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Cross-country bank-firm lending relationships: How can the Legal Entity Identifier help?[1]

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

Cross-country bank-firm lending relationships: How can the Legal Entity Identifier help?

Jose Maria Serena Garralda

Abstract

Bank-firm lending relationships are often constructed combining loan, firm, and bank data from commercial providers. In this paper we emphasize that datasets are best combined using borrowers and lenders' global identifiers. The three advantages are: flexibility to define relationships on a solo or a consolidated basis; efficiency to mobilise data without ad-hoc cross-checks; and relevance, since exposures reflect the actual legal arrangements in loan contracts. The Legal Entity Identifier system is theoretically well-suited for this purpose: it uniquely identifies legal entities engaged in financial transactions, provides entity-parent hierarchies, and certifies quality. However it is still incomplete. Thus we use the parallel systems of global identifiers developed by the financial industry. To illustrate the advantages of our approach, we examine the credit risks in banks' loans portfolios using borrowers' debt to EBITDA.

Keywords: bank-firm exposures, syndicated loans, matching datasets, Legal Entity Identifier.

JEL classification: C80, C81, F36, G15

Contents

1. Introduction

The Great Financial Crisis (GFC) was a major banking crisis impacting in the world economy through a contraction in bank lending. In its aftermath the lack of data on cross-country bank-firm exposures was perceived as a major gap. Data availability has increased, partly as a result of the Data Gaps Initiative (DGI) and data collected by the International Data Hub (IDH) of the BIS.

Cross-country bank-firm exposures can also be constructed combining three commercial datasets: syndicated loans, firm, and bank-level datasets. This requires firstly matching syndicated loan borrowers and lenders to, respectively, firm and bank-level datasets. Second estimating the outstanding credit of a bank to a firm using loans' issuance and original maturity dates.

The main challenge of the exercise is to match borrowers / lenders to firm / bank-level datasets. So far this is done comparing their names. Names have been traditionally compared manually -ie judging ad-hoc if they are similar enough. More recently name comparison is conducted using fuzzy matching: an algorithm computes a string similarity metric (eg Levenshtein distance), to evaluate if two names are similar enough -ie if the metric is below a threshold.

Fuzzy matching is fast but has some drawbacks. First, name similarity does not guarantee accuracy –eg two different companies could have the same name. Second, results need not be consistent with the complex arrangements between borrowers and lenders. For instance a firm might borrow through an affiliate, and the loan contract make explicit that the ultimate exposure corresponds to the parent. If the borrower name is unrelated to the parent name, name comparison is misleading. Third, matches are not flexible: researchers may be *alternatively* interested in measuring exposures on a consolidated, or an entity-level basis.

To address these problems we propose combining loan, firm, and bank through entities' global identifiers. This is feasible, since loans are legal contracts, unambiguously expliciting which entities are borrowing and lending. The Legal Entity Identifier (LEI) system is theoretically well-suited for this exercise, as was introduced precisely to accurately identify legal entities involved in financial transactions; provides entity-parent hierarchies, and the quality of LEIs is regularly checked. The main drawback of the LEI system is the lack of coverage among non-financial corporates, implying that many borrowers have not issued an LEI. As an alternative we use the system of global identifiers developed by the financial industry (Thompson Reuters permanent ID). They identify entities across datasets, and provide (static) entity-parent links. Our proposal is thus related with efforts to improve combination techniques using information on hierarhichal relationships (Cohen et al., 2018).

The dataset we construct is useful for a variety of purposes. We highlight the advantages examining credit risks in banks' loans portfolios. Credit risks can be assessed analysing borrower's financial health (debt to EBITDA ratio), for the outstanding loans of each bank. The data are useful for a variety of additional purposes. For instance, it can help to evaluate the impact of reforms on banks' lending to firms, and their activity. Some aspects of the dataset can be improved looking ahead –in particular the size of credit exposures. The actual size might depart from our estimations, since we do not adjust for risk transfers after the origination of the loan. This assumption is restrictive, since banks might buy CDS to gain protection; sale the loan; or change the terms and conditions after its inception.

The remainder of the paper is structured as follows. Section 2 reviews previous work constructing bank-firm relationships using commercial data. Section 3 presents our methodology, emphasizing the importance of using global identifiers; and the actual limitations to the use of the LEI, due to lack of coverage among loan borrowers. Section 4 summarises the data we use. Section 5 presents the main results. Section 6 concludes.

2. Literature review

The literature has explored two alternative ways of gauging cross-country bank-firm lending relationships using commercial data.

The first one consists in using data on bank-firm relationships, as collected by a data provider -for instance Kompass. Such data are ultimately obtained from chambers of commerce, firm registries, and phone interviews (Kalemli-Ozcan, Laeven, and Moreno, 2018). Survey data has drawbacks since ensuring responses are consistent on the cross-section and over time issue is challenging. Besides survey data does not provide information on the type of relationship (eg type of loan, currency, remaining maturity, and so on).

The second, more popular alternative consists in constructing lending relationships from loan data, gathered by commercial data providers. Loan data are reported by banks, which have the incentives to disclose deals to signal their market share. Loan data includes syndicated loans, but also some smaller deals (bilateral and club deals). Previous literature, focused on the US, has constructed bank-firm lending relationships comparing the names of borrowers (lenders) to the names of firms (banks) in their corresponding datasets. For instance, Chava-Roberts (2008) estimated borrower-firm links comparing the names of borrowers in Dealscan to the names of firms in Compustat.[1] Name comparison is also used to construct lender-bank links (Schwert, 2018a).

Name comparison is now automatized through probabilistic techniques (fuzzy matching) which estimate the similarity between names (eg Levenshtein distance, Jaro-Winkler); and use a threshold to evaluate if names are similar enough. Recent research has concluded that the results obtained using these techniques are enhanced using corporates hierarchical information (Cohen et al., 2018). Adjustments on entity-parent links through mergers and acqusitions (Schwert, 2018b) have also been used to define lender-bank links (Schwert, 2018b).

3. Methodology

3.1. Benefits and limits of identifiers

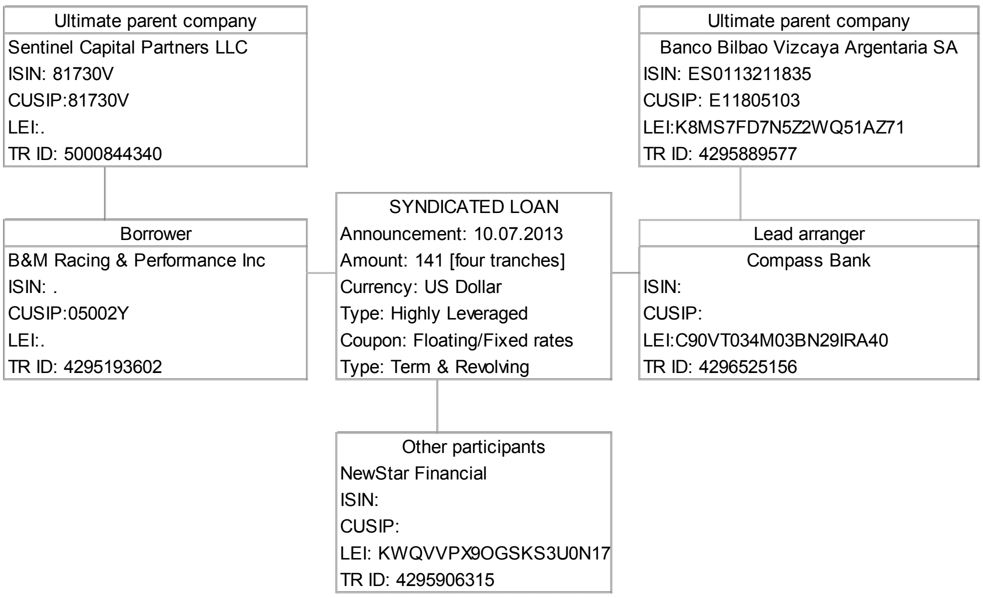
We argue that matching datasets using plain name comparison has three problems: name comparison is not accurate (Mehrhoff, 2018), the links may lack economic

1 Chava-Roberts links are widely used in economic research to investigate bank-firm relationships (eg Acharya et al., 2018).

meaning, and they lack flexibility. These problems simultaneously appear, for instance, when firms use special purpose vehicles (SPVs) to raise funds. SPVs names can be loosely related to the ultimate borrower name, raising doubts on the relevance of the matches; and matches are likely inaccurate (thus requiring ad-hoc cross-checks).[2] Concerning flexibility: researchers need to simultaneously know the direct borrower, its immediate and ultimate parent. Reserchers may be interested in the direct borrower, if they seek to understand location; or in the parent entity, if the interest is on credit risk.

We argue that these problems can be tackled using a system of global identifiers. Diagram 1 sketches how bank-firm exposures can be estimated using global identifiers. Loans are complex legal contracts, and the terms and conditions are discussed and agreed on by parties. Among other aspects loans make explicit the legal entities acquiring the credit and the liability. Financial data providers identify each party by an (several) alphanumeric code(s): LEI, Thompson Reuters permanent ID, ISIN, or SDC CUSIP. Besides within their systems each entity related to its parent (if any).

