Increasingly Networked Lenders and Their Impact on Lending Spreads

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Abstract

A large fraction of syndicated loans are now syndicated by top lenders. Top lenders have become more networked than smaller ones. Spreads of top lenders, however, have become persistently lower than those of small lenders. We provide evidence that top lenders have lower costs, but these translate to profitability rather than lower spreads. Syndication connections of lenders are found to strongly associate with lower spreads, pointing to the importance of information and diversification as sources of lending efficiency. While this finding is benign, increased network concentration should remain on the research and regulatory agenda.

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1 Introduction

In recent years, economists and policy makers have noted and expressed concerns that the increasing market power of large firms (and, on occasion, “superstar” firms) has consequences for other stakeholders. We present our findings on rising banking concentration and its effect on the finance sector.

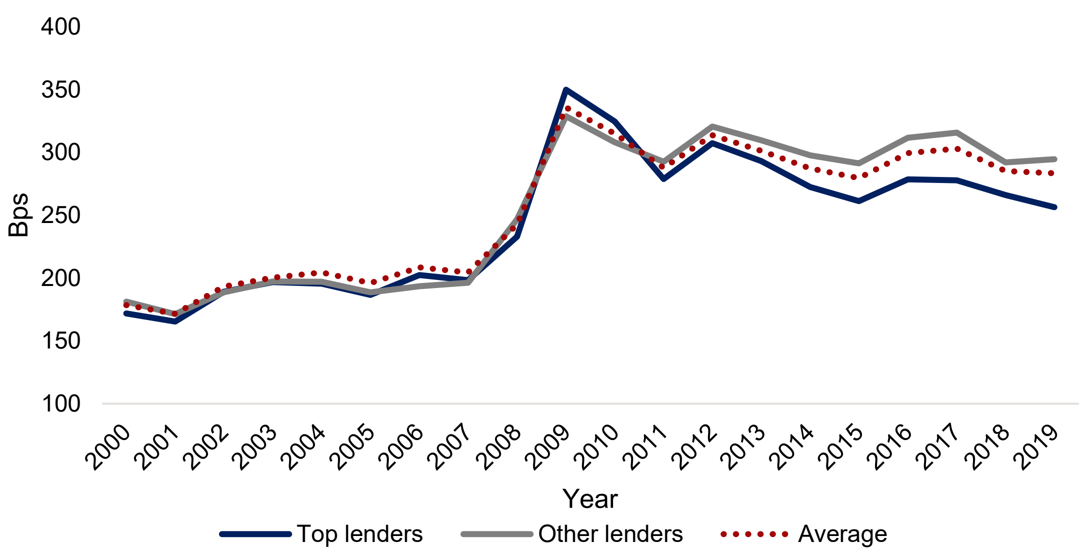
As the finance sector intermediates credit to the economy, market power and any effects on borrowing costs have important consequences. Key work by De Loecker, Eeckhout, and Unger (2020) provides extensive evidence on how markups have increased in the upper end of industry distribution, how market shares have shifted from low-markup to high-markup firms, and how these markups have come on top of the increase in overhead costs, resulting in greater profits. Autor, Dorn, Katz, Patterson, and Van Reenen (2020) show similar findings and that this development is connected with declining labor shares. The International Monetary Fund (2019) highlights similar concerns regarding market power (“winner takes all”) and finds some association with weaker investments.

That said, the impact of increasing concentration on costs and markups is still not well studied, which could be due to a few factors. First, borrowing terms in the finance sector are often deemed commercially sensitive and are seldom public information. Second, policy interest rates remained low post financial crisis in the late 2000s. They continue to be low in the aftermath of the coronavirus disease (COVID-19) pandemic in 2020, meaning that borrowing costs have remained low despite the rise in spreads. More generally, interest rates have been falling for much of the past three decades (the “Great Moderation”). Third, financial deregulation could have introduced efficiency or competition that offset any impact from increasing concentration, leading to the neglect of the causes and impact of rising lending spreads.

The impact of increasing concentration on costs and markups is an important topic. We turned to preliminary data taken from the syndicated loan market to provide a clearer motivation for this research. Post financial crisis, based on data from the syndicated loan market, spreads rose by about 100 basis points (bps) compared with precrisis levels and have remained at this elevated level (Figure 1). Spreads rose to a lesser extent among top lenders.[1]

[1] Top lenders are the 100 biggest finance institutions ranked by total assets in any given year.

Figure 1. Spreads between Top and Other Lenders



Bps = basis points.

Source: Thomson One and Eikon databases.

The increase in spreads—directly affecting borrowing costs—has a nontrivial impact on the economy. Consider the following. United States (US) corporates have about USD10 trillion in debts. A 100 bps rise in borrowing cost, hypothetically applied to the entire loan stock, translates into an additional USD100 billion in interest payments per year. Investments will be lower as a result of borrowing costs.

Higher markups could be the result of market power or the need to cover higher fixed costs. Post crisis, banking has faced regulatory changes that have added to costs. One of the most important changes is, no doubt, the Basel III requirements for higher capital and liquidity provisions, which might have added about 50 basis points to spreads (Ma, 2016). Other overheads—for example, in information, communication and technology (ICT) and cybersecurity requirements, and costs not related to human resources (HR)—have increased in recent years.

Lending institutions should be concerned with information asymmetry, costly monitoring, credit shocks, among many others. The advantage of larger banks is not restricted to spreading fixed costs such as ICT. Larger banks might also have a systematic information advantage, benefiting from, among others, better data on borrowers' credit histories, more deal-side relationships with other banks, and sector and geographic diversification that allows banks to better withstand credit shocks. The diversification advantage, particularly in light of increased risk management requirements post crisis, could also be the source of improved performance.[2]

Before the 2008 financial crisis, the top-100 finance institutions and the smaller ones had roughly the same spreads. But that changed after the crisis, with larger lenders—despite their increased market power—recording noticeably lower spreads than smaller ones even though overall spreads of large lenders had increased (Figure 1). The difference was about 50 bps in 2019, which remains unexplained in the literature. While 50 bps might not seem like much, it is highly significant considering how tight spreads can be in efficient markets. The difference also hints at potential efficiency gains of larger finance institutions through improved cost or informational advantage, which is what our research attempts to unpack.

1.1 Review of the Literature and the Contribution of the Study

The relationship between market concentration in the finance sector and financial access has attracted the attention of many researchers. Broadly, the discussions center around the structure conduct versus information hypotheses. The former suggests that concentration leads to higher borrowing costs and reduced financial access, while the latter suggests efficiency gains and improved access.

Diamond (1984) found that lenders can pool together for diversification to reduce the cost of monitoring and increase efficiency. Owen and Pereira (2018) found that greater banking concentration improves financial access up to a point. Similarly, Berger and Hannan (1998) highlighted that benefits from efficiency gains of concentration outweigh mispricing arising from market power. Using international firm-level survey data matched to country-specific characteristics, Beck, Makisovic, and Demirgüç-Kunt (2004) found that market concentration increases the cost of finance and reduces its availability. The debate, as is widely acknowledged, is empirical in nature.

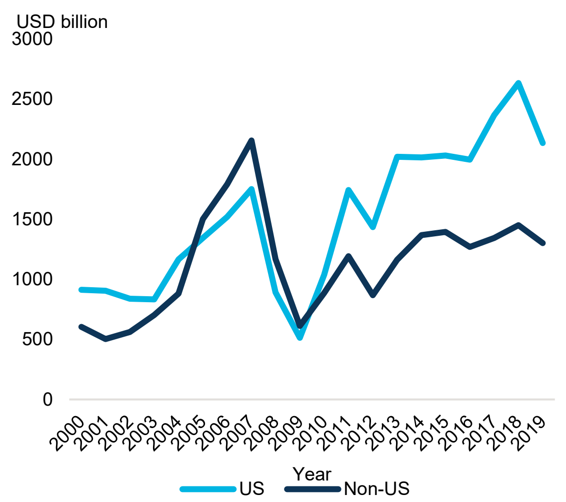
Our focus is the credit spreads, using data in the syndicated loan market. The market is an important one, where about USD4.8 trillion of credit was intermediated in 2018 (with the US accounting for slightly more than half of the market) by groups of lenders working together in a syndicate (Figure 2). Large corporate finance is typically done through this market, which

[2] Economic capital is the estimated amount of risk capital that a bank has to set aside to remain solvent at high confidence. The amount to be set aside in part depends on the correlation of its characteristics with other assets in the bank. Lower diversification of a bank's lending portfolio will result in higher economic cost of capital (Bank of International Settlement, 2009).

allows large loans to be syndicated across many lenders, including nonbank lenders, thereby diversifying risks and/or overcoming constraints of any single lender (Simons, 1993; Dennis and Mullineaux, 2000; Ivashina and Scharfstein, 2010; Lim, Minton and Weisbach, 2013; Thia, 2019].

