Which network measures explain the interest rate spread in the Mexican secured and unsecured interbank markets?[⋆]

Isela-Elizabeth Tellez-Leon[a,1], Luis Escobar-Farfan[b], Serafín Martínez-Jaramillo[c], Ronald Hochreiter[d]

[a] *IIASA, Schlossplatz 1, 2361 Laxenburg, Austria.*
[b] *Banco de México, Avenida 5 de Mayo 2, Colonia Centro, 06000 Cuauhtémoc, CdMx.*
[c] *CEMLA. Durango 54, Colonia Roma Norte, 06700 Cuauhtémoc, CdMx.*
[d] *Webster Vienna Private University. Praterstrasse 23, 1020 Vienna, Austria.*

Abstract

In an economy, it is essential to know the determinants of the interest rate spread, because it reflects the positions of lenders and borrowers. We determine which network centrality measures explain that relationship, during pre-crisis, crisis, and other financial stress periods. From a perspective of Networks Theory and econometric models with machine learning fundamentals, we analyze the structural properties of the secured and unsecured interbank markets in Mexico, finding evidence to support the "too-big-to-fail" and "too-interconnected-to-fail" hypotheses. In both markets, PageRank is a major determinant of the spread. Metrics associated with the notion of influence and systemic risk (Katz and DebtRank) affect the unsecured market in each period. In general, a bank that is central or systemically important can charge higher interest rates and finance itself at lower interest rates.

Keywords: Financial Networks, Financial Econometrics, Regularization Methods (Ridge, Lasso and Elastic Net), Mexican Financial Markets.

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[*]Corresponding author: tellez@iiasa.ac.at

1. Introduction

It is essential to know the interbank interest rate spread or cost of intermediation. If this cost is low, the firms are incentivized to take out credits. While consumers have an incentive to deposit their money in a bank if they get a high interest rate on savings, thus they could postpone their present consumption intentions and put the money into savings. The interbank interest rate spread has been studied from different perspectives, for instance, with respect to macroeconomics and microeconomics outlooks; in the present study, our focus is on centrality measures that provides information on the relationships between lenders and borrowers. We analyze the impact on interest rate spreads through structural properties of the Mexican overnight secured and unsecured interbank markets.

An interest rate spread is the difference between interest rates on each transaction in the financial market, with the weighted average as defined in Temizsoy et al. (2017). The secured interbank market is the interbank market for repurchase agreements; the unsecured interbank market is the interbank loan market (hereafter, secured and unsecured markets). The volume traded in the secured market in particular is up to four times that in the unsecured market.

We assess the impact (if any) of local and global network metrics on interest rate spreads; we also determine whether any of the metrics impact either of the two markets, and whether such effects on the spread are positive or negative. Thus, this paper contributes to the literature concerning the impact of network structure on interbank interest rates, with implications in the analysis of systemic risk in Mexican interbank markets.

We perform the analysis on the secured and unsecured Mexican interbank markets because of their importance within the funding structure of the Mexican financial system. As both markets represent important vehicles for liquidity transmission and contagion, the analysis relates to monetary policy implementation. Our research adds to the innovative literature that uses networks and econometric models in combination, as in Ductor et al. (2014), thus providing more tools for understanding these important interbank markets. Those are important tools in the policy decision-making processes with regard to the achievement of greater financial stability, monetary policy transmission, and stress-testing.

Therefore, this analysis presents hard evidence that can be used to determine if the relationships of a financial institution in the network are related to the price of its financing. It also shows the price charged for the liquidity that it offers on the interbank market. We calculate the financial network metrics from monthly aggregated data that contain the total amount of money lent/borrowed between each pair of institutions for a given month. These matrices are constructed using regulatory information from Central Bank of Mexico databases with transaction-level data. The data make it possible to obtain detailed information on the bilateral positions of banks in both markets. To obtain monthly data, we aggregated daily data as suggested by Finger et al. (2013). An aggregation process across time is useful to uncover meaningful relationships regarding networks and, as a consequence, to obtain more robust centrality measures and less noise for the regressions.

