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How are network centrality metrics related to interest rates in the Mexican secured and unsecured interbank markets?☆

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A B S T R A C T

In financial stability, it is essential to know the determinants of interest rates in interbank markets because they are important vehicles for liquidity allocation among banks and are relevant for monetary policy transmission. Recent research indicates that banks with excess liquidity exercise their market power by rationing liquidity during periods of financial stress. This confirms the value of knowing the banks connections and identifying liquidity spreaders in such markets to manage contagion risk, liquidity hoarding and to preserve financial stability. In addition to well studied bank features such as size, liquidity and credit risk, we study which network metrics relate to interest rates during different periods. Using transaction level data on unsecured and secured lending, we apply an approach that employs network theory, econometric models and machine learning to analyze the structural properties of the secured and unsecured interbank markets in Mexico. Our findings support the "too-interconnected-to-fail" hypothesis. In the secured interbank market, PageRank shows a relationship with interest rates, while metrics associated with the notion of influence and systemic risk (Katz and DebtRank) are relevant in the unsecured interbank market. In general, a bank with high centrality lends at higher rates and gets funding at lower rates.

1. Introduction

This analysis presents evidence that can be useful for determining if the position of a financial institution in a network relates to the price of its funding and to the price it charges for the liquidity that offers in the market. Interbank markets, both secured and unsecured, represent important vehicles for liquidity transmission and are essential for the transmission of monetary policy. The secured interbank market is the market for repurchase agreements (repos); the unsecured interbank market is the short-term lending market (hereafter, secured and unsecured markets). To provide an initial comparison between the two markets, the volume traded in the secured market is as much as four times that of the unsecured market.

Additionally, we perform our analysis on the secured and unsecured Mexican interbank markets because of their importance within the funding structure of the Mexican banking system. Because both markets represent important vehicles for liquidity transmission and contagion, the analysis relates to monetary policy implementation and financial stability. Our research contributes to the innovative literature that uses networks and econometric models in combination, as in Ductor et al. (2014), thus providing more tools to understand these important markets. Econometric and network models are important tools in the policy decision-making processes with objectives such as the pursuit of financial stability, adequate monetary policy transmission, and the elaboration of stress-testing frameworks.

Specifically, we analyze the relationship between interest rate spreads and structural properties (resorting to financial networks) in

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the Mexican overnight secured and unsecured interbank markets. Where an interest rate spread is the difference between the interest rate on each transaction in a particular day in the interbank market, and the market weighted average of all the transactions in that day, as defined in Temizsoy et al. (2017). The interbank interest rate spread has been studied from different perspectives, such as with respect to macroeconomic and microeconomic outlooks. In the present study, our focus is on centrality metrics that provide information about the structural relationships among lenders and borrowers. It is also essential to study the interbank interest rate spread or cost of intermediation, which has important implications for the analysis of systemic risk in the Mexican interbank markets and financial stability, in the sense implied, for example, in Acharya et al. (2012) and León et al. (2018).

We calculate financial network metrics from monthly aggregated data that contains the total amount of money borrowed between each pair of institutions in a given month. These matrices are constructed using transaction-level regulatory data from the Central Bank of Mexico's databases. This database makes it possible to obtain detailed information on the bilateral transactions of banks in both markets. We aggregated daily data to obtain monthly information, as suggested by Finger et al. (2013). An aggregation process across time is useful for uncovering meaningful relationships to define the networks and, as a consequence, to obtain more robust and less noisy centrality metrics for the econometric analysis, as a single-day network could be very different from that of the previous and following days.

For our analysis, we selected a set of variables that cover not only the most important structural aspects of financial networks, but also each institution's contributions to them. As an exploratory analysis, first we estimated correlations, the Variance Inflation Factor (VIF) test, ordinary least squares with and without controls, models with the Generalized Method of Moments (GMM), and Generalized Linear Models (GLM) with machine learning fundamentals. All those specifications were used to determine whether there is a relationship between the network metrics and the interest rate spread for each market. The correlations and the VIF analysis provided insights into the information contained in the set of variables, while the econometric models provided the fundamental variables that are related to the interest rate spread robustly.

Here, we present a model that corrects for multicollinearity and provides the main centrality metrics that relate to the interest rate spread, which is the paper's main objective. We present and analyze the regularized methods using machine learning techniques (for training, validation, and testing data sets). We obtained robust models with regularization techniques: Ridge, Lasso and Elastic Net. In short, we observed similar results in all the estimated models, which indicates the robustness of our conclusions.

We show the results of the models by type of metric and by financial stress period. The results of the GLM model presented includes control variables (transaction ratio, stress index, delinquency ratio and capital ratio). The transaction ratio and stress index variables are more relevant for the secured market, whereas the transaction ratio is relevant for the unsecured market. The periods analyzed are as follows: full sample period, pre-Lehman default period crisis period, European crisis (relatively stable period for Mexico); uncertainty about the rescue program for Greece; the period of the minutes about the reduction in the assets purchase program (a relatively calm period for Mexico) and the period at the end of the asset purchase program (a more stressful period for Mexico). We discuss the respective results in detail in Section 4.

In general, if we compare the estimated results for the secured and unsecured markets, we find that global and local network metrics relate to the interest rate spread. In the majority of the specifications, the signs of the coefficients and their magnitude suggest that being central in the secured and unsecured network conveys important benefits in terms of interest rates. This reinforces the argument about being "too interconnected to fail" (TITF).[2] PageRank is highly relevant in both markets. This centrality metric implies that a bank's importance also depends on the importance of the banks connected to it. Thus, a bank that is systemically important or TITF can charge higher interest rates and secure funding at lower rates.

The results are important for financial stability because in periods of financial stress, banks with excess liquidity exert market power by rationing liquidity, as documented in Acharya et al. (2012) and León et al. (2018). This highlights the importance of researching the interconnection of banks in financial stability, because there are liquidity super-spreaders and super-hoarders. Therefore, banks' positions on the interbank networks make them possible propagators of solvency, monetary policy transmission facilitators and possible drivers of contagion risk.

The rest of the paper is structured as follows. In Section 2, we present a short review of the existing literature. Section 3 contains a statistical and comparative analysis of the interbank markets analyzed, as well as, an analysis of the variables we used in the econometric models, including the interest rate spread (dependent variable), the financial and network metrics (independent variables) and the variables used as controls. In brief, this section shows the importance of studying the markets and presents the descriptive statistics of the variables being studied. Section 4 contains the econometric analysis, the results of the estimated regularized GLMs by periods, the interpretation of the results and possible policy implications in the context of financial stability in the Mexican interbank market. Finally, Section 5 presents the conclusions and possible extensions of this research.

2. Literature review

This section presents the state of the art concerning the topic under study. In this paper, we are interested in the relationship between the place (centrality) occupied by each bank in the interbank network and the price the bank pays or charges in the interbank market. Previous analyses have demonstrated that an institution's position in the network relates to the volume and the interest rate of unsecured loans, as in Temizsoy et al. (2015), Afonso and Lagos (2015), and Bräuning and Fecht (2017). Although some papers have already studied the determinants of rates in interbank markets, we study the unsecured and secured interbank markets simultaneously and use a wider range of network metrics. From this body of work, we can distinguish two strands in the literature: trading relationships and network centrality. Then, we combine the analysis of financial networks with econometric models and machine learning techniques to provide evidence concerning which network properties relate to the interest rate spreads in the unsecured and secured interbank markets.

From the research line on trading relationships, using data for transfers sent and received by banks in the Fedwire Funds Service, Afonso et al. (2013) found that banks rely less on non-recurring transactions, for liquidity purposes and more on funds from institutions with which they have stable financing relationships. Overall, borrowers obtain a better price when trading with frequent lenders. Afonso and Lagos (2015) analyzed the market for Federal Funds, an over-the-counter (OTC) market, for unsecured loans of the dollar reserves that each bank keeps at the Federal Reserve Bank. Loans are mostly overnight, and their purpose is to reallocate reserves among banks. The authors developed a model to characterize such a market, taking into account the distinct features of an

[2] The "Too interconnected to fail" hypothesis holds that institutions which are TITF benefit from their position in the network regardless of credit risk or other related characteristics.

unsecured market, and applied it to answer relevant questions regarding prevalent trading relationships and the effectiveness of some policies for this market. While, Han and Nikolaou, (2016) investigated the influence of trading relationships in another market. Using data from the US tri-party repo market (TPR) from September 2012 to June 2015, they provided evidence that although trading parties conduct transactions with a large number of counterparts, they tend to trade with a small set of such counterparts. Consequently, they allocate large volumes to these counterparts. Furthermore, stable relationships with the same counterparts on other funding markets have a positive effect on counterpartie's relationships in the TPR market. These affect the probability of trading and the terms of such trade.

About network studies also exist for the Market for Federal Funds. Bech and Atalay (2010) found that the market underlying network is sparse (a common characteristic of financial networks, such as the ones we study here). The authors found evidence of the small-world phenomenon and highly disassortative behavior. They also stressed the importance of centrality to rate prediction. Some other studies that focused on networks, interbank markets and financial stability are: León et al. (2018), Battiston and Martinez-Jaramillo (2018), Constantin et al. (2018), Silva et al. (2018, 2016a) and Caceres-Santos et al. (2020).