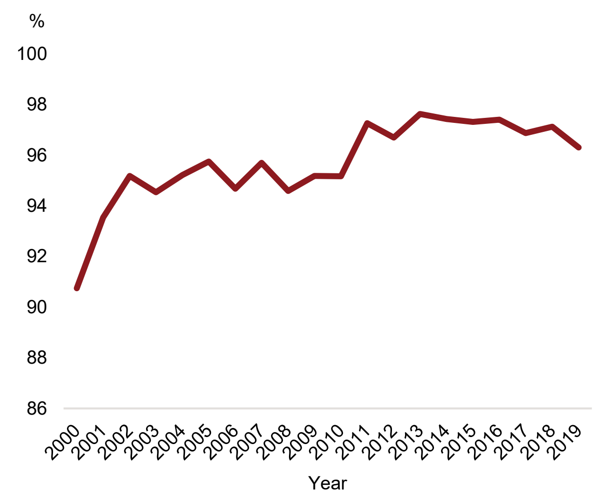
In the syndicated loan market, deals are often cross-border, involving international lenders. Unlike the rest of banking, this market is considerably more transparent; the identity of the borrower, the group of lenders (syndicate) and the spread and tenor of the loan are often recorded. The share of deals by the top-100 finance institutions has also increased (Figure 3).

Figure 2. Total Value of Syndicated Loans, United States and Non–United States



US = United States.
Note: Does not include single-lender loans. However, the data set records deals with only a single lender, which could be due to loans failing to be syndicated, in which case the underwriting lender provides the full finance. The data could have omissions, where other syndicating banks are not recorded.
Source: Authors' calculation from Thomson One syndicated loan dataset.

Figure 3. Share of Syndicated Loans (by Value) with at Least a Top-100 Finance Institution



Note: Does not include single-lender loans.
Source: Authors' calculation from Thomson One syndicated loan dataset.

Particularly useful for this research is the fact that borrowing cost data are reported in two components: the reference rate and the spread above the reference rate. The reference rate is typically the London interbank offered rate (LIBOR), which acts like the marginal cost in this market, that is, a lender's borrowing cost from other finance institutions or the interest it earns by lending to other finance institutions.[3] Lending spread is analogous to markups. The separation of borrowing costs into these two components allows us to study spreads with some confidence that they are freer of confounding effects. For example, monetary policy will act through LIBOR or other reference rates, with less direct impact on spreads (Thia, 2020).

In banking, market power comes not only through size or market shares for loans but also through network effects. Finance institutions are interconnected on the funding side and in loan syndication, which helps banks diversify risks but also create channels of contagion. A large body of research analyzes the tradeoff between interconnectedness and financial stability (see Glasserman and Young, 2016). Our research focuses not on financial stability or risks posed by such interconnectedness per se but on the effects interconnectedness might have on cost structures and markups. We do not study competition in the funding market.

We add to the literature by considering not just lenders' size but also how interconnectedness might affect markups. We construct a large data set that combines loan characteristics in the syndicated loan market with lender characteristics. To the best of our knowledge, the data set is the first assembled on such a loan–lender network, providing a rich data set for this and future research.

First, we document the rise in banking concentration in the syndicated loan market. Top lenders now conduct a larger fraction of syndicated loan deals, measured by assets. Second, we highlight the correlation between the size of lenders and the number of connections (or relationships) with other lenders in the syndicated loan market. We show that larger lenders are better connected in general, with more syndicating connections with other lenders. Third, we find a surprising result in light of De Loecker, Eeckhout and Unger (2020) and Autor, Dorn, Katz, Patterson and Van Reenen (2020). Spreads for larger lenders have increased but to a lesser extent than for smaller ones post financial crisis of the late 2000s. No prima facie evidence exists, therefore, that increased concentration has led to an increase in markups. Fourth, we provide regression evidence that points to efficiency gains of large lenders arising from better connections, against other hypotheses, as the source of efficiency and lower spreads.

All things considered, and not ruling out potential confounding factors, that there are efficiency gains in larger lenders leading to lower spreads for borrowers is a welfare-positive

[3] Depending on the market, reference rates may sometimes be the Tokyo interbank offered rate (TIBOR) or the European interbank offered rate (EURIBOR), but they are highly correlated. See Figure A2 in Annex A for the time series of LIBOR, TIBOR and EURIBOR.

development. Section 2 describes the data set in detail, including how two data sets are merged and how connections between banks are constructed. Section 3 summarizes the discussion on trends in spreads and cost structures between large and small finance institutions. Section 4 provides the regression estimates, which attempt to uncover the bank and loan characteristics that affect spreads, including effects of network. Sections 5 and 6 discuss the results and draw conclusions.

2 Data

We use two extensive databases, Thomson One (T1) for syndicated loans and Eikon by Refinitiv for lender data, drawing on key attributes of both sources.

2.1 Syndicated Loan Data from Thomson One

The T1 data set records financing deals in the syndicated loan market. Each data point is a loan containing three sets of information. First, the borrower profiles (the name of the borrower, its economic sector and the country of headquarters, among others) are recorded. Second, each data point contains information on the finance institutions participating in the syndication, including the lead finance institutions. Third, each data point contains information on the terms, including the amount, reference rate, spreads and maturity date, among others. Each loan deal could be part of a wider package of financing. For example, a USD1 billion package of financing from the syndicate could be made up of separate loans, each with slightly different terms pertaining to spreads and maturity dates, among others. Both the overall loan sum (labelled as principal sum) and the component loans (labelled as proceed) are recorded.

Syndicated loan deals are identified when there are two or more lenders.[4] In total, there were 126,582 such syndicated loan deals in 2000-2019, with 95,558 containing well-recorded loan spread data. From each data point, we can extract the names of lenders and match them to the next data set containing lender characteristics.

In the syndicated loan market, some nonbank lenders participate in syndicated lending, including investment banks (such as Goldman Sachs and Morgan Stanley), insurance companies (such as Zurich Insurance Group and Swiss Re) and international finance institutions (such as the International Finance Corporation of the World Bank Group). We do not make a distinction between them except to provide additional discussion on banks where

[4] We include single-lender loans in the computation of average spreads of a finance institution as the spreads hold legitimate information on the markup. Time series of spreads between single-lender loans and those with at least two lenders are in Figure A2 in Annex A.

necessary. In the rest of the paper, lenders refer to all banks and finance institutions participating in syndicated lending.

2.2 Lender Characteristics from Eikon

The Eikon data set contains firm-level information of all listed companies. Firm-level characteristics such as total assets, operating expenses, operating profits and labor expenses —items common in most annual reports—are found in this data set. However, data quality is not perfect and entries for some variables are missing.

The Thomson Reuters Business Classification (TRBC) can identify finance institutions, including banks. TRBC consists of 10 economic sectors. Finance institutions are defined as companies in the "financials" economic sector. The database has a total of 12,107 finance institutions. The data set contains information on publicly listed firms and does not capture unlisted finance institutions, which should not be a major issue for the research as few private lenders are systemically large.[5]

Based on asset data, we rank the finance institutions for each year. The top-100 finance institutions by assets are marked out for each year and are our working definition of top lenders. We compare the characteristics of top institutions against those of other non-top lenders. Top lenders are defined by their assets across all their operations, not just the syndicated loan market. The composition of the top 100 will change from year to year, although a group of lenders are consistently in the top 100 (e.g., JP Morgan [US], Mitsubishi UFJ Financial Group [Japan] and Barclays [United Kingdom]).

In recent years, finance institutions in China have been rising to the top 100. In 2018, of the 100 largest listed finance institutions by total assets, 16 were Chinese banks, compared with six in 2007. The Industrial and Commercial Bank of China ranked second by total assets in 2018 and 2019.

2.3 Matching Loan and Lender Characteristics

No unique firm identifier allows us to match T1 and Eikon easily. Data recording has been inconsistent within and between each data set. We made a significant effort, therefore, to clean and match the data. Some multinational lenders operate under slightly different names or through subsidiaries in different markets. We encountered many naming discrepancies such as misspellings and abbreviated names of the same lender. We manually corrected and

[5] One of the larger banks that are not public is Zuercher Kantonalbank (ZKB), which had 40 unique connections in 2019.

standardized lender names in both databases. Some of the key rules are presented in the table below.

