Global Banking Networks and Loan Pricing

A-young Park [1], Gabjin Oh [2]

[1] *Financial Market Stabilization Department, Financial Supervisory Service, Seoul, 03171, South Korea*
[2] *Division of Business Administration, Chosun University, Gwangju, 61452, South Korea*

Abstract

This paper examines the impact of interconnectedness, based on syndicated loan portfolios, on the cost of credit in loan contracts. Using syndicated loan from financial institutions across 39 countries between 2000 and 2020, we constructed an interbank network, distinguishing between core and peripheral banks. Our findings show that banks with higher interconnectedness within the network experience increased realized volatility. Moreover, a higher bank degree is positively associated with the cost of credit, even after accounting for bank-specific, country-specific, and other fixed effects. These insights offer valuable guidance for governments and regulators in managing financial market stability and enhancing bank resilience.

Keywords: Connectedness, Loan Pricing, Bank network, Syndicated loan market

JEL Classification Code(s): C60, F34, G01

---

1. Introduction

Measuring the connectedness between financial institutions is crucial for understanding how risk propagation could trigger global financial crises and shape economic forecasts (see, e.g., Battiston et al. 2012; Demirer et al. 2018; Corsi et al. 2018; Acharya et al. 2017). The syndicated loan contract, functioning as a multi-layer network, explains how interconnectedness transmits negative shocks into the financial market (Cai et al. 2018b; Ivashina and Scharfstein 2010; Fahlenbrach, Prilmeier, and Stulz 2012).

Technological advancements and globalization have amplified financial interdependence. Syndicated loans, where multiple lenders jointly finance a borrowing firm to distribute credit risk, have become a crucial external financing source for many firms. The structure of these loans provides a valuable platform for exploring the interdependence among financial institutions. This paper investigates the interbank networks within syndicated loans, focusing on the common exposures among financial institutions with overlapping portfolios, and aims to offer insights into loan pricing based on counterparty exposures.

Our work focuses on understanding the activities of financial institutions in international markets. During periods of economic growth, banks typically utilize their networks to encourage information sharing, with the aim of expanding business and increasing profits. However, during economic contractions, these banks may be subject to stringent obligations and constraints, potentially inhibiting their capacity to stimulate restructuring within their networks. In this context, lenders play a crucial role in mitigating risk exposure by effectively monitoring and screening their borrowers.

This paper investigates the evolution of interbank networks using a large dataset of syndicated lending structures. This work extends the findings of a previous study that demonstrated a positive relationship between connectedness within interbank networks and bank performance, as measured by ROA (Oh and Park 2021). The results suggest that collusion among networked banks may lead to abnormal profits. From this perspective, a key focus of this paper is to examine how much interest rates are raised depending on the degree of interbank network connectedness based on the similarity in loan portfolios.

Furthermore, a diversified loan portfolio have implications on bank performance and respond to external market frictions (Loutskina and Strahan 2011; Matvos, Seru, and

Silva 2018). Prior research provides evidence that interconnectedness has a considerable impact on the economy from the perspective of risk exposure (Cont, Moussa, and Santos 2010; Shleifer and Vishny 2011; Acemoglu et al. 2012). Negative shocks and financial distress can propagate rapidly within a network, with credit concentration amplifying the cascading effect (Cai et al. 2018b).

To propose criteria for monitoring activities of financial institutions, this study introduces a measure of the connectedness based on the similarity between loan portfolios. While previous literature has focused on market-wide interconnectedness from a macro perspective, our approach extends this concept to a multi-level vulnerability indicator at both micro and macro levels. (Cai et al. 2018b). We employ the Planar Maximally Filtered Graph (PMFG) method as an optimization algorithm, since a network structure that excludes redundant links is crucial for accurately estimating the properties of individual agents, institutions, or the overall network effects (Tumminello et al. 2005).

Main finding, that connectedness increases interest rates and realized volatility at the bank level, suggests that higher systemic risk is associated with increased correlation among banks. This phenomenon, where banks have strong incentives to excessively correlate their investments with those of their counterparties, is referred to as 'risk-matching'. It indicates that financial institutions deliberately choose to align their risk profiles, which can elevate systemic risk due to the heightened correlation between their investments (Jackson and Pernoud 2019).

These findings make a significant contribution in several ways. Firstly, this study offers an alternative approach to measuring systemic risks, providing valuable insights for risk management (Hasan, Politsidis, and Sharma 2021). Secondly, our research enhances the understanding of loan pricing mechanisms, which could be further explored to examine the interactions between banks and firms. Thirdly, it sheds light on potential collusion among financial institutions that occupy central positions within interbank networks. Furthermore, these insights could be valuable for regulators and policymakers in monitoring lending activities and ensuring financial stability.

The rest of the paper proceeds as follows. Section 2 presents a description of the database and the methodology that we employed. Section 3 and Section 4 contain the empirical results. Section 5 concludes the paper.

2. Data and Methodology

We explain the process for the sample construct and summarize methodology to construct interbank network and regression models.

2.1. Data Source

Company accounting information is obtained from Standard & Poor's Compustat, and loan information is sourced from Thomson Reuters' LPC Dealscan, creating a comprehensive sample of syndicated loans along with associated borrower and lender information from 2000 to 2020. Our starting points are the Dealscan-Compustat Link and the Lender link (Chava and Roberts 2008, Schwert 2018). We then obtain information about loan contract from Dealscan, financial statement from Compustat, and stock return from CRSP. Our sample includes lenders with at least $10 billion in outstanding loans or at least 50 outstanding loans (Schwert 2018).

Syndicated loans play a crucial role in the corporate market. These loans are typically offered by a group of lenders. The lenders in a syndicate are large banks that fall into two categories of lenders: lead arrangers and participants. Lenders are classified into lead arrangers and participants based on the literature (Cai et al. 2018b). [1] Following the literature, we exclude loans made to financial companies (i.e., SIC codes between 6000 and 6999) as well as classified companies belonging to the Fama-French 12th industrial classification.

We use the sample to investigate the relationship between connectedness and loan spread. We analyze syndicated loan facilities from Dealscan, which contains the most extensive and recorded loan-deal details available on the international syndicated loan market. Our sample span from 1 January 2000 to 31 July 2020, including the year of the 2008-2009 global financial crisis and the global COVID-19 pandemic. We exclude loans without conventional pricing. These 67,076 loans(facilities) are granted by 70-194 lead arrangers headquartered in 26 international countries to 120-556 non-financial firms in the United States.

[1] We designate a lender as a lead arranger if the lead arranger's credit of it is yes or the lender's role of it is administrative agent, agent, arranger, book runner, coordinating arranger, lead bank, lead manager, mandated arranger, or mandated lead arranger. We designate a lender as a participant if it is not the lead arranger.

2.2. Network Construction

Literature on financial network has been studied to analyze connectedness above a certain threshold through the correlation coefficient of stock returns when constructing a network. In addition, studies have been conducted to measure systemic risk through networks measured through stock volatility of financial institutions through variance decomposition and Granger causality. Recently, the connectivity measured using data from syndicated loans, not stock returns, could be used as an indicator of systemic risk (Cai et al. 2018b). When the network is constructed through syndicated loans, it is possible to consider the comprehensive relationship between financial institutions and the real economy.

The sample is constructed by syndicated loans to non-financial firms in the U.S. from financial institutions in 26 international countries. Lending specialization is classified by two-digit Standard Industrial Classification (SIC) codes. To measure the similarity of banks in a S-dimensional space, the Euclidean distance between bank i and bank j is estimated for each month as follows.

$$Distance_{i,j,t} = \frac{1}{\sqrt{2}} \times \sqrt{\Sigma_{j=1}^{n}(w_{i,s,t} - w_{j,s,t})^2} \tag{1}$$

where $w_{i,s,t} = \frac{L_s}{\sum_{s=1}^{n} L_s}$, with syndicated loan of bank i invested in specialization s, L_s, within the 12 months prior to month t. The distance is normalized between 0 and 1; 0 refers to perfectly matched portfolios and 1 refers to portfolios that do not overlap at all. Figure 2 illustrates the processo of network construction based on the syndicated loan. Lenders are divided into two groups: lead arranger and participant. We make the interbank loan network of lead arranger banks. That is why the lead arranger is the major decision marker for loan agreements and set the interest rate of loan pricing.

