



Lending Diversification and Interconnectedness of the Syndicated Loan Market

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We investigate the effects of syndicated loan network centrality on bank performance. Syndicated loan network centrality measures the similarity and influence of the other banks within a given banks network. The network centrality constructed by syndicated loans can allow banks to gather and transfer valuable information and can thus facilitate profit-making acquisition in loan investment decisions. We use a planar maximally filtered graph to construct an interbank network using syndicated loan portfolios at the industry level. We show that the syndicated loan portfolios of high-centrality banks exhibit a higher level of portfolio diversification than those of low-centrality banks. We also document that our composite centrality measure of the bank network showed statistical significance in terms of bank performance even after controlling for the financial variables of market size, loan allocation, total asset, and loan diversification. Our findings suggest that the performance of a bank in a syndicated loan hierarchy is related to its position in this hierarchy.

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1. INTRODUCTION

The connectivity between banks demonstrates the ways in which the contagious nature of high levels of risk among financial institutions can cause financial crises and affect future economic conditions [1–4]. The network structure of the interbank market created by the syndicated loan market suggests that connections between banks should be an important channel of contagion among financial institutions [5–7]. Information contagions between banks represent a significant channel that might explain how information travels through financial systems. Recently, the application of complex networks to solve this challenging problem has become increasingly widespread in diverse areas [8–10].

In this paper, we study interbank networks in the form of common exposures among financial institutions to analyze bank performance based on banks' exposure to large syndicated loans. Syndicated loans represent one of the crucial sources of external financing for many firms and provide an ideal experimental setting for studying the interconnectedness of banks. In this study, the network between banks is constructed from data sets that contain information regarding both the borrowers and lenders of syndicated loans. The common exposures of banks are able to measure bank's investment strategies in this market in terms of loan portfolio diversification.

Prior research provides evidence that interconnectedness has a considerable impact on the economy from the perspective of risk exposure. Interconnection between companies or industries amplifies and propagates shock within an economy [11]. Negative shock and financial distress contribute to asset fire sales [12]. Consistent with these concepts, credit concentration tends to lead to

a cascade effect of shock in an economy [13]. [5] defined market connectedness using banks' loan specializations in a syndicated loan market that reflected systemic risk. Furthermore, prior studies that have examined the role of diversification have focused on performance. For example, banks with a greater number of geographically-concentrated mortgage loans performed better than others with fewer of these loans [14]. In terms of mergers and acquisitions, diversification is correlated with fluctuations in external market friction [15].

Based on the social exchange theory as proposed by [16]; we present different perspectives to understand the banking industry in the United States; these perspectives recognize the complex and rich social relationships that define interbank network. When the economy is growing, banks actually benefit from promoting the sharing of information with network members for business expansion; as a result of this sharing, they are able to increase their profits. Nonetheless, during periods of economic contraction, banks cannot force network members to restructure because they may be subject to strict constraints due to their obligations. Banks are expected to expend effort monitoring and screening their borrowers to mitigate risk exposure. Additionally, bank performance is negatively affected within a contracting economy.

To assess the level of connectedness between the banks of syndicated loan portfolios, we establish a measure of interconnectedness that utilizes the similarity between bank's syndicated loan portfolios at the industry level as proposed by [5]. An advantage provided by the use of loan portfolios is the ability to investigate the response of banking systems via direct connections. To extract meaningful information from all-to-all connected networks, we employ the planar maximally filtered graph (PMFG) [17]. We utilize centrality measures to drive an important component that may affect whether a bank's centrality in the interbank network created in the financial sector is related to its performance. In this paper, the centrality is measured by the principal component analysis (PCA) method based on four common measures of centrality in the context of networks: degree, eigenvector, closeness, and betweenness.

To date, only the lending relationship between banks and firms has been studied through analyzing the characteristics of individual banks or firms using corporate loan data. The aim of this paper is to study an interbank network, namely, the syndicated loan market. We investigate the evolution of several types of syndicated loans over time using a Dealscan database, with a special emphasis on the amount of syndicated loans that have been extended. More interestingly, the syndicated loan data used in this study allows us to investigate the effect of the centrality of interbank networks on bank performance.

We show that banks with a higher level of network centrality are more likely to pursue diversification and that this diversification is more likely to increase during market instability. To extend our examination of the relationship between interbank networks and bank performance, we move beyond bank-to-firm lending by studying interbank networks in the context of the syndicated loan market. We further find that banks with a high level of centrality have higher returns than do

banks with a low level of centrality. Since a bank's centrality within the network plays an important role in its loan portfolio strategy, it also plays a significant role for lending market participants. We also found that in the core group, there was a negative correlation between diversification and centrality; however, a positive relation was observed in the peripheral group.

The paper is organized as follows. **Section 2** explains the methodology that we employed. **Section 3** presents a description of the database used, and **Section 4** contains an empirical analysis. **Section 5** concludes this paper.

2. METHODOLOGY

In this section, we explain the network construction and regression variables. For each month, we define an interconnectedness based on the similarities between syndicated loan portfolios. The results are not qualitatively sensitive to bank performance measures, e.g., we obtain essentially the same results even if we use different financial variables to measure bank performance.

2.1. Network Construction

In this subsection, we explain the way in which we estimate the distance between two banks based on their loan portfolios. We then describe the way in which we construct an interbank network. To map our interbank network, we obtain information on the relationships between banks and firms between 1990 and 2017 from the DealScan database.