Table 1. Standardizing Lenders' Names

Rules	Examples
Local branches of the same company	"JP Morgan (Asia)" and "JP Morgan–Tokyo" are merged as "JP Morgan."
Abbreviations and other discrepancies	"Bank of America Corp." and "Bank of America Corporation" are standardized to "Bank of America."
Subsidiaries of the same parent company	"UBS Securities" and "UBS Asset Management" are merged as "UBS."
Miscellaneous misspellings	"Bk of China" and "The Bank of China" are standardized to "Bank of China."

We cleaned up the data and consolidated the branches and subsidiaries into 612 finance institutions, which allowed matching of the T1 and Eikon data sets. Even though the matching is not exhaustive, most significant lenders have been consolidated in the data set.

The 612 finance institutions account for a total of USD127.5 trillion in assets, or 74 percent of total assets in the finance sector (based on 2018 data).[6] For each lender, including its subsidiaries and localized entities, we summed items such as assets, operating expenses and labor costs, and these became consolidated lenders' characteristics for the regressions.

While the total syndicated loan amount in each deal is recorded, the loan amounts are not broken down by lender in the syndicate. While we can say that Bank X was involved in deals

[6] The matching was conducted from the top- to lowest-ranked finance institutions, ranked by total assets, using the Eikon database. The largest lenders are matched, covering a large part of the market. The exceedingly small lenders (outside the top 612) are not matched. It is difficult to match the two data sets for the group of significantly smaller lenders because of data quality issues. Not all the consolidated 612 finance institutions appeared as syndicators in loan deals in any given year. In 2018, 267 of the 612 consolidated institutions were involved in at least one syndicated loan deal. The 267 finance institutions covered 56 percent of total public finance assets in 2018.

worth a certain value and compare it against the size of the market, we are unable to provide the exact lending amount by Bank X. The definition of market power has to be caveated accordingly, as it is the value of the bank's deals rather than the amount of direct lending.

2.4 Identifying Syndicated Loan Lenders' Connections

We computed how many other lenders each lender in the syndicated loan database is connected with in the same loan syndication deals (annual data) to measure the level of connectedness.

Two dimensions of lender connectedness are measured: unique connections and total connections. Unique connections are the number of distinct links a lender has in a network. They capture the diversity of information shared between lenders and their syndicating counterparts. For example, a lender that syndicates with 10 distinct lenders will presumably obtain market information from more diverse sources than a bank that connects to only three distinct counterparts. Total connections capture the number of syndications by the lender (annual data).

Suppose there are three deals in the market. Lender A has two connections with B (AB), in deal 1 and deal 3; one connection with C (AC), in deal 1; and one connection with E (AE), in deal 3. A has three unique connections (AB, AC, AE) and four total connections since AB appears twice:

Deal	Lenders	Deal Connections
1	A, B, C	AB, AC, BC
2	C, B, F	CB, CF, BF
3	A, B, E	AB, AE, BE

Similarly, B has four unique connections (AB, CB or BC, BE, BF) and six total connections as AB and BC appear twice. After finding the unique and total connections of each lender, the unique connections for deal 1 are defined as the sum of the unique connections of A, B and C. The same method is used to compute the total connections in deal 1:

Deal	**Lenders**	**No. of Unique Connections**	**No. of Total Connections**
1	A	3	4
1	B	4	6
1	C	3	4
	Total	10	14

We applied this method to all the syndicated loan deals and computed the unique and total connections for each lender for each year. Unique connections are a useful measure of the extensive margin of information, that is, how widely a lender connects with other lenders. Total connections capture the extensive and intensive margins of information.

Further details on matching and computation of connections are in Annex B.

3 Key Observations

3.1 Cost Trends

To allow for better comparability, we limit the comparisons in this subsection to banks that are among the top-100 finance institutions. Banks, in any case, form the bulk of the lenders. In 2018, 70 banks were among the top-100 finance institutions by assets. We compared the revenue and cost trends of the larger or top banks versus other banks outside the top 100.

Generally, larger banks have had lower operating costs as a percentage of revenue in recent years (Figure 4), driven by a lower ratio of HR expense to revenue (Figure 5). The most striking aspect of the data is revenue per employee. The top banks perform significantly better (Figure 6) but the difference in cost per employee is more marginal (Figure 7).

Figure 4. Total Operating Expense as a Percentage of Revenue

Figure 5. Total Human Resource Expense as a Percentage of Revenue

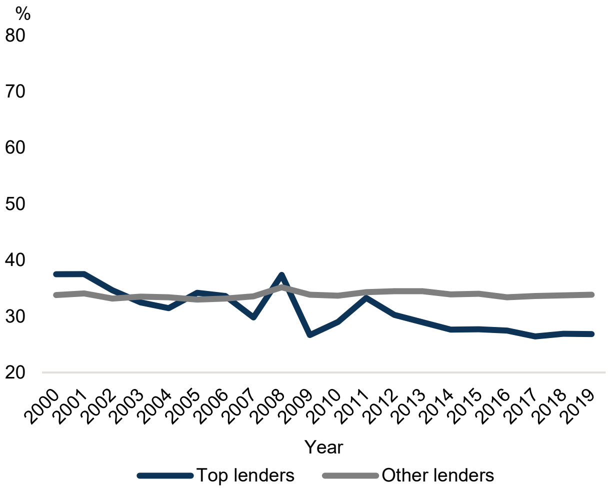


Figure 6. Revenue per Full-Time Employee

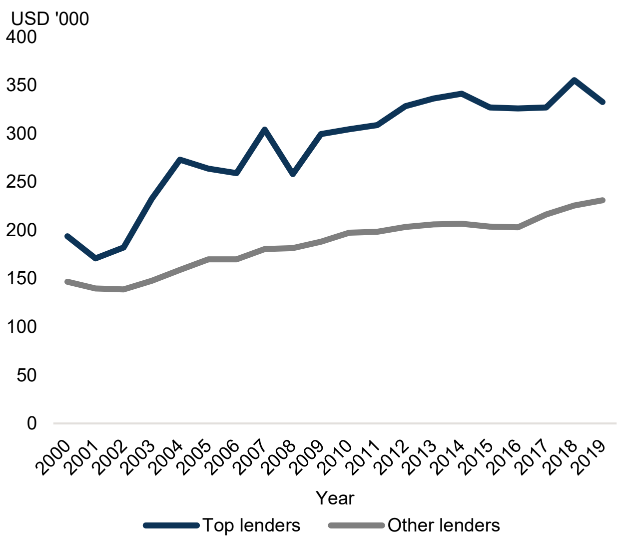
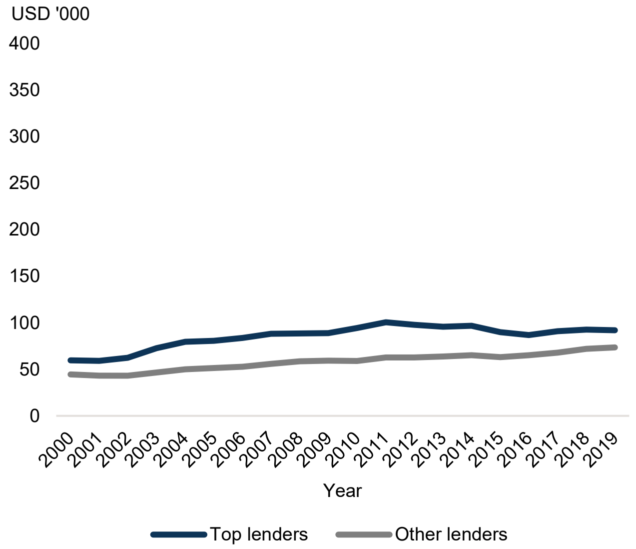