For our analysis, we selected a set of variables that cover not only the most important structural aspects of the financial networks, but also each institution's contribution to them. We estimated correlations, the Variance Inflation Factor (VIF) test, ordinary least squares with and without controls, panel models with fixed effects (with and without controls), Dynamic Panels following the Arellano and Bond (1991) methodology, models with the Generalized Method of Moments (GMM), and Generalized Linear Models (GLM) with machine learning fundamentals. All those specifications were used to determine the relation between the network measures and the interest rate spread per market. The correlations and the VIF gave us insights into the information contained in the set of variables. While the econometric models provided the fundamental variables to explain robustly the interest rate spread.

We decided to present the model that corrects for multicollinearity and to provide the main centrality measures that explain the interest rate spread, this is our objective in this paper. We thus present and analyze the regularized methods using machine learning (training, validation, and test data sets). We obtained robust models with regularization techniques: Ridge; Lasso (least absolute shrinkage and selection operator); and Elastic Net, as those techniques minimize overfitting. In short, we observed similar results in all estimated models that indicates the robustness of the conclusions presented.

We show the results of the models by type of metric and also by financial stress period. The results of the GLM model presented include control variables (transaction ratio, stress index, delinquency ratio, and capital ratio). The transaction ratio and stress index variables are most relevant to the secured market, while the transaction ratio is relevant to the unsecured market. The periods analyzed were: full sample period; pre-Lehman default period; crisis period; European crisis (relatively stable period for Mexico); uncertainty about the rescue program for Greece; minutes period of the reduction in the assets purchase program (relatively calm period for Mexico); and period of the end of the asset purchase program (more stressful period for Mexico). We discuss in detail the results according to period the **??** section.

In general, if we compare the secured and unsecured markets with the GLM with machine learning, we find that global and local financial measures are related to the interest rate spread. In the majority of 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 big to fail and, even more importantly, we also find evidence of the "too interconnected to fail" hypothesis. Because, PageRank is highly relevant in both markets and this metric implies that the importance of a bank depends on the relevance of the banks connected to it. Thus, a bank that is central or systemically important can charge higher rates and finance itself at lower rates, resulting in an interest rate spread that is favorable to itself.

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 that we use in the econometric models; including the interest rate spread (dependent variable), the financial metrics (independent variables), and the variables used as controls. 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, as well as the interpretation of the results and possible policy recommendations for achieving financial stability in the Mexican interbank market. Last, section 5 presents the conclusions and possible extensions of this investigation.

2. Literature review

In the present work, we are interested in the impact that the place (centrality) of each bank in the interbank network has, on the price that a bank pays in the interbank market. Previous analyses have demonstrated, that the position of an institution in the network has an impact on the volume or the interest rate on unsecured loans. Although, some papers have already studied the determinants of rates in interbank markets, we study both the unsecured and secured interbank markets. From this body of work, we can distinguish two strands in the literature: trading relationships and centrality in the network; we combine the analysis of financial networks with econometric models and machine learning fundamentals, to provide evidence of which interconnection properties in networks might influence the interest rate spreads in the unsecured and secured interbank markets.

This section briefly presents the state of the art about our study topic. Using data of transfers sent and received by banks in the Fedwire Funds Service, Afonso et al. (2013) found that the liquidity of banks relies less on non-frequent transactions, and more on funds from institutions with which they have a stable financing relationship. Overall, borrowers obtain a better price when trading with frequent lenders. Afonso and Lagos (2015) analyzed the market for Federal

Funds, this is an over-the-counter (OTC) market, for unsecured loans of dollar reserves that each bank keeps at the Federal Reserve Bank. Loans are mostly overnight, and their purpose is chiefly to reallocate reserves among banks. Those authors developed a model to characterize such a market, taking into account the distinct features of an unsecured market, and applied it to answer relevant questions regarding prevalent trading relationships and the effectiveness of some policies for such a market.

Network studies also exist for the Market for Federal Funds. Bech and Atalay (2010), for example, find that the market is sparse (a common characteristic of financial networks, such as the ones we are studying here). Though, those authors present the small-world phenomenon and high disassortative behavior, they also stress the importance of centrality to predict rates.