We then construct inter-bank networks by Planar Maximally Filtered Graph (PMFG) (Tumminello et al. 2005). The most common method for form a stock network is based on the correlation of stock returns using threshold (Onnela, Kaski, and Kertész 2004; Chi, Liu, and Lau 2010). This method has a problem where the correlation coefficient only assumes linear relationship and leading to neglect information. In addition, the minimum spanning tree (MST), a tree formed by a subsets of edges of a given undirected graph, is also a common method in network analysis (Onnela, Chakraborti, et al. 2003). However, this method reflects hierarchical clustering with information lost to generate an efficient network. To address this issue, we use the PMFG algorithm to construct optimal network structures based on syndicated loans.

2.3. Key Variables

2.3.1. Degree Centrality

Generally, centrality refers to a bank's location in a network compared to that of others. The four indices of centrality are frequently discussed in the social network literature (Newman 2003). These four indices are degree centrality, eigenvector centrality, closeness centrality, and betweenness centrality. These indices represent different dimensions of connectedness that affect information sharing via a network or risk propagation. Degree centrality is the sum of the first-degree connections of an entity in a network. The raw score is divided by the total number of nodes in the network minus 1 because the size of the interbank network changes each month (Wasserman, Faust, et al. 1994).

2.3.2. Cost of credit

The dependent variable cost of credit is the natural logarithm of the All In Spread Drawn(AISD) of loan facility l initiated at time t, defined as the total (fees and interests) annual spread paid over LIBOR for each dollar drawn down from the loan. This variable is a well-known proxy for the pricing of the syndicated loan. It means the interest margin of the interbank loan rate charged to borrowers on the drawn portion of the loan, denoting the spread over LIBOR followed by the literature (Berg, Saunders, and Steffen 2016; Hasan, Politsidis, and Sharma 2021). The main finding is not sensitive to loan spread measures. This paper provides consistent results when we use All-In Spread Undrawn(AISU) as a proxy of bank spread.

2.3.3. Control variables

We control the variables at the bank level and loan contract level following the literature (Schwert 2018; Cai et al. 2018b; Hasan, Politsidis, and Sharma 2021). To control bank characteristics, we use bank capital and bank size measured by the log of total assets. Bank ROA is defined as the net income divided by total assets. To control loan level, we use loan maturity, number of lenders, and loan amount. The loan amount is the bank allocation of the loan contract. In addition, the log of GDP per capital and GDP growth are included in control variable. Refinancing is an indicator variable that shows having previous relationship between the bank and the firm. Then, we check the lender-,

lender country-, borrower industry-, and year-fixed effect. To robustness check, we also utilize the fixed effect by deal purpose and loan type.

In our sample, a significant proportion of lead arrangers operate as subsidiaries of large bank holding companies. In our analysis, we utilize accounting variables at the bank holding company level rather than at the subsidiary level. Lead arrangers affiliated with bank holding companies are subject to control over management and corporate policies. In contrast, lead arrangers that are not owned by holding companies typically operate under their own regulatory framework. Figure 3 indicates distinct patterns between these two groups. The distance of loans to industries among lead arrangers associated with bank holding companies is lower than that among lead arrangers that are not owned by holding companies, which means high similarity of loan portfolio strategy among lead arrangers under the control of bank holding companies. It is consistent concept with the literature that the loan growth at banking subsidiaries is sensitive to the overall position and policies of the holding company (J. Houston, James, and Marcus 1997; Ashcraft 2008; Schwert 2018).

2.3.4. Instrument Variable

To quantify this influence and its potential impact on loan decisions, we employ the "peer degree centrality" as an instrumental variable in our two-stage least squares (2SLS) regression. This measure captures the average centrality of a bank's peers in the syndicated loan market. Peers are identified based on their joint roles as lead arrangers for a loan facility within a specific month. A higher value of peer degree centrality suggests that a bank's peers are more central and potentially have a greater influence within the syndicated loan market. Banks with higher peer degree centrality might be better positioned to access market sentiments or soft information due to their extensive interactions and relationships with other market participants (J. F. Houston, Lee, and Suntheim 2018). A bank with a high peer degree centrality might indirectly benefit from this soft information through its relationships with central peers. This instrumental variable isolates the direct impact of a bank's centrality from the indirect effects stemming from its peers, providing a differ understanding of the determinants of loan decisions in the syndicated loan market.

3. Syndicated Loan Network and the Risk Exposure

In this section, we examine the degree distribution of the PMFG network created from syndicated loans in 26 international countries. We then investigate the impact of network topology and investment characteristics on loan pricing. Interbank networks that emerge due to information asymmetry during the lending process could affect loan pricing. Banks, in the absence of information on borrower creditworthiness, need to rigorous screening and monitoring. They might seek higher compensation through loan pricing. Previous studies on systemic risk have identified network connectivity and centrality as channels that transmit contagions related to negative events, indicating that a highly interconnected structure can increase systemic risk (Battiston et al. 2012; Elliott, Golub, and Jackson 2014; Demirer et al. 2018; Cai et al. 2018b). Therefore, we expect that banks with greater connectivity within the syndication network are positioned more precariously in terms of risk exposure. This increased susceptibility to systemic shocks is hypothesized to translate into higher loan spreads, serving as a compensatory mechanism for the heightened risk profile.

3.1. The Analysis of Interbank Network

The structure of interbank networks created during bank-firm lending processes can affect bank performance due to the degree of information asymmetry. Banks with higher information asymmetry may emulate the loan portfolio structure of banks with lower information asymmetry to reduce such asymmetry and generate profits. The literature on systemic risk highlights network connectivity and centrality as channels that transmit contagions related to the tranquil period, meaning that a highly interconnected structure can increase systemic risk (see, e.g.,Battiston et al. 2012; Elliott, Golub, and Jackson 2014; Demirer et al. 2018; Cai et al. 2018b). Ultimately, higher connectivity and rapid propagation of negative shocks in bank-to-bank networks can enable high-centrality banks to address market instability. Therefore, we expect that well-connected banks experience higher levels of pricing information, including lower levels of information asymmetry than poorly connected banks.

Since the amount of syndicated loans is related to asset exposure, a decline in asset prices can affect the stability of the banking system. We analyze syndicated loans issued from 2000 to 2020 and observe that the number of syndicated loans reflects the state of the financial market (see Figure 1). We measure the market size of syndicated loans in each quarter as the total amount of syndicated loans divided by the number of loans. Both the market size and the number of syndicated loans follow a similar pattern. The market size of syndicated loans gradually increased in 2003 and continued to rise until Q4 of 2007, finally decreasing in 2009. However, the number of syndicated loans increased in 2009. It could be the case that a number of syndicated loans with small market size were issued in 2009. It is also possible that the increase in the number of loans was due to changes in the market conditions, such as increased demand for credit or changes in lending standards.

The main objective of this paper is to investigate the relationship between the bank degree and loan spread. We assume that banks with higher connections to other banks possess more private information about firms than others according to monitoring such as due diligence. To test the validity of our hypothesis, we construct an interbank network using the PMFG method based on loan portfolio data in Figure 2 (Tumminello et al. 2005). During the global financial crisis, the largest 200 lenders had massive connections with lenders from 26 international countries in Figure 4. We check the our sample including the majority of Systemically Important Financial Institution. When each bank's loan portfolio tends to have a distinct and unique investment strategy, the interbank network would be disconnected, and each bank would correspond to a random network. With this concept of sectoral similarity, Oh and Park 2021 reveals the interbank networks we constructed as same ways tend to follow the distribution of power law, which means the existence of hub lenders. Some hub lenders have better connections than other lenders, causing information asymmetry among lenders in the syndicated loan market. When a lender has more information than other lenders, they can earn a profit from the loan contract. Moreover, they have greater risk exposure due to default risk during tranquil periods.