Diagram 1. Bank-firm exposures using global identifiers



Source: TR Eikon, own elaboration.

Using global identifiers for statistical, large-scale production has some problems: some identifiers are not always available (eg the LEI), or can change over time (eg CUSIP). The financial industry has produced systems of global identifiers (FIGI, Thompson Reuters ID) which address some of these problems: each legal entity receives a unique alphanumeric code, stable over time. Still, these systems are not designed for economic research, and have some limits. The lack of historical information on entity-parent links is a major problem, which requires mobilising mergers and acquisitions data.

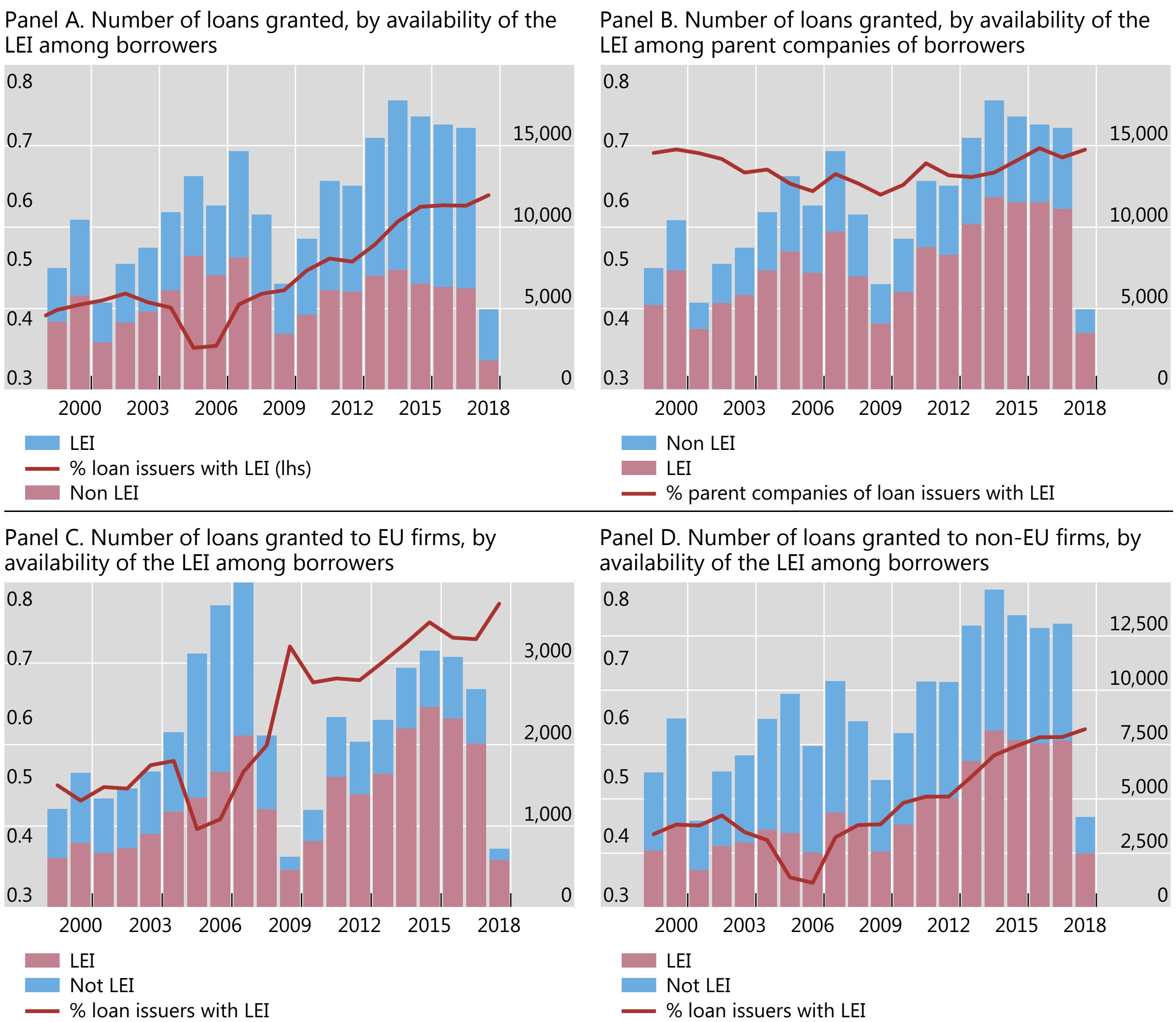
[2] See Cohen (2018) for a careful exposition of the limits of matching datasets using plain name comparison, and avenues to enhance matches using data cleaning and entity-parent links.

3.2. Loan contracts and the Legal Entity Identifier

In the aftermath of the GFC the Financial Stability Board (FSB) Plenary supported the development and implementation of a global identifier (FSB (2012)) precisely to uniquely identifying these legal entities involved in financial transactions (eg syndicated loans). The LEI system design was well-suited for large-scale statistical management: the LEI is a unique alphanumeric code assigned to a single entity; the system has entity-parent links (ie an entity LEI is associated to the LEI of the parent); and the quality is certified.

Loan borrowing in global markets. Availability of Legal Entity Identifiers

Graph 1



Sources: DealScan; authors' calculations.

The use of the LEI system for statistical production has some drawbacks: it lacks universal coverage, in particular among borrowers. As of today, in half of the loans (149,359) the LEI of the borrower is missing; the LEI of the borrower ultimate parent company is more broadly available, but it is still missing in one-third of the loans (in 90,337 instances). Panels A and B in Graph 1 represent this pattern. On the other hand the LEIs are becoming more broadly available in the in the last years. In 2017 73% of the loan borrowers had issued a LEI. Besides the number of LEIs is uneven across regions, and more often available in the EU. This likely reflects that the EU regulation has required entities active in capital markets to issue a LEI (Panels C and D).[3] Finally, statistical production requires historical information (eg LEIs for inactive companies).

3.3. Lending relationships and credit exposures

To construct exposures we retrieve the Thompson Reuters permanent ID of the borrower and lender, and their immediate and ultimate parent. For each of these entities we obtain the sector, country and incorporation, type of organisation, year of incorporation (in some instances these fields are missing).

We define the actual borrowers / lenders in a loan contract as follows. On the borrower side we consolidate at the ultimate parent level non-bank financials owned by non-financial corporation (we consolidated into the immediate parent if the ultimate parent is the government). On the lender side we consolidate always, unless the entity is as independent subsidiary.

Using these borrower-lender links we compute the amount lent by a bank to a firm in a given year; for this we use the original maturity to estimate redemptions. A bank claim on a firm is the difference between cumulated issuances and redemptions (by construction, claims have a lower bound at zero).

We assume that a lending relationship exists if this claim is positive. Further we estimate the credit exposure, which is given by the size of the claim. To estimate credit exposures we use solely term loans, since we do not have information on the amount drawn from credit lines.

Our estimations of credit exposures have limitations, since we are not adjusting for risk transfers after the origination of the loan. There are many potential risk transfers: banks can sale loans, and actually there is an active secondary market (Ivashina and Scharfstein, 2010); they can renegotiate terms, including cancelling them before the original maturity date; they may buy CDS protection against the borrower. There are other important biases in the credit exposures we estimate: we are not using all loans, as trade finance or smaller loans not recorded in Eikon; we do not have information on corporate deposits on banks, which might decrease net exposures.

Some of these problems could be adjusted using additional data sources; in particular loan sales in secondary markets or renegotiations of terms and conditions. Others problems are more structural, and constitute a limit of this approach. In particular, it seems unlikely to obtain data on corporate deposits, credit derivative markets, or small loans from banks.