In particularly, Temizsoy et al. (2015) studied the impact of lending relationships in the e-MID interbank market (an electronic platform for interbank deposits and loans in the euro area and in the United States). Using a panel regression they found that long-term relationships exist between banks and have a positive impact on the rates and volume for lending and borrowing. Bräuning and Fecht (2017) presented similar results for the German interbank market during the financial crisis. We found similar evidence for the interbank markets in Mexico. In addition to studying two important funding markets and estimating methods with machine learning fundamentals, another innovation in our work, in comparison to Gabrieli (2012) and Temizsoy et al. (2017) is the incorporation of a binary variable for whether an institution belongs to the core, according to the model presented in Craig and von Peter (2014). In the context of interbank markets, banks in the core play the role of intermediaries, whereas banks in the periphery interact as lenders or borrowers through the core banks.

An important issue in this literature is the impact of the network structure, specifically regarding how the centrality[3] of market participants relates to rates. Regarding studies about the e-MID interbank market, Barucca and Lillo, (2016) proposed a method for classifying networks according to their structure and applied it to the e-MID interbank market. They found that when the degree of the nodes is taken into account, a bipartite structure emerges. However, Nowicki and Snijders, (2001) used Stochastic Block Models (SBMs) on aggregated (over a week-old) data and found that the network presents a core-periphery structure Craig and von Peter, (2014).

More research has been done on the interbank e-MID market, as it is one of the few interbank markets with available transaction-level data. Iori et al. (2008) performed a network analysis of this market and found clear evidence of structural changes over time (from 1999 to 2002), alongside a quasi-scale-free network displaying a degree distribution with a heavier tail than a random network. One study in the same line of research, which we analyze here, is Iori et al. (2014). The authors conducted an analysis of the determinants of spreads on the e-MID by accounting for the behavior of banks and market microstructure. They found that liquidity cost suffers significant variations due to the sensitivity of rates and the time of trading. Therefore, the spread is proportional to the trading volume at the beginning of the trading day. In other words, trading becomes more expensive for borrowers in the morning and more beneficial for lenders by the end of the trading day. Quoters, regardless of their positions as lenders or borrowers, obtain better rates by trading higher volumes.

Another relevant work is Finger et al. (2013), in which the authors assessed the effect of aggregation concerning the e-MID market. The results indicate that the network obtained from daily data has an almost random behavior, and there is no evidence on the true underlying network structure for the market. However, aggregating longer time periods reveals a non-random structure of the market. Thus, it is fundamental to provide evidence that an aggregation process might be useful for uncovering a significant structure. In the case of Mexican markets, data aggregation for more extended periods also reduces the error on the fit of the core-periphery structure, thus we also use monthly-aggregated data. As in the previously cited studies, we consider only overnight transactions.

Regarding the importance of study periods in this matter, Gabrieli (2012) investigated the role of network centrality on the determinants of interest rates. The study used data from the e-MID interbank market from January 2006 to November 2008. Even though the study included the major distress period of the financial crisis, it would have been interesting to study a more extended period to assess a transition to calmer periods. The results show that the collapse of Lehman Brothers had a significant effect on the market, which is in line with the results presented in Martinez-Jaramillo et al. (2014). Before the crisis, reputation and risk perception were the most relevant factors for determining interest rates, and there was no clear advantage to benefit from centrality or size. However, after the collapse of Lehman Brothers, interconnectedness of institutions measured by centrality became important, but with a negative coefficient, which means that the markets became much more aware of the risk of being highly connected in a period of distress. In addition, reputation became significantly more important.

Most of the studies mentioned above involve only interbank unsecured lending markets. In this research, we examine another essential liquidity source in Mexico, the secured market, also known as the repo market. Thus, a contribution more of our study is the analysis of both markets (the unsecured and secured interbank markets). Another study of a market that examined the impact of the network structure on interbank rates is Craig et al. (2015), in which the authors matched credit exposure data of German banks, from 2000 to 2008, with data from the repo auctions of the European Central Bank (ECB). They found that banks borrowing from a diversified set of institutions faced less pressure in the auctions and did not consider paying higher rates to obtain liquidity from the ECB. Regarding the network structure, Craig et al. (2015) showed that central lenders place more aggressive offers in ECB auctions. This suggests that central lenders in the money market reallocated funds from repo auctions, and that systemically important banks paid higher rates for liquidity to continue their intermediation activities.

In the line of studies applied to Mexico, Usi-López et al. (2017) provided an exhaustive description of this crucial funding market for commercial banks, brokerage houses, and development banks in Mexico. They also analyzed the network structure of the market, showing that connectivity has decreased in the interbank secured markets, partly because the number of banks has increased. Usi-López et al. (2017) also found that the network presents a high clustering coefficient despite its low density. This can have a positive impact on the liquidity flow in the market, if the interpretation that Silva et al. (2016b) gave to the clustering coefficient is considered

[3] Freeman (1978) introduced the concept of centrality in social networks, which can be extended to many other networks, particularly financial networks. Bonacich (1987) further discussed centrality and its relation with the power that a participant has in a network. Babus (2016) presents a theoretical model for explaining how financial networks are formed endogenously and how these are related to systemic risk.

(that is to say, how easy it is to substitute a liquidity provider). Another relevant feature of the interbank secured market in Mexico, found in Usi-López et al. (2017), is the absence of a core-periphery structure. Finally, the authors found strong disassortative mixing in the network, meaning that banks with a small degree tend to connect with banks with large degree.

Using exposures data for the Mexican interbank market and from the Electronic Interbank Payments System (SPEI), Martinez-Jaramillo et al. (2014) explore various network centrality metrics and proposed a unified centrality metric that captures the most favorable properties of some widely used centrality metrics. A result from Martinez-Jaramillo et al. (2014) is that there are important outliers in the relationship between a bank's interconnectedness (its centrality) and its size, which are important to identify for financial stability purposes. Centrality is closely related to the contagion that it might cause in a financial network. When considering the flow of funds in the interbank network, interconnectedness and centrality have important implications for the dispersion of funds.

Finally, in the literature that contributes with financial stability analysis, we found the research of Poledna et al., (2015), who used daily frequency data on exposures from 2007 to 2013; they quantified the contribution to systemic risk of four different exposure networks (credit, derivatives, foreign exchange, and securities) at the individual and the aggregated level. The authors show that focusing on individual layers underestimates systemic risk by up to 90%. Poledna et al., (2021) stress the importance on indirect interconnections, which can be an essential driver of financial contagion. Indirect interconnections come from overlapping portfolios, that is, portfolios with the same securities. Poledna et al., (2021) show that very similar portfolios are prone to amplify losses if one of the similar positions is liquidated, producing a shock on the price.

For the above, we analyze the effect of network metrics on the interest rate spread in the secured and unsecured markets. One reason we decided to consider more than one liquidity market comes from the development of multiplex financial networks. Many state-of-the-art studies on financial networks claim that minimizing the importance of the complexity of the interaction between institutions leads to a severe underestimation of systemic risk. This complexity stems from the fact that banks interact in different markets, and with a wide range of different instruments. Moreover, the interbank repo market in Mexico is a market that presents higher volume than its unsecured counterpart and follows closely the reference rate. To describe the structure of the interbank markets studied in this research, we present a statistical analysis of them in the next section.

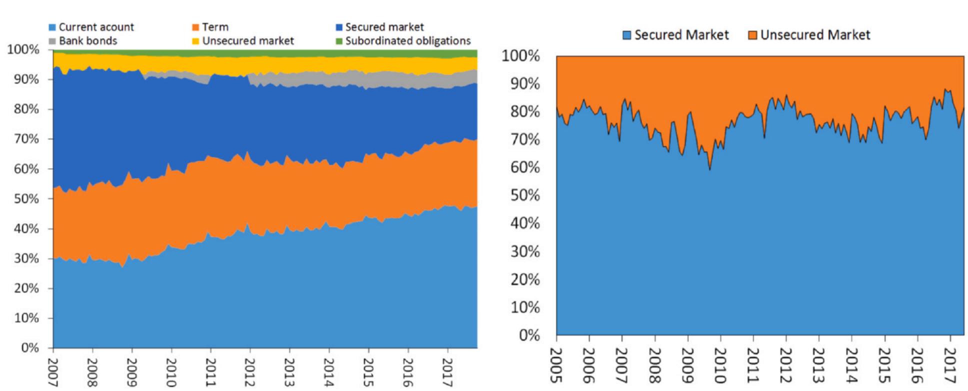
3. Statistical analysis and methods

Using a comprehensive data-set from the Central Bank of Mexico, Usi-López et al. (2017) described the repo market in Mexico over a long period that includes the financial crisis, which started in 2007. The secured market in Mexico is very active, with around 60,000 transactions processed every day in 2016, and a daily average volume of 35 million Mexican pesos. Most of the activity comes from overnight transactions that constitute more than 95% of total transactions. The most important types of counterparties are domestic individuals and domestic companies, whose contribution amounts to more than 90% of the total number of transactions. However, in terms of the volume of the transactions, other counterparts (such as investment funds, commercial banks, and brokerage houses) contribute the most –more than 60%– compared with domestic firms.