First, we investigate bank syndicated loans in the United States. lending industry classified using two-digit SIC industry codes. This measure was developed by [5] and uses the Euclidean distance between two banks. For each month, we calculate the distance between bank i and bank k by quantifying the similarity of these two banks in a n -dimensional space as follows.

$$Distance_{i,k,t} = \frac{1}{\sqrt{2}} \times \sqrt{\sum_{j=1}^n (w_{i,j,t} - w_{k,j,t})^2} \quad (1)$$

where $w_{i,j,t} = \frac{L_j}{\sum_{j=1}^n L_j}$, with syndicated loan of bank i invested in industry j , L_j , within the 12 months prior to month t . The distance is normalized between 0 and 1; 0 refers to perfectly matched portfolios and one refers to portfolios that do not overlap at all. We then construct a filtered network that connects all the banks so that a planar maximally filtered graph (PMFG) can be used [17]. The most common method of forming a stock network is based on the correlation of stock returns using threshold [18, 19]. This method has a problem in which correlation coefficient only assumes a linear relationship and lead to neglect some information. In addition, the minimum spanning tree (MST), a tree formed by a subset of edges of a given undirected graph, is also a common method in complex network analysis [20]. However, this method reflects hierarchical clustering with information loss to generate an efficient network. To address these issues, we use PMFG measure to construct a network based on the syndicated loans.

2.2. Main Dependent and Independent Variables

We investigate how network structure affects bank performance using the banks in the United States between January 1, 1990 and December 31, 2017. We use the Return on asset (ROA) variable as the dependent variable to measure bank's performance and employ several financial variables, such as the bank size, an amount of syndicated loan, etc. as control variables to examine network effect on bank's performance.

2.2.1. Diversification

In information theory, following [21]; the entropy of a discrete random variable X is denoted as

$$H(X) = \frac{-p(x_i)\sum_i^n \log(p(x_i))}{-p^m(x_i)\sum_i^n \log(p^m(x_i))} \tag{2}$$

where $p(x_i)$ is the probability distribution of outcome X and $p^m(x_i)$ is defined by $1/n$. x_i is the proportion of the total loan amount of industry i held by a bank and n is the number of industries invested by the bank. It is well known that entropy is viewed as a measure of the uncertainty of a random variable. Entropy have manifested useful across a wide range of fields, so it is remarkable they have begun to make noticeable effect into economics and finance. It has also been a popular diversity index in previous literature. In this paper, we use the concept of diversification that corresponds to the above measure within the range of zero to one. When H is zero, the bank has concentration of loan portfolio. Otherwise, when H is one, the bank has perfect diversification of loan portfolio.

2.2.2. Network Centrality

The effect of bank network centrality on bank performance is due to the importance of bank-firm lending structure in the context of information asymmetry. A bank's network created by bank-to-firm loan information should affect the profit of lending banks. 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 [22]. 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. 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 [23]. Eigenvector centrality measures an individual bank's ability to obtain or influence information within the network. This measure increases as connections with other highly connected neighbors are added. The raw score is divided by the total number of nodes in the network minus one because the size of the interbank network changes each month. Closeness centrality is the inverse of the mean of the shortest path length between an individual bank and all the other reachable banks in the network. The raw score is multiplied by the total number of nodes in the network minus one because the size of the interbank network changes each month. Betweenness centrality describes the extent to which an individual bank is

TABLE 1 | The effect of diversification and network centrality on bank performance.

Variables	Coefficient	t-value	Coefficient	t-value
Intercept	-2.1×10^{10}	(-0.4797)	-1.3×10^{10}	(-0.2783)
CCI			0.0084***	(10.5008)
CCIxDummy			-0.0170***	(-6.6791)
DIV	0.0344***	(5.0023)	0.0216***	(3.0677)
Market size	0.0820***	(4.3706)	0.0850***	(4.5429)
Market share	-0.0140***	(-5.8422)	-0.0197***	(-8.0319)
Bank size	-0.0623***	(-29.2561)	-0.0626***	(-29.3747)
Observations	33,289		33,289	
Year FEs	Yes		Yes	
Adj. R ²	0.2224		0.2255	

*This table reports the regressions of diversification and centrality on ROA. ROA is defined as the net income divided by total assets. DEGREE is the degree centrality. Diversification (DIV) is measured by the Shannon entropy of bank portfolio calculated as the amount of loans extended to ten industries by each bank. Composite centrality index (CCI) is calculated by using principal component analysis of four centrality measures pertaining to the PMFG network, namely, degree centrality (DEGREE), eigenvector centrality (EIGEN), betweenness centrality (BTWN), and closeness centrality (CLOSE). Market size is defined as the log of the sum of all outstanding loans. Market share is defined as the log of the amount of loans extended by each bank. Bank size is defined by log of total assets of each bank. Year fixed effects are included to account for time characteristics. The t-statistic is reported in brackets. The symbols *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.*

connected to the other banks in the network. When the shortest path of all bank pairs passes through a bank, the betweenness centrality of that bank is high; this is the reason why it is important to control the flow of the entire network. The raw score is divided by the total number of the connected nodes because the size of the interbank network changes each month.

To generate our composite centrality index (CCI) in **Table 1**, we standardize the centrality indices to a mean of 0 and a standard deviation of 1. Consistent with [24–26]; we use the factor score to aggregate CCI using the first principal component for each bank with four centrality indices in the PMFG network.

2.2.3. Bank Performance Measure

Return on assets (ROA) is an indicator of how well a company generates profit from its total assets. We calculated ROA by dividing firms' profit or loss before taxes by their total assets in month t and converted this figure to a percentage. The previous studies related to the current research area show that ROA is the best measure of performance when comparing similar companies with the same industry.

3. DATA DESCRIPTION

To test the hypotheses outlined in **Section 1**, we construct a sample of syndicated loans matched according to firm and bank characteristics. Below, we describe the sample construction and summarize the sample characteristics.

3.1. Data Source

We build our datasets from a comprehensive sample of syndicated loans and the associated lender and borrower

TABLE 2 | Pearson correlation of regression variables.