Overall these caveats suggests that lending relationships derived from term loans are the most reliable part of our results. Lack of information on risk transfers casts important doubts on credit exposure estimations. However as long as banks retain a

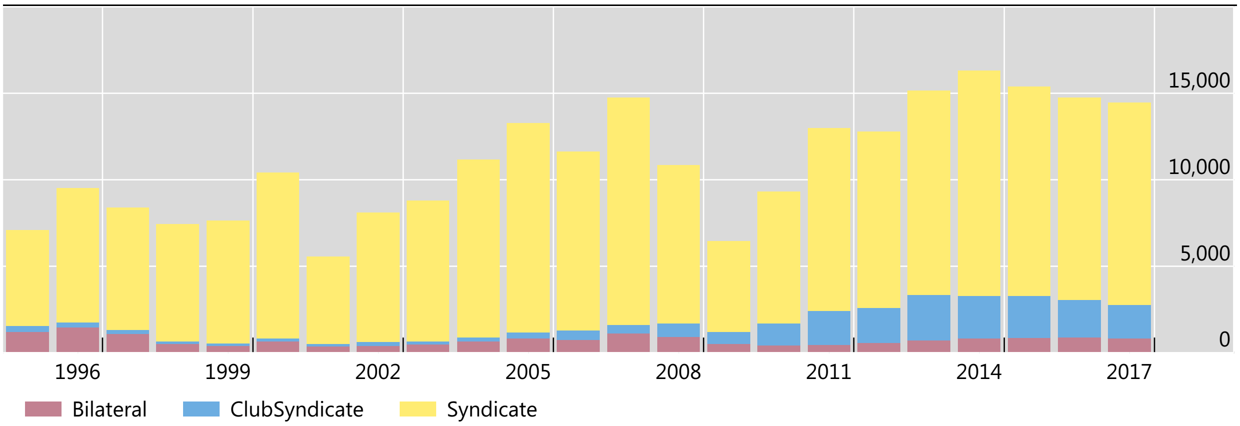
[3] It is instructive to compare the evolution of the number of ISINs and LEIs. The ISIN of an entity is sometimes used as a global ID. Its coverage in the full sample is similar to the LEI (it is available in half of the instances); however its coverage has remained constant over time.

fraction of the loans they originate, or do not fully hedge their exposures, lending relationships would still be valid. Similarly, we are not able to assess if banks draw credit lines, which suggests focusing on term loans.

4. Data

We use data on all loans to non-financial corporations, provided by Thompson Reuters Eikon. As in previous research our unit of observation are tranches. The features of the data are well know: the total number of all loans (tranches) in Eikon is over 300,000, of which 256,000 are to non-financial firms (ie excluding loans to the government and financial companies). The time span covers 1983 to 2018. The number of deals peaks in 2014, and the market was already active in the 1990s.

Number of loans to NFC. Breakdown by type[1] Graph 2



[1] For firms with an outstanding loan as of Dec 2017.

Sources: Eikon; authors' calculations.

Most of the loans in the dataset are syndicated (233,403), but there are also bilateral bank loans (18,026), and club syndicate loans (23,681); the latter are smaller deals, and typically cannot be sold in secondary markets. The dataset includes both term loans and credit lines; more specifically there are 141,478 term loans, and 117,514 credit lines. The remaining are bridge loans, which we leave aside. We do not know if credit lines are used, or the portion drawn, so we restrict the estimation of credit exposures to term loans. Graph 2 depicts some patterns in loan issuance.

There are 62,605 loan borrowers. We consolidate financial vehicles, resulting in 50,179 firms. These firms are incorporated in 144 countries. The countries with more borrowers are the US (17,117), Japan (6,085), United Kingdom 2,309), China (1,424), and Canada (1,331).

We treat banks on a (partially) consolidated basis, treating listed subsidiaries as independent banks. There are 27,849 different lenders, with different roles in the loan (eg lead arrangers, other participants). We focus on the lenders which account for 75% of the deals, and consolidate them into their 265 parent institutions. These institutions might be listed subsidiaries of another bank (eg Santander UK is treated in our sample as a separate entity from Santander).

5. Main results

5.1 Lending relationships

We assume that a bank-firm lending relationship exist when there is an outstanding loan from the bank to the firm. Table 1 describes the evolution of lending relationships over time, for the main lenders. The number of relationships has grown over time. The number of relationships by bank tends to increase, and is above 600 in 2016. The number of firms with an outstanding loan also grows, and hovers around 7,000 in 2016. The number of lenders per firm remains broadly constant, fluctuating around 10. This seems a high number, but reflects that most loans in our sample are syndicated (and thus many parties are involved).

Lending relationships based on syndicated loans data — Table 1

	Bank*Firm	# Banks	Av.# firms per Bank	# Firms	Av. # banks per firm
2000	12,863	53	243	2,155	10
2004	18,524	58	319	3,532	10
2008	24,327	58	419	4,939	13
2012	29,951	58	516	5,721	11
2016	35,925	58	619	6,975	10

[1] Lending relationships defined treating banks on a consolidated basis; for firms we just consolidate financial vehicles.

Sources: own elaboration, Eikon, Thompson Reuters.

Cross-border lending relationships based on syndicated loans data — Table 2

	Bank*Firm	# Banks	Av.# firms per Bank	# Firms	Av. # banks per firm
2000	9,359	51	184	1,767	10
2004	11,491	58	198	2,220	9
2008	14,426	58	249	2,949	12
2012	17,304	58	298	3,586	12
2016	20,440	58	352	4,281	10

[1] Lending relationships defined treating banks on a partially consolidated basis; for firms we just consolidate financial vehicles.

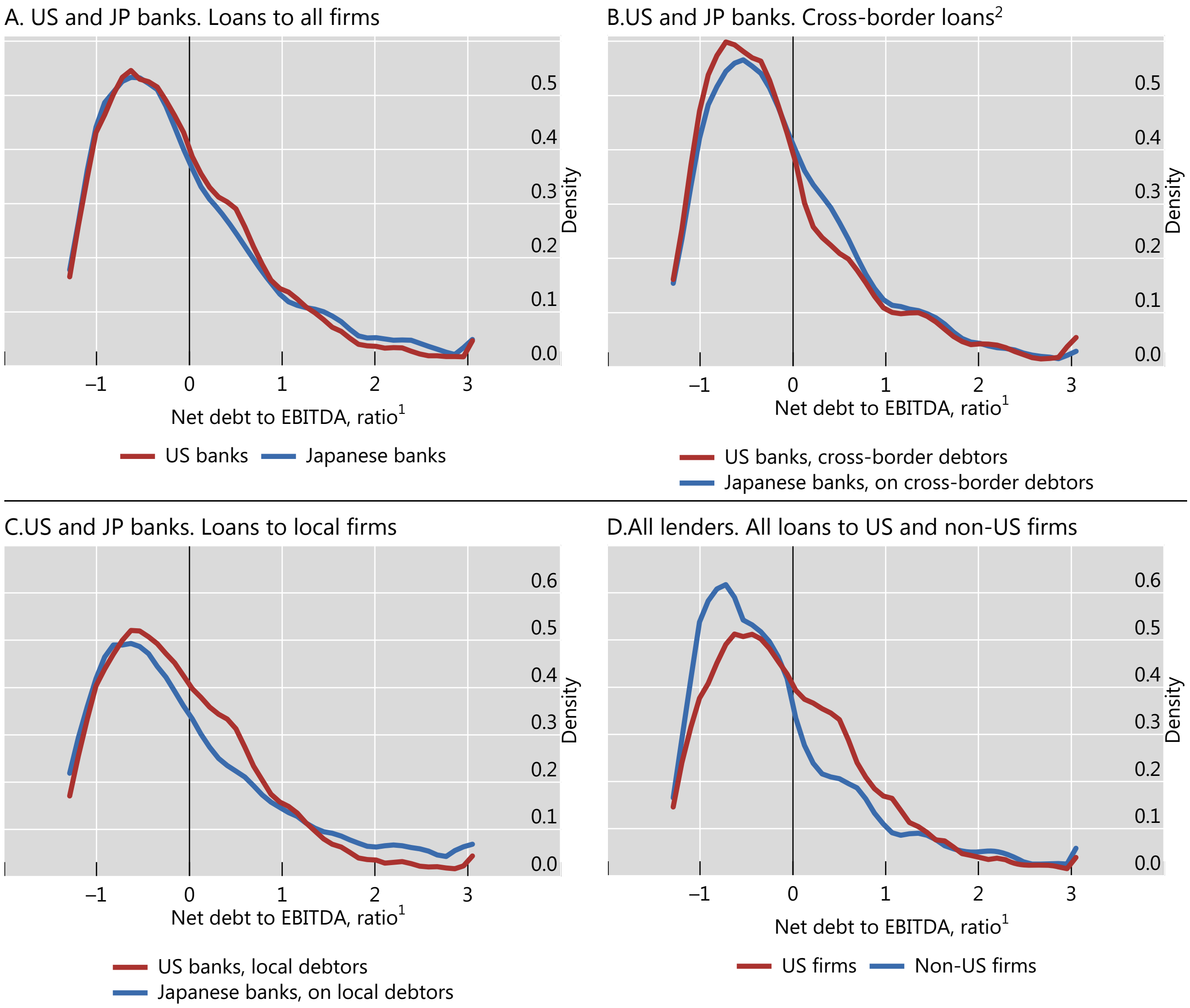
Sources: own elaboration, Eikon, Thompson Reuters.

Since we have information on the country of incorporation of banks and firms we can examine bank-firm lending relationships when banks and firms are incorporated in different countries. It is important to note that we are not treating banks and firms on a solo basis, so these are not cross-border lending relationships at an entity level.[4] Table 2 shows that many of these relationships are between banks and firms incorporated in different countries.

Credit risk; portfolio of loans to NFC[1]

Outstanding loans as of Dec 2017

Graph 3



[1] Credit risks measured with firms' net debt to EBITDA ratio. Borrowers with an outstanding loan as of Dec 2017. .

Sources: Eikon; Thompson Reuters; authors' calculations.