3.2. Hierarchical Structure of Interbank Network

Figure 6 shows a time series pattern between average degree centrality and CBOE Volatility Index (VIX). The VIX index represents market expectations of investor for volatility and is often used the "fear index" because it tends to spike during times of market turmoil. The relationship implies that as the interbank network becomes more interconnected (i.e., higher average degree centrality), there's a correspondence with market volatility. Specifically, transition probabilities like CC(from core to core) or PC(from peripheral to core) indicate the chances of a bank moving from one category (core or periphery) to another over time. An increase in these probabilities during a recession indicates that more banks are moving towards the core in the Figure 7. The core in network theory usually refers to central, highly connected nodes. The observed transition in the network, especially during market instabilities, might be due to a "flight to quality" effect. This is an investment strategy where investors move their capital to safer assets or sectors during periods of market turmoil. In the context provided, it seems banks prefer not to invest in specific industries that might be perceived as risky during economic downturns. By using the Figure 8, this paper also ruled out the possibility that the observed network changes were simply due to an increase in the number of core lenders. This is important as it strengthens the argument that the observed patterns are indeed due to underlying economic and market dynamics and not just structural changes in the number of core lenders.

In summary, during periods of market instability, the structure of interbank networks based on sectoral similarity changes, reflecting a possible flight to quality among banks. This change in network structure also related with increased market volatility.

3.3. Realized Volatility and Degree of Interbank Network

This section seeks to investigate the association between a bank's position in a syndicated loan network and the volatility observed in the bank's stock returns. The degree of centrality is a measure of the importance or influence in the interbank network. The lenders with a high degree centrality mean that the lenders are more connected and has a significant role within the network. This centrality is used to gauge a bank's risk exposure, especially how vulnerable it might be to the propagation of financial shocks. We employ the following specification:

$$Realized\ volatility_{it} = a_0 + a_1 Bank\ degree_{it} + a_2 X_{it} + u_{lt} \tag{2}$$

The dependent variable of Realized volatility is the historical return volatility of stock return. It measures standard deviation of stock returns within the 12 months prior to month t. It is possible to construct a systemic risk indicator based on the concepts of realized volatility measure (Diebold and Yılmaz 2014; Dungey, Luciani, and Veredas 2018) The independent variable of Bank degree is the bank's measure of risk exposure to the entire syndicated loan market. The vector a_0 denotes different types of fixed effects, X is a vector of control variables and u is a stochastic disturbance. Column (1) of Table 2 offers the most parsimonious specification, where we regress the Bank realized volatility on Bank degree and a constant term. The coefficient on our network measure is positive and statistically significant at the 1% level. The sign and magnitude of coefficients are in line with the prior literature (see Hasan et al. 2021).

This result suggests that banks occupying a central position in the syndicated loan network are notably more exposed to systemic risks within the global syndicated loan market. Institutions with high leverage are especially vulnerable to these systemic risks. When these central banks face adverse shocks, the leveraging effect can amplify the impact, leading to a significant decline in their equity value. This amplified effect, in turn, manifests as heightened volatility in their stock returns. Such pivotal banks, given their interconnectedness, are more susceptible to reverberations from global financial shocks, a susceptibility that is reflected in the greater volatility of their stock prices. Therefore, in this context, we equate the degree of a bank in the syndicated network with its risk exposure.

4. Syndicated Loan Network and the Loan Pricing

4.1. The Effect of Interbank Network's Degree on Loan Pricing

In this section, we investigate the impact of interbank network degrees on loan pricing. As illustrated in Figure 5, there appears to be a positive correlation between the degree of connections a bank has and its informational advantage, likely stemming from its extensive dealings and interactions with other financial institutions. This informational edge could potentially empower banks in the bargaining process when setting loan prices. To ensure robustness in our analysis and account for other factors that might influence loan pricing, we control for loan maturity, loan amount, and the number of lenders in the syndicated loan, as well as bank properties such as size, ROA, and capital. Following the literature Hasan, Politsidis, and Sharma 2021, we include the one-year lags of bank control variables. In addition, our regression model accounts for bank-, lender country-, borrower industry-, and year- fixed effects. The regression equation is as follows:

$$Cost\ of\ credit_{lt} = a_o + a_1 Bank\ degree_{bt} + a_2 Controls_{kt} + u_{lt} \tag{3}$$

The dependent variable is the all-in spread drawn (AISD) of the loan facility, which represents the interest margin on the drawn portion of the loan relative to LIBOR, following previous studies (Berg, Saunders, and Steffen 2016; Hasan, Politsidis, and Sharma 2021). Table 3 shows that the coefficient of bank degree is positive (16.8) and statistically significant at the 1% level, indicating that a one standard deviation increase in network degree leads to a 0.6 basis point increase in the AISD (=16.8 basis point $\times$ 0.0036). This finding suggests that higher-degree banks charge higher interest rates on loans, highlighting the impact of the interbank network on loan pricing. One limitation in our study is its restricted control over borrower-side attributes, with only borrower industry effects considered. The financial health of a borrower may influence the quality and quantity of information accessible to banks. We believe this area warrants further exploration. In addition, consistent results are observed when we adopt an alternate measure for bank spread, specifically the all-in spread undrawn (AISU), as seen in Table 8.

Syndicated loans have different loan characteristics, such as deal purpose and loan type, could potentially influence loan pricing (Berg, Saunders, Steffen, and Streitz 2017; Cai et al. 2018a; Berlin, Nini, and Edison 2020). Loans can serve various purposes, from refinancing to acquisition financing or addressing working capital needs. Each purpose might have distinct risk implications that could affect pricing. Similarly, the type of loan, be it a term loan, revolving credit, or bridge loan, brings its own set of parameters, including repayment structures and associated covenants. By using the fixed effects based on these loan-specific characteristics, this approach helps to address the potential omitted variables related to the nature of the loan itself in Table 9.

As a result, the positive association between network degree and loan pricing underscores the significance of diverse connections in the interbank network. Banks with vast and varied interactions can gain a competitive edge, not just in terms of information but also in terms of their influence on loan pricing. For the perspective of loan supplier, understanding the importance of their position in the syndicated loan network can be strategically crucial. If centrality in the network translates to higher loan pricing, banks might pursue strategies to expand and diversify their connections. Otherwise, banks with lower degree centrality tend to specialization into specific industry, so they used to lock in effect in bargaining process (Gupta et al. 2023).

4.2. Analyzing Peer Interactions in Syndicated Loan Decisions

The syndicated loan market, characterized by its collaborative structure, inherently fosters an environment ripe for peer effects. Multiple banks unite to finance a single borrower, leading to extensive information sharing and benchmarking against peers. This frequent interaction cultivates robust interbank relationships, where actions of one institution can influence others. Additionally, the need for risk diversification and coordination amplifies the tendency of banks to align their strategies with those of their peers. In such a setting, market norms and conventions, often set by influential banks, can quickly become standard practice, further reinforcing the strength of peer effects in this market.

Table 4 shows a two-stage least-squares regression to elucidate the relationship between degree centrality excluding peer effect and the All-In Spread Drawn. We use peer degree centrality as an instrument variable, which banks might consider their strategies based on peer actions. Peer effects have influenced investment decisions and financial market instability (Bursztyn et al. 2014). We define peer degree centrality as the mean centrality of peer banks, identified when lead arrangers have jointly worked on another facility as lead arrangers within a specific month. We focus on the lead arranger because there is information asymmetry between lead arrangers and participants. Dependent variable in the first stage is degree centrality and this in the second stage is All-In Spread Drawn. This Two-stage Least Square method findings align with the OLS regression in Table 3, underscoring the consistency and robustness of our results.