	ROA	Market size	Market share	Bank size	DIV	CCI	DEGREE	EIGEN	BTWN	CLOSE
ROA	1.00	-0.05	-0.12	-0.27	-0.04	0.02	-0.09	-0.09	0.02	-0.13
Market size		1.00	0.37	0.57	0.15	0.00	-0.07	-0.06	-0.02	0.03
Market share			1.00	0.38	0.08	0.57	0.45	0.57	0.36	0.63
Bank size				1.00	0.16	0.03	0.08	0.11	0.02	0.18
DIV					1.00	0.62	0.44	0.62	0.36	0.69
CCI						1.00	0.84	0.88	0.88	0.76
DEGREE							1.00	0.82	0.78	0.67
EIGEN								1.00	0.70	0.86
BTWN									1.0	0.56
CLOSE										1.0

This table presents correlation coefficient of two variables. The value in **Table 2** has statistical significance ($p < 0.01$). ROA is defined as the net income divided by total assets. Market size is defined as the natural logarithm of the sum of all outstanding loans. Market share is defined as the natural logarithm of the amount of loans extended by each bank. Bank size is defined by natural logarithm of total assets of each bank. Diversification (DIV) is measured by the Shannon entropy of bank portfolio calculated as the amount of loans extended to ten industries by each bank. Composite centrality index (CCI) is calculated by using principal component analysis of four centrality measures pertaining to the PMFG network, namely, degree centrality (DEGREE), eigenvector centrality (EIGEN), betweenness centrality (BTWN), and closeness centrality (CLOSE).

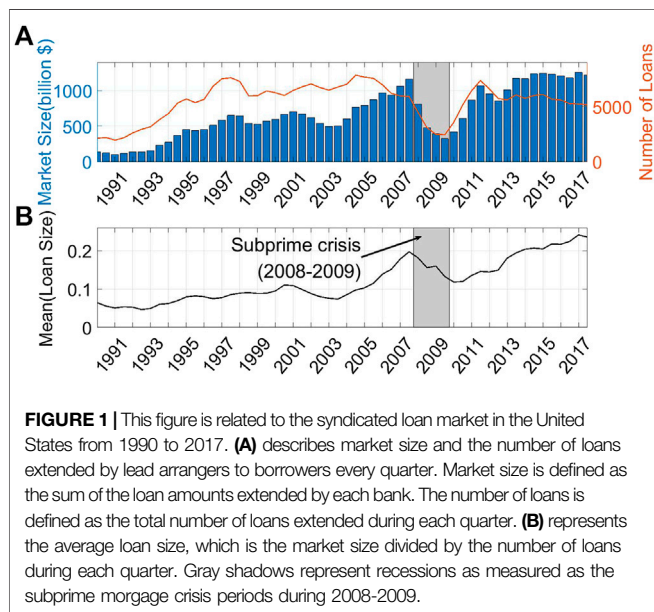


FIGURE 1 | This figure is related to the syndicated loan market in the United States from 1990 to 2017. **(A)** describes market size and the number of loans extended by lead arrangers to borrowers every quarter. Market size is defined as the sum of the loan amounts extended by each bank. The number of loans is defined as the total number of loans extended during each quarter. **(B)** represents the average loan size, which is the market size divided by the number of loans during each quarter. Gray shadows represent recessions as measured as the subprime mortgage crisis periods during 2008-2009.

information by merging data derived from Standard & Poor’s Compustat and from Thomson Reuters’ LPC Dealscan from 1990 to 2017. The Compustat database is free of survival bias, as it contains the monthly historical accounting data of borrowing companies, and data regarding syndicated loans are included in the Dealscan database. Our starting points are the DealScan-Compustat Link [27] and the Lender link [28].^a

Syndicated loans play a crucial role in the American corporate loan 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. In this study, following the work of [5]; we classify lenders as lender-to-lead arrangers and participants. We designate a lender as a lead arranger if lead arranger

credit of it is yes or lender 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. We refer to lead arrangers as banks from now on, but we do not refer to participants in this way. Following the literature, we exclude loans made to financial companies (i.e., SIC codes between 6,000 and 6,999) as well as classified companies belonging to the Fama-French 12th industrial classification (i.e., others).^b

The use of syndicated loan data allows us to explore the activities of the financial intermediaries in the loan market. Our loan data, with 52,685 facilities and 35,632 packages, comprises a complex structure. After excluding banks with negative total assets, the study sample is composed of banks listed in the United States during the period 1990–2017.