Figure 7. Labor Expense per Full-Time Employee



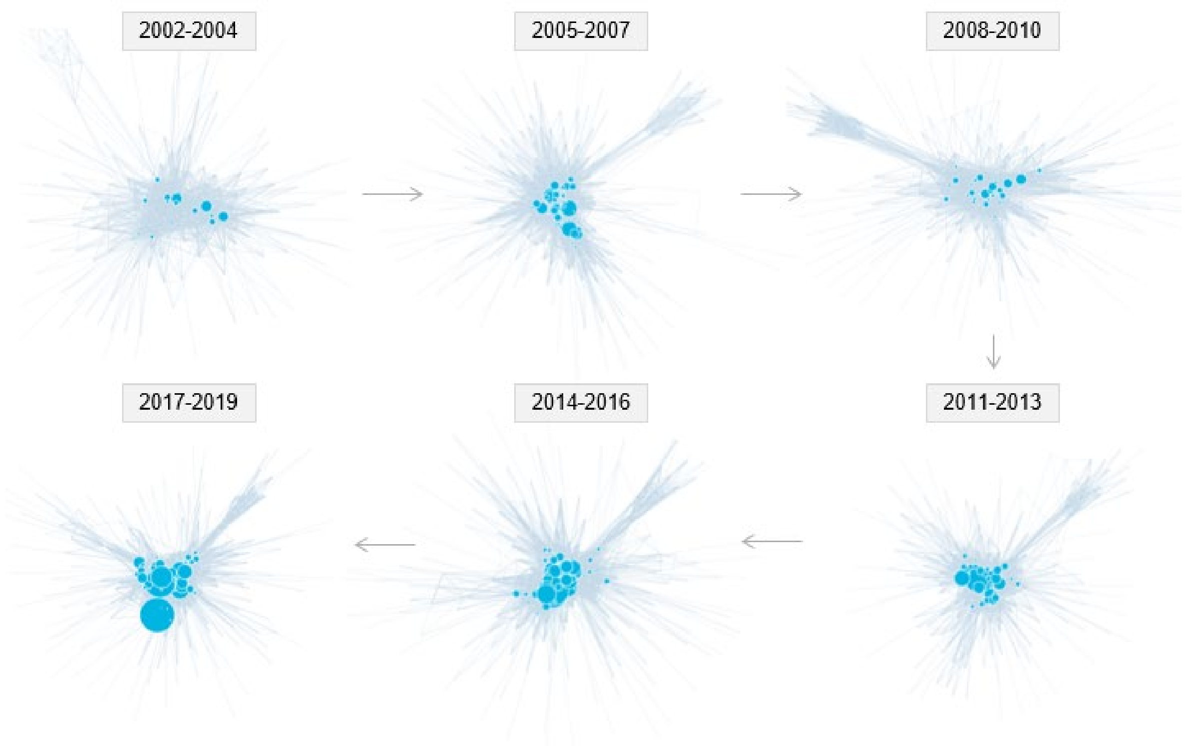
Source: Authors' calculation

Based on what is observed in the syndicated loan market, top banks have lower average spreads. The higher revenue per employee in the top banks is not, therefore, the consequence of charging higher markups. Rather, top banks can increase market shares with lower spreads, hold cost per employee at about the same level as smaller banks and generate more revenue per employee. In the regressions, we formally tested whether HR or non-HR costs affected spreads.

3.2 Network Connections

Over the past two decades, we have observed an increased level of network concentration in the syndicated loan market and show it through the analysis of syndication links. When two or more lenders are in a syndication deal, we record a pair-wise unique business or network link. For example, when lenders A, B and C are in a syndication deal, we record three unique links consisting of AB, AC and BC pairs. If Banks A and B are involved in another syndicated loan, there is a repeat network link AB. Lenders with more total links (unique and repeats) are represented by bigger bubbles, allowing us to visualize the network of syndicated loans (Figure 8).

Figure 8. Syndication Networks over Time

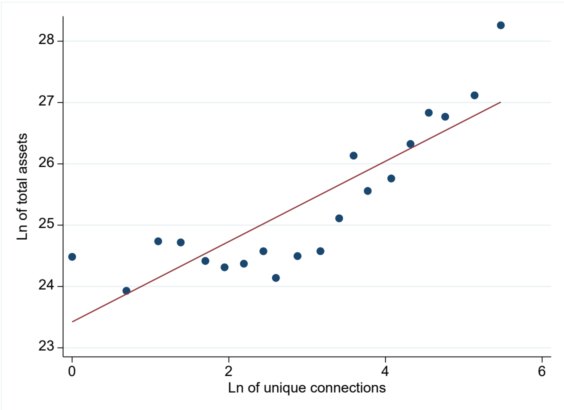


Note: Node (lender) size denotes the total number of connections of a particular node. Lines in the chart represent connections between the nodes.
Source: Asian Infrastructure Investment Bank, based on the syndicated loan database.

We observe that (1) the number of unique links has grown steadily over the years as shown by the lines, and (2) some banks are involved in many syndication deals and increasingly so. The syndicate loan market before and during the Global Financial Crisis in 2008-2010 had scattered connections and smaller bubbles. There were larger bubbles but they were relatively small, suggesting lower network concentration. By the late 2010s, however, there were a number of large connector lenders, i.e., lenders involved in many deals, as shown by the large bubbles.

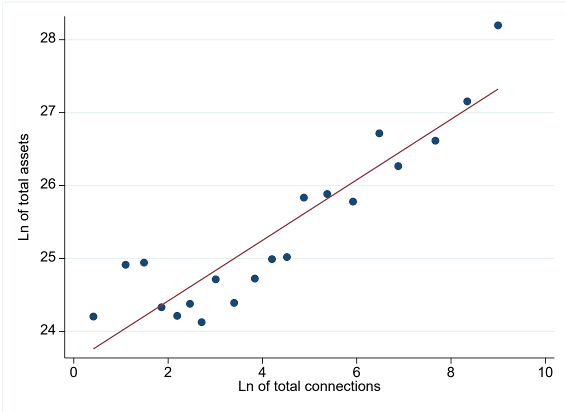
Concentration in the lender network is positively correlated with asset size. As the number of sample points is large, we leverage a binscatter plot to show the correlation.[7] The largest lenders, by assets, are those with the most syndicating links with other lenders (Figure 9 and Figure 10).

Figure 9. Binscatter Plot between Assets and Unique Connections (2018)[8]



ln = natural log.

Figure 10. Binscatter Plot between Assets and Total Connections (2018)



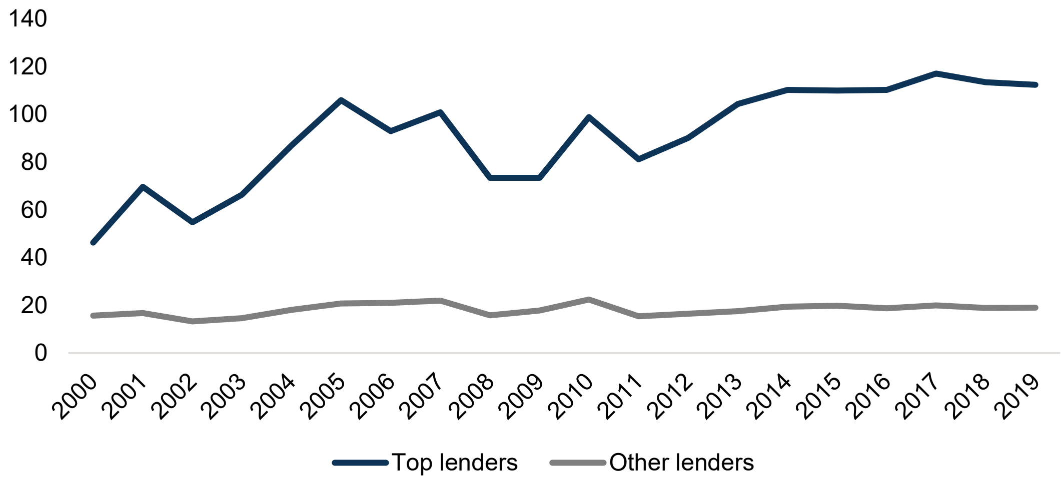
ln = natural log.

Source: Authors' calculation

Big lenders have more unique and total connections (in syndication) with other lenders than do small lenders and have become more networked over time. In 2000, the top-100 lenders had, on average, 46 unique syndication links (or relationships) with other lenders, and by the late 2010s, about 112 (Figure 11). For smaller lenders, the number of unique relationships has remained at about 20. In short, the larger lenders have become much more networked in the syndicated loan market than the smaller lenders. There was a spike post financial crisis. The large lenders are not necessarily connecting more with each other within their group. Rather, they are becoming more connected with more lenders in the market, including smaller ones.

[7] The binscatter plot groups the x-axis variable into equal-sized bins and computes the mean of the x-axis and y-axis variables within each bin.
[8] Data for this figure are limited to the lenders that are matched.