In Fig. 1, we see the structure of the main deposits of commercial banks in Mexico. We constructed the chart with regulatory balance sheet data obtained from an institutional repository at the Central Bank of Mexico. Sight deposits and term deposits account for more than 50% of the total system financing. In second place comes the secured transactions, which constitute more than 85% of these two types of interbank funding, leaving the unsecured market with only about 10%.

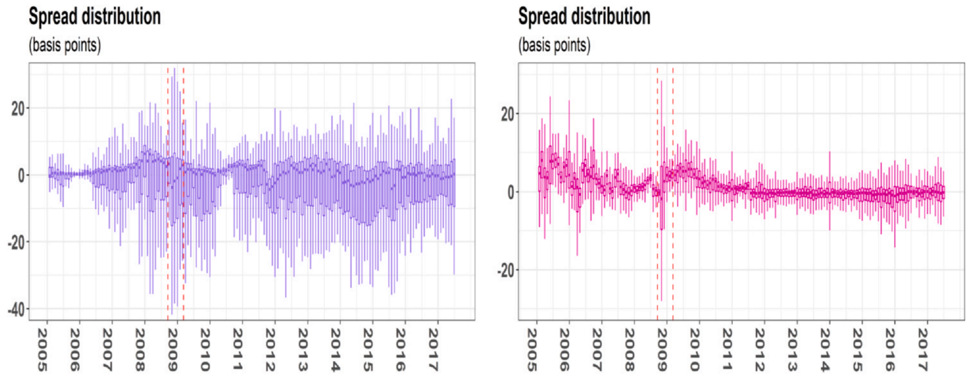
If we compare the above information concerning the total liabilities of the banking system, we see that repurchase agreements represent between 15% and 20% of total liabilities, versus 5% for the unsecured market. This information was obtained from public balance sheet data from the National Banking and Securities Commission (*CNBV*, acronym in Spanish).

Regarding volume, the importance of the secured market is also evident. In Fig. 1, we can see the proportion of the volume of unsecured loans (loans without collateral) to secured operations. The volume of transactions in the secured market is consistently higher, up to four times that of the unsecured market. Despite the secured market has a slightly lower number of transactions per month, the average volume in the secured market is much higher. While the average amount in the unsecured market had decreased as of September 2009, the average amount of repurchases had maintained an upward trend (except for a couple of slumps that quickly returned to



(a) Funding structure (b) Participation of each market in banking activity

Fig. 1. Characteristics of the secured and unsecured market. (a) Funding structure of the banking system. This shows the importance of each component of the banking system in the funding structure. (b) Participation per market in banking activity. We can see the dynamic of the markets regarding the total.
Source: Data from the National Banking and Securities Commission (in Spanish, *Comisión Nacional Bancaria y de Valores) and the Central Bank of Mexico.*



(a) (b)

Fig. 2. Unsecured and secured interbank markets. These graphs show the dynamics of the distribution of interest rate spreads. a) Unsecured, b) Secured.
Source: Authors, with data from the Central Bank of Mexico.

earlier levels). The average secured volume became very important in the second half of 2009.

3.1. Descriptive statistics

We used monthly data[4] to built the centrality metrics for the unsecured market (52 institutions) from January 2005 to June 2017 and the secured market database (48 institutions) for the same period. Due to the data structure, the data analysis allowed us to study the heterogeneity of the institutions over time for the two markets.

The centrality and other relevant metrics estimated in this paper are: Accessibility, Affinity, Betweenness, Core-Periphery, Closeness, Clustering, Cross-Clique, DebtRank, Degree, DebtRank Vulnerability, Entropic Eigenvector Centrality (EEC), Eigenvector, Expected force, Herfindahl-Hirschman Index (HHI), Katz centrality, PageRank, Participation ratio (Part)[5], Percolation, SinkRank and Strenght. "L" after the name of the centrality network means lender and a "B" means borrower. See Section 1 of the supplementary information to find a detailed definition of each centrality metric.

Regarding the centrality metrics of the unsecured interbank market, for example in Fig. 1 of section 2 in the supplementary information, we show the evolution of strength that exhibits a clear upward trend for the entire distribution. We also show the evolution of the betweenness centrality distribution, which also has an upward distribution trend that could be linked to the presence of more links in this market. Further, we show distributions of the secured interbank market across time. Fig. 2 of section 2 in the supplementary information depicts the weighted version of Katz centrality. The distribution steadily declined until the fall of Lehman Brothers, after which it remained low.

Degree and entropic eigenvector centrality can be seen in Figs. 1 and 2 of section 2 in the supplementary information. The evolution of the degree distribution has not undergone any major changes; despite the entry of new banks to the markets, banks on average connect to around eight counterparts, thus the crisis seems to have had little effect on this metric. It is important to note that the distribution of strengths for the secured interbank market (Fig. 2 of section 2 in the supplementary information) is at a considerably higher level than that of the unsecured interbank market (Fig. 1 of section 2 in the supplementary information). Regarding the statistics and the plots of the metrics, in general, there is an apparent increase in centrality that we consider to be linked to an increase in system connectivity, except for the case of weighted Katz centrality in the secured market. Fig. 2 shows the distribution of the spread across time for both interbank markets (unsecured and secured). For the unsecured market, we can observe that the spread has an upward trend until the default of Lehman Brothers (vertical dotted line). After this event, the distribution shifts downwards for a period until it collapses at close to zero for a short period at the end of 2010. Since then, the distribution has had a substantial mass below zero. Meanwhile, the secured market spread distribution shows fascinating behavior. At the beginning of the study period, it was well above zero, and then it declined until just before the Lehman default. Then, for a brief period lasting only a few days, it declined sharply (a possible explanation for these phenomena is a flight-to-quality episode); after that it went up again and stayed above zero for a period. Finally, at the end of 2010, the distribution shows a downward trend until the end of the study period.

3.2. Statistical modeling of variables

We built the data sets (one per market) from the existence of a transaction between two institutions. The spread is calculated as the difference, between the rate at which each transaction was agreed during the month and the weighted average rate of the entire system in the same period. Therefore, if two institutions interacted within the month, there is a spread, and this is present in the data set. It is important to consider that in every transaction in both markets, one institution registers the transaction as an asset and the other registers it as a liability; this means that one institution lends money (lender) and another receives it (borrower). The data sets contains measures of the activity of each institution as a borrower and as a lender in the network, regardless of its role in the specific spread.

The dependent variable, the interest rate spread is calculated as suggested Temizsoy et al. (2017). We calculate the monthly volume-weighted average interbank interest rate spread for each bank pair ij as follows:

$$S_{ij,t} = \frac{1}{\sum_{n=1}^{N_{ij,t}} v_{ij,n}} \sum_{n=1}^{N_{ij,t}} (r_{ij,n} - \bar{r}_m^d)^* v_{ij,n}, \tag{1}$$

where

$$\bar{r}_m^d = \frac{\sum_{n=1}^{N_{ij,d}} \sum_{j=1} \sum_{i=1} r_{ij,n}{}^* v_{ij,n}}{\sum_{n=1}^{N_{ij,d}} \sum_{j=1} \sum_{i=1} {}^* v_{ij,n}}, \tag{2}$$

[4] The database contains daily transactional data; for a detailed explanation of the aggregation process used to convert this to monthly data, see Section 2 of the supplementary information.

[5] The participation ratio, which is not considered among the classic centrality metrics, is the ratio of the amount of money that passed by a node to the total money that moved in the totality of the network.

$r_{ij,n}$ and $v_{ij,n}$ being the transaction-level interest rate outstanding and the volume of the transaction, respectively, for each pair of banks ij where $i \neq j$. $N_{ij,t}$ is the number of transactions for the bank pair ij where $i \neq j$ at period t and n refers to the transaction. Finally, $\bar{r}_m^d$ is the daily average-weighted interest rate over all transactions carried out by all bank pairs.

For the calculation of the network measures is helpful to represent the network connections in matrix form. We denote this matrix by W, with its entries $w_{ij} \geq 0$ representing the amount of money that institution j borrows from institution i, that is, an interaction in which institution j is the borrower and institution i is the lender. Given that an institution cannot borrow money from itself, $w_{ii} = 0 \ \forall \ i \in \{1, \ldots, N\}$, where N is the number of institutions represented in W. By accounting for the direction of money flows in the network, we can define two additional matrices: the outflow matrix W^+ and the inflow matrix W^-. Accordingly, the entry w_{ij}^+ defines a money flow from institution i to institution j and the entry w_{ij}^- defines a money flow from institution j to institution i: this implies that $W = W^+ + W^-$ and $W^+ = (W^-)^T$. Some of the network measures below are calculated from the adjacency matrix A, defined by

$$a_{ij} = \begin{Bmatrix} 0 & w_{ij} = 0 \\ 1 & otherwise. \end{Bmatrix} \tag{3}$$

There are also in and out adjacency matrices A^+ and A^-, defined by analogy to W^+ and W^-, which implies that $A = A^+ + A^-$ and $A^+ = (A^-)^T$. On this basis, the network measures we consider in our study are calculated as fully described in Section 1 of the supplementary information. For a characterization of every financial metric, see Martinez-Jaramillo et al. (2014).