3.2. Sample Characteristics

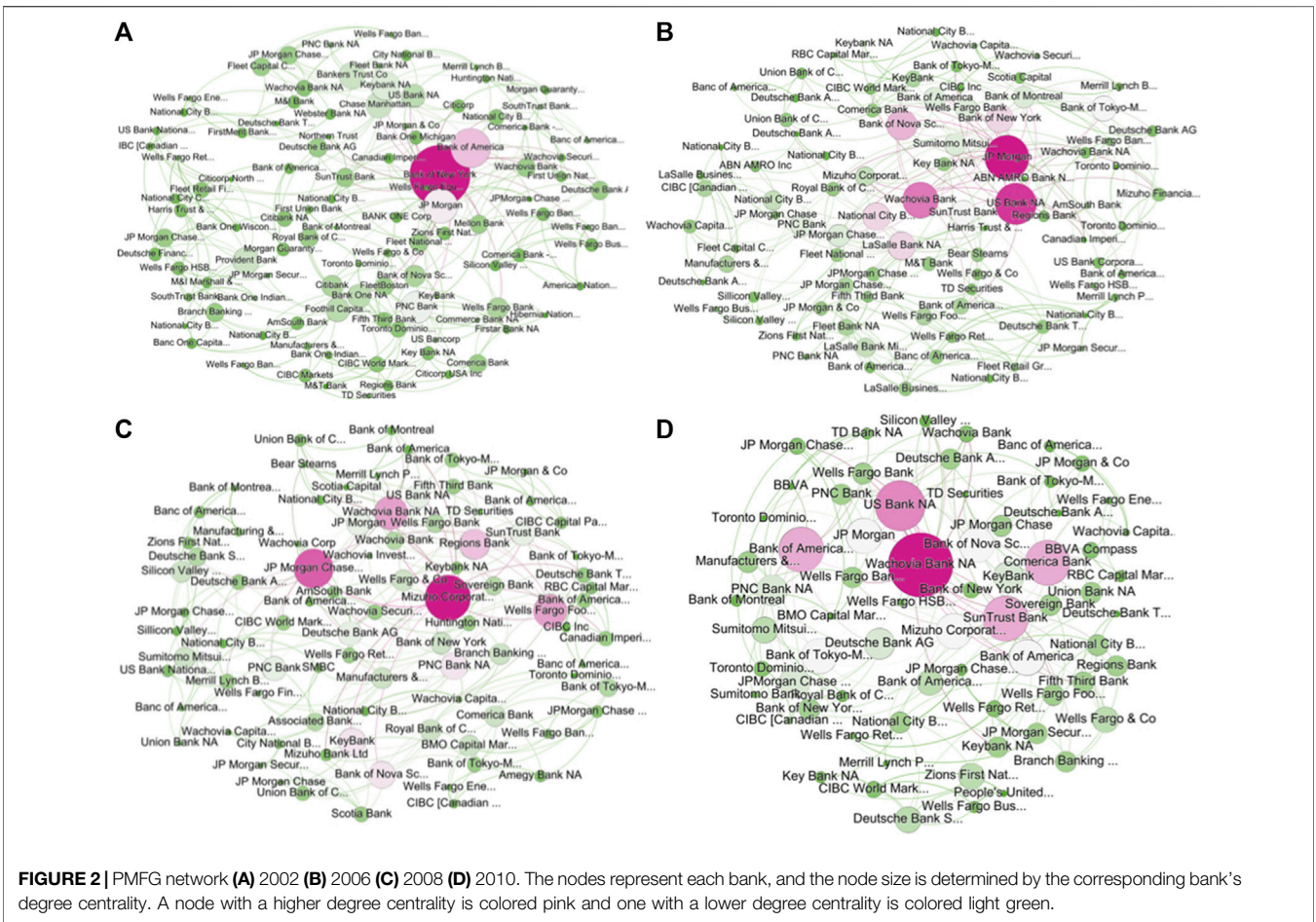
Table 2 summarizes the composition of the sample in terms of diversification, centrality indices, and the control variables described in **Section 2.2**. The correlation coefficients of the variables are reported at the lead-arranger level. Our sample is consisted of 33,386 matched lead arranger-month sets drawn from U.S. institutions heavily invested in the U.S. syndicated loan market. Diversification (DIV) is highly correlated with the composite centrality index (CCI) (0.62) in **Table 2** and **Figure 1**. In terms of multicollinearity, we control the effect of dummy variables related to 2008–2009 financial crisis in the centrality variables.

4. EMPIRICAL RESULTS

In this section, we first empirically explore the degree distribution of the PMFG network in the U.S. syndicated loan market. We then examine the ways in which network topology and investment characteristics impact bank performance. We investigate the effect

^aThe lenders in our sample have at least \$10 billion in outstanding loans or at least 50 outstanding loans, following [28].

^bWe downloaded the 12 classification data at Fama-French website (<http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html>).



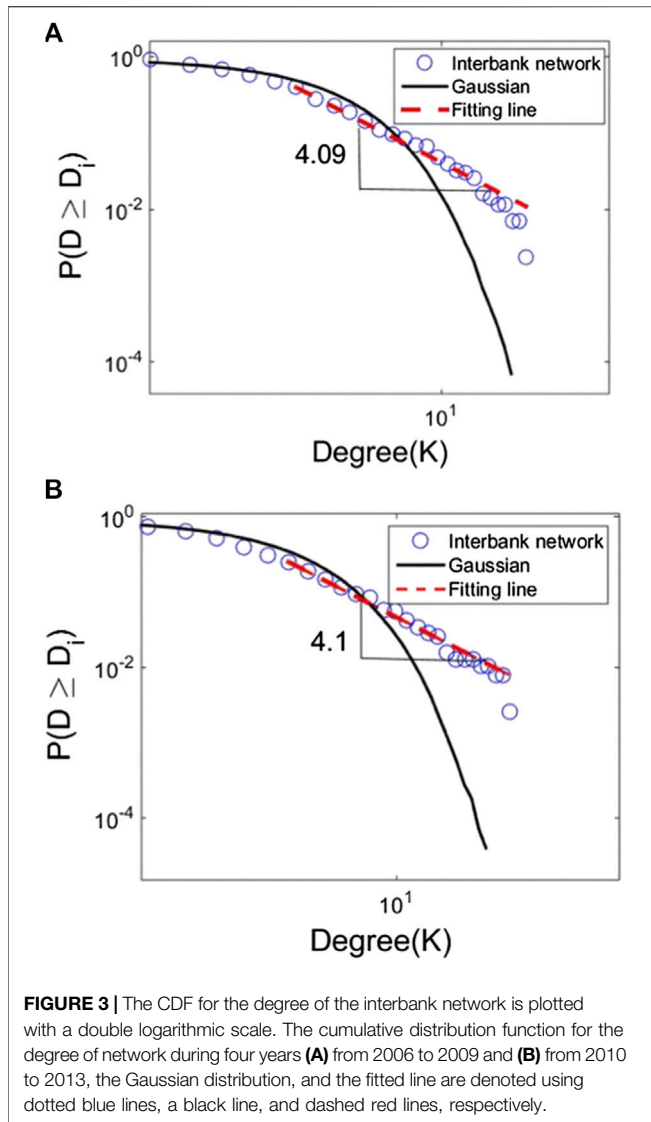
of bank network centrality on bank performance because of the importance of the bank-firm lending structure in terms of information asymmetry. The structure of an interbank network should affect bank performance. Interbank networks, which are created by the degree of information asymmetry during the bank-firm lending process, should affect the performance of lending banks. A bank with a higher level of information asymmetry might mimic the loan portfolio structure of a bank with a lower level of information asymmetry to reduce this asymmetry and generate profits. The systemic risk research has identified network connectivity and centrality as channels that transmit contagions related to negative events [1, 2, 5, 29]. This implies that a highly interconnected structure can increase systemic risk. Ultimately, increased connectivity and rapid propagation in bank-to-bank networks can allow high-centrality banks to address market instability. In summary, we expect that well-connected banks should experience lower levels of information asymmetry than do poorly connected banks and that they should also experience higher levels of market performance.