Bank-firm relationships might be useful to conduct cross-country comparisons of banks' loans portfolios. Panel A in Graph 3 plots the distribution of the net debt to EBITDA ratio of firms with an outstanding loan from US and Japanese banks (as of Dec 2017). Assuming that higher levels of net debt to EBITDA signal higher credit risk, US banks have riskier balance-sheets. This patterns reflects the higher risks of local debtors (Panel B), and actually the distribution of cross-border loans of Japanese banks is riskier (Panel C). In other words, the higher risk of US banks' portfolio reflects

[4] This definition of "cross-border claims" differs from the BIS International Banking Statistics definition https://www.bis.org/statistics/bankstatsguide_glossary.pdf.

the higher net debt to EBITDA ratios of US borrowers (Panel D). We remind that this exercise is for illustration purposes, and the purpose is not to extract conclusions about banks' credit risks.

5.2 Credit exposures

A bank credit exposure to a firm is the estimated amount of the outstanding loans. Our estimations of credit exposures are subject to the many limitations discussed above; in particular we are not adjusting for risk transfers after origination (eg loan sales or financial hedge). The biases are likely stronger at a granular level (ie for some bank-firm pairs). The aggregate results in Table 3 have to be taken with caution, but overall suggest there has been an increase in the size of the exposures over time.

Credit exposures based on syndicated loans data

Table 3

	Bank*Firm	# Banks	# Firms	Total exposures
2000	12,863	53	2,155	995
2004	18,524	58	3,532	1,844
2008	24,327	58	4,939	3,726
2012	29,951	58	5,721	4,508
2016	35,925	58	6,975	6,711

[1] Lending relationships defined treating banks on a partially consolidated basis; for firms we just consolidate financial vehicles.

Sources: own elaboration, Eikon, Thompson Reuters.

6. Conclusions

We construct bank-firm lending relationships matching loan-level data from commercial data providers to firm and bank-level information. Our key contribution is to match datasets using the global identifiers of borrowers and lenders. This has three advantages: it is accurate, consistent with the terms agreed on the loan contract, and flexible. Leveraging on this flexibility we consolidate borrowing by non-bank financials. On the lender side: we partially consolidate banks, treating listed subsidiaries as independent banks

We illustrate how the data is useful to define bank-firm lending relationships, and eventually conduct cross-country analyses of credit risks in banks' loans portfolios. There are several ways to improve these estimations. On the one hand some work can be done to adjust data from risk transfers: banks' loan holdings can be adjusted using data on loan sales; further, data on loan amendments after origination can be used to check if loan terms have been renegotiated (including cancelled earlier than originally agreed).

Finally, we argue that the LEI system is well-suited and could support this statistical work: the LEI is a unique identifier, has entity-parent links, and the quality is certified. Its main drawback is the coverage: it is good on the lender side, but there are gaps on the borrower side. An improvement on the LEI coverage would be of great help for statistical purposes.

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Basel, 30-31 August 2018

Cross-country bank-firm exposures: what can we learn from public data?[1]

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

Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

CROSS-COUNTRY FIRM-BANK EXPOSURES: WHAT CAN WE LEARN FROM PUBLIC DATA?

Jose Maria Serena Garralda*

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

Bank for International Settlements

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

INTRODUCTION. POST-GFC DATA NEEDS

- Post-GFC data needs on bank-firm interlinkages -the GFC was a major banking crisis transmitted worldwide.
- Data availability has improved thanks to DGI: IDH –top 30 banks, highly confidential, credit and liability exposures, I-A.
- Besides central banks have mobilized their country-level data; limits to data sharing often prevent pooling them
- However some data needs persist: cross-country (I-I) bank-firm exposures, needed for policy evaluation/risk assessment.

INTRODUCTION. POST-GFC DATA NEEDS

- Research question: can we define (I-I) bank-firm exposures from public loan data (ie large loans reported by banks, and disseminated by commercial data providers)?

- Our paper: use lenders and borrowers' common identifiers to match loans to firm/bank-level datasets ; use maturity date to define:
  - Lending-relationships: exist if there is an outstanding loan
  - Credit exposures: size of the exposure (US mn)

- Main conclusion: bank-firm lending relationships seem reliable; credit exposures require further adjustments –work ahead.

OUTLINE

1. Introduction
2. Measuring cross-country firm-bank exposures
3. Data
4. Main results
5. Conclusions

MEASURING CROSS-COUNTRY FIRM-BANK EXPOSURES.

- **Key figures**: 282,912 loans (not only syndicated), 1983-2018:
  - Average loan is 300 USD mn (median 50 USD mn); USD loans account for 60% of the total
  - Type liability: 50% are term loans; 40% are credit lines; the remaining are project finance, bridge loans.

- **Borrowers**: 78,443 issuers, with significant dispersion; 60,020 at consolidated level, based in 119 countries; top 5 are US, JP, UK, CA, AU (44%, 13%, 7%, 3%, 2%). Focus on NFC.

- **Lenders**: 16,107 lenders (any role in the deal), with remarkable concentration among banks; 549 account for 75% of all deals, ie 1,3 mn lending relationships.

MEASURING CROSS-COUNTRY FIRM-BANK EXPOSURES.

- **What we do?** We compute outstanding loans of bank i to firm j at time t, using the original maturity of the loan; then we define:
  - Lending relationships: exists if there is an outstanding loan.
  - Credit exposures: size of the exposure (US mn).

- **How we do it?** We match borrowers/lenders to firm/bank level data using their common identifiers (eg LEI); this has benefits:
  - Efficient
  - Credible
  - Economic meaning
  - Cross-border

MEASURING CROSS-COUNTRY FIRM-BANK EXPOSURES. LIMITATIONS

1. No liability-side exposures (eg corporate deposits on banks);

2. No information on important asset classes, such as small loans, trade finance, derivatives, guarantees.

3. Sample of firms is biased towards large companies.

4. We do not adjust for secondary market transactions; we assume a bullet payment, and no amendments. No information on credit hedges.

Bottom-line: public data will never be as good as supervisory data; but allows measuring cross-country, cross-border, exposures

MAIN RESULTS

1. **Lending relationships**
   - Bank*Firm relationships over time
   - Loan portfolio risk analysis

2. **Credit exposures, term loans:**
   - Top 10 bank-firm exposures, end-2017
   - Banks’ exposures to distressed firms –eg Toys “R” Us ‘17

MAIN RESULTS (I). LENDING RELATIONSHIPS

- A lending relationship from bank i to firm j at year t exists when there is an outstanding loan.

Lending relationships based on syndicated loans data — Table 1

	Bank*Firm	# Banks	Av.# firms per Bank	# Firms	Av. # banks per firm
2000	12,634	55	230	2158	10
2004	18,476	61	303	3533	10
2008	24,468	63	388	4956	13
2012	30,153	63	479	5750	12
2016	36,811	63	584	7031	10

[1] Lending relationships defined treating banks/firms on a consolidated basis.

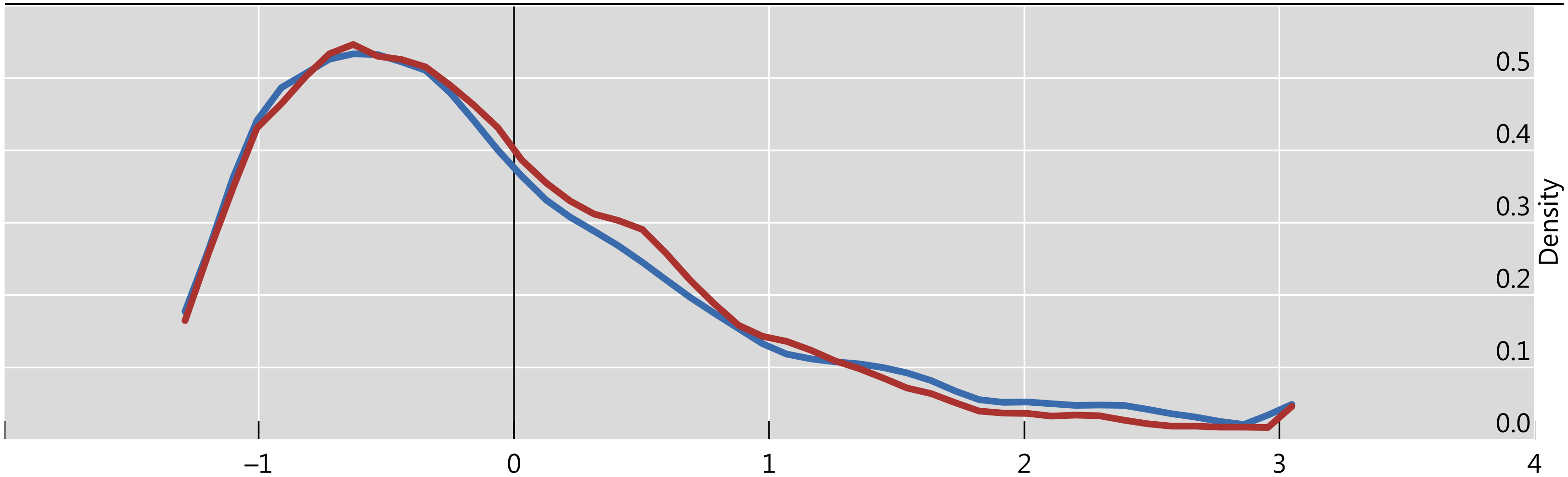
Sources: own elaboration, DealScan, Thompson Reuters.