While, Han and Nikolaou (2016) investigate the influence that trading relationships have in another OTC market. Using data from the US tri-party repo market (TPR) from September 2012 to June 2015, they provide evidence that although trading parties (especially large ones) perform transactions with a large number of counterparts, they tend to have a small set of these counterparts with whom they prefer to trade. Consequently, they allocate large volumes to them. Furthermore, having stable relationships with the same counterparts on other funding markets has a positive effect on their relationships in the TPR market, and these affect the probability of trading and the terms of such trade.

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 (USA). Using a panel regression, they found that long-term relationships exist between banks and have a positive impact on the rates and volume, for both lending and borrowing. Similar results are presented in Bräuning and Fecht (2017), for the German interbank market during the financial crisis.

The second part of the study assesses the impact of the network structure, specifically on rates, with a focus on how the centrality[1] of market participants affects rates. In Boss et al. (2004), the researchers made a structural analysis of the Austrian interbank market. They found that banks are clearly divided into communities, and that this division is a perfect match with the actual regional organization of the banks in Austria. Moreover, the network can be divided into two sub-networks, each with a power law distribution for the degree.

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) did 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, that we are analyzing here, is Iori et al. (2014). This conducted an analysis of the determinants of spreads on the e-MID by taking into account the behavior of banks and market microstructures. They found that liquidity cost suffers significant variations due to the sensitivity of rates and the time of trading. Hence, the spread is proportional to the trading volume at the beginning of the trading day, that is, trading becomes more expensive for borrowers in the morning and, in contrast, 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.

Gabrieli (2012) investigated the role of network centrality on the determinants of interest rates. The study used data from the e-MID interbank market ranging from January 2006 to November 2008. Even though in the study, the author includes the major distress period of the financial crisis. It would have been interesting to research a more extended period, in order to assess a pe-

[1] Freeman (1978) introduces the concept of centrality in social networks, this can be extended to financial networks. Bonacich (1987), there are further discussion on the centrality and its relation with the power that a participant has in a network. Babus (2016) presents a theoretical model to explain how financial networks are endogenously formed and how these are related to systemic risk.

riod of transition to calmer periods. The main results show that the collapse of Lehman Brothers had a significant effect on the market that corresponds to 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 making a profit from the centrality or size of banks. However, after the collapse of Lehman Brothers, the interconnectedness of institutions became important, but with a negative sign, meaning that markets became much more aware of the risk of being highly connected in a period of distress. Also, reputation also became significantly more important.

Our work provides evidence in the sense of Temizsoy et al. (2017). Because, the authors moved from the impact of trading relationships presented in Temizsoy et al. (2015) to the role of centrality in interbank market. In the present work, we used data from the e-MID to construct a panel containing the spread, from the reference rate for each pair of institutions, as well as their network metrics for this market. Their analysis differs from the one in Gabrieli (2012), in the panel specification, adding more control variables, a broader set of centrality measures, and an additional year to her 2012 study period. We based our econometric specification on the idea defined in Temizsoy et al. (2017); but our estimated model incorporates Machine Learning fundamentals, thus the model absorbs more information from the data. However, we used a slightly different set of variables over a much longer period and, as already mentioned, we applied this model on two panels, one from the secured market and one from the unsecured market.

Temizsoy et al. (2017) 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. Even more, that this effect became more significant during the crisis of 2008, both for the entire network and for individual institutions. They provide evidence about the "too-interconnected-to-fail" hypothesis, demonstrating that borrowers obtain better rates by positioning themselves as important intermediaries in the market, while central lenders usually receive lower rates. An apparent effect of the crisis is that, before it, major lenders were able to obtain better rates. While, after it, the opposite happened, that is, banks became more aware of the risk of being highly exposed with very exposed institutions.