We consider several additional control variables to account for some co-effects that could affect the impact of the network measures mentioned above. For the secured and unsecured markets, we use the transaction ratio, the regulatory capital ratio, the delinquency ratio, and the am_pm ratio (only for the secured market).

Transaction ratio identifies significant relationships in the markets. It is defined as the percentage that represents the number of operations between each pair of institutions in the data set, with respect to the total number of operations on a given date. If the value is close to one, it means that the majority of the operations completed in a period occurred between this pair of institutions.

Capital ratio measures the ratio of assets to debt and represents the amount of losses that can be absorbed by the capital of each bank such that

$$Regulatory\ capital\ ratio = \frac{Core\ capital}{Risk - Weighted\ assets} \tag{4}$$

Ratio AM/PM represents the percentage of operations that occur in two different partitions of a day of activity (before and after 1:00 pm). We calculate the ratio as:

$$Ratio\ \frac{AM}{PM} = \frac{Morning\ operations - Evening\ operations}{Total\ operations\ in\ the\ day} \tag{5}$$

If the ratio has a negative value, it means that the number of transactions arranged after one o'clock in the afternoon is higher than the number of morning operations. This is motivated by the findings in Baglioni and Monticini (2008) who found a decreasing trend in the rate as the day progressed.

Finally, *delinquency ratio* is a measure of the quality of a bank's loan portfolio. This metric is used as a proxy for credit risk of the counterpart. The formula used for its calculation is:

$$Delinquency\ ratio = \frac{Amount\ of\ \ delinquent\ \ loans}{Total\ amount\ of\ current\ loans} \tag{6}$$

In summary, first we calculated the spread, as suggested in Temizsoy et al. (2017), and the centrality metrics of the network obtained from the secured and unsecured markets. Given that we are analyzing the unsecured market in Mexican pesos, we refer only to transactions that occurred in the domestic currency in the secured market for the sake of consistency.

We specify the following convention in the names of the variables: variable name - position spread, where "position spread" can be B or L, depending on whether the institution is a borrower or lender in the transactions considered for computing the spread. In Section 3 of the supplementary information, we present a correlation analysis between the variables, and in Section 4 of the supplementary information a multicollinearity analysis for the complete period, to observe how the financial metrics are related to each other. This paper presents only the results from regularization techniques and GLM (Ridge, Lasso, and Elastic Net); however, many specifications were estimated for the sake of verifying the robustness of our results and are presented in the supplementary information.

3.3. Econometric modeling

The econometric analysis performed includes the correlation test (VIF), as well as different specifications using the GMM model. In addition, some regularization techniques from the GLM models were used, namely: Ridge, Lasso, and Elastic Net. The GLM models with machine learning fundamentals were used to train the models, from which we present the results in the following sections, alongside the definitions of the implemented models.

Estimating GLM models using machine learning techniques makes it possible to obtain robust models, to treat the multicollinearity issue (which is useful, since we are interested in selecting the centrality measures that best explain the interest rate spread in the interbank market), and consequently, to obtain better models in case we need to make predictions. And most importantly, estimating GLM models using machine learning techniques allows for splitting the data in training and testing sets, helping us to avoid overfitting in the models. We present the generic formulation of the regularized models.

Consider the following definition $\hat{\beta} = \text{argmin}_{\beta}\{\sum_{i=1}^{n}(y_i - \beta_0 - \sum_{j=1}^{p}\beta_j X_{ij}) + \delta_\lambda(\beta)\}$, where $\beta = (\beta_1, \ldots, \beta_p)$, $\lambda \geq 0$, and $\delta_\lambda(\beta) = \lambda\sum_{j=1}^{p}\delta_j(|\beta_j|)$ is the increasing function of penalty β, which depends on λ. The family of penalty functions used is the norm - Lq $\delta_\lambda = \lambda(||\beta||_q)^q$. This model provides estimators called Ridge.

First, we present the Ridge regression that has a norm $L2$ and $\alpha = 0$; then we estimate the Lasso regression of norm $L1$ and $\alpha = 1$; and, finally the Elastic Net regression that contains the two previous cases for α. In the analysis of the results, we compare the λ parameter from the three previous methods.

3.3.1. Ridge regression

This technique was initially proposed by Hoerl and Kennard (1970) to avoid collinearity. The Ridge method shrinks the regression coefficients due to the penalty term (λ) in the objective function. If λ is higher, the shrinkage is greater. The Ridge specification is $\hat{\beta}^{ridge} = \text{argmin}_{\beta}\{\sum_{i=1}^{n}(y_i - \beta_0 - \sum_{j=1}^{p}\beta_j X_{ij})^2\}$ s.t. $\sum_{j=1}^{p}\beta_j^2 \leq \kappa$. To clearly see the function of λ, we can write the above optimization problem as $\hat{\beta}^{ridge} = \sum_{i=1}^{n}(y_i - \beta_0 - \sum_{j=1}^{p}\beta_j X_{ij})^2 + \lambda\sum_{j=1}^{p}\beta_j^2$, where $\lambda \geq 0$ and λ is determined after the estimation of the coefficients. Once the coefficients have been estimated, the second step is to look for the value of λ that minimizes the error estimate of the expected prediction.

3.3.2. Lasso regression

The Ridge method tends to shrink coefficients; however, in the end there is no selection of variables, which is why Tibshirani

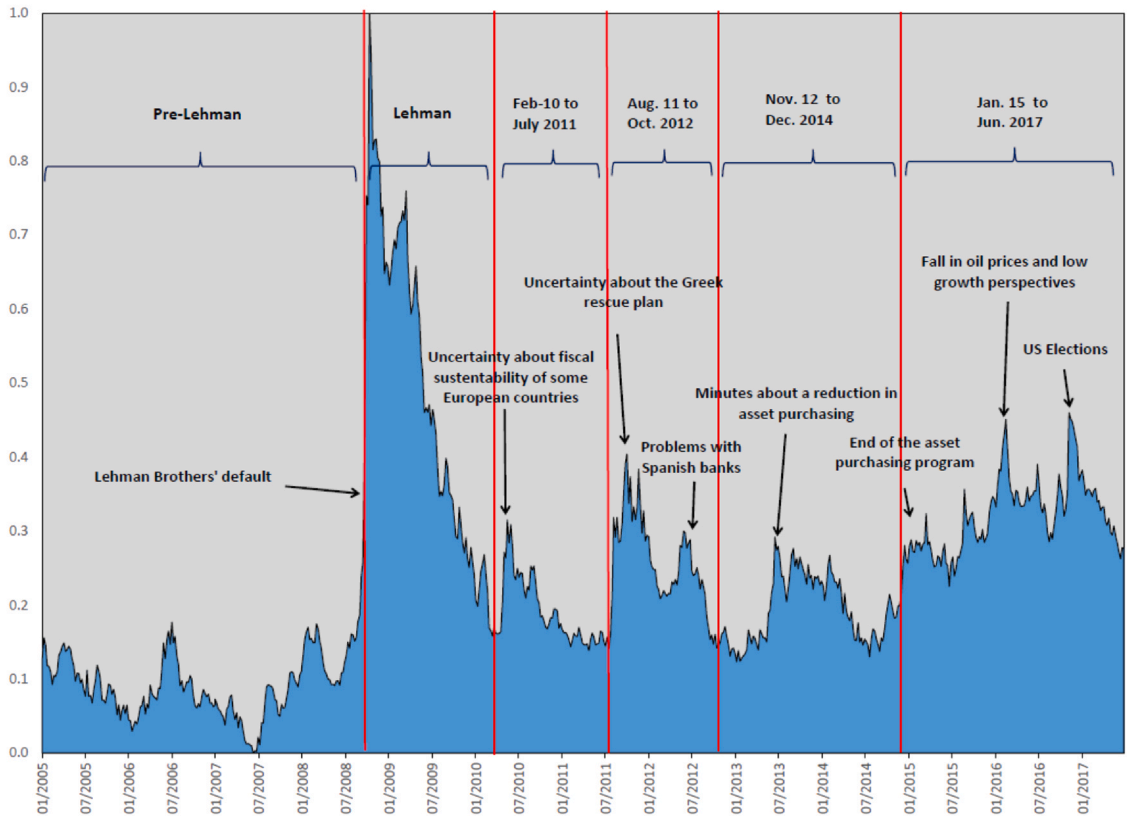


Fig. 3. This graph shows the tested breakpoints in Table 1, those are analyzed as subsamples in the next section.
Source: Authors, with data from Central Bank of Mexico.

(1996) developed the least absolute shrinkage and selection operator (Lasso) method $\hat{\beta}^{lasso} = \text{argmin}_{\beta}\{\sum_{i=1}^{n}(y_i - \beta_0 - \sum_{j=1}^{p}\beta_j X_{ij})^2\}$ s.t. $\sum_{j=1}^{p}|\beta_j| \le \kappa$. Rewriting the above expression, we have $\hat{\beta}^{ridge} = \sum_{i=1}^{n}(y_i - \beta_0 - \sum_{j=1}^{p}\beta_j X_{ij})^2 + \lambda\sum_{j=1}^{p}|\beta_j|$, where $\lambda \ge 0$ when the pairwise correlations are high between predictors. The Ridge method is, in general, better than Lasso. Lasso tends to select only one variable of the group, but it sometimes matters which one it selects. However, as the Lasso method can give a reduction of the variance in the trade-off with a small increase in bias, it can estimate more accurate predictions.