- Exposures of top 100 banks according to total assets sep-18. Some might be large subsidiaries. Large number of lenders per firm (reflecting loans are syndicated).

MAIN RESULTS (I). LENDING RELATIONSHIPS. LOAN PORTFOLIO RISK ANALYSIS. US vs JAPANESE BANKS

- Loan portfolio US banks: 8 banks have 10,493 loans to 3,534 firms. US banks seem to have riskier portfolio -measured with firms' net debt to EBITDA.

Credit risk of US and JP banks; portfolio of loans to NFC[1] Graph 1



[1] For firms with an outstanding loan as of Dec 2017.

Sources: DealScan; authors' calculations.

MAIN RESULTS (II). CREDIT EXPOSURES. TOP 10 IN 2017, TERM LOANS.

- Credit exposures: size of bank i exposure to firm j at time t; as before we can analyse cross-border credit exposures

Credit exposures based on syndicated loans data — Table 3 A

	Bank*Firm	# Banks	# Firms	Total exposures, US bn
2000	12,863	53	2,155	995
2004	18,524	58	3,532	1,844
2008	24,327	58	4,939	3,726
2012	29,951	58	5,721	4,508
2016	35,925	58	6,975	6,711

[1] Lending relationships defined treating banks/firms on a consolidated basis.

Sources: own elaboration, DealScan, Thompson Reuters.

Cross-border credit exposures based on syndicated loans data — Table 3 B

	Bank*Firm	# Banks	# Firms	Total exposures, US bn
2000	9,359	51	1,767	634
2004	11,491	58	2,220	1,088
2008	14,426	58	2,949	2,279
2012	17,304	58	3,586	2,294
2016	20,440	58	4,281	3,103

[1] Lending relationships defined treating banks/firms on a consolidated basis.

Sources: own elaboration, DealScan, Thompson Reuters.

MAIN RESULTS (II). DRILLING DOWN INTO CREDIT EXPOSURES. BANKS' EXPOSURES TO DISTRESSED FIRMS

- Toys "R" Us filed for bankruptcy in sep 17, owned by private equity firms (Bain-KKR-Vornado). Top 10 exposures:

Top creditors of Toys R US Inc -September 2017. All loans

Table 5

Bank	Exposure	Country	LEI	Tier1 Capital Pct	Net Loans YoY %	Assets
Bank of America Corp	1,405	US	9DJT3UXIJIZJI4WXO774	13.2	2.40	22,812
JPMorgan Chase & Co	1,402	US	8I5DZWZKVSZI1NUHU748	14.4	4.16	25,336
Goldman Sachs Group Inc	792	US	784F5XWPLTWKTBV3E584	12.7	.	9,168
Citigroup Inc	728	US	6SHGI4ZSSLCXXQSBB395	14.5	6.92	18,425
Deutsche Bank AG	449	DE	7LTWFZYICNSX8D621K86	15.4	-1.76	17,691
Barclays PLC	415	UK	213800LBQA1Y9L22JB70	13.3	-6.93	15,313
Wells Fargo & Co	237	US	PBLD0EJDB5FWOLXP3B76	14.1	-1.09	19,518
HSBC Holdings PLC	76	UK	MLU0ZO3ML4LN2LL2TL39	17.3	11.78	25,218
U.S. Bancorp	62	US	N1GZ7BBF3NP8GI976H15	10.8	2.64	4,620
Toronto-Dominion Bank	62	CA	PT3QB789TSUIDF371261	12.3	4.60	9,927

- However: banks might have renegotiated debt/sold them (Irani, Iyer, Meisenzahl and Peydro, 2018).

CONCLUSIONS

- We construct (I-I) bank-firm exposures using public loan data: lending relationships and credit exposures.

- Our main contribution is to use lenders/borrowers common identifiers; we gain accuracy and do not loss data.

- Not easy to check the quality of results. Our guess is that:
  - Results on lending relationships are good enough for economic analysis.
  - The assumptions required to estimate credit exposures are too strong (ie no risk transfers/risk mitigation).

- Potential work ahead: further refine credit exposures adjusting for secondary market sales or loan contract amendments.

THANK YOU FOR YOUR ATTENTION

MEASURING CROSS-COUNTRY FIRM-BANK EXPOSURES. RELATED WORK (I)

- Gadanecz, B, and K. von Kleist (2002), “Do syndicated credits anticipate BIS consolidated banking data?” *BIS Quarterly Review, March 2002* [Loan data vs BIS IBS]

- Gadanecz, B., K. Tsatsaronis and Y. Altunbaş (2006), “External support and bank behaviour in the international syndicated loan market”, *BIS Working Papers No 265* [Loan retention shares]

- Bruche, M., F. Malherbe, and R. Meisenzahl, “Pipeline Risk in Leveraged Loan Syndication” FEDS Working Paper No. 2017-48 [Loan retention shares]

MEASURING CROSS-COUNTRY FIRM-BANK EXPOSURES. RELATED WORK MATCHING LOAN-FIRM DATA (II)

- Kalemli-Ozcan, S., L. Laeven, and D. Moreno (2018), “Debt overhang, rollover risks, and corporate investment: Evidence from the European Crisis”, *NBER WP 24555 April 2018*

- Gropp, H., T. Mosk, S. Ongena, and C. Wix (2018), “Bank Response to Higher Capital Requirements: Evidence from a Quasi-Natural Experiment”, *forthcoming Review of Financial Studies*

- Hale, G., T. Kapan, and C. Minoiu (2016). “Shock transmission through cross-border bank lending: credit and real effect” *Working Paper Series 2016-1, Federal Reserve Bank of San Francisco.*

- Ivashina, V. and D. Scharfstein (2010), “Loan Syndication and Credit Cycles” *American Economic Review: P & P 100 May 2010*

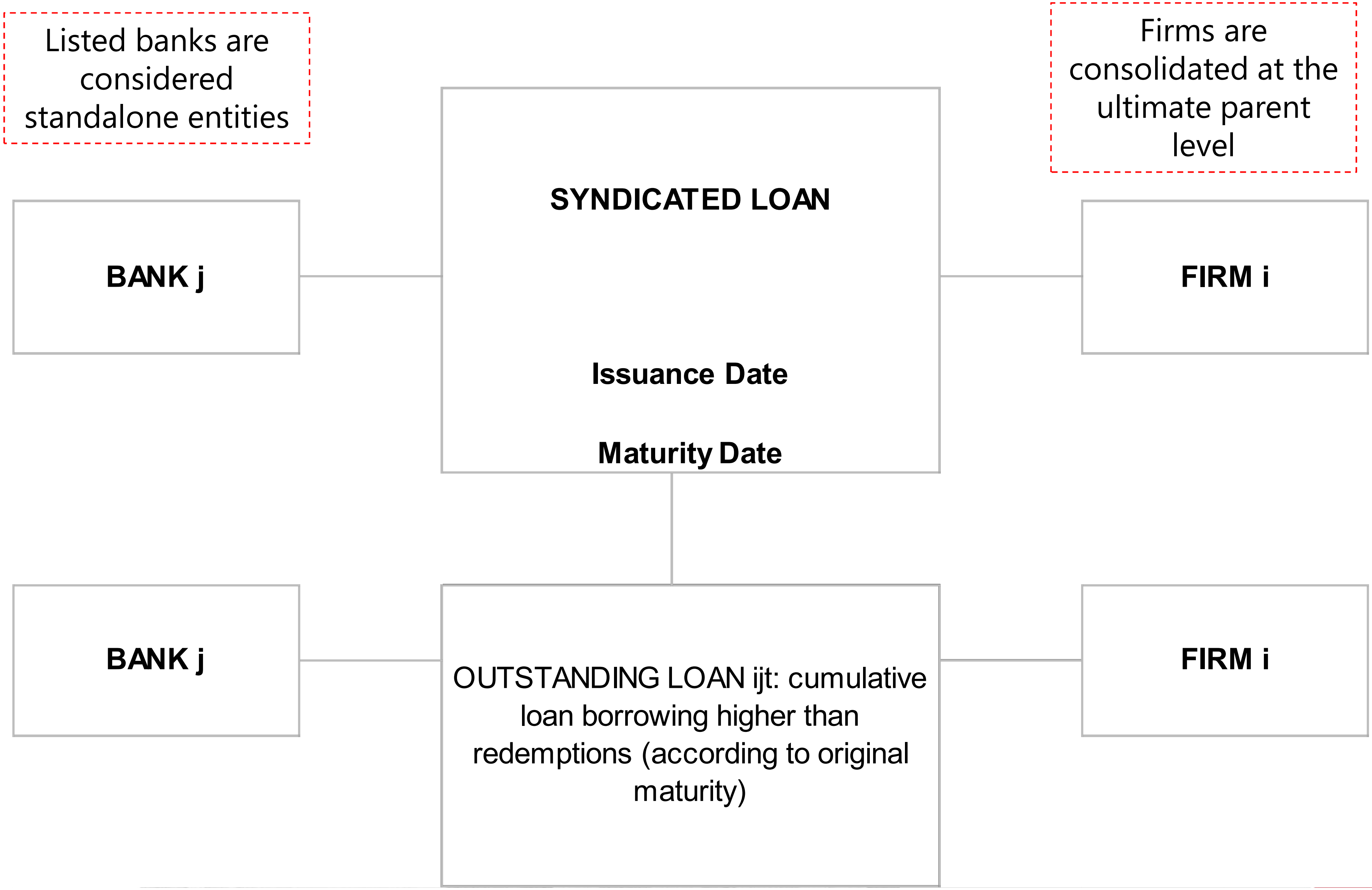
MEASURING CROSS-COUNTRY FIRM-BANK EXPOSURES. RELATED WORK ON COMMON IDENTIFIERS (III)