Figure 11. Unique Connections between Top and Other Lenders



Source: Authors' calculation

3.3 Correlations of Connections and Key Variables

Unique connections (Figure 12) and total connections (Figure 13) are correlated to the number of full-time employees. Clearly, however, the correlation is more linear and, to a certain extent, stronger for the latter. This observation is intuitive because total correlations are a better proxy for the number of deals a lender is involved in, which thus bears a better correlation with the lenders' staff numbers. Unique connections, however, measure the extensive margin of networks, and the relationship with full-time employees is thus flatter at higher levels.

Figure 12. Binscatter Plot between Full-Time Employees and Unique Connections

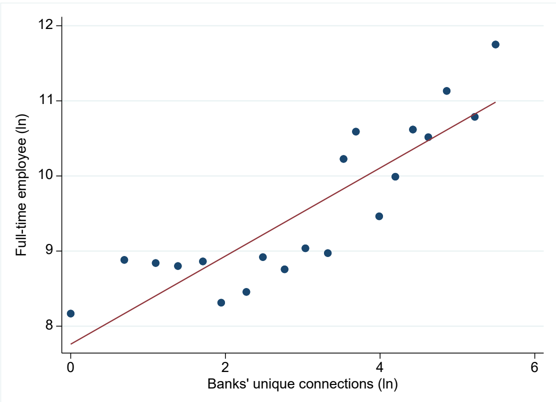
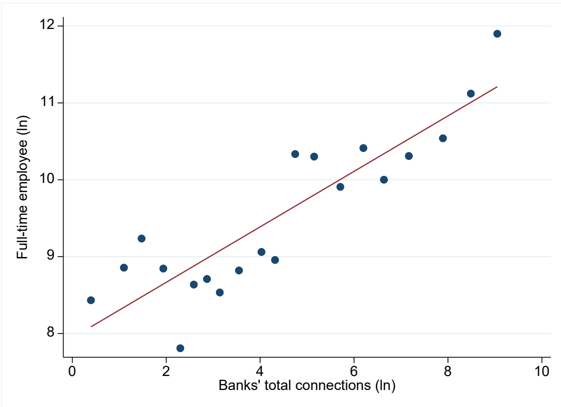


Figure 13. Binscatter Plot between Full-Time Employees and Total Connections



ln = natural log.

Source: Authors' calculation

We present the correlation between banks' average spreads and asset size, as well as the number of unique connections. We see that the correlation between assets and spreads is weak (Figure 14). Lenders with more unique connections have lower average spreads although the relationship flattens out at about 200 bps (Figure 15). We test the effects of assets and connections on spreads in the next section.

Figure 14. Binscatter Plot of Spreads and Assets (2018)

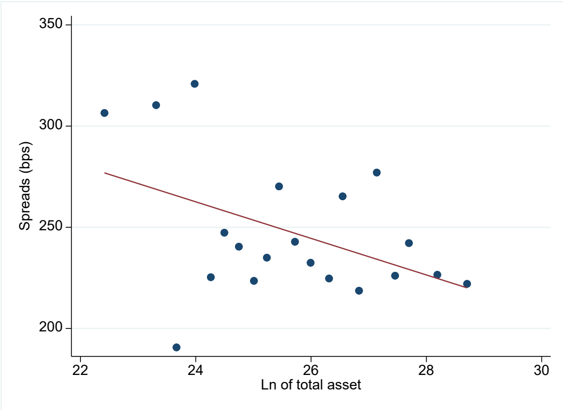
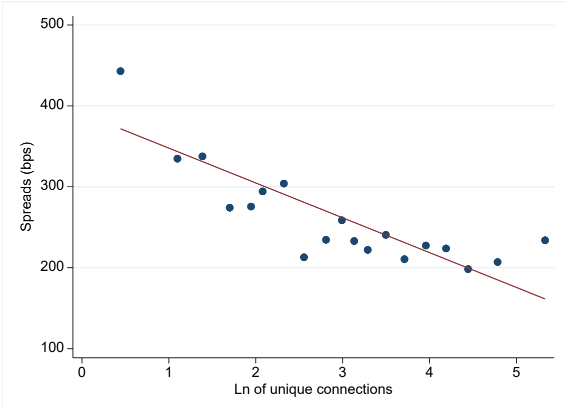


Figure 15. Binscatter Plot of Spreads and Unique Connections (2018)



ln = natural log.

Source: Authors' calculation

4 Regression Estimates

We present two sets of regression estimates, one at the lender level and another at the loan level. Both sets use the data set created in this research, which combines deal-level data from T1 and lender characteristics from Eikon.

4.1 Regressions on Lender Average Spread (or Markup) and Profitability

In the first set of regressions, we seek to explain lenders' average spread. The combined data set from T1 and Eikon allows us to construct an unbalanced panel data of lenders. Each sample records the average spread for each lender in a particular year (averaged across all the deals the lender participated in from the T1 data set), and lender's characteristics such as revenue, costs, profitability and number of connections, among others:

$$s_{j,t} = \boldsymbol{\alpha_1} + \boldsymbol{\theta_1} \boldsymbol{X}_j + \mu_1 C_{j,t} + \varepsilon_{j,t}$$

where $s_{j,t}$ is the average spread for bank j across all the deals it participated in for year t, $\boldsymbol{\alpha_1}$ is the vector of possible fixed effects (e.g., year fixed effects),[9] $\boldsymbol{X_j}$ is the vector of bank-specific characteristics and $C_{j,t}$ is the measure the bank's connections. For all the regressions, we use the between estimator, given that the key thrust of our analysis is the difference between lenders.

For regression (1) (Table 2), we include the operating cost variable (as a percentage of revenue) as a regressor. For regressions (2) and (3), it is replaced by HR and non-HR costs as a percentage of revenues, respectively. In regression (4), both HR and non-HR cost ratios are included.[10] In regression (5), we repeat the setup of regression (4) but replace unique connections with total connections.

Table 2. Regression Results of Average Spreads of Lenders

	(1)	(2)	(3)	(4)	(5)
Total assets (ln)	3.710	3.858	4.589	4.833	2.963
	(3.809)	(3.806)	(3.879)	(3.898)	(4.043)
Unique connections (ln)	-21.30***	-21.89***	-21.77***	-22.16***	
	(5.536)	(5.566)	(5.536)	(5.568)	
Human resource expense (% of revenue)		30.23		23.61	23.81
		(33.77)		(34.25)	(34.76)
Non–human resource expense (% of revenue)			-29.99	-27.23	-26.99
			(23.35)	(23.71)	(23.96)
Operating expense (% of revenue)	-0.124				
	(0.210)				
Total connections (ln)					-10.71***
					(3.746)
Indicator that lender is a bank	-88.14***	-87.78***	-90.52***	-90.81***	-95.07***
	(13.71)	(13.60)	(13.83)	(13.84)	(13.90)
Constant	374.8***	356.1***	355.1***	342.0***	377.0***
	(128.3)	(130.0)	(129.0)	(130.5)	(132.5)

[9] The inclusion of year fixed effects in the regression is helpful in absorbing some across-the-board changes. For example, Basel II and III were introduced in 2004 and 2010, respectively, resulting in changes to the cost of capital that would have an impact on spreads.
[10] HR and non-HR cost ratios sum to total cost ratio.

Year fixed effect	Yes	Yes	Yes	Yes	Yes
Observations	3,303	3,303	3,303	3,303	3,303
R-squared	0.357	0.358	0.359	0.360	0.347
Number of lender groups	401	401	401	401	401

ln = natural log.

Note: Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Across all model specifications above, the coefficients of unique connections are negative and statistically significant. Lenders with more unique connections tend to have lower average spreads in their loans. The impact of total connections on spreads is negative and statistically significant but smaller. As variables, total connections perform less well than unique connections.

On average, a natural log point increase in the number of unique connections is associated with a 21-22 bps decline in average spreads. Consider the 25th percentile lender with about four connections (based on 2018 data), versus a 75th percentile lender with 28 connections. With the above coefficients, the spread is about 40 bps lower for the 75th percentile lender.

The results also show that bank lenders have spreads lower by about 88-95 bps than nonbank lenders, which is consistent with Lim, Minton and Weisbach (2013). This is not surprising. Banks have access to lower-cost and more diversified funding (e.g., deposits, borrowings from central banks, among others). Lender size (measured by assets) has no impact on spreads.

The coefficient for the ratio of HR cost to revenue is positive but insignificant. The operating cost ratio is not found to have any impact on spreads. That HR and total costs do not appear to significantly impact lender spreads, despite the earlier observation that large lenders' HR costs have declined, implies that the lower costs seen in larger institutions have translated into higher profits rather than lower spreads.