3.3.3. *Elastic net regression*

The technique of regularization and selection, introduced by Zou and Hastie (2005), automatically selects variables and performs continuous contraction (Lasso advantage). We adapt this for our study and estimate seven alpha values in each model. The specification of the problem is as follows: $\hat{\beta}^{ene} = \text{argmin}_{\beta}|y - X\beta|^2$ s.t. $\alpha|\beta|_1 + (1-\alpha)|\beta|^2 \le \kappa$ for some κ. The Elastic Net penalty is $\alpha|\beta|_1 + (1-\alpha)|\beta|^2$, which is a convex combination of the Lasso and Ridge penalties. We can rewrite the optimization problem as a simple "Elastic Net" $\hat{\beta}^{ene} = \text{argmin}_{\beta}L(\lambda_1, \lambda_2, \beta) = |y - X\beta|^2 + \lambda_2|\beta|^2 + \lambda_1|\beta|_1$, where $|\beta|^2 = \sum_{j=1}^{p}\beta_j^2$, $|\beta|_1 = \sum_{j=1}^{p}|\beta_j|$, $|y - X\beta|^2$ and $\alpha = \frac{\lambda_2}{\lambda_1+\alpha_2}$.

In the next section, we present the results of the GLM models with regularization techniques in different periods of financial stress. We based the selection of periods on a stress index[6] computed at the Central Bank of Mexico. The index is computed with relevant market indicators such as the credit default swap spread (CDS) of the five-year Mexican bonds and the Chicago Board Options Exchange Volatility Index (known by its ticker symbol VIX). Fig. 3 shows the time evolution of this index as well as the selected dates that we used to split the sample and to statistically test if banks change their behavior at different levels of financial stress.

4. Results

In this section we present the main results. In line with the main objective of this research, we identify which centrality metrics are related to the behavior of the interest rate spread in the secured and unsecured interbank markets; that is, we observe if there is evidence of systemic risk or connectivity metrics, or other measures of contact among banks that relate with the interest rates between lenders and borrowers. In the following subsections we present the results for the estimated shrinkage methods (Ridge, Lasso and Elastic Net). Figures and tables with the estimated results, according to all the periods and markets, are found in Section 5 of the supplementary material.

The results of the estimated models for different markets indicate that, in general, several centrality metrics are statistically significant and persistent on each of the markets, this allows us to identify the network metrics that relate to the spreads, including network metrics that are used for systemic risk and financial stability purposes. Instead of focusing only on a pre-crisis, during crisis, and post-crisis period, we decided to split the sample into several periods by taking into account a number of events that lead to higher or lower stress in the financial system, as indicated by the stress index used at the Central Bank of Mexico.

We chose the different periods on the basis of a test for the stress index and found statistical evidence, both economic and financial, that supports the split. As the stress index shows (Fig. 3), there are episodes where there was an increase in financial stress and the

[6] We are grateful to our colleagues from the Financial Stability Directorate in the Central Bank of Mexico, who shared the stress index time series with us, in particular, we thank Yahir López Chuken.

Table 1
The table shows the results from the Chow break-point test for the dates 2008M09, 2010M01, 2011M06, 2012M09, 2014M11, and 2017M06. This test shows that the null hypothesis (no breaks at specified breakpoints) is not accepted, at 95% confidence and for the given sample. Thus, we need to split the study periods to study the relationship between spreads and centrality properly.

Dates tested: 2008M09 2010M01 2011M06 2012M09 2014M11 2017M06			
Null hypothesis: No breaks at specified breakpoints			
Varying regressors: All equation variables			
Equation sample: 2005M03 2017M12			
F-statistic	2.064807	Prob. F(18,133)	0.0104
Log likelihood ratio	37.94996	Prob. Chi-Square(18)	0.0039
Wald Statistic	37.16652	Prob. Chi-Square(18)	0.0050

Source: Authors, with data from the Central Bank of Mexico.

periods following Lehman's default are by no means homogeneous. We tested statistically the periods by applying the Chow break-point test, where the null hypothesis (no breaks at specified breakpoints) is not accepted because the F probability is less than 0.05; thus, we found that the proposed dates are breakpoints (Table 1). Fig. 3 shows the selected periods based on the statistical test to detect breakpoints. The test was performed on the Stress Index that allows us to know the periods of marked stress.

The next subsection shows the results by interbank market (secured and unsecured). The Ridge method was the best method found for analyzing the secured market, except during the European crisis period, where the Lasso method proved to be better. In Section 7 of the supplementary information, we present all results (main determinants of the interest rate spread by periods) for other methods (Elastic Net for different values of alpha). For the unsecured market, the best model depends on the period.

4.1. Results of the estimated models for the secured market by period

For the full sample, we can see that the Ridge method gives the minimum Mean Squared Error (MSE), this shows the average squared difference between the estimated interest rate spread and the real interest rate spread value, also known as the precision error. Table 2 shows the MSE alongside the value of log (λ). For the secured market, the Ridge method provides the best model with a minimum MSE, except for the European crisis period, for which the Lasso is better.

The shrinkage methods, penalized or regularized, set penalties for the coefficients to reduce them progressively to zero; only important coefficients are found with the minimum variance model. For the secured market, the best regression is obtained using the Ridge method with the penalty parameter.

In Fig. 4 panel (a), the curves present the centrality metrics against the L-norm of the whole coefficient vector, when λ takes different values. The axis number above indicates the nonzero coefficients at the current value of λ; we can therefore observe that the majority of the variables are close to zero, and five variables significantly affect the variability of the interest rate spread in the full sample in the secured market. We can detect from Fig. 4 panel (b) that when the penalty is high (λ grows from $0 \to \infty$), the coefficients will be zero or close to zero, in this sense the plot shows the coefficients against log(λ). Fig. 4 panel (c) shows the deviation of the fraction explained by the variables, and panel (d) shows the evolution of the test error (MSE) for different values of log(λ), the red dotted curve is the cross-validation curve with upper and lower standard deviation and the log(λ)s are indicated by the vertical line, enabling us to see the best lambda with the minimum MSE. We also estimate predictions based on the fitted models, which are close to the selection of real variables. The estimated models can learn the complex patterns of the variables, with the penalization mechanism

Table 2
Secured Market_Full period. Comparison between models with different alpha values (best log(λ) and MSE). This table presents a comparison of the MSE of the econometric methods, such as Ordinary Least Squares (OLS) and penalized regression methods or regularized regressions, with different alpha values. In addition, we present the log(λ) with the lowest precision error in this case, for the full period in the secured market. The Ridge method has the minimum MSE. Section 5 of the supplementary information shows the MSE and the log(λ), for all the methods, by period and market.

Method	MSE	Log(λ) with the lowest precision error
OLS	0.017222	–
Ridge_(alpha = 0)	0.017209	-6.464507
Lasso_(alpha = 1)	0.017221	-13.37226
Elastic Net_(alpha = 0.1)	0.017221	-11.06968
Elastic Net_(alpha = 0.25)	0.017221	-11.98597
Elastic Net_(alpha = 0.5)	0.017221	-12.40001
Elastic Net_(alpha = 0.75)	0.017221	-13.08458
Elastic Net_(alpha = 0.95)	0.017221	-13.32097

Source: Authors, with data from the Central Bank of Mexico.

reducing overfitting; this gives us robust models. The figures by subsamples and methods for both the secured and unsecured markets are provided in section 6 of the supplementary information.

For the secured market, the results by period show that around five centrality metrics are significant in different periods (see Fig. 5).[7] During the first three periods, most of those five metrics of centrality are important. We can also observe that borrowing and lending network metrics are compatible with the TITF hypothesis; in general, in all the periods in this market, being central is linked to cheaper access to liquidity and better lending conditions.

During the pre-Lehman period, the centrality metrics that relate to the interest rate spread were: PageRank_B (-), PageRank_L (+), Katz_cent_B (-), part_B (+), and HHI_L_B(-). The results for PageRank, Katz and Participation ratio (how important an institution is as a funds provider or funds taker) are the most relevant financial metrics for relating to the interest rate spread; this supports the TITF hypothesis. Particularly, we see that PageRank_L implies that lenders assume importance in line with the relevance of banks connected to their network; the banks' importance has a positive effect on spread, and banks charge higher than market average interest rate. In sum, we observe that in this period, if a bank is systemically important, it is reflected in the spread.

In the crisis period, the main centrality metrics are the same as in the pre-crisis period. Thus, in this period, the TITF hypothesis is supported. In particular, we find that PageRank_Lenders is the most important determinant of the interest rate spread.

For the European crisis period, PageRank_B is one of the most important metrics relating to the spread. Interestingly, Katz and Participation ratio have coefficients with positive signs, which means higher financing cost for borrowers due to the number of lenders and money transactions during this period.