4.3. The Impact of Degree on Loan Pricing according to Bank Capital

Bank capital plays an important role in the bank-firm matching mechanism and in the volatility of connectedness in the syndicated loan market (see Schwert 2018; Chen 2022). To investigate this further, we divided banks into three categories based on their capital with upper(lower) bound 30%: Small, Middle, and Large. Table 5 presents the results of the OLS regression of degree on loan spread, using Equation 3 for each bank capital category. We find positive and significant coefficients across all three subsamples, indicating that the degree of a bank's syndicated loan network plays a significant role in loan pricing, regardless of bank capital. Interestingly, the coefficient for large banks (7.61, $P<0.01$) is lower than that for small banks (19.12, $P<0.01$), suggesting that smaller banks may have a stronger influence of degree on loan pricing. For omitted-variable bias, we also include additional fixed effects for loan purposes and loan types. Our results are consistent with the baseline findings. When analyzing the variation in connectedness based on firm size, consistent with findings related to bank capital, we observe consistent results, corroborating the insights of Cai et al. 2018b. Further, we shift to external, macro-level factors like government restrictions due to the pandemic in the next subsection.

4.4. Government Restriction related to COVID-19 Pandemic

In this section, we discuss the impact of government restrictions related to the COVID-19 pandemic on the domestic economy and lenders' exposure, drawing on existing literature (Hasan, Politsidis, and Sharma 2021). With the rapid spread of the pandemic, governments implemented regulations to control its speed, which resulted in increased demand for limited funding sources by firms, leading to abnormal supply situations. To capture the uncertainty levels of lenders in each country, we used the stringency index of Hale et al. 2020. It represents variation of individual policy response indicator reflected by the degree of risk-aversion of each country.

Table 6 shows that loans from lenders in countries with high stringency index result in additional costs for borrowers, suggesting that higher levels of restriction during the COVID-19 pandemic deepen the impact on borrowers' costs. To further control for economic status, we classified the sample into the normal period and tranquil period using the 2008-2009 global financial crisis and the COVID pandemic. Regardless of the economic status, our results show that degrees have a statistically positive impact on loan spread in Table 7.

5. Conclusion

Banks occupying central positions in the interbank loan network inherently possess enhanced access to information, giving them a pronounced influence within the syndicated loan market. This paper employed network centrality measures to explore the relationship between loan spread and network topology.

In summarizing our results, banks with a high number of connectedness have a substantial impact on realized volatility, indicating their critical role in the market. This increased risk exposure subsequently leads to higher borrowing costs for borrowers, a crucial insight for risk management. During the COVID-19 pandemic, consistent result were observable due to lenders' exposure across different jurisdictions, including Global Systemically Important Bank (G-SIB).

A primary contribution of our work is the identification of a subset of systemically important (core) banks within the network, facilitating the analysis of systemic risk. Understanding the topology of the syndicated loan network is paramount for ensuring financial stability and resilience. Firms encounter a range of borrowing conditions that can shift considerably throughout the business cycle. This knowledge is invaluable for subsequent studies focusing on crisis management, bank decision-making monitoring, and banks' own risk management strategies.

In conclusion, our study offers insights relevant to both future research and policymakers. It highlights the evolving landscape of financial intermediaries and the importance of network centrality in the syndicated loan market. Additionally, our findings provide valuable perspectives on the risk management and lending mechanisms between banks and firms. Furthermore, these results suggest that future research could explore the interaction between investment in technological development for borrowers or projects related to sustainable finance.

6. Acknowledgement

The authors thank seminar participants and discussant, Junho Oh, Soku Byoun, Jocelyn Evans, and Hyeong Keun Koo, as well as attendees at and the conference of Financial Management Association 2023, Computing in Economics and Finance 2023 in Nice, Econophysics Colloquium 2022, Networks 2021 "A Joint Sunbelt and NetSci Conference", and the conference of 2019 NetSci-X in the University of Vermont Complex Systems Center, Burlington for helpful comments and suggestions. The conclusions, views, opinions and errors are those of the authors. This work was supported by NRF (National Research Foundation of Korea) Grant funded by the Korean Government(NRF-2022R1F1A1068796).

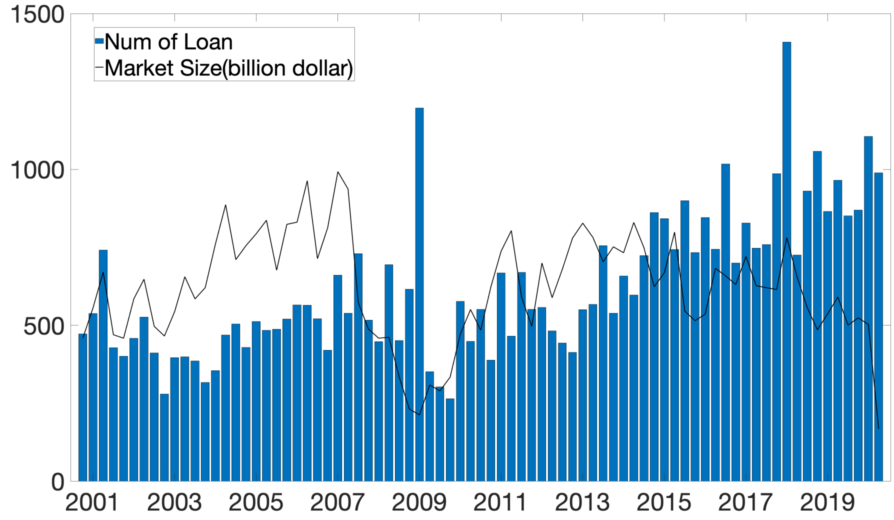

Figure 1: Syndicated loan market in the United States from 2000 to 2020. The figure describes market size and the number of loans extended by lead arrangers to borrowers every quarter. Market size is defined as the mean of the loan amounts extended by each bank.

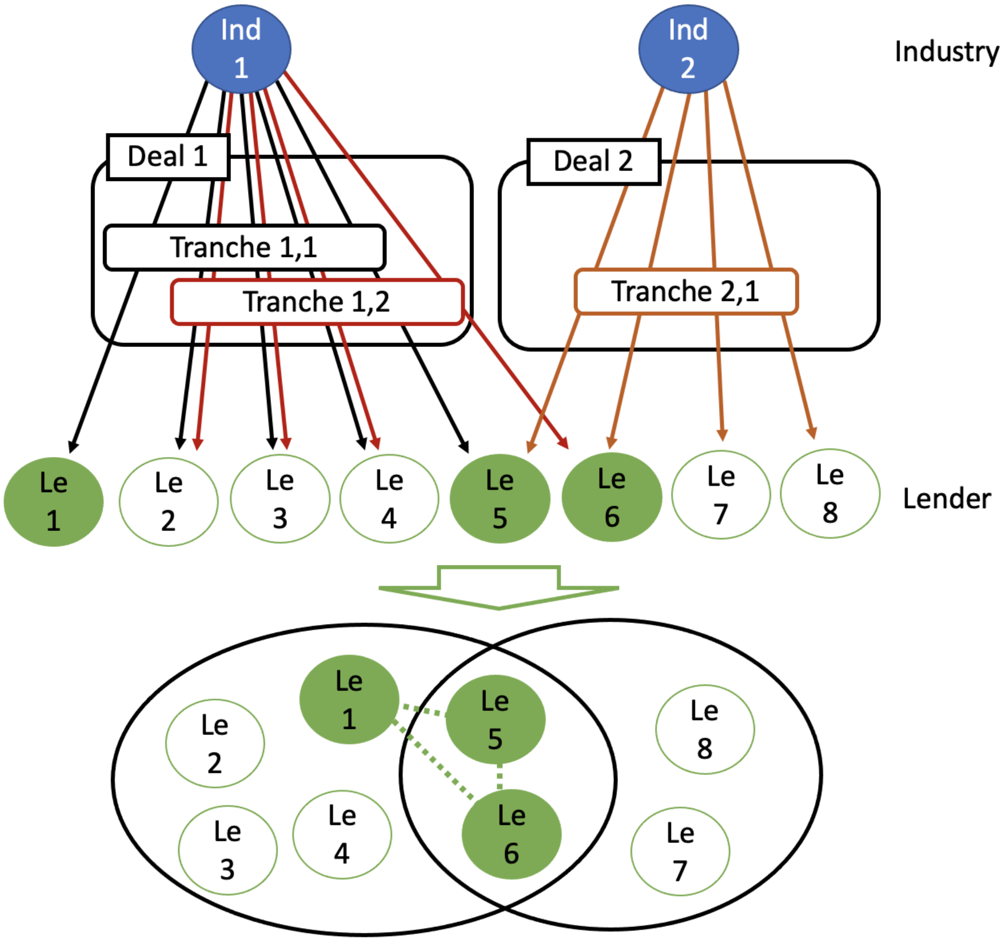

Figure 2: An example of loan structure for network construction. This figure illustrates the network construction by PMFG algorithm. The similarity of loan portfolio between two banks is calculated by 12 industrial classification based on SIC.