We test for this implication formally by regressing the profit margin of lenders against key variables.[11] Table 3 shows that HR and non-HR expenses are, not surprisingly, negatively correlated with the net profit margin. What is surprising is that unique and total connections are positively associated with higher profitability even after controlling for other costs.

[11] Net profit margin is defined by Refinitiv as "income available to company excluding extraordinary items divided by total revenue." Total revenue is "revenue from all of a company's operating activities after deducting any sales adjustments and their equivalents."

Table 3. Regression Results of Net Profit Margin of Lenders

	(6)	(7)	(8)
Indicator that lender is a bank	1.595	1.268	1.551
	(1.902)	(1.865)	(1.863)
HR expense (% of revenue)	-9.635**	-14.33***	-14.73***
	(4.607)	(4.637)	(4.653)
Non-HR expense (% of revenue)	-29.67***	-26.96***	-27.09***
	(2.775)	(2.787)	(2.778)
Total assets (ln)	-1.471***	-2.825***	-2.963***
	(0.462)	(0.545)	(0.561)
Unique connections (ln)		3.062***	
		(0.688)	
Total connections (ln)			2.166***
			(0.481)
Constant	53.52**	73.63***	74.66***
	(22.11)	(22.14)	(22.17)
Year fixed effect	Yes	Yes	Yes
Observations	4,087	4,087	4,087
R-squared	0.304	0.332	0.333
Number of lender groups	484	484	484

HR = human resource, ln = natural log.

Note: Standard errors in parentheses.

*** p<0.01, ** p<0.05, * p<0.1.

A concern is potential endogeneity: Do spreads affect connections? Our assessment is that it is not a significant factor. Lenders have no incentive to deliberately lower spreads to drive up the number of syndication connections. After all, lower spreads will erode the profitability of loans. To attract other syndicators, lenders do not drive up spreads either, given that higher spreads would reduce demand for loans or result in undercutting by competitors.

4.2 Regressions on Observed Deal Spreads

At the deal level, observed spreads are negatively correlated with the number of syndicators (Figure 16) and with the sum of the connections of these syndicators (Figure 17). In this subsection, we formally test for the effects of these on loan spreads.

Figure 16. Binscatter Plot of Spreads and Number of Syndicators (2018)

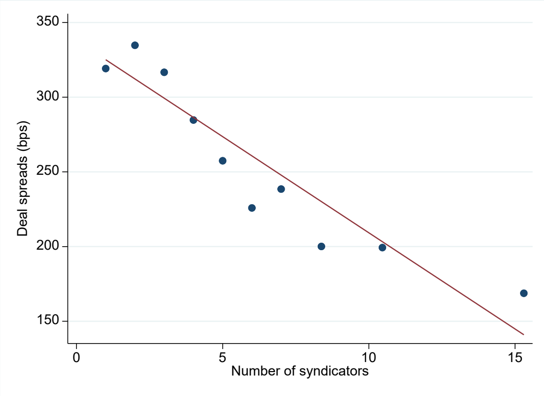
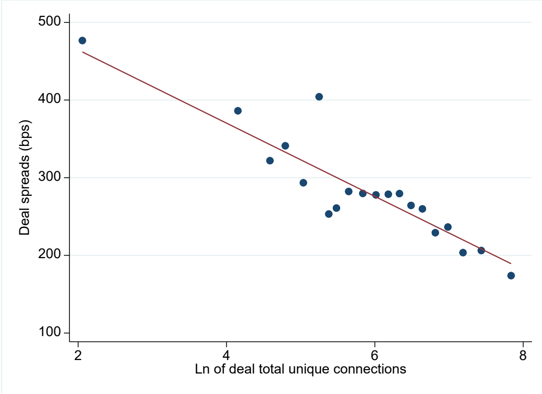


Figure 17. Binscatter Plot of Spreads and Unique Connections (2018)



ln = natural log.

Source: Authors' calculation

In the second set of regressions, we seek to explain the drivers of the observed spreads at the loan level:

$$s_i = \boldsymbol{\alpha_2} + \boldsymbol{\theta_2 Z}_i + \mu_2 C_i + \varepsilon_i$$

where s_i is the spread for loan i; $\boldsymbol{\alpha_2}$ is the vector of possible fixed effects (e.g., year, sector,[12] company type[13] fixed effects); $\boldsymbol{Z}_j$ is the vector of loan specific characteristics; and C_i is the measure the connections of the syndicate.

For the regression, an important point is that one of the loan characteristics is the size of the deal. A larger loan will, in principle, require a higher spread to compensate lenders, given that it will more likely hit risk, liquidity or other lenders' constraints. However, loan size is endogenous to the spreads; higher spreads lower demand for loans. We instrument loan size by the number of tranches, which is positively correlated with size, but should not, in principle, affect spreads.[14]

As the loans are individual, regressions are carried out using pooled ordinary least squares with instruments. In regression (9), we show the results using the number of banks in the syndicate as the explanatory variable. In regression (10), we replace the number of banks with the sum of unique connections of the syndicators. In regression (11), the number of banks and

[12] Including consumer products and services, consumer staples, energy and power, financials, government and agencies, health care, high technology, industrials, materials, media and entertainment, real estate, retail and telecommunications.

[13] Mainly categorized as public and private, these company types account for slightly less than 70 percent of the samples. The others are governments and sub-national entities, joint ventures, among others.

[14] Without instrumenting, the loan size variable would have the wrong sign (as negative), which would be interpreted as larger loans having lower spreads.

the sum of their connections are included. Regressions (12) and (13) are variations of the previous ones but using the unique connections of bookrunners instead of all the lenders.[15]

Table 4. Regression Results of Deal Spreads

	(9)	(10)	(11)	(12)	(13)
Principal amount (ln)	82.36***	75.02***	81.05***	94.17***	85.95***
	(2.169)	(1.956)	(2.084)	(2.555)	(2.353)
Tenor	5.298***	3.467***	3.927***	9.128***	7.744***
	(0.387)	(0.393)	(0.390)	(0.538)	(0.534)
Number of lenders in syndicate	-27.03***		-11.95***	-16.80***	-6.644***
	(0.506)		(0.345)	(0.380)	(0.287)
Lenders' total unique connections (ln)		-73.69***	-58.15***		-87.25***
		(1.278)	(1.171)		(2.216)
Bookrunners' total unique connections (ln)				-67.14***	-18.60***
				(1.450)	(1.125)
Constant	-202.3***	134.0***	54.54***	6.680	262.6***
	(12.95)	(9.629)	(10.89)	(13.24)	(11.84)
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Company status fixed effect	Yes	Yes	Yes	Yes	Yes
Sector fixed effect	Yes	Yes	Yes	Yes	Yes
Instrument	Tranches	Tranches	Tranches	Tranches	Tranches
Observations	134,678	134,678	134,678	93,556	93,556
Centered R-squared	-0.054	0.012	0.003	-0.024	0.027
Uncentered R-squared	0.532	0.562	0.568	0.512	0.537

ln = natural log.

Note: Robust standard errors in parentheses.

*** p<0.01, ** p<0.05, * p<0.1.

In this set of deal-based regressions, the coefficient on total unique connections per deal remains negative and statistically significant, consistent with the earlier lender-based results. Overall, a natural log point increase in the number of total unique connections in the syndicate is associated with deal spreads lower by 58-87 bps. Based on this estimate, a deal where syndicate lenders have 972 total unique connections (75th percentile) is estimated to have

[15] Bookrunners are lenders designated by the borrower to coordinate the syndication process. The bookrunner is responsible for structuring the financing and for designing and implementing the transaction.

spreads lower by 70-106 bps than a deal with lenders that have only 289 unique connections (25th percentile).[16]

We see similar effects in regression (12) when the regressor is the bookrunners' connection rather than the whole syndicate of lenders. When both bookrunners' and the whole lending syndicate's connections are used, the latter are more economically significant.

The principal amount and tenor show statistically significant positive coefficients. Syndicated loans with larger principals and longer tenors use up a larger portion of lenders' capital, which drives up spreads and could also be due to the risk associated with the larger and longer tenor loans. The models estimate that an increase in the tenor by an additional year increases spreads by 3-9 bps. As for the loan principal amount, a USD555 million syndicated loan (75th percentile) is estimated to have spreads higher by 163-205 bps than a USD63 million loan (25th percentile).

We found that the number of lenders is negatively associated with spreads and that its coefficient is statistically significant. This finding is consistent with the risk-sharing aspect of loan syndication. The explanatory power of the number of lenders declines with the inclusion of connections. The number of unique connections, whether measured for the total syndicate or for bookrunners only, remains a highly significant explanation for observed spreads.