The fourth period, with the uncertainty about the rescue program for Greece, was an interesting one in Mexico. Along with the significant concerns about the suitability of the rescue plan for Greece, there were major concerns about the Spanish banks, because two important subsidiaries in Mexico are Spanish. As a consequence, this period can be classified as a period of high financial stress. In the model PageRank_L shows a difficult situation for lenders in this period.

The period labeled "Minutes" can also be classified as a period of high financial stress, and the borrowers were those that explain small movements in the interest rate spread in this period.

[7] The tables with the coefficients are available upon request.

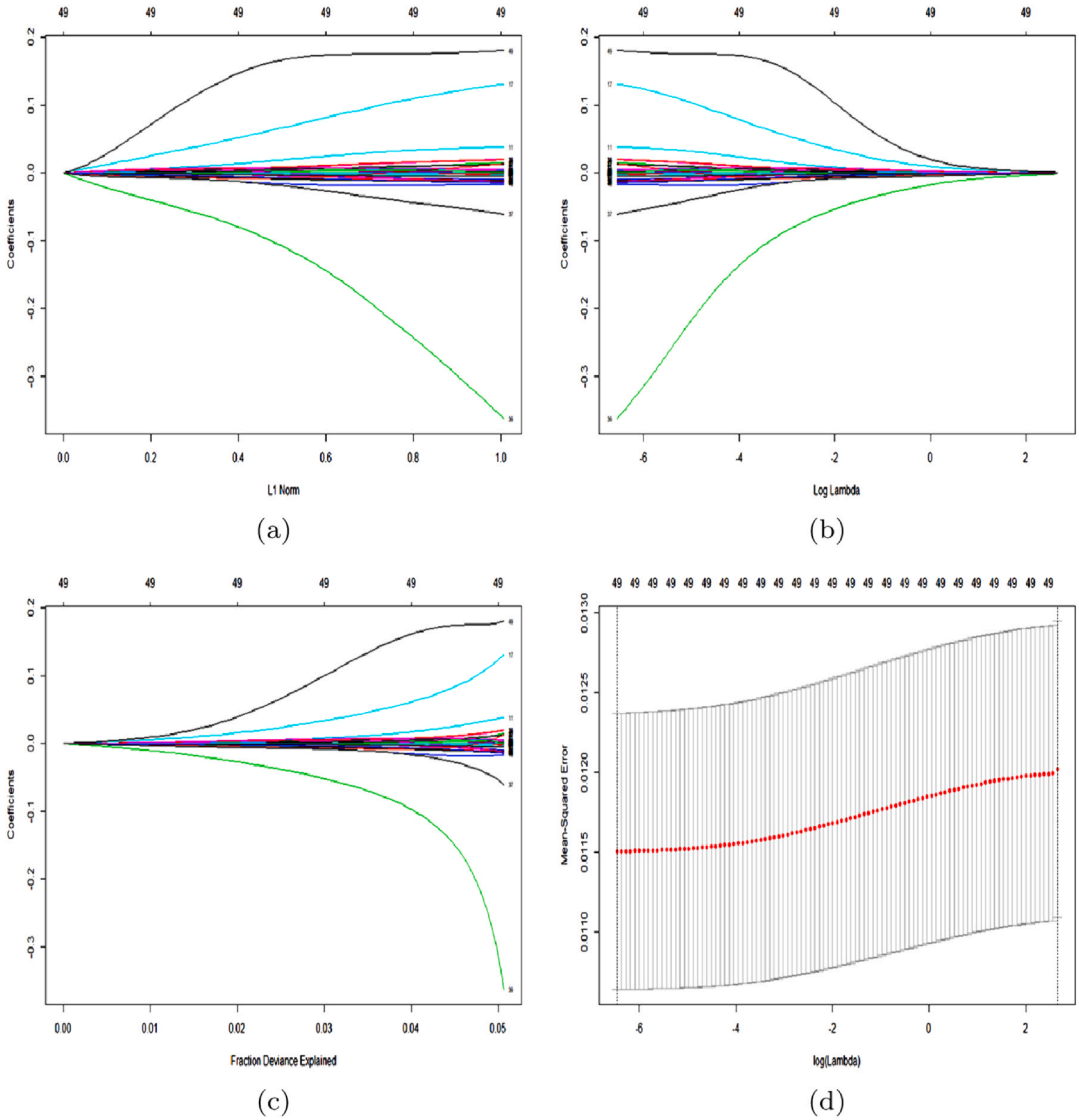


Fig. 4. Secured market: Outputs from the Ridge method. These graphs show the outputs from the Ridge method, the method with the lower MSE for the full period in the secured market. a) The graph shows the estimated coefficients with different λ values against the L1-norm. b) The plot indicates the regression coefficients against log(λ), c) Here, we can see the percentage of deviation explained by training data. d) This plot shows the evolution of the error against every log(λ). Section 6 of the supplementary information shows these plots for all the methods according to the market.
Source: Authors, with data from the Central Bank of Mexico.

In the last period, HHI_L_B and Katz_cent_B (number of borrowers connected in a transaction) support the TITF hypothesis for the borrowers and indicate a lower financing cost for them.

It appears that a bank with systemic relevance, that is well connected, has influence and carries out many financial transactions, can charge high interest rates and fund itself at a lower interest rate. This involves an important economic policy implication: regulations need to focus beyond bank size, and the authorities should consider banks' connections and the number of transactions conducted. In terms of the centrality network measures, we found PageRank, Katz and Participation ratio (how important an institution is as a funds provider or funds taker) to be important for the determination of the interest rate spread, in several periods. for the secured interbank market. The general picture that emerges is that the TITF hypothesis holds for most of the periods, especially in the global periods of financial stress, pointing to a change in behavior by the participants in this market.

4.2. Results of the estimated models for the unsecured market period

For the unsecured market, the best method varies for different periods. Table 3 and Fig. 6 show the dynamics in the unsecured market for the full sample. The minimum MSE is found in the Elastic Net method ($\alpha = 0.75$).

Fig. 6 panel (a) shows the nonzero coefficients for this market determined by Elastic Net regression ($\alpha = 0.75$). Those are Eigenvector_L, Accessibility_B, and PageRank_B, which are plotted versus L-norm. Fig. 6 panel (b) shows the coefficients against the log (λ) values; we can observe how the penalty increases when λ grows from $0 \rightarrow \infty$. In the unsecured market, a different effect on the interest rate spread is found due to the connection relationship. This means that the connections are seen as a source of systemic risk because of the unsecured market characteristics. The effect on the spread due to connectivity could be contrary to that analyzed in the secured market, it will depend on the financial stress period. Then,

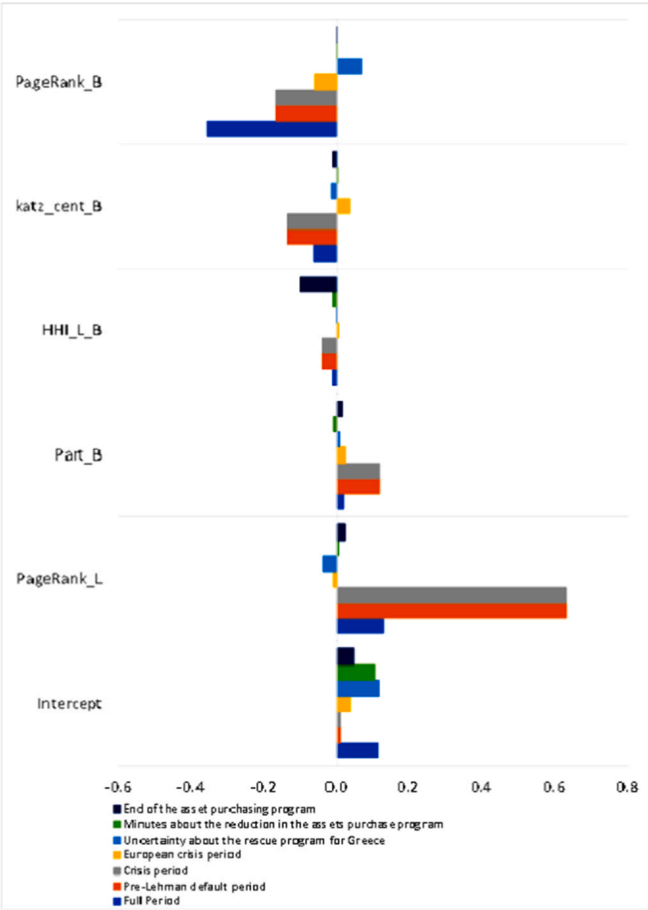


Fig. 5. Results by period for the secured interbank market Ridge ($\alpha = 0$) model. This graph shows the centrality metrics from the Ridge method, the method with the lowest MSE in the secured market according to different periods. The periods are full period (navy blue), pre-Lehman default period (orange), crisis period (gray), European crisis period (yellow), uncertainty about the rescue program for Greece (blue), the period of the minutes in the reduction in the asset purchase program (green), and the end of the asset purchase program (dark blue). Section 7 of the supplementary information shows the estimation by period according to the other methods. For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.
Source: Authors, with data from the Central Bank of Mexico.