- Buch, C. (2017), "Keynote Speech. Data needs and statistics compilation for macroprudential analysis" in I*CF Bulletin No 46*

- GLEI-SWIFT (2018), "BIC to LEI mapping table. Factsheet"

- IAG (2017), "Update on the Data Gaps Initiative and the Outcome of the Workshop on Data Sharing" *March 2017*

MEASURING CROSS-COUNTRY FIRM-BANK EXPOSURES. ESTIMATE POSITIONS USING ORIGINAL MATURITY



How we do it? Matching loans to firm-level data using borrowers' names is costly, inaccurate, and not meaningful.

Ultimate parent company
Wilmar International Ltd
ISIN: SG1T56930848
SEDOL: B17KC69
LEI: 549300H2EAI4YRLWBB20

Borrower
Wii Pte Ltd
ISIN: .
SEDOL:.
LEI:549300ZZI8LH8D8RPL28

SYNDICATED LOAN
Announcement: 10.07.2013
Amount: 365
Currency: US Dollar
Type: Near Investment

Syndicate
National Australia Bank
Westpac Banking
Hang Seng Bank Ltd (Hong Kong)
National Bank of Kuwait (Sing)
Bank of China Ltd
First Commercial Bank (Taiwan)
Agricultural Bank of China(SG)
Bank of East Asia (Singapore)
JA Mitsui Leasing Ltd
Sumitomo Mitsui Trust Bank Ltd
Land Bank of Taiwan
Metropolitan Bank & Trust
Mega Intl Coml Bank Co Ltd
Commonwealth Bank of Australia
Hongkong & Shanghai Bank (HK)
United Overseas Bank Ltd
DBS Bank Ltd
Bank of Tokyo-Mitsubishi UFJ
CIMB Bank Bhd
Bank of Philippine Islands
Bank of Communications Co Ltd
Aozora Bank Ltd
Sumitomo Mitsui Banking Corp
Hua Nan Financial Holdings
ABN AMRO Bank
Industrial & Comm Bank China
Habib Bank Ltd
Taiwan Cooperative Bank
E Sun Commercial Bank Ltd
Banco De Oro Unibank Inc

MEASURING CROSS-COUNTRY FIRM-BANK EXPOSURES. METHODOLOGICAL CHOICES

1. Borrowers are consolidated at the ultimate parent level [as long it is a non-financial firm]: consolidation of SPVs is not controversial; but some affiliates could be financially independent.

2. Lenders are consolidated up to the level of the first listed entity: since we assume that listed banks are standalone.

3. The definition of a "cross-border exposure" differs from BIS IBS (which is based on issuers/lenders location) as a result of [1] and [2] .

4. Loan allocation rule between arrangers and others is ad-hoc and reflects lack of data. Further work could be done.

MAIN RESULTS (I). LENDING RELATIONSHIPS

BANK j

SYNDICATED LOAN

Issuance Date

Maturity Date

FIRM i

BANK j

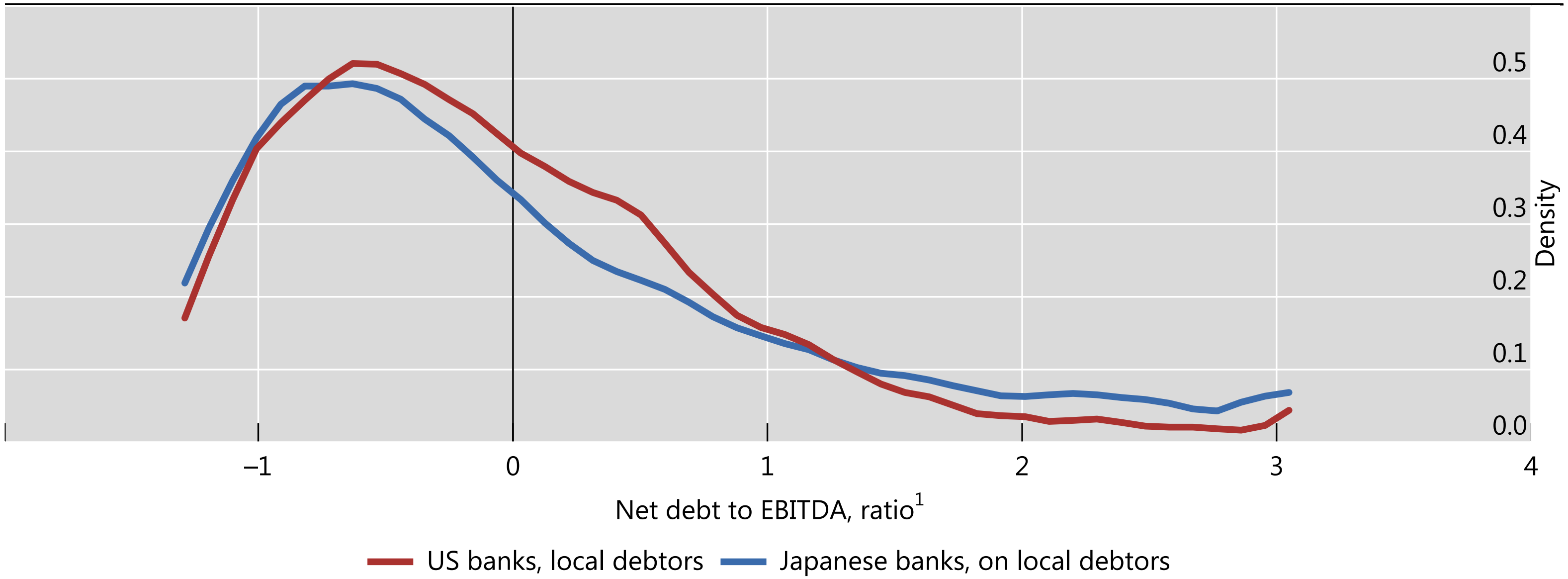
LENDING RELATIONSHIP: bank j has an outstanding claim on firm I

FIRM i

MAIN RESULTS (I). LENDING RELATIONSHIPS. LOAN PORTFOLIO RISK ANALYSIS. US vs JAPANESE BANKS

- Domestic loan portfolio US banks: US safer than Japanese banks' portfolio.

Credit risk of US and Japanese banks' portfolio of local loans to NFC[1] Graph 3



[1] For firms with an outstanding loan vs US and Japanese banks as of Dec 2017.

Sources: DealScan; authors' calculations.

MAIN RESULTS (I). CREDIT EXPOSURES. TOP 10 IN 2017, TERM LOANS.

- Top 10 credit exposures, term loans: 4 out the 10 top 10 credit exposures are cross-border; in three instances European banks.

Credit exposures as of end-2017, term loans

Table 4

Bank	Firm	Exposure	Bank country	Firm country	Firm assets
Bank of America Corp	Broadcom Inc	11,940	US	US	544,180
Societe Generale SA	Cheniere Energy Inc	10,985	FR	US	279,060
Bank of America Corp	Charter Communications Inc	9,201	US	US	1,466,230
JPMorgan Chase & Co	Western Digital Corp	9,141	US	US	298,600
Bank of America Corp	Royalty Pharma AG in Liquidation	8,948	US	CH	.
Mitsubishi UFJ Group	SoftBank Group Corp	8,805	JP	JP	2,211,727
Deutsche Bank AG	Hilton Worldwide Holdings Inc	7,392	DE	US	142,280
Credit Agricole SA	SoftBank Group Corp	7,137	FR	JP	2,211,727
Bank of America Corp	HCA Healthcare Inc	7,081	US	US	365,930
Bank of America Corp	Level 3 Communications Inc	6,579	US	US	331,350

MAIN RESULTS (II). DRILLING DOWN INTO CREDIT EXPOSURES. BANKS' EXPOSURES TO DISTRESSED FIRMS

- Toys "R" Us filed for bankruptcy in sep 17, owned by private equity firms (Bain-KKR-Vornado). Top 10 exposures:

Top creditors of Toys R US Inc -September 2017. All loans

Table 6

Bank	Exposure	Country	LEI	Tier1 Capital Pct	Net Loans YoY %	Assets
Bank of America Corp	1,405	US	9DJT3UXIJIZJI4WXO774	13.2	2.40	22,812
JPMorgan Chase & Co	1,402	US	8I5DZWZKVSZI1NUHU748	14.4	4.16	25,336
Goldman Sachs Group Inc	792	US	784F5XWPLTWKTBV3E584	12.7	.	9,168
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Toronto-Dominion Bank	62	CA	PT3QB789TSUIDF371261	12.3	4.60	9,927

- Not easy to check the quality of results, since banks might have renegotiated debt; and some loans matured in 2018.