In addition to studying two important funding markets, one of the main innovations in our work, in comparison to Gabrieli (2012) and Temizsoy et al. (2017), is the incorporation of a binary variable on whether an institution belongs to the core or not. Barucca and Lillo (2016) propose a method for classifying networks according to their structure and apply it to the e-MID interbank market. They find that when the degree of the nodes is taken into account, a bipartite structure emerges. However, in (Nowicki and Snijders, 2001) who used Stochastic Block Models on aggregated (over a week-old) data, the network presents a core-periphery structure (Craig and von Peter, 2014).

Such results are in line with those reported in Finger et al. (2013), who assess the effect of aggregation on the e-MID market. The results reveal that the network obtained from daily data has an almost random behavior, and there is no evidence on the true subjacent network structure of the market aggregating lengthier periods of time; however, 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, aggregation of data for more extended periods also reduces the error on the fit of the core-periphery structure, therefore we also use monthly-aggregated data. As in the previously cited studies, we consider only overnight transactions.

Another study examining the impact of the network structure on interbank rates is Craig et al. (2015), where the authors match credit exposure data from German banks from 2000 to 2008, with data from the repo auctions of the European Central Bank (ECB). They find that banks borrowing from a diversified set of institutions are less pressured in the auctions, and do not consider paying higher rates to obtain liquidity from the ECB. Regarding the network structure, Craig et al. (2015) show that central lenders place more aggressive offers in ECB auctions, this would suggest that central lenders in the money market are reallocating funds from repo auctions, and that systemically important banks pay higher rates for liquidity to continue their intermediation activities.

Most of the studies mentioned above involve interbank unsecured lending markets. In this research, we study another essential liquidity source in Mexico, the secured market (in Mexico known as the repo market). López et al. (2017) provided an exhaustive description of this market that is a 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. López et al. (2017) also find that the network presents a high clustering coefficient, even though it has low connectivity. This can have a positive impact on the liquidity flow in the market, if the interpretation that Silva et al. (2016) give to the clustering coefficient is taken into consideration (i.e., how easy is to substitute a liquidity provider).

Another relevant feature of the interbank secured market in Mexico is found in López et al. (2017), this is the absence of a core-periphery model. Finally, the said authors find a strong disassortative mixing in the network, meaning that banks with a small degree tend to connect with banks with a high degree.

Using exposure data for the Mexican interbank market and from the Electronic Interbank Payments System (SPEI), Martinez-Jaramillo et al. (2014) explore the main advantages and disadvantages of different network centrality measures, and propose a “unified centrality” measure that captures the most favorable properties of some widely used centrality measures. They find that some aspects of the topology of the Mexican interbank exposure network changed after the collapse of Lehman Brothers.

A significant result from Martinez-Jaramillo et al. (2014) that inspire our study, is the interconnectedness of an institution (and hence its centrality) is not necessarily related to its size. It is closely related to the contagion that it might cause—contagion in a financial network is a propagation process. When, we consider the flow of liquidity in the interbank network, interconnectedness and centrality in the network could have an effect not only on the interest rates, but also on the dispersion of funds.

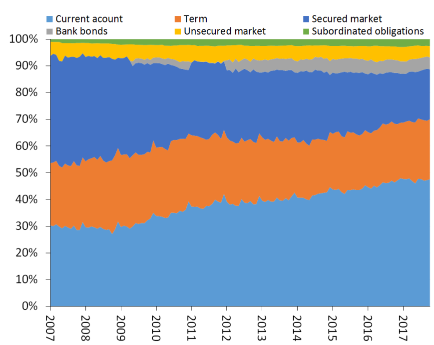
The e-MID is an unsecured market that has been studied. Here, we also investigate the effect of network characteristics on the secured market. One of the reasons we decided to consider more than one liquidity market comes from the development of multiplex financial networks. Many state-of-the-art studies 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.

To quantify the contribution to systemic risk of four different exposure networks (credit, derivatives, foreign exchange, and securities), we found the research of Poledna et al. (2015). Who studied daily frequency from 2007 to 2013, both individually and aggregated. Those authors show that focusing on individual layers underestimates systemic risk by up to 90%. Poledna et al. (2018) stress the importance on "indirect interconnections", this can be an essential driver of financial contagion. Indirect interconnections come from overlapping portfolios, that is, portfolios with similar securities. The 2018 study shows that very similar portfolios are prone to amplify losses if one of the similar holdings were to suffer a shock on the price. Similarly, a bank with high centrality in multiple markets could have a positive (or negative) effect on the rates, if it secures to lend or borrow liquidity in all the markets that it participates, or even further, on the rates in all markets. To determine the structure of the interbank markets studied, we present a statistical analysis of them in the next section.

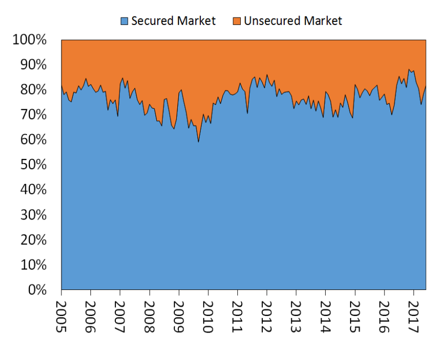
3. Statistical analysis and methods

Using a comprehensive dataset from the Mexican central bank, López et al. (2017) described the market in Mexico over a long period that includes the financial crisis, this 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 counterpart 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—investment funds, commercial banks, and brokerage houses—contribute the most, more than 60%, compared with domestic firms.

In Figure 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 Central Bank of Mexico. Sight deposits and term deposits total more than 50% of the total system financing. Then come secured transactions that constitute more than 85% of the deposits, leaving the unsecured market with only about 10%.



(a) Funding structure



(b) Participation of each market in banking activity

Figure 1: Characteristics of the secure and unsecured market. Panel (a) Funding structure of the banking system. This shows the importance of each component of the banking system in the funding structure. Panel (b) Participation and number of transactions per market. 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 Central Bank of Mexico.

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 (*CNVB*, acronym in Spanish).

Regarding volume, the importance of the secured market is also evident. In Figure 1, we can see the proportion of the unsecured volume of loans (loans without collateral) against secured operations. The volume of transactions in the secured market is consistently up to four times that of the unsecured market. Despite the secured market having a similar number of transactions per month, the average volume in the secured market is much higher.

It can even be seen that as of September 2009 the average amount in the unsecured market had decreased, while the average amount of repurchases had maintained an upward trend, except for a couple of falls that quickly returned to earlier levels. It must be noted that the average secured volume became very important in the second half of 2009, after of the financial crisis.

3.1. Descriptive statistics

We used monthly data[2] to analyze the unsecured market (52 institutions) from January 2005 to June 2017 and the secured market database (48 institutions) for the same period. As the number of periods for each institution in each database is not the same, our analysis was on an unbalanced panel—a long or macro panel, because the number of periods is higher than the number of institutions under study. Due to the data structure, the panel data analysis allowed us to study the heterogeneity of the institutions over time for the two markets analyzed.

Regarding the centrality metrics of the unsecured interbank market, for example in Figure 1 of Section 2 in the supplementary information, we show the evolution of strength that exhibits a clear upward trend for the entire distri-

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

bution. We also show the evolution of the betweenness centrality distribution, this also has an upward distribution trend that could be linked to the presence of more links in this market. We also show some distributions of the secured interbank market across time. Figure 2 of Section 2 in the supplementary information, shows the weighted version of Katz centrality, the distribution steadily declined until the fall of Lehman Brothers, after that it remained low.

Degree and Entropic Eigenvector centrality can be seen in Figure 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 (Figure 2 of Section 2 in the supplementary information) is at a considerably higher level than that of the unsecured interbank market (Figure 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.

Figures 1 and 2 of Section 2 in the supplementary information, show 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), see Figure 1 of Section 2 in the supplementary information. 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 (Figure 2 of Section 2 in the supplementary information). At the beginning of the study period, it was well above zero and then 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 panels (one per market) from the presence of a direct relationship between two institutions. This ratio is calculated as the spread 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 panel. It is important to consider that in every contract in both markets, one institution registers the transaction as an asset and the other registers it as a liability; this means that one institution gives money (lender) and another receives it (borrower). The panel contains measures of the activity of each institution as a borrower and as a lender in the network, regardless of their role in the specific spread.

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