4.1. The Analysis of Interbank Network

Since the amount of syndicated loans is related to exposure to assets, a decline in asset prices should affect the stability of the banking system. We analyze syndicated loans issued during each

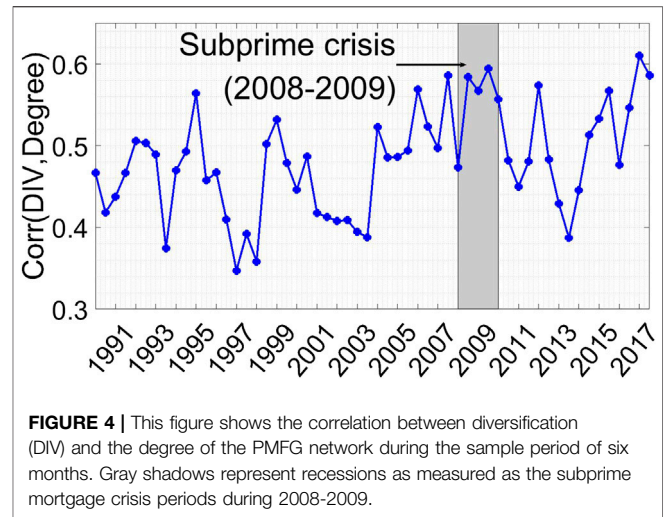
quarter from 1990 to 2017. A visual inspection of the amount of syndicated loans over time suggests that this figure reflects the state of the financial market. **Figure 1A** shows the amount of syndicated loans as a measure of overall banking loans and the number of syndicated loans. We measure the total amount of syndicated loans in each quarter. First, we find that both the overall amount and the number of syndicated loans follow a similar pattern. The total amount of syndicated loans started to increase in 2003 and continued to rise until Q4 of 2007, finally decreasing in 2009. After the subprime crisis, these loans rapidly increased until 2012. Second, the mean amount of syndicated loans is calculated as follows: $\text{Mean (Loan)} = \text{Market size}/\text{number of loans}$. **Figure 1A** shows a pattern similar to that of the results in **Figure 1A**.

The main goal of this paper is to conduct more rigorous tests on the relationship between the interconnectivity of banks and bank performance. To test the validity of our hypothesis, we construct an interbank network using the PMFG method developed by [17] based on loan portfolio data in **Figure 2**. In January 2002 (2006), this interbank network for the normal market status consisted of 513 (428) connections and 105 (88) nodes. The interbank network during and after the financial market crisis consisted of 423 (328) connections and 87 (68) nodes in January 2008 (2010). If the loan portfolio of each bank tended to have a distinct and unique investment strategy, then the



interbank network would be disconnected, and each bank would correspond to a random network. We construct interbank networks for normal and abnormal periods based on the banks' loan portfolio structures to test whether the characteristics of the network are related to the market status. The obtained interbank network, shown in **Figure 2 A–D**, displays the banks with higher connections between banks, regardless of market status, suggesting that the syndicated loan portfolios of banks are shared with other banks.

The degree (k) distribution of the interbank network indicates that most of the banks are linked to a few other banks, whereas a few banks with a large amount of capital are connected to many individual banks. As shown in **Figure 3**, the degree distribution in 2006 (2010) follows the power-law distribution with an exponent of 4.09 (4.1). Consistent with [30, 31]; **Table 3** compiles the results of the likelihood ratio test and includes judgments supported by statistical methods for the power-law hypothesis for each distribution over four years. We find that the degree



distributions follow a power-law when comparing to exponential, stretched exponential, power law with cutoff, and log normal distributions. The power-law exponents of degree distributions of PMFG network are in the range 3.49 and 4.43. As a result, we think that there are the influential banks with a lot of connections in the interbank network.