MAIN RESULTS (II). DRILLING DOWN INTO CREDIT EXPOSURES. FIRMS' EXPOSURES TO DISTRESSED BANKS

- Firms can lose access to credit when banks default. We compute top 10 exposures to Lehman Brothers, 2008:

Top outstanding corporate loans of Lehman Brothers -September 2008 Table 7

A. Term loans			B. Credit lines		
Firm	Exposure	Country	Firm	Exposure	Country
Suitcase One Ltd	3,154	UK	Pfizer Inc	1,500	US
Vale SA	2,778	BR	Imperial Brands PLC	1,264	UK
Riverdeep Group Plc	1,088	US	AT&T Inc	1,000	US
Las Vegas Sands Corp	1,053	US	America Movil SAB de CV	1,000	MX
America Movil SAB de CV	1,000	MX	Cox Enterprises Inc	917	US
Fidelity National Information Services Inc	875	US	Kimberly-Clark Corp	844	US
Prysmian SpA	823	IT	HP Inc	750	US
Imperial Brands PLC	711	UK	Encana Corp	600	CA
Zimmer Biomet Holdings Inc	629	US	Nextera Energy Inc	500	US
NXP Semiconductors NV	542	NE	Walmart Inc	495	US

- Subject to the important caveats mentioned: implicit assumption of no risk transfers after origination; lending is often and "original-to-distribute" business (Ivashina and Scharfstein, 2010).

MEASURING CROSS-COUNTRY FIRM-BANK EXPOSURES. RELATED WORK

- **Methodological contributions**: comparison with aggregate data, Gadanecz and von Kleist (2002); loan retention shares, Gadanecz, Tsatsaronis and Y. Altunbaş (2006), and Bruche, Malherbe, and Meisenzahl (2017).

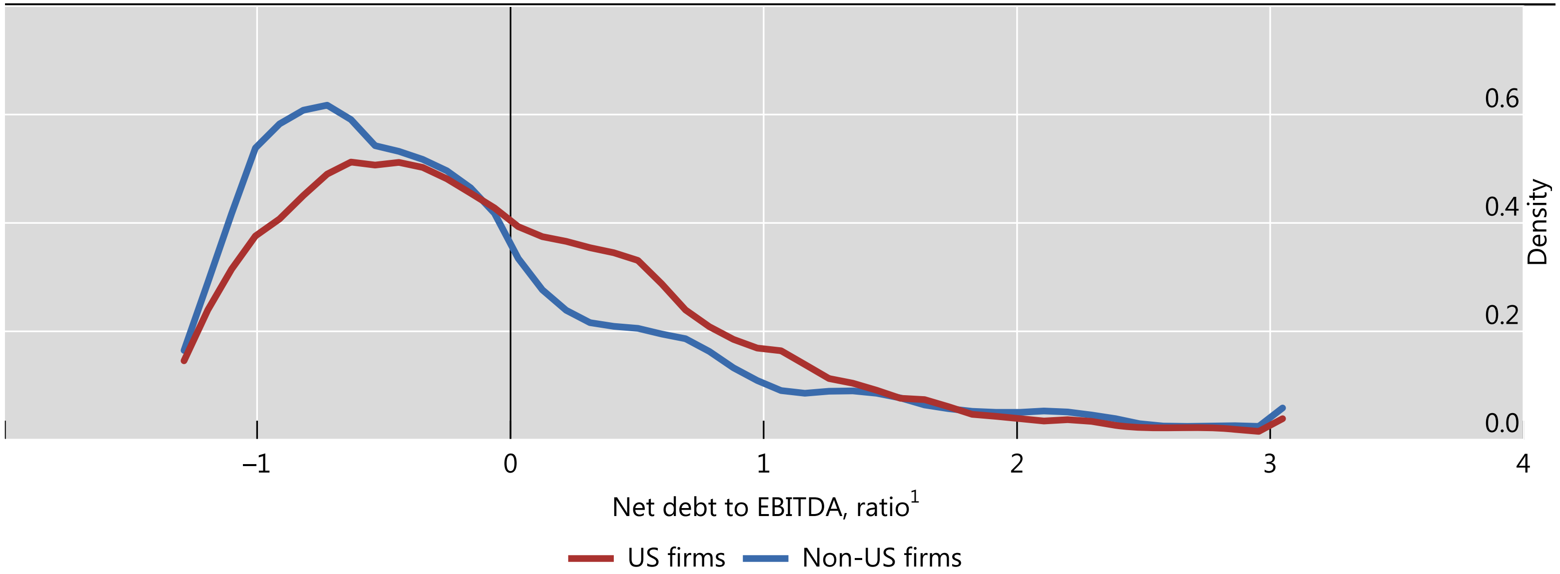
- **Construction bank-firm exposures**: Kalemli-Ozcan, Laeven, and Moreno (2018); Gropp, Mosk, Ongena, and Wix (2018); Hale, Kapan, and Minoiu (2016); Ivashina and Scharfstein (2010),

- **Discussion common identifiers**: Buch. (2017), GLEI-SWIFT (2018), IAG (2017)

MAIN RESULTS (I). LENDING RELATIONSHIPS. LOAN PORTFOLIO RISK ANALYSIS. US vs JAPANESE BANKS

- US borrowers have higher net debt to EBITDA ratios. This explains the riskiness of US banks loan portfolio.

Credit risk of US and non-US firms with outstanding loans as of Dec 2017[1] Graph 4



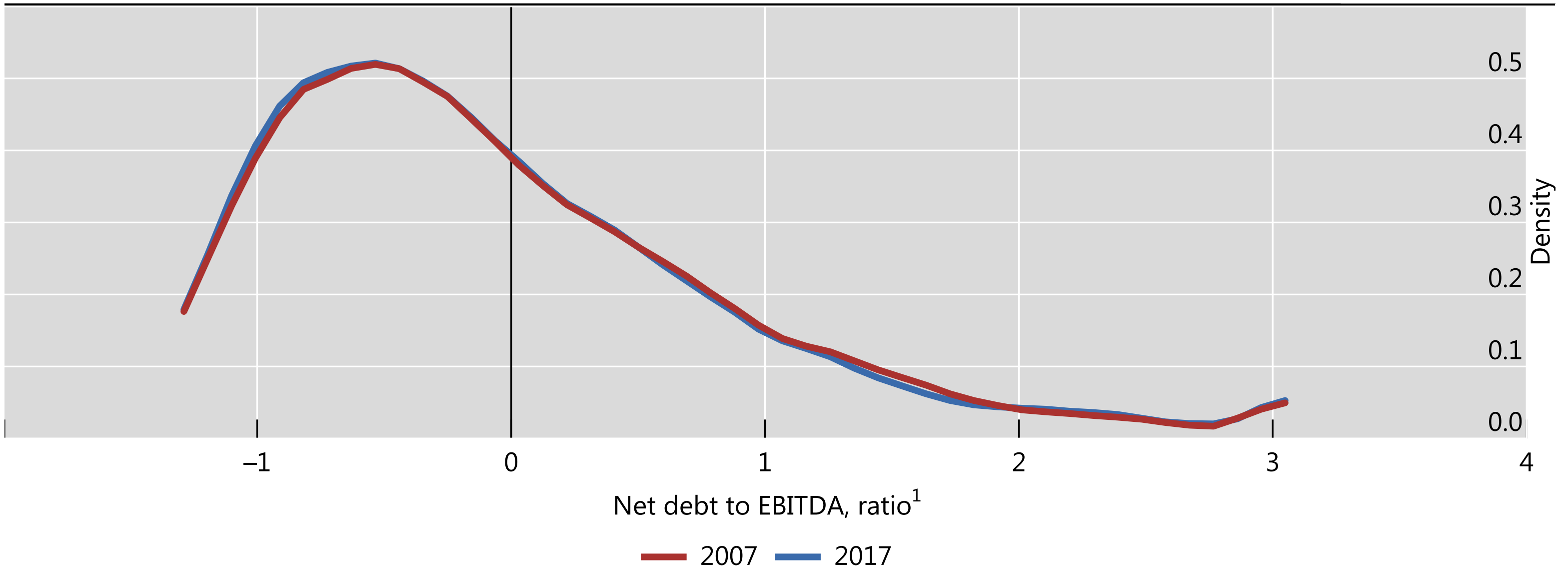
[1] For firms with an outstanding loan as of Dec 2017. All lenders.