5 Discussion and Implications

Based on the most recent data, about 95 percent of all syndicated deals involve at least a top-100 lender. These large lenders are becoming increasingly connected, with unique syndication connections far exceeding those of smaller ones.

Spreads between top lenders and the rest of the market were largely similar but diverged after the financial crisis at the turn of the last decade. There is a persistent, unexplained difference in average lending spreads between the two groups. While HR and operating costs have declined more for top lenders, it is not a significant explanation for lower spreads. Instead, the number of syndication connections is strongly associated with the lower spreads observed in top lenders.

The negative correlation between spreads and connections holds even after controlling for year fixed effects and lender size. Lender cost structure does not appear to have any significant impact on spreads. We present evidence that the lower costs of top lenders

[16] For all 25th and 75th percentiles of connection data, we excluded deals that have only one syndicator, which account for about half of the total sample size used in the regression.

translate into higher profits. We do not suggest, however, that this is a pessimistic result. In standard economic models of firms with heterogeneous productivity, more-productive firms will enjoy higher profits, at least in the ex-post sense.

At the deal level, the negative correlation between connections (of the syndicate) and spreads holds even after accounting for year, sector, firm type fixed effects and other loan-related characteristics. Even the inclusion of the number of syndicators in the deal, which is expected to reduce spreads through the diversification effect, does not remove the explanatory power of connections. Simply put, a deal with three lenders that are well connected will likely see a lower spread than another one with three less-well-connected lenders, all things being equal. Such is the power of banking connections.

The study has several important limitations. First, the syndicated loan market, while large, might not be representative of the lending landscape. In the syndicated loan market, borrowers tend to be large corporates, which will likely have some countervailing market power. This market is highly competitive, as evidenced by the participation of many international banks. Because loans are syndicated across many lenders, the degree of transparency rises and loan terms become public information. This research, for example, is possible only because data on loan terms are available.

Second, top lenders might be better able to lower spreads because they have other forms of revenue generation from borrowers (e.g., treasury or other finance services). We are unable to tackle such bundling of services in the research. However, the spread divergence between top and other lenders has occurred only since 2010, after the financial crisis. Bundling of services alone is unlikely to explain such a divergence, as it is difficult to argue that bundling occurred only in recent years and not before.

We are unable to fully explain why connections have such explanatory power. Our best explanation is that syndication connections capture the informational advantage enjoyed by the lender: for example, its knowledge of other lenders, market sectors and geographies and borrowers. This body of information gives a lender the confidence and ability to enter a syndicated deal. We tested for the explanatory power of unique versus total connections and found the former to consistently perform better in regressions. This result points to the importance of extensive information—that is, the diversity of information a lender is able to gain about various markets—as the source of efficiency and lower spreads, more so than repeat syndication business with the same group of lenders. Despite the study’s limitations, an important result is that syndication connections can explain the lower average spreads of larger lenders.

5.1 Policy Implications

The study results have several policy implications. A key attribute of the syndication market is its relative transparency. When it is clear what spreads are being offered and to whom and for what tenor and loan size, it becomes difficult for lenders to have unreasonable markups. This fact can be incorporated into regulatory design. For example, the finance sector regulator can require lenders to declare the spreads of all loans and borrowers' profiles. Even if such information cannot be made public, it will be valuable for regulators to detect abuse.

Competition in the syndicated market, often with the presence of international lenders, is likely a contributory factor to curbing the spreads of large lenders. Even though we find that more-connected lenders have lower spreads, our research does not contradict the structure-conduct hypothesis.

Large lenders have become more systemically important, linking many smaller lenders in the syndication market. This market development is not by itself negative. It is a form of collaboration between large and smaller lenders. We cannot take for granted, however, that the market power of the large lenders will be benign over the longer term. It is unclear what effect increasing connections through large lenders will have during macroeconomic or financial stress. Will they help or impede credit transmission? This question could be an area of future research.

6 Concluding Remarks

Harnessing the information from two large data sets, this research contributes to the literature by documenting the lower spreads observed in top lenders and providing evidence that the spreads are associated with increased syndication network connections at the lender and the deal level. This network effect on spreads remains strong even after controlling for different lender and deal characteristics. The research shows that higher syndication connection is associated with higher profitability despite the lower spreads.

The top lenders in the syndicated loan market are becoming more connected than other lenders, providing the top lenders more diverse sources of market information in competition. This development is not negative for the market. While the findings of this paper are largely benign, the increasing network connections should continue to be on the research and regulatory agenda.

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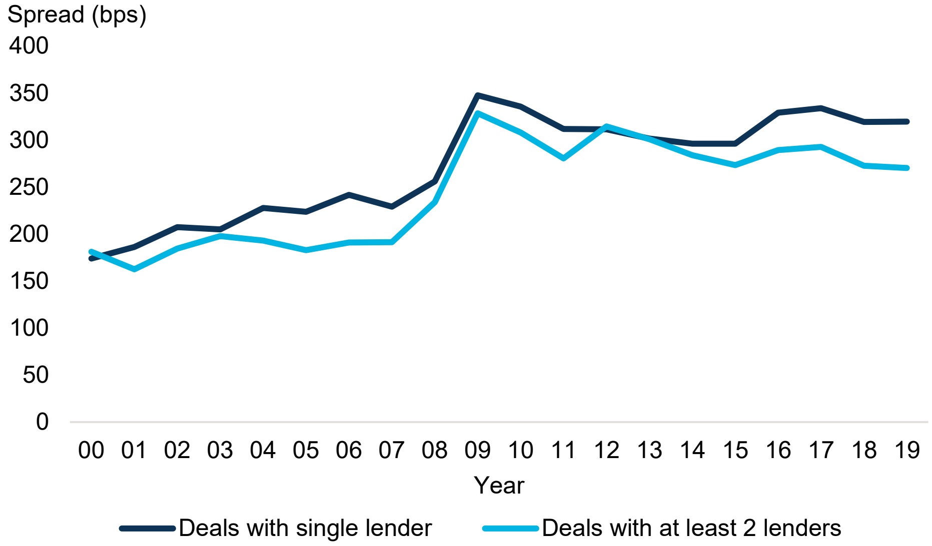
Annex A

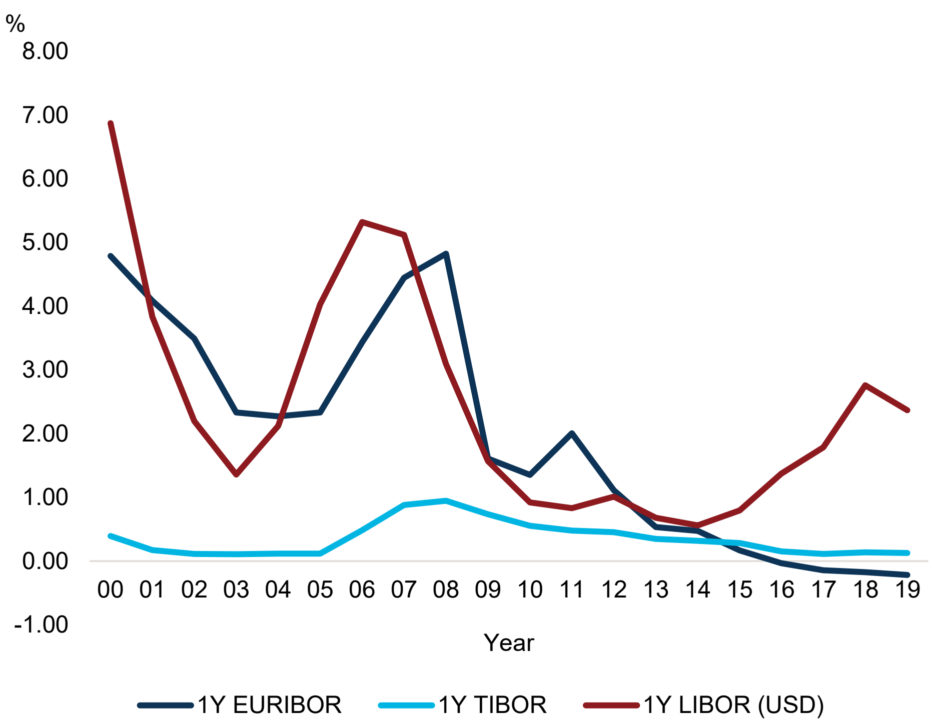
Figure A1. Time Series of Spreads between Single Lender Loans and Those with at Least Two Lenders (Annual)



bps = basis points.