Table 3
Unsecured Market_Full period. Comparison between models with different alpha values (best log(λ) and MSE). This table shows the comparison through MSE of the econometric methods, as (OLS) and penalized regression methods or regularized regressions, with different alpha values. We also present the log(λ) with the lowest precision error, in this case, for the full period in the unsecured market. The Elastic Net method with alpha equal to 0.75 has the minimum MSE. Section 5 of the supplementary information shows the MSE and log(λ) for all the methods by period and market.

Method	MSE	Log(λ) with the least precision error
OLS	0.005735	–
Ridge_(alpha = 0)	0.005797	−5.270106
Lasso_(alpha = 1)	0.005682	−10.13112
Elastic Net_(alpha = 0.1)	0.005705	−9.22404
Elastic Net_(alpha = 0.25)	0.005696	−9.582129
Elastic Net_(alpha = 0.5)	0.005681	−9.531006
Elastic Net_(alpha = 0.75)	0.005679	−9.843437
Elastic Net_(alpha = 0.95)	0.005681	0.000042

Source: Authors, with data from the Central Bank of Mexico.

the models estimation was made by period too. The graphs by subsamples and methods for the secured and unsecured markets are in section 6 of the supplementary information.

We can observe that the effect of connectivity on the interest rate spread is different depending on the period. There is a bigger systemic risk in the unsecured market, during financial stress periods. In this market, the transaction ratio is a relevant control variable. Fig. 6 panel (c) shows the percentage of deviation that is explained by the training data. Colored lines only show examples for each coefficient, and panel (d) shows the cross-validation curve. We can thus observe that regularization of L forces the parameters to be close to zero, if they do not have more information to provide than the main explanatory variable; therefore, the larger penalty yields a robust model.

The results for the unsecured market by period are represented graphically in Fig. 7. There are around six types of centrality metrics that relate with the interest rate spread in this market.

For the pre-Lehman period, we found that PageRank_B indicates that the importance of banks connected to a borrower affects their dynamics. This means a higher financing cost because of the bank's connections. The systemic risk in this period is very important, as we observe a negative effect from PageRank_L, indicating that the lenders' connections affect the bank. This makes sense in an interbank market without collateral.

For the crisis period (October 2008 to February 2010; see Fig. 7), there is strong evidence that systemic importance (centrality) benefits lenders and borrowers. In particular, DebtRank_B, Katzcent_B, and PageRank_L relate to the spread. This supports the TITF hypothesis because borrowers have a lower funding cost and lenders have a positive spread. For a market with more risk, because there is no collateral, DebtRank is an important variable to determine the interest rate spread. For the Lehman period, there is evidence of the benefits of being central for lenders and borrowers, as well as of systemic risk affecting the spread.

Our work provides evidence aligned with the work of Temizsoy et al. (2017), who obtained evidence to support their claim that centrality plays an essential role in terms of the rates that banks obtain on the unsecured money market. Furthermore, this effect became more significant during the crisis of 2008, both for the entire network and for individual institutions. They provide evidence about the TITF hypothesis demonstrating that borrowers obtain better rates by positioning themselves as important intermediaries in the market. An apparent effect of the crisis is that major lenders were able to obtain better rates. However, afterward the opposite happened; that is, banks became more aware of the risk of being highly exposed with very uncovered institutions.

The European crisis period offers strong evidence supporting the TITF, namely, that being central can be beneficial for lenders and borrowers. On the borrower side, Katz_cent_B and DebtRank_B indicate borrowers with connections and systemic relevance. While, Katz_cent_L and DebtRank_L have a positive effect on interest rate spread, this means that lenders with important connections and systemic relevance, due to the density in their connections and the relevance of their counterparts, can charge higher interest rates and obtain financing at a lower interest rate.

There is a special dynamic in the period we called uncertainty about the rescue program for Greece. PageRank is the most important centrality measure in this period. The signs mean that borrowers faced higher financing cost due to the uncertainty in a market with higher systemic risk than in the secured interbank market. The Greece period was characterized by uncertainty about the rescue plans for Greece, as well as by serious problems in Spanish banks that had effects for the Spanish subsidiaries in Mexico.

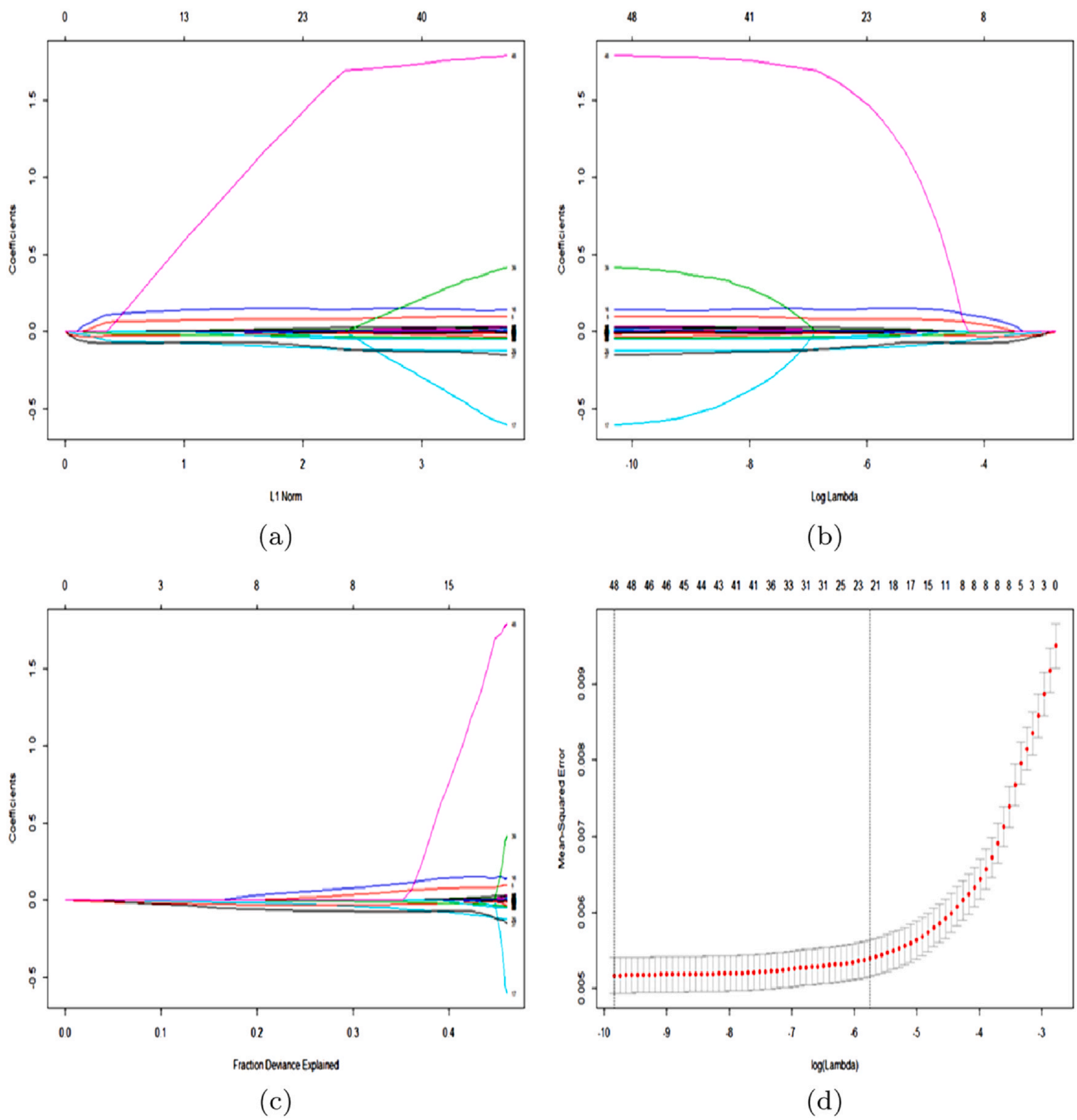


Fig. 6. Unsecured market: Outputs from Elastic Net ($\alpha = 0.75$) method. These graphs show the outputs from Elastic Net ($\alpha = 0.75$) method, the method with the lower MSE for the full period in the unsecured market. (a) This graph shows the estimated coefficients with different lambda values against the L1-norm. (b) This plot indicates the regression coefficients against log(λ). (c) Here, we can see the percentage of deviation explained by training data. (d) This plot shows the evolution of the error against every log(λ). Section 6 of the supplementary information shows these plots for all the methods by market.
Source: Authors, with data from the Central Bank of Mexico.

The fifth period can be considered a less stressed period; we called it the minutes period. There are various structural metrics that are relevant. It is still important for the lenders to have important connections (PageRank_L and Katz_cent_L) and systemic relationships (DebtRank_L); this determines a positive spread. Then, they can charge a higher interest rate. DebtRank_B and Katz_cent_B indicate that a relevant borrower can find lower funding cost with their counterparts.

For the last period (Fig. 7), the main centrality measures that explain the interest rate spread are Katz and DebtRank. For lenders and borrowers, the interconnection and systemic relevance are fundamental to determine the interest rate spread. In the unsecured market for some periods the interconnections and the systemic relevance play in favor or against of the lenders and borrowers, that depends on the financial stress period. There is greater sensitivity to conditions of financial stress in the unsecured market because this market has no collateral.