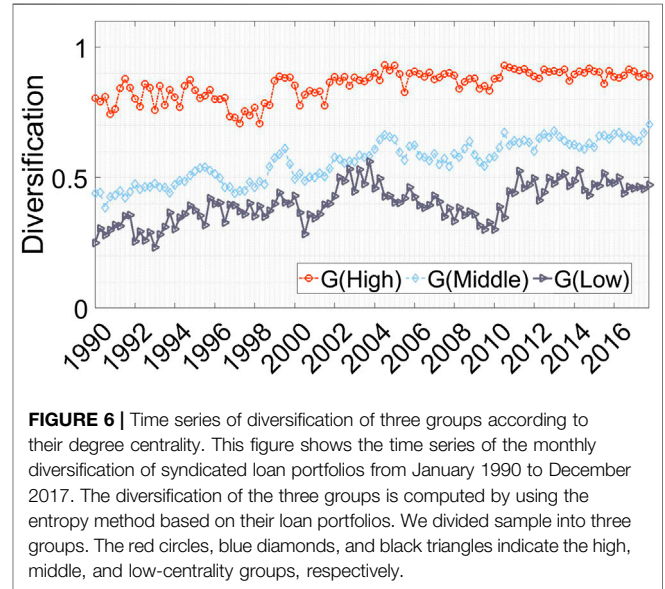
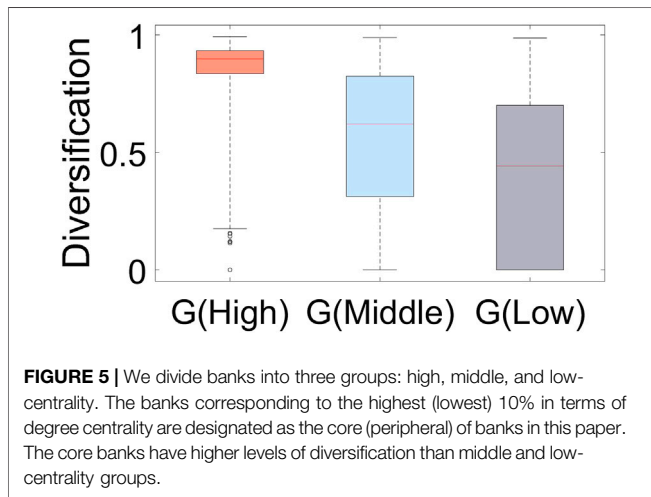
The diversification of loan portfolios has important implications of the role that banks' investment strategies play in the syndicated loan market. Is this loan portfolio strategy, i.e., the diversification of syndicated loans at the industry level, related to the interbank network? We estimate the correlation between the diversification of portfolios and network structure to test whether the investment strategy of a bank is related to the other banks in the network. **Figure 4** shows the correlation between diversification and the degree of network centrality for each year. Overall, there is a positive correlation between diversification and degree of centrality, regardless of the subperiod observed. In particular, the correlation value starts to increase in 2002 and continues to rise until 2007 before the subprime crisis; after this, it decreases in 2011, suggesting that the correlation between the loan portfolio strategies of banks and the centrality of the network connectivity among banks should be understood as indicators of the financial crisis.

To observe the relationship between the degree of network centrality and portfolio strategies, we divided the whole sample into three groups according to centrality: G (high), G (middle), and G (low). **Figure 5** displays the distribution function of these three groups using box plots and calculates the similarity of each distribution function using the Kolmogorov-Smirnov test (K-S test) [32]. The results are reported in **Table 3**. In addition, we calculate the average diversification of the three groups over time. **Figure 6** shows the time evolution of the average diversification of these three groups defined according to their degrees of network centrality from January 1990 to December 2017. The diversification of the three groups is calculated based on the loan portfolios using the entropy method. The red circles, blue diamonds, and black triangles indicate the high-, middle-,

TABLE 3 | Comparisons of the fitted power-law behavior to alternatives.

Year	Power law ρ	Est. α	Exponential		Stretched exp		Power law + cutoff		Log-normal	
			LR	ρ	LR	ρ	LR	ρ	LR	ρ
1990	0.43	4.23	2.32	0.02	1.03	0.30	4.44	0.00	-0.14	0.89
1994	0.34	4.43	2.74	0.01	1.22	0.22	5.85	0.00	-0.47	0.64
1998	0.10	3.76	4.29	0.00	0.87	0.06	8.60	0.00	-0.02	0.99
2002	0.02	3.57	2.41	0.02	1.74	0.08	5.77	0.00	0.29	0.77
2006	0.41	4.10	3.27	0.00	2.13	0.03	5.94	0.00	0.75	0.45
2010	0.30	4.11	1.86	0.06	1.36	0.17	4.85	0.00	-0.31	0.76
2014	0.22	3.49	1.50	0.13	1.17	0.24	4.49	0.00	0.05	0.96

We checked the power law test proposed by [30, 31] for the degree distribution of PMFG networks during four years. Statistically significant values are given in bold. Estimated α is the power-law exponent of the degree distribution.



and low-centrality groups, respectively. As shown in **Figure 6**, we find that since 2004, the diversification levels of low-centrality groups have moved more volatile than high-centrality groups.

4.2. The Effect of Centrality and Diversification on Bank Performance

To the extent that interbank networks in the United States have heterogeneous characteristics, we suggest that the strategic behaviors of banks and the central characteristics of banks have impacts on performance. We focus on two properties of banks: structural properties and strategic properties. We use the four measures of centrality as structural properties in the PMFG network. The relationships between lenders and borrowers are likely to mitigate the problem of information asymmetry because lending banks collect a considerable amount of information about the corporate management of their borrowers and have stable and long-term relationships with the managers of these organizations [33]. Sometimes, banks place their directors on borrower’s boards of directors to improve the quantity and quality of information regarding operations that they receive [25]. We found that capitalized banks tend to centralize their networks. Therefore,

we assume that banks with a high level of centrality in their networks have the unique abilities of quickly obtaining resources through the members of their network and of reducing the level of information asymmetry between lenders and borrowers.

Based on our assumption, centralized banks would feel more secure when expanding their business. In this context, we would expect to see that these banks hold portfolios that are more diverse. Diversification in the syndicated loan market creates the potential advantage of reducing credit risk exposure [5]. Banks become more resilient to common shocks such as exposure to risk when holding diversified portfolios. We estimate the following regression with pooled data:

$$ROA_{i,t} = \alpha + \beta_1 DIV_{i,t} + \beta_2 Centrality_{i,t} + \beta_3 Centrality_{i,t} \times Dummy + \beta_4 Marketsize_t + \beta_5 Marketshare_{i,t} + \beta_6 Banksizet_{i,t} + e_{i,t}, \tag{3}$$

where the dependent variable $ROA_{i,t}$ is a financial indicator of profitability during month t $DIV_{i,t}$ measures the diversification of bank i based on its syndicated loan portfolio during the twelve months prior to month t and dummy as an indicator

TABLE 4 | Dimensions of connectedness and likelihood of performance.