Source: Authors' calculation

Figure A2. Time Series of LIBOR, TIBOR and EURIBOR (Annual)



bps = basis points, EURIBOR = European interbank offered rate, LIBOR = London interbank offered rate, TIBOR = Tokyo interbank offered rate, Y = year.

Source: Refinitiv Eikon

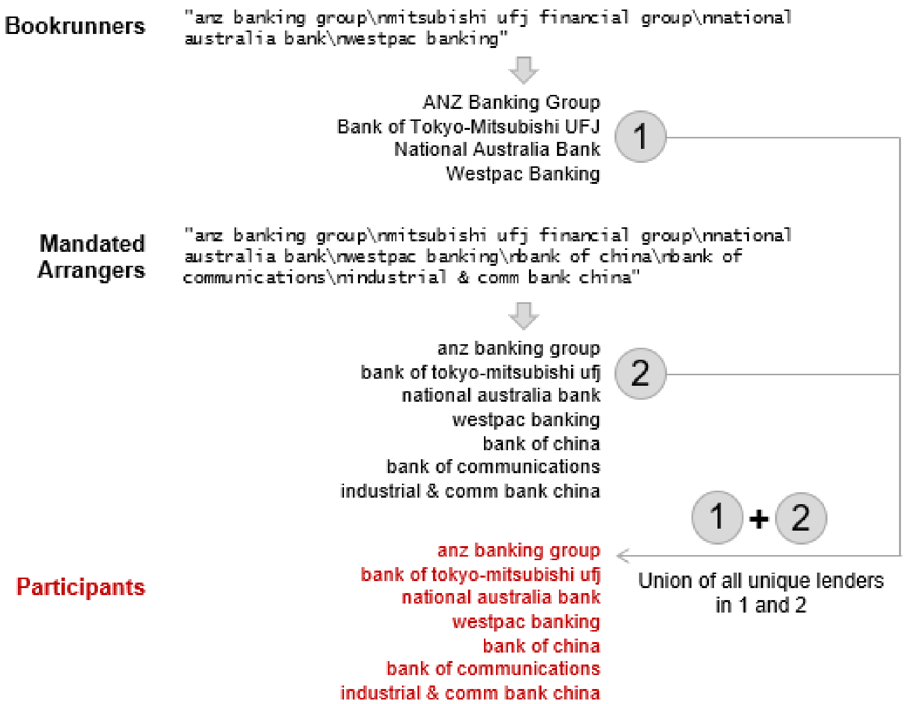
Annex B

We elaborate how the Thomson One (T1) syndicated loan database was processed and transformed for this research. This section explains how lender connections were identified, unique, how total connections calculated, and how top lenders identified and matched. We used R as the primary programming tool for most of the process, combined with Stata and Excel for smaller tasks such as aggregating and manual cleaning.

Identifying Lender Connections

Information about syndicators in the T1 syndicated loan database comes in two variables: bookrunners and mandated arrangers. Both variables are in text format, where lenders are contained in a single string, with each lender separated by the new line character "\n." We used this separator to identify existing pairs of connections by extracting all individual lenders in the database. We constructed a new variable—participants—which contains all lenders and lists all bookrunners and mandated arrangers without duplication in the deal (Figure 20).

Figure B1. Split Lenders from String



Computing Connection Variables

With the results from the previous section, we can compute the number of unique and total connections of every lender in the syndicated database in any given year. We need to further transform the data into a connection-based format. Specifically, based on the participants variable constructed in the previous step, we can find all possible two-lender combinations without replacement in every deal.

The participants variable from the previous example results in $C_7^2 = 21$ distinct two-lender combinations (Figure B2). X1 and X2 simply denote the two lenders in pairs. We rearranged the order of X1 and X2 such that X1 always alphabetically precedes X2, to avoid duplicated calculations of unique connections later. This means, for instance, every time the pair "bank of china" and "westpac banking" appears, X1 is always "bank of china" and X2 "westpac banking," not vice versa.

Figure B2. Transforming Deal Participants to Pair-Wise Format

Participants

anz banking group
bank of tokyo-mitsubishi ufj
national australia bank
westpac banking
bank of china
bank of communications
industrial & comm bank china

$$C_7^2 = 21$$

	X1	X2
1	bank of communications	mitsubishi ufj financial group
2	mitsubishi ufj financial group	westpac banking
3	bank of china	bank of communications
4	anz banking group	bank of china
5	anz banking group	national australia bank
6	mitsubishi ufj financial group	national australia bank
7	anz banking group	ind & com bank of china
8	anz banking group	mitsubishi ufj financial group
9	ind & com bank of china	mitsubishi ufj financial group
10	ind & com bank of china	national australia bank
11	bank of communications	national australia bank
12	bank of communications	westpac banking
13	ind & com bank of china	westpac banking
14	bank of china	national australia bank
15	national australia bank	westpac banking
16	bank of china	mitsubishi ufj financial group
17	bank of china	ind & com bank of china
18	anz banking group	westpac banking
19	bank of communications	ind & com bank of china
20	anz banking group	bank of communications
21	bank of china	westpac banking

We applied this method to every deal in the database and populated it in pair-wise format. This transformation resulted in a total of 1,595,109 X1-X2 pairs, compared with 133,181 data points in the original syndicated loan database. Note that loans with a single recorded lender will not have a paired relationship. The next step is to calculate the unique and total connections of each lender. With the pair-wise database, these calculations are straightforward:

1. **Total connections.** This variable is the number of pairs where either X1 or X2 is a given lender. If we filter the pair-wise database by the condition "either X1 or X2 is 'bank of china'," then the number of rows of this filtered subset is the number of total connections of "bank of china."

2. **Unique connections**. If we use the filtered subset above and go one step further and extract all the unique pairs with either X1 or X2 as "bank of china," then the number of such distinct pairs is the unique connections "bank of china" has in the network. "Bank of china-X" and "X-bank of china" are treated as the same unique connection, by ordering X1 and X2 alphabetically.

Figure B3 uses as an example calculating Bank of China's total and unique connections in a sample pair-wise data set. We applied the same method to all existing lenders in the syndicated loan database, aggregating total and unique connections by year and lender.

Figure B3. Total and Unique Connections

	X1	X2
	bank of america	westpac banking
	bank of america	national australia bank
	bank of america	dbs group holdings
	bank of america	ccb
	bank of america	ind & com bank of china
	bank of america	mitsubishi ufj financial group
	bank of america	export development canada
	bank of america	oversea-chinese banking
1	abn amro bank nv	bank of china
2	bank of china	jpmorgan chase &
3	anz banking group	bank of china
4	bank of china	dnb asa
5	bank of china	royal bank of canada
6	bank of china	royal bank of canada
7	bank of china	mizuho financial group
8	bank of china	oversea-chinese banking
9	bank of china	ccb
10	bank of china	commonwealth bank of australia
11	bank of china	dnb asa
12	bank of china	export development canada
13	bank of america	bank of china

Total Connections = 13

unique(X1, X2)

1	abn amro bank nv	bank of china
2	bank of china	jpmorgan chase &
3	anz banking group	bank of china
4	bank of china	dnb asa
5	bank of china	royal bank of canada
	bank of china	royal bank of canada
6	bank of china	mizuho financial group
7	bank of china	oversea-chinese banking
8	bank of china	ccb
9	bank of china	commonwealth bank of australia
	bank of china	dnb asa
10	bank of china	export development canada
11	bank of america	bank of china

Unique Connections = 11

bank of china – royal bank of canada, bank of china – dnd asa occurred twice, so unique connections is 2 less than total connections.

Matching Top Lenders with Firm Characteristics

To match the top lenders with firm characteristics, we went through two steps:

1. **Find top finance institutions ranked by assets.** We identified the top 1,100 biggest finance institutions by assets per year in 2000-2019 using the Eikon database. We produced a sample of 1,847 different firms that were among the top 1,100 at least once historically in 2000-2019. To get the top-100 lenders used for this study, we simply picked the top 100 financial institutions ranked by assets every year.

2. **Correct the names of the top finance institutions.** We went through all the 1,847 top firms and manually standardized their names so they matched the syndicated loan lenders. About one-third (612) of the top firms were matched perfectly in the syndicated loan database. The syndicated loan database has 3,579 different lenders after name standardization, so the matched 612 firms capture 17 percent of all syndicated loan lenders. We could not find any deals for the unmatched ones in the loan database.