review November 2015*

REFERENCES. MATCHING CORPORATE BONDS WITH BOND-HOLDERS DATA

- Barbu, A., C. Fricke, and E. Moench, "Reach for Yield in Investment Funds", *mimeo*

- Cornejo, A., J. Huerga, F. Mayerlen, J. Micheler (2017),"Unique identifiers in micro-data Management –the Centralised Securities Database (CSDB) experience", in *"IFC Bulletin No.43 -"*

- Cornejo, A. and J. Huerga, (2016)," The Centralised Securities Database (CSDB) - Standardised micro data for financial stability purposes", in *"IFC Bulletin No.41 -"*

- *ECB (2015),* "Who Holds What? New Information on Securities Holdings", *ECB Economic Bulletin Issue 2 /2015*

REFERENCES. MATCHING CORPORATE BONDS WITH FIRM-LEVEL DATA

- Bruno, V. and H. Shin (2017), "Global dollar credit and carry trades: a firm-level analysis", *Review of Financial Studies*, vol 30, no 3, 2017

- Fuertes, A. and J. M. Serena (2016), "How firms borrow in international bond markets: Securities regulation and market segmentation", *Banco de Espana Working Paper* No. 1603

- IADB (2016), "Time to Act: Latin America and the Caribbean Facing Strong Challenges"