Sources: DealScan; authors' calculations.

MAIN RESULTS (I). LENDING RELATIONSHIPS, AT BANK-LEVEL: BANK OF AMERICA DISTRIBUTION

- We could further drill down into the loan portfolio: Bank of America has 2,119 lending relationships in 2017; 1,396 in 2007.

Credit risk of Bank of America, portfolio of loans to NFC - Historical evolution[1] Graph 5



[1] For firms with an outstanding loan as of Dec 2017.

Sources: DealScan; authors' calculations.

- Up to now we have not looked at the size of the exposure.

MEASURING CROSS-COUNTRY FIRM-BANK EXPOSURES. ESTIMATE POSITIONS USING ORIGINAL MATURITY

Listed banks are considered standalone entities

Firms are consolidated at the ultimate parent level

BANK j — **SYNDICATED LOAN**

Issuance Date

Maturity Date — **FIRM i**

BANK j — **LENDING RELATIONSHIP**: bank j has an outstanding claim on firm i — **FIRM i**

CREDIT EXPOSURE: bank j has an outstanding claim of x US bn on firm i

- Data gaps in loan allocation across lenders: half for lead arrangers (pro-rata) and half for rest of the members of the syndicate (pro-rata).

How we do it? Instead we retrieve the common identifiers of the ultimate parent of the borrower/lender (eg LEI).

Ultimate parent company
Wilmar International Ltd
ISIN: SG1T56930848
SEDOL: B17KC69
LEI: 549300H2EAI4YRLWBB20
Headquarters: Singapore

Borrower
Wii Pte Ltd
ISIN: .
SEDOL:.
LEI:549300ZZI8LH8D8RPL28
Headquarters: Singapore

SYNDICATED LOAN
Announcement: 10.07.2013
Amount: 365
Currency: US Dollar
Type: Near Investment

Syndicate	
National Australia Bank	F8SB4JFBSYQFRQEH3Z21
Westpac Banking	EN5TNI6CI43VEPAMHL14
Hang Seng Bank Ltd (Hong Kong)	5493009Z5F07LWZYMK62
National Bank of Kuwait (Sing)	549300NB7FE83IH6BW96
Bank of China Ltd	54930053HGCFWVHYZX42
First Commercial Bank (Taiwan)	.
Agricultural Bank of China(SG)	549300E7TSGLCOVSY746
Bank of East Asia (Singapore)	CO6GC26LCGGRTUESIP55
JA Mitsui Leasing Ltd	
Sumitomo Mitsui Trust Bank Ltd	.
Land Bank of Taiwan	
Metropolitan Bank & Trust	549300SQYI82RVWFN715
Mega Intl Coml Bank Co Ltd	
Commonwealth Bank of Australia	MSFSBD3QN1GSN7Q6C537
Hongkong & Shanghai Bank (HK)	.
United Overseas Bank Ltd	IO66REGK3RCBAMA8HR66
DBS Bank Ltd	
Bank of Tokyo-Mitsubishi UFJ	353800V2V8PUY9TK3E06
CIMB Bank Bhd	549300FYDN5UD7USZW18
Bank of Philippine Islands	549300UW4UH6XT2X8C50
Bank of Communications Co Ltd	549300AX1UM10U30HK09
Aozora Bank Ltd	X0XUGKC9FD2CYUQNC010
Sumitomo Mitsui Banking Corp	35380028MYWPB6AUO129
Hua Nan Financial Holdings	.
ABN AMRO Bank	724500DWE10NNL1AXZ52
Industrial & Comm Bank China	5493002ERZU2K9PZDL40
Habib Bank Ltd	549300N63RJKPUYAY631
Taiwan Cooperative Bank	.
E Sun Commercial Bank Ltd	.
Banco De Oro Unibank Inc	.

MAIN RESULTS (I). LENDING RELATIONSHIPS. CROSS-BORDER

- Cross-border lending relationships: if bank i and firm j are headquartered in different countries.

Cross-border lending relationships based on syndicated loans data — Table 2

	Bank*Firm	# Banks	Av.# firms per Bank	# Firms	Av. # banks per firm
2000	9,359	51	184	1,767	10
2004	11,491	58	198	2,220	9
2008	14,426	58	249	2,949	12
2012	17,304	58	298	3,586	12
2016	20,440	58	352	4,281	10

[1] Lending relationships defined treating banks/firms on a consolidated basis.

Sources: own elaboration, DealScan, Thompson Reuters.

- Country of headquarters: for banks we use its country of incorporation (not the ultimate parent); for firms the country of incorporation of the ultimate parent.

MAIN RESULTS (II). CREDIT EXPOSURES. TOP 10 IN 2017, TERM LOANS.

- Top 10 credit exposures, term loans: numbers are not implausible, eg as of Aug 18 Broadcom Inc reports 40 US bn outstanding loans; Cheniere Energy Inc. reports 33 US bn.

Credit exposures as of end-2017, term loans

Table 4

Bank	Firm	Exposure	Bank country	Firm country	Firm assets
Bank of America Corp	Broadcom Inc	11,940	US	US	544,180
Societe Generale SA	Cheniere Energy Inc	10,985	FR	US	279,060
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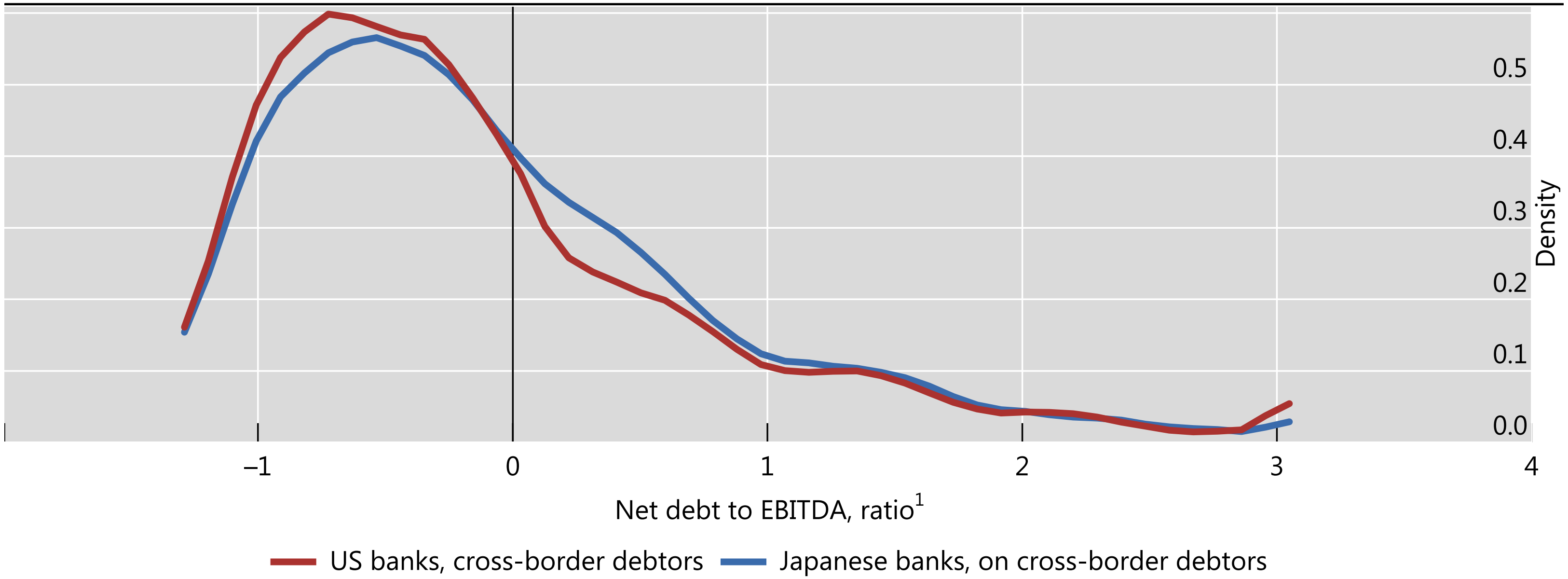
- Cross-border exposures: 4 out the 10 top 10 credit exposures are cross-border; in three instances European banks

MAIN RESULTS (I). LENDING RELATIONSHIPS. LOAN PORTFOLIO RISK ANALYSIS. US vs JAPANESE BANKS

- Cross-border loan portfolio US banks: Japanese banks' cross-border loan portfolio are riskier.

Credit risk of US and JP portfolio of cross-border loans to NFC[1] Graph 2



[1] For firms with an outstanding loan vs US and Japanese banks as of Dec 2017.

Sources: DealScan; authors' calculations.