For this market, the most important result is that a topological centrality metric (PageRank), in some periods, points to a different address than a systemic risk metric (DebtRank) does. Our results are robust for the many models that were estimated. DebtRank reflects the characteristics of the unsecured market by periods. In this market, with no collateral, systemic relevance measured by the DebtRank centrality metric is consistent with the TITF hypothesis, unlike that measured by the PageRank metric. Moreover, most of the other centrality metrics point to the same conclusion as DebRank, notably Katz centrality. Then, we observed that a researcher or monetary authority could analyze the systemic relevance metric to study these type of markets, since different conclusions can be made if one centrality metric is chosen over the other, in certain markets due to their inherent characteristics. We can say that given the specific characteristics of the unsecured market, a systemic risk metric makes more sense to analyze its relationship with the interest rate spread. This finding is very important in the choice of the

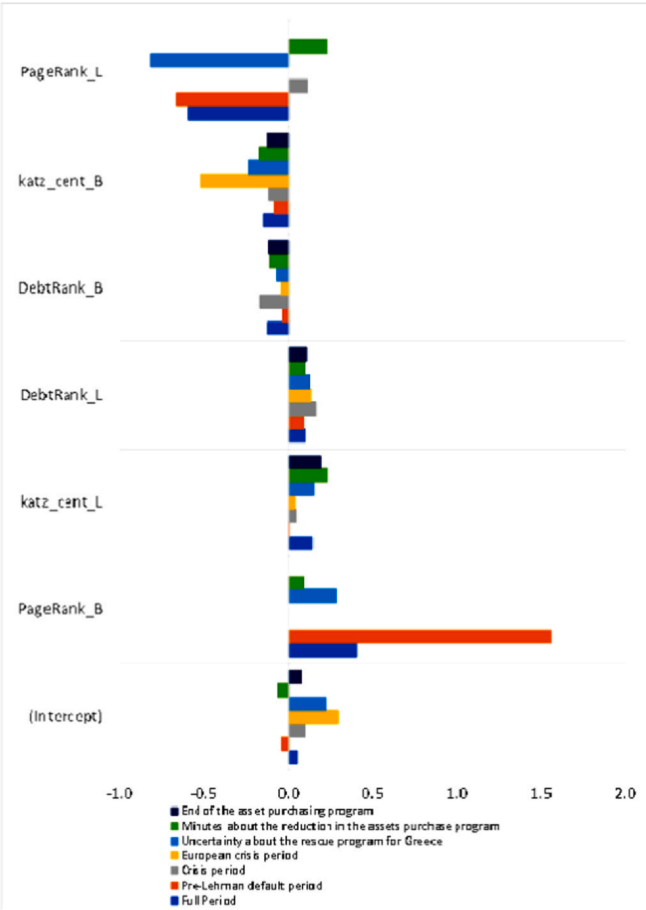


Fig. 7. Results by period, for the unsecured interbank market Elastic Net ($\alpha = 0.75$) model. This graph shows the centrality networks from the Elastic Net ($\alpha = 0.75$) method, the method with the lowest MSE in the unsecured market according to period. The periods are full period (navy blue), pre-Lehman default period (orange), crisis period (gray), European crisis period (yellow), uncertainty about the rescue program for Greece (blue), the minutes period on the reduction in the asset purchase program (green), and the end of the asset purchase program (dark blue). "_L" after the name of the centrality network means lender and a "_B" means borrower. Section 7 of the supplementary information shows the estimation by period according to the other methods. For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.
Source: Authors, with data from the Central Bank of Mexico.

centrality measure by market and study period, for future financial stability analyzes. To study markets without collateral or more sensitive to risk in financial stress periods, it is essential to use DebtRank.

In sum, we assess the relationship of local and global network metrics with the interest rate spread, we also determine whether any of the metrics are relevant in either market, and whether such relationship with the interest rate spread is positive or negative. Thus, this paper contributes to the literature concerning the relationship of the underlying network structure of the Mexican interbank market. We observe that PageRank and Katz are important measures of the financial network for the secured interbank market. While DebtRank is fundamental to explain the unsecured interbank market because its nature. For both the secured and unsecured markets, we see evidence of the TITF hypothesis, with the effect on the interest rate spread depending on connections, systemic relevance in the markets, and varying according to different periods. In general, this means that the banks have a better interest rate spread if they connect with central banks in the network, in certain periods.

5. Conclusions

We explored the structural properties of the Mexican secured and unsecured interbank markets. The purpose of the analysis was to discover the relationship between interbank networks and the interest rate in such markets. We estimated econometric models using different estimation methods: least squares, GMMs, and GLMs with machine learning fundamentals. Due to space issues, we only present the results of the latter model in this paper. It is important to point out that the results of the other models are in line with those presented here. We specifically present the results of the regularized GLMs by time periods, where we used training, validation, and testing data sets. We found that mainly the importance of a bank according to the importance of the institutions that are connected to it (PageRank) explains the relationships between lenders and borrowers in the Mexican secured interbank market. While a network measure that quantifies the node's importance in a system (DebtRank) is fundamental to study the interest rate spreads in the Mexican unsecured interbank market, because of its nature, it is more sensitive to periods of financial stress and systemic risk. These results are very important for financial stability. Given that we analyzed 20 centrality measures and found which ones explain the interest rate spread in the secured and unsecured interbank markets. The paper presents in the respective results section, which centrality measures explain the interest rate spreads by market (depending on their characteristics, secured and unsecured markets) and by financial stress periods. This is very important to choose the centrality measure that best explains the structure of the studied markets when researchers or monetary authorities are analyzing financial stability.

In line with Acharya et al. (2012) and León et al. (2018), knowing the interconnection of banks is very important, because they are super-spreaders in the interbank markets that influence financial stability. Acharya et al. (2012) show how banks with excess liquidity, especially during the global financial crisis, exert market power by rationing liquidity. This emphasizes the importance of knowing the super-spreaders in an interbank market, as they are possible propagators of contagion and the banks that will enable the transmission of monetary policy. The study of the issue raised is highly relevant because of the implications in terms of financial stability. For example, Acharya et al. (2012) point out that liquidity rationing by super-spreaders also occurred before the global financial crisis, such as the collapse of Long-Term Capital Management in 1998 and Amaranth Advisors in 2006. The relevance of the study in terms of financial stability is also stressed in León et al. (2018), who identified the central bank liquidity super-spreaders in interbank funds network.

Our work exhibits the following innovations: 1) The period investigated is wider than in previous studies, which allows to explore different subsamples as financial stress periods. 2) We study two important interbank markets using the same approach. This allows us to observe what financial network measures are important in a market with collateral (less systemic risk, such as a secured interbank market) and in an unsecured market. 3) We include new network metrics and observe that for the unsecured market, those explain the interest rate spread for several periods.

In general, there are five centrality metrics that relate to the interest rate spread for the secured market and six for the unsecured market from around 20 different network metrics. Moreover, the coefficients indicate that higher centrality implies lower rates for borrowers and eventually higher rates for lenders. This supports the TITF hypothesis, with Katz_cent explaining the interest rate spread in almost all the periods and markets. That metric shows the number of all banks that can be connected through a path. As well as the TITF hypothesis is supported by the metrics results that explain the interest rate spread particularly in the secured and unsecured interbank markets, which have been explained and refer to PageRank and DebtRank, respectively. Importantly, we realized that in the unsecured market, a systemic risk measure (such as DebtRank) explains the interest rate spread for different periods, as well as the other results presented in this paper by market and periods of financial stress.

We found that there are important effects of the connections between lenders and borrowers in the interbank market on the interest rate spread. These depend on the financial stress level, the benefits of being central, the concentration of the transactions, the systemic relevance, the density of the connections, the importance of the counterparts connected to the bank, and the number of the banks connected in a lending or borrowing path. In particular, immediately after the fall of Lehman Brothers, the benefits of being central and connected increased.

All these results suggest that the place of an institution in the network and its connections are beneficial for its funding prices, as well as for the price that an institution charges for liquidity in both interbank markets. Moreover, banks that play the role of intermediaries obtain lower rates as borrowers and charge higher rates as lenders. All of the above support the argument of being “too interconnected to fail” (TITF), because a bank that is central or systemic can charge higher rates and fund itself at lower rates.

In sum, the results for different time periods indicate that banks change their behavior over time and that splitting the sample has important implications for statistical purposes, in terms of financial interpretation, in particular for the unsecured market, which has higher systemic risk because there is no collateral in such transactions. Specifically, we find that for the unsecured market, DebtRank explains the interest rate spread in a greater amount, while PageRank describes the interest rate spread in the secured market. In addition, in pre-crisis and crisis periods, the network measures mentioned above explain the interest rate spread to a greater extent.

A future extension of this study could consider other relevant variables, like macroeconomic and financial series, or variables related to the collateral used in secured transactions. Future work could use the same approach to include more intermediaries (for example, pension funds, investment funds, and brokerage firms), which are relevant non-bank counterparts. It would be interesting to see if their centrality in the inter-financial network has an impact on their credit conditions in the secured market.

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