Variable	(1)		(2)		(3)		(4)	
Intercept	-7.2×10 ¹⁰	(-0.1475)	-1.85×10 ¹¹	(-0.3832)	-1.1×10 ¹¹	(-0.2178)	-6.7×10 ¹⁰	(-0.1377)
DEGREE	0.3970***	(9.3934)						
DEGREE × Dummy	-1.1628***	(-9.1937)						
EIGEN			22.2780***	(10.6610)				
EIGEN × Dummy			-50.1001***	(-10.2535)				
CLOSE					0.3078***	(9.8138)		
CLOSE × Dummy					-0.8945***	(-10.9380)		
BTWN							0.0853***	(8.7560)
BTWN × Dummy							-0.1878***	(-5.1339)
DIV	0.0339***	(4.9161)	0.0196***	(2.7594)	0.0094	(1.2388)	0.0338***	(4.9143)
Market size	0.0920***	(4.8797)	0.0979***	(5.1879)	0.0927***	(4.9039)	0.085***	(4.5681)
Market share	-0.0193***	(-7.8407)	-0.0193***	(7.9123)	-0.0167***	(-6.9458)	-0.0180***	(-7.3890)
Bank size	-0.0622***	(-29.1980)	-0.0628***	(-29.5153)	-0.0623***	(-29.3096)	-0.0623***	(-29.2473)
Observations	33,289		33,289		33,289		33,289	
Year FEs	Yes		Yes		Yes		Yes	
Adj.R ²	0.2256		0.2263		0.2244		0.2266	

This table reports the regressions of four dimension of connectedness and diversification on ROA: degree centrality (DEGREE), eigenvector centrality (EIGEN), closeness centrality (CLOSE), and betweenness centrality (BTWN). ROA is defined as the net income divided by total assets. Consistent with Section 2.2, the centrality indices of the banks are measured for each month. Diversification (DIV) is measured by the Shannon entropy of bank portfolio calculated as the amount of the loans extended to ten industries by each bank. Market size is defined as the log of the sum of all outstanding loans. Market share is defined as the log of the amount of loans extended by each bank. Bank size is defined by log of total assets of each bank. Year fixed effects are included to account for time characteristics. The t-statistic is reported in brackets. The symbols *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

variable as follow: Dummy is one if the observation is from financial crisis period, otherwise 0. As a proxy for structural importance in the PMFG network, centrality_{i,t} is replaced by four representative types of centrality: degree centrality, eigenvector centrality, closeness centrality, and betweenness centrality.

By including the variables market size, market share, and bank size in this regression, we control for the systematic and idiosyncratic effects that we cannot directly observe. Market share is measured by the natural logarithm of the amount of outstanding loans held by each bank [34]. use that as a proxy for a lead arranger’s reputation in terms of market participants’ perceptions of its screening and monitoring of borrowers. We control for market share to identify the effects of banks’ reputations. Market size is calculated as the natural logarithm of the sum of the loan amounts of newly originated syndicated loans in billions of United States. dollars. Controlling high performance of bank with higher asset, bank size is estimated by the natural logarithm of total assets of each bank. In all regressions, we include market size and year fixed effects to remove the time characteristics.

We report the results related to diversification and four centrality measures of the interbank networks. In all models, the regression coefficients of the measures of diversification are statistically highly significant, and they indicate a positive relationship (0.3970, $p < 0.01$; 22.2780, $p < 0.01$; 0.3078, $p < 0.01$; 0.0853, $p < 0.01$) in Table 4. These findings are in line with the results of the descriptive studies by [35]; which report that product-diversified firms have high levels of performance and innovation. There are simply too many results and perspectives about the agency theory of diversification to include them in this paper. Our results support the existing evidence regarding diversification and profitability in terms of lead arrangers’ loan portfolios. Each type of centrality

represents a different aspect of a bank’s structural position in the network. These findings allow us to determine whether each type of centrality is able to represent a factor of composite centrality index (CCI) in Table 1. Overall, our results suggest that higher levels of the individual dimensions of centrality based on loan portfolio similarities are related to increases in the profitability of banks.

Next, we establish dummy variable with centrality indices to exclude the financial crisis effect in 2008–2009. They are statistically significant with negative coefficients of DEGREE × Dummy, EIGEN × Dummy, CLOSE × Dummy, BTWN × Dummy ($-1.1628, p < 0.01$; $-50.1001, p < 0.01$; $-0.8945, p < 0.01$; $-0.1878, p < 0.01$) in Table 4. As shown in columns 1–4 of Table 4, although the dummy variable has a negative sign, the main effect for the dimension of centrality and diversification is positive and significant. It means that the impact of network centrality on performance is negative during 2008–2009 financial crisis and positive during the normal period. We then show the results of the regression using our composite centrality index (CCI) through principal component

TABLE 5 | The relation of the diversification of the subsets of banks to degree centrality.

	High	Middle	Low
High	1	0.7906*** (7.82E ⁻⁵¹)	0.5488*** (7.82E ⁻⁵¹)
Middle		1	0.7072*** (7.70E ⁻²²)
Low			1

The table represents the Pearson correlation among the three groups of banks. We construct two groups from the sample bank. One is the core as designated by High with the highest 10% degree centrality and another is the peripheral as designated by Low with the lowest 10% degree centrality. The other group of banks is the Middle in table. A two-sample Kolmogorov-Smirnov test asymptotic significance value (2-tailed) is shown in the bracket. ($P < 0.01$) rejects the null hypothesis of the other population distributions.