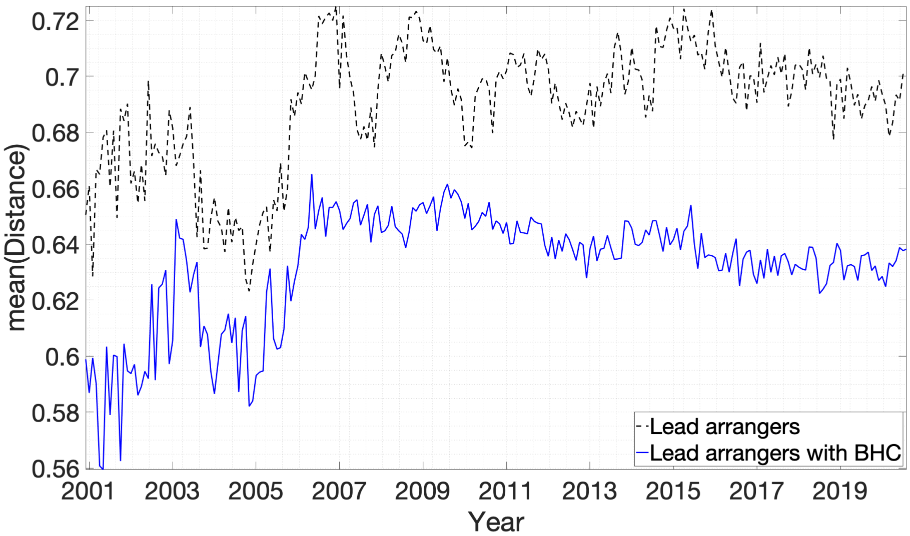

Figure 3: Distance of loan to industries among lead arrangers. This figure explains the time varying trend of average distance using two distinct groups: one group is lead arrangers that are not owned by holding companies, the other group is lead arrangers with Bank Holding Company (BHC). Distance is calculated by the dissimilarity of loan to each industry sector between the lead arrangers.

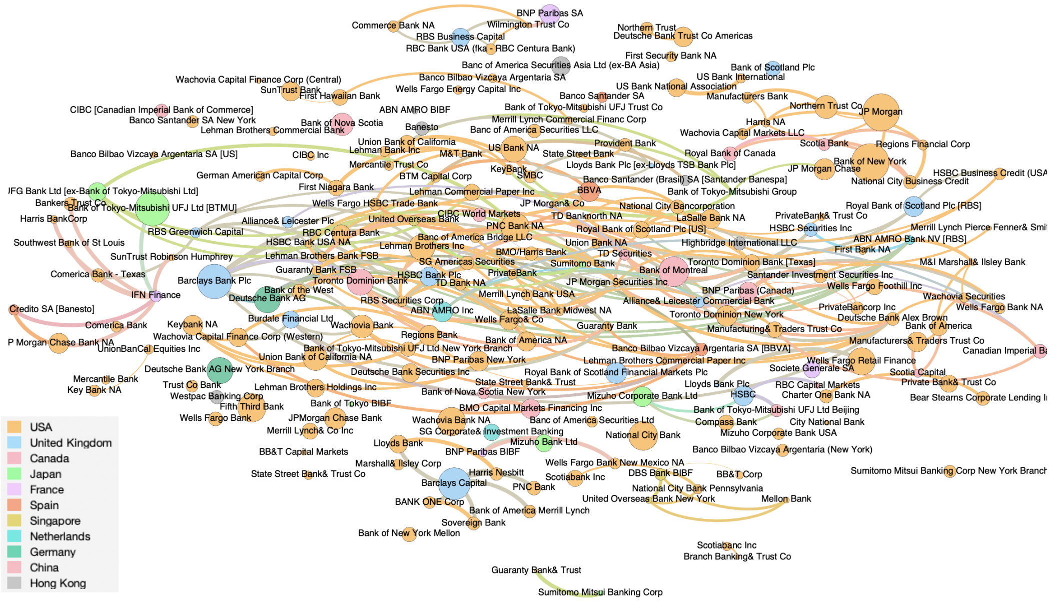

Figure 4: Configuration of Syndicated Loan Network using largest 200 banks in 2008. The nodes represent each bank, and the node size is determined by the corresponding bank's degree centrality. A node color represent each country.

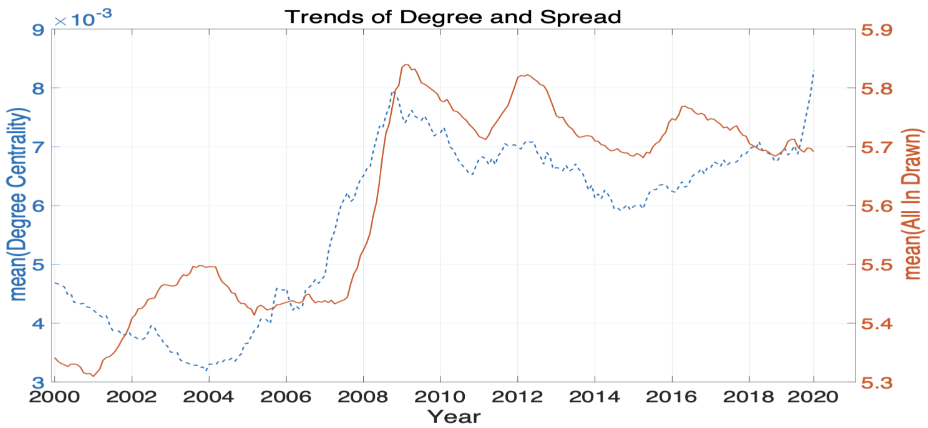

Figure 5: Relation between degree of interbank network and the cost of credit. The interbank networks are constructed by PMFG algorithm based on the similarlity of loan portfolio during 12 months. The cost of credit is the log of the All In Spread Drawn(AISD), defined as the total (fees and interests) annual spread paid over LIBOR for each dollar drawn down from the loan.

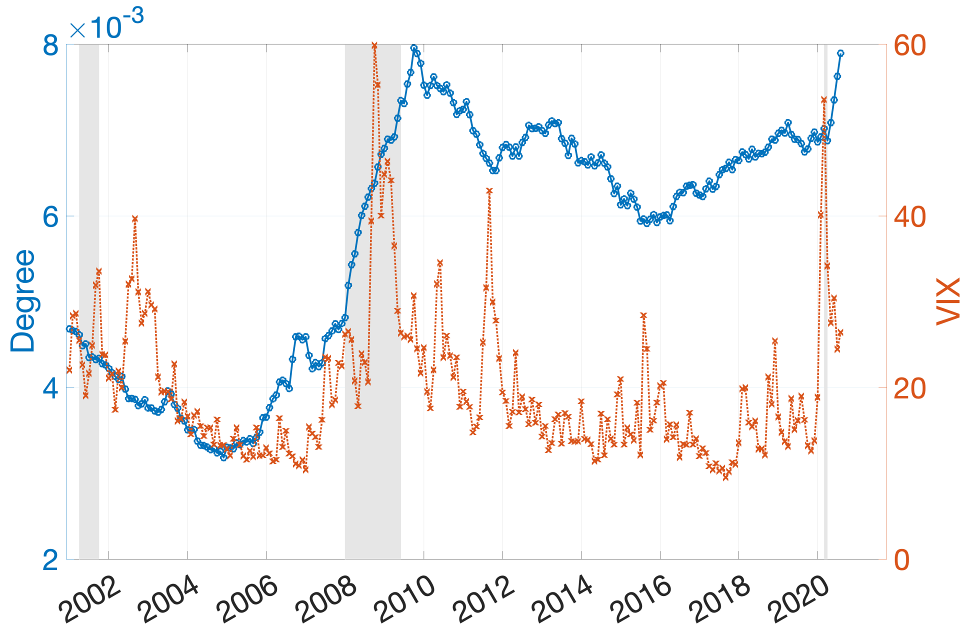

Figure 6: Relation between degree centrality of interbank network and CBOE Volatility Index from 2000 through 2020. The interbank networks are constructed by PMFG algorithm based on the similarlity of loan portfolio during 12 months.

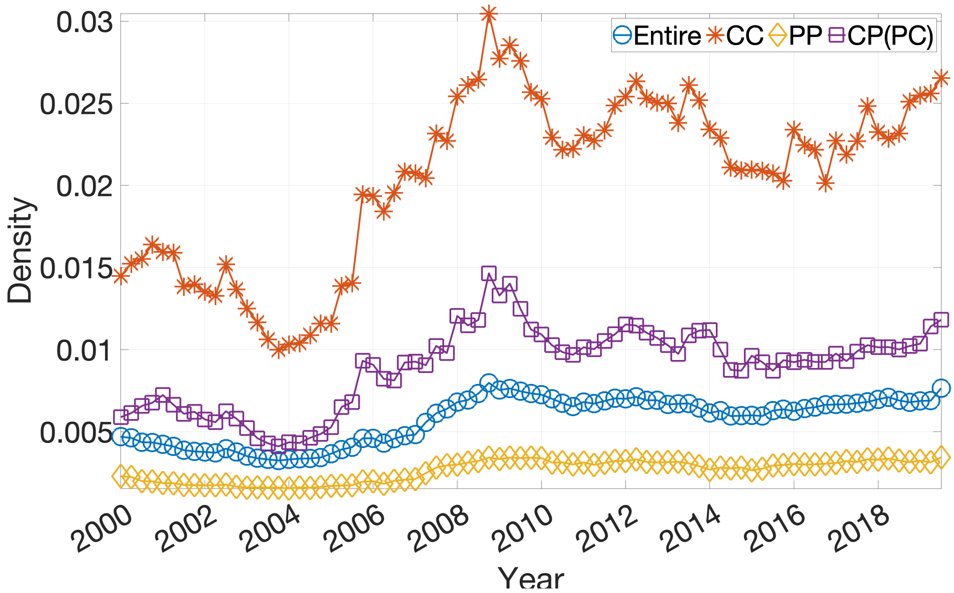

Figure 7: Transition Probability among Core lenders and Peripheral lenders. Core lenders are designated as central position in the interbank network.

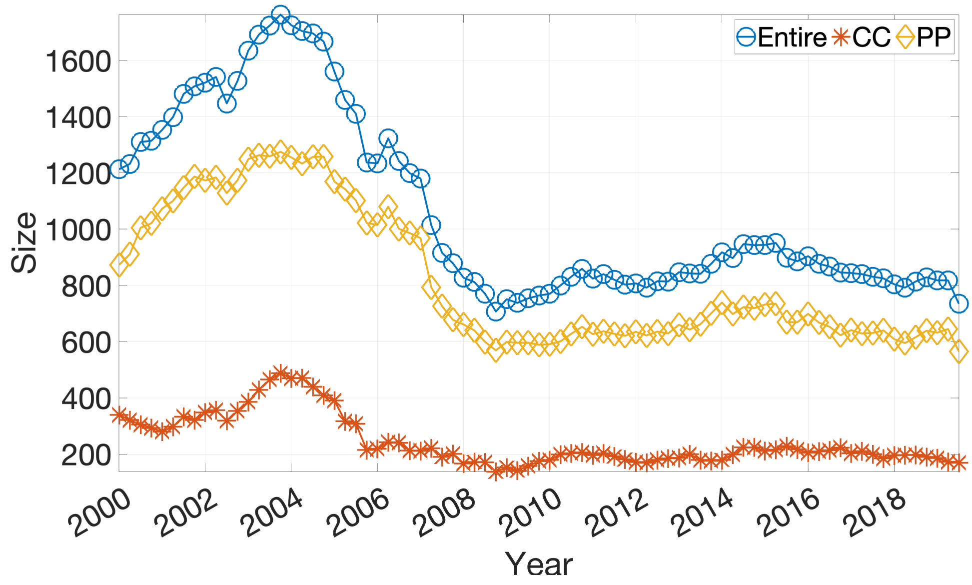

Figure 8: The number of nodes classified as Core lenders and Peripheral lenders. Core lenders are designated as central position in the interbank network.

Table 1: Summary statistics. This table reports summary statistics (number of observations, mean, standard deviation, minimum, and maximum) for all variables used to estimate the main text. All variables are defined in Section 2.

	Obs.	Mean	Std	Min	Max
AISD	54,528	5.0870	0.7448	2.9957	6.5511
Degree	54,528	0.0069	0.0036	0.0014	0.1691
BankSize	54,528	13.7698	0.7080	10.8545	14.8288
BankROA	54,528	0.0059	0.0026	0.0004	0.0185
BankCapital	54,528	0.0482	0.0121	0.0241	0.1201
LoanAmount	54,528	5.8684	1.3684	1.6094	8.5172
Maturity	54,528	3.8528	0.5501	2.0794	4.4998
RealizedVol	54,528	0.7375	0.9174	0.0000	8.4106
GDPperCapita	54,528	10.9800	6.6607	1.0000	46.0000
GDPgrowth	54,528	10.5933	0.2465	6.0125	11.7254

Table 2: Degree centrality via syndicated loan network and realized volatility. The table reports coefficients and t-statistics. The dependent variable is realized volatility and all variables are defined in section 2. The estimation method is OLS regression. All specifications include year, and lender's country fixed effects. The symbols *, **, and *** indicate statistical significance at 10%, 5%, and, 1%, respectively.

	(1)		(2)		(3)		(4)	
Degree	2.5422***	(3.1492)	2.2373***	(2.7704)	2.6507***	(3.2932)	2.1326***	(2.5033)
Bank size			0.0306***	(7.331)	0.0202	(4.7995)	0.0596***	(11.8590)
Bank ROA					-15.6740***	(-14.4472)	-24.587***	(-20.0910)
Bank Capital							5.1028***	(16.3870)
Intercept	0.3844	(0.4707)	-0.0183	(-0.0224)	0.2764	(0.3392)	-0.4847	(-0.5717)
Observations	26,796		26,796		26,796		23405	
Year FEs	Yes		Yes		Yes		Yes	
Country FEs	Yes		Yes		Yes		Yes	
Adj. R^2	0.216		0.217		0.223		0.211	

Table 3: Lender's degree and spread(2000-2020). The table reports coefficients and t-statistics. The dependent variable is AISD and all variables are defined in section 2. The estimation method is OLS regression. All specifications include bank- lender's country-, borrower industry-, year fixed effect. The symbols *, **, and *** indicate statistical significance at 10%, 5%, and, 1%, respectively.

Dependent Variables	Spread	
Degree	16.6719***	(21.3980)
Bank ROA	-40.2334***	(-25.5609)
Bank Size	-0.0377**	(-4.3223)
Bank capital	-4.0111***	(-11.2396)
Loan amount	-0.1627***	(-71.9167)
Maturity	0.2686***	(55.6156)
Num. of Lenders	-0.0216***	(-46.4671)
GDPperCapita	-0.0174***	(12.0607)
GDP growth	0.0985***	(5.1087)
Refinancing	-0.1195***	(-21.2950)
Intercept	-45.1628***	(-24.0162)
Observations	54,528	
FEs	Yes	
Adj. R^2	0.421	

Table 4: Two-stage least squares regression using peer degree centrality as the instrumental variable. The table reports coefficients and t-statistics. Peer degree centrality is defined by the average centrality of peer banks. They are designated when the lead arrangers have collaborated on another facility as lead arrangers together for a given month. In the first stage, the dependent variable is degree centrality. In the second stage, the dependent variable is All-In Spread Drawn, and all variables are defined in section 2. All specifications include bank- lender's country-, borrower industry-, year fixed effect. The symbols *, **, and *** indicate statistical significance at 10%, 5%, and, 1%, respectively.

Dependent Variables	First Stage: Degree		Second Stage: Spread	
Degree			0.0388***	(14.7908)
PeerDegree	0.2401***	(25.4658)		
ROA	-0.0136	(-1.2513)	-56.4088***	(-29.6798)
Size	0.0012***	(21.3366)	0.0787***	(7.7296)
Capital	-0.0741***	(-29.7914)	-5.7613 ***	(-12.9713)
Loan amount	0.0001***	(5.8088)	-0.1392***	(-58.2040)
Duration	0.0000	(-1.2093)	0.2750***	(50.5407)
NumLender	0.0000	(0.0020)	-0.0234***	(-45.1210)
GDPperCapita	0.0000***	(-3.7372)	-0.0120 ***	(-7.7152)
GDP growth	-0.0015***	(-11.8810)	0.0386*	(1.7482)
Refinancing	0.0000	(-0.9743)	-0.1279***	(-21.3138)
Intercept	-0.3701***	(-29.6782)	-38.6806***	(-17.8555)
Observations	41,489		41,488	
FEs	Yes		Yes	
Adj. R^2	0.243		0.417	

Table 5: Lender's degree and spread according to bank capital. The table reports coefficients and t-statistics. The dependent variable is AISD and all variables are defined in section 2. The estimation method is OLS regression. All specifications include bank- lender's country-, borrower industry-, year fixed effect. (1)Small, (2)Middle, and (3)Large banks are classified by the upper(lower) bound 30% capital of banks. The symbols *, **, and *** indicate statistical significance at 10%, 5%, and, 1%, respectively.

	(1)		(2)		(3)	
Degree	19.1224***	(10.5063)	8.5951***	(8.1547)	7.6120***	(5.5151)
Bank ROA	-3.0941	(-0.9098)	-39.1476***	(-16.2538)	-23.2962***	(-7.6995)
Bank size	-0.2431***	(-12.2818)	-0.0333**	(-2.3258)	-0.0087	(-0.5700)
Bank capital	-9.7948***	(-6.6286)	-19.7224***	(-14.0943)	5.4133***	(6.4916)
Loan amount	-0.2061***	(-42.2022)	-0.1411***	(-44.2986)	-0.1357***	(-36.3854)
Maturity	0.2743***	(30.8954)	0.2662***	(35.6624)	0.2995***	(36.6732)
Num. of Lender	-0.0205***	(-22.3994)	-0.0207***	(-30.0135)	-0.0158***	(-19.3796)
GDPperCapita	0.0000***	(-16.5114)	0.0000***	(5.0069)	0.0000	(-0.9870)
GDPgrowth	-0.0481***	(-13.7971)	-0.0324***	(-12.2602)	-0.0059***	(-3.1199)
Refinancing	-0.0560***	(-4.7995)	-0.1206***	(-14.9535)	-0.1298***	(-13.9695)
Intercept	-258.5902***	(-31.1540)	-59.5003***	(-19.5870)	-36.8744***	(-10.9827)
Observations	16,419		21,821		16,288	
Year FEs	Yes		Yes		Yes	
Lender FEs	Yes		Yes		Yes	
BorrowerIndustry FEs	Yes		Yes		Yes	
LenderCountry FEs	Yes		Yes		Yes	
Adj. R^2	0.451		0.439		0.436	

Table 6: Government restrictions related COVID-19 Pandemic (2020). The table reports coefficients and t-statistics. The dependent variable is AISD and all variables are defined in section 2. The estimation method is OLS regression. Second specifications include the interactions of the lender exposure measures with lender stringency measures by Hale, Angrist, Kira, Petherick, Phillips and Webster (2020). The lender's stringency measure is an index (0-100) that aggregates various measures of government responses to COVID-19 in the lender's country. Fixed effects include lender country-, borrower industry- fixed effects. The symbols *, **, and *** indicate statistical significance at 10%, 5%, and, 1%, respectively.

	(1)		(2)	
Degree	9.9338***	(5.8861)	5.2759***	(2.9593)
Bank ROA	-17.2777***	(-4.9103)	-18.0582***	(-5.1606)
Bank size	-0.0129*	(-1.781)	-0.0109	(-1.5131)
Bank capital	2.7060***	(4.1480)	2.8757***	(4.4318)
Loan amount	-0.1197***	(-25.6387)	-0.1191***	(-25.6627)
Maturity	0.0878***	(9.0623)	0.1173***	(11.3208)
Degree*Stringency Index			0.1925***	(7.7148)
Intercept	5.3019***	(24.1605)	5.1429***	(23.4707)
Observations	4930		4930	
BorrowerIndustry FEs	Yes		Yes	
LenderCountry FEs	Yes		Yes	
Adj. R^2	0.196		0.206	

Table 7: Lender's degree and spread according to market status. The table reports coefficients and t-statistics. The dependent variable is AISD and all variables are defined in section 2. The estimation method is OLS regression. All specifications include bank- lender's country-, borrower industry-, year fixed effect. Normal period is excluding observations corresponding 2008-2009 financial crisis and COVID pandemic. The symbols *, **, and *** indicate statistical significance at 10%, 5%, and, 1%, respectively.

Panel A: 2008-2009 global financial crisis		
Degree	17.71***	(11.76)
Bank size	-0.04***	(-8.15)
Bank ROA	-45.22**	(-29.53)
Bank capital	-3.58***	(-8.49)
Loan amount	-0.12***	(-27.85)
Maturity	0.12***	(10.61)
Intercept	6.52***	(54.94)
Observations	9,837	
FEs	Yes	
Adj. R^2	0.21	
Panel B: COVID pandemic (2020)		
Degree	5.01***	(2.64)
Bank size	-0.01	(-1.38)
Bank ROA	-11.53***	(-2.94)
Bank capital	2.40***	(3.73)
Loan amount	-0.12***	(-24.33)
Maturity	0.13***	(12.29)
Intercept	5.14***	(33.08)
Observations	4,243	
FEs	Yes	
Adj. R^2	0.20	
Panel C: Normal period		
Degree	9.43***	(30.35)
Bank size	-0.00	(-0.10)
Bank ROA	-17.11**	(-47.12)
Bank capital	-0.34***	(-4.16)
Loan amount	-0.21***	(-242.53)
Maturity	0.28***	(117.59)
Intercept	-39.86***	(-72.89)
Observations	224,569	
FEs	Yes	
Adj. R^2	0.33	

Table 8: Baseline result with variation by dependent variable (2000-2020). The table reports coefficients and t-statistics. The dependent variable is AISU and all variables are defined in section 2. The estimation method is OLS regression. All specifications include bank- lender's country-, borrower industry-, year fixed effect. The symbols *, **, and *** indicate statistical significance at 10%, 5%, and, 1%, respectively.

Dependent Variables	Spread	
Degree	15.8233***	(13.4858)
ROA	-34.3821***	(-15.3148)
Size	-0.0911***	(-7.1092)
Capital	-3.8035***	(-7.6714)
Loan amount	-0.2222***	(-61.6537)
Duration	0.3326***	(48.2085)
NumLender	-0.0056***	(-8.2041)
GDPperCapita	-0.0251***	(-11.4936)
GDP growth	0.1901***	(6.8309)
Refinancing	-0.0701***	(-7.6001)
intercept	10.1328***	(3.8474)
Observations	30,131	
FEs	Yes	
Adj. R^2	0.293	

Table 9: Lender's degree and spread with different fixed effect. The table reports coefficients and t-statistics. The dependent variable is AISD and all variables are defined in section 2. The estimation method is OLS regression. All specifications include bank- lender's country-, borrower industry-, year fixed effect. In addition, deal purpose and loan type fixed effect are included. The symbols *, **, and *** indicate statistical significance at 10%, 5%, and, 1%, respectively.

	(1)		(2)		(3)	
Degree	16.4138***	(22.5649)	16.5169***	(23.0512)	16.3223***	(23.8454)
Bank ROA	-41.3543***	(-28.5868)	-39.0763***	(-27.4329)	-39.7195***	(-29.1737)
Bank size	-0.0307***	(-3.7828)	-0.0280***	(-3.5077)	-0.0230***	(-3.0064)
Bank capital	-2.4769***	(-7.4587)	-2.7221***	(-8.3135)	-1.6356***	(-5.2271)
Loan amount	-0.1386***	(-64.9214)	-0.1820***	(-84.5215)	-0.1615***	(-77.2808)
Maturity	0.1643***	(34.6656)	-0.0280***	(-3.7399)	-0.0872***	(-11.8075)
Num. of Lender	-0.0181***	(-40.8610)	-0.0097***	(-21.5663)	-0.0100***	(-23.0981)
GDPperCapita	-0.0190***	(-14.1741)	-0.0162***	(-12.2820)	-0.0177***	(-14.0107)
GDPgrowth	0.0514***	(2.8381)	0.1518***	(8.5308)	0.1143***	(6.6675)
Refinancing	0.0398***	(6.8259)	-0.0886***	(-16.9210)	0.0272***	(4.9289)
Intercept	-33.0057***	(-18.6972)	-35.1109***	(-20.2941)	-27.6311***	(-16.5713)
Observations	54,528		54,528		54,528	
Deal Purpose FEs	Yes				Yes	
Loan Type FEs			Yes		Yes	
Year FEs	Yes		Yes		Yes	
Lender FEs	Yes		Yes		Yes	
BorrowerIndustry FEs	Yes		Yes		Yes	
LenderCountry FEs	Yes		Yes		Yes	
Adj. R^2	0.497		0.511		0.555	

References

Acemoglu, Daron et al. (2012). "The network origins of aggregate fluctuations". In: *Econometrica* 80.5, pp. 1977–2016.

Acharya, Viral V et al. (2017). "Measuring systemic risk". In: *The review of financial studies* 30.1, pp. 2–47.

Ashcraft, Adam B (2008). "Are bank holding companies a source of strength to their banking subsidiaries?" In: *Journal of Money, Credit and Banking* 40.2-3, pp. 273–294.

Battiston, Stefano et al. (2012). "Debtrank: Too central to fail? financial networks, the fed and systemic risk". In: *Scientific reports* 2.1, pp. 1–6.

Berg, Tobias, Anthony Saunders, and Sascha Steffen (2016). "The total cost of corporate borrowing in the loan market: Don't ignore the fees". In: *The Journal of Finance* 71.3, pp. 1357–1392.

Berg, Tobias, Anthony Saunders, Sascha Steffen, and Daniel Streitz (2017). "Mind the gap: The difference between US and European loan rates". In: *The Review of Financial Studies* 30.3, pp. 948–987.

Berlin, Mitchell, Greg Nini, and G Yu Edison (2020). "Concentration of control rights in leveraged loan syndicates". In: *Journal of Financial Economics* 137.1, pp. 249–271.

Bursztyn, Leonardo et al. (2014). "Understanding mechanisms underlying peer effects: Evidence from a field experiment on financial decisions". In: *Econometrica* 82.4, pp. 1273–1301.

Cai, Jian et al. (2018a). "Loan syndication structures and price collusion". In: *Available at SSRN 3250817.*

— (2018b). "Syndication, interconnectedness, and systemic risk". In: *Journal of Financial Stability* 34, pp. 105–120.

Chava, Sudheer and Michael R Roberts (2008). "How does financing impact investment? The role of debt covenants". In: *The Journal of Finance* 63.5, pp. 2085–2121.

Chen, Yehning (2022). "Bank interconnectedness and financial stability: The role of bank capital". In: *Journal of Financial Stability* 61, p. 101019.

Chi, K Tse, Jing Liu, and Francis CM Lau (2010). "A network perspective of the stock market". In: *Journal of Empirical Finance* 17.4, pp. 659–667.

Cont, Rama, Amal Moussa, and Edson Bastos e Santos (2010). "Network structure and systemic risk in banking systems". In: *Available at SSRN.*

Corsi, Fulvio et al. (2018). “Measuring the propagation of financial distress with Granger-causality tail risk networks”. In: *Journal of Financial Stability* 38, pp. 18–36.

Demirer, Mert et al. (2018). “Estimating global bank network connectedness”. In: *Journal of Applied Econometrics* 33.1, pp. 1–15.

Diebold, Francis X and Kamil Yılmaz (2014). “On the network topology of variance decompositions: Measuring the connectedness of financial firms”. In: *Journal of econometrics* 182.1, pp. 119–134.

Dungey, Mardi, Matteo Luciani, and David Veredas (2018). “Systemic risk in the US: Interconnectedness as a circuit breaker”. In: *Economic modelling* 71, pp. 305–315.

Elliott, Matthew, Benjamin Golub, and Matthew O Jackson (2014). “Financial networks and contagion”. In: *American Economic Review* 104.10, pp. 3115–53.

Fahlenbrach, Rüdiger, Robert Prilmeier, and René M Stulz (2012). “This time is the same: Using bank performance in 1998 to explain bank performance during the recent financial crisis”. In: *The Journal of Finance* 67.6, pp. 2139–2185.

Gupta, Abhimanyu et al. (2023). *Networks and Information in Credit Markets*. Tech. rep.

Hale, Thomas et al. (2020). “Variation in government responses to COVID-19”. In.

Hasan, Iftekhar, Panagiotis N Politsidis, and Zenu Sharma (2021). “Global syndicated lending during the COVID-19 pandemic”. In: *Journal of Banking & Finance* 133, p. 106121.

Houston, Joel, Christopher James, and David Marcus (1997). “Capital market frictions and the role of internal capital markets in banking”. In: *Journal of financial Economics* 46.2, pp. 135–164.

Houston, Joel F, Jongsub Lee, and Felix Suntheim (2018). “Social networks in the global banking sector”. In: *Journal of Accounting and Economics* 65.2-3, pp. 237–269.

Ivashina, Victoria and David Scharfstein (2010). “Bank lending during the financial crisis of 2008”. In: *Journal of Financial economics* 97.3, pp. 319–338.

Jackson, Matthew O and Agathe Pernoud (2019). “Optimal Regulation and Investment Incentives in Financial Networks”. In: *Available at SSRN 3311839*.

Loutskina, Elena and Philip E Strahan (2011). “Informed and uninformed investment in housing: The downside of diversification”. In: *The Review of Financial Studies* 24.5, pp. 1447–1480.

Matvos, Gregor, Amit Seru, and Rui C Silva (2018). “Financial market frictions and diversification”. In: *Journal of Financial Economics* 127.1, pp. 21–50.

Newman, Mark EJ (2003). “The structure and function of complex networks”. In: *SIAM review* 45.2, pp. 167–256.

Oh, Gabjin and A-young Park (2021). “Lending Diversification and Interconnectedness of the Syndicated Loan Market”. In: *Frontiers in Physics* 8, p. 581994.

Onnela, J-P, Anirban Chakraborti, et al. (2003). “Dynamics of market correlations: Taxonomy and portfolio analysis”. In: *Physical Review E* 68.5, p. 056110.

Onnela, J-P, Kimmo Kaski, and Janos Kertész (2004). “Clustering and information in correlation based financial networks”. In: *The European Physical Journal B* 38.2, pp. 353–362.

Schwert, Michael (2018). “Bank capital and lending relationships”. In: *The Journal of Finance* 73.2, pp. 787–830.

Shleifer, Andrei and Robert Vishny (2011). “Fire sales in finance and macroeconomics”. In: *Journal of Economic Perspectives* 25.1, pp. 29–48.

Tumminello, Michele et al. (2005). “A tool for filtering information in complex systems”. In: *Proceedings of the National Academy of Sciences* 102.30, pp. 10421–10426.

Wasserman, Stanley, Katherine Faust, et al. (1994). *Social network analysis: Methods and applications*. Vol. 8. Cambridge university press.