TABLE 6 | The effect of diversification on the bank performance of core and peripheral banks.

Variables	Core		Peripheral	
Intercept	-1.1×10^{12}	(-0.5745)	-2.1×10^{12}	(0.1175)
DIV	-0.0635*	(-1.7079)	0.0651***	(5.2336)
Market size	0.0735	(1.3409)	0.1548***	(4.0456)
Market share	0.0372**	(3.7565)	-0.0380***	(-8.1899)
Bank size	-0.1200***	(-15.6491)	-0.0650***	(-14.8352)
Observations	4,241		7,330	
Year FEs	Yes		Yes	
Adj. R^2	0.2315		0.2427	

We investigate the effect of diversification on ROA for (1) the core of banks and (2) peripheral of banks. ROA is defined as net income divided by total assets. Diversification (DIV) is measured by the Shannon entropy of bank portfolio calculated as the amount of loans extended to ten industries by each bank. The control variable is consistent with Eq. 3. Year fixed effects are included to account for time characteristics. The t-statistic is reported in brackets. The symbols *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

analysis, including degree centrality, eigenvector centrality, closeness centrality, and betweenness centrality based on the results shown in Table 4. The results of the regression including CCI are reported in Table 1 using equation model 3. Consistent with the preceding regressions, we use the dummy variable with CCI to remove the recession trends. We find a negative and significant coefficient for the $CCI \times Dummy$ ($-0.0170, p < 0.01$), whereas the coefficients of CCI and DIV are positive and significant ($0.0084, p < 0.01$; $0.0216, p < 0.01$), consistent with the results in Table 1. Together, these results suggest that overall centrality consistently moderates the increase in a bank's profitability when it holds a diversified portfolio.

4.3. The Effect of Diversification on Bank Performance According to the Level of Centrality

In this section, we examine the different ways in which the structural importance of the PMFG network affects bank's strategic actions. We also consider the way in which the relationship between strategic actions and relative profitability identified in the full sample may vary based on banks' degree of centrality. Several papers have highlighted the likelihood that board interlocking between banks has more power and information in the market when they reduce financial risk [22, 34, 36, 37]. Because the importance of each bank in the network is not homogeneous, we group the banks by their degrees centrality into groups consisting of core banks and of peripheral banks. We designated the upper (lower) 10% of banks in terms of degree centrality as high (low) groups to define the cores and peripheral in the PMFG network. Table 5 represents the Pearson correlation of diversification between each subset of banks. The high- and middle-centrality groups have positive correlations (0.7906), and the low-centrality groups also have positive correlations with the other groups (0.5488, 0.7072). Additionally, we investigate a two-sample Kolmogorov-Smirnov test to assess the distribution of the two samples in brackets. This test implies a heterogeneous distribution of diversification among the three groups of banks. As a result, we conclude that the three groups classified by degree centrality could have investment

strategies with differing characteristics. Our interpretation is consistent with the results in Figure 5 and Figure 6. Specifically, we run the following regression on two sets of banks; core and peripheral.

$$ROA_{i,t} = \alpha + \beta_1 DIV_{i,t} + \beta_2 Marketsize_t + \beta_3 Marketshare_{i,t} + \beta_4 Banksizes_{i,t} + e_{i,t}, \quad (4)$$

Table 6 shows the results of the linear regressions regarding bank diversification using the same explanatory variables we used for the subset of banks. These results indicate that core banks could obtain better private information than peripheral banks. This result is consistent with the study of [14]; who insist that concentrated lenders had higher profits than diversified lenders during the financial crisis. Additionally [38], find that the diversification of bank assets is not guaranteed to produce superior return performances or greater safety for banks. These findings are different from the comprehensive perspectives of the market power view and the resource view in terms of profit maximization. Note, however, that these studies do not control for network centrality. Consistent with the systemic risk literature [5], we consider core banks to have high levels of risk exposure, and concentrated lenders have high levels of performance during our sample periods ($-0.0635, p < 0.1$). As shown in column 2 of Table 6, the group composed of peripheral banks has a statistically significant positive effect on performance ($0.0651, p < 0.01$). This means that the subsets of banks in the interbank network reflect the different risk cultures among banks.

5. CONCLUSION

Banks that are centrally located in a syndicated loan network have access to better information and more influence in the syndicated loan market. Adding to the previous studies on the role of network centrality among banks, we employ a network centrality measure to test the connection between bank performance and network structure. In terms of the diversification of loan portfolios, we show that banks with higher levels of network centrality are more likely to pursue diversification, and that this diversification is more likely to

increase during periods of market instability. The evidence shows that sample banks' lending strategies exhibited a significant relationship with these banks' degrees of network centrality, regardless of the market status. We further find that banks with a high level of centrality have higher returns than banks with a low level of centrality. We then test whether the diversification of the syndicated loan portfolios of individual banks is related to the performance of these banks according to their centrality position in the interbank network. Since a bank's centrality in the network plays an important role in its loan portfolio strategy, this centrality also plays a significant role for lending market participants. We found that in the core group, diversification showed a negative correlation with centrality; however, a positive relation was observed in the peripheral group.

We contribute to the literature on the bank-firm lending process in the field of finance by introducing the interbank network based on the syndicated loan market. Our findings extend the existing literature on the lending mechanisms between banks and firms and show that banks' centrality within the interbank network influences their portfolios in

the syndicated loan market. Future studies can help to shed light on bank performance and lending mechanisms.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

AUTHOR CONTRIBUTIONS

All authors listed have made a substantial, direct, and intellectual contribution to the work and approved it for publication.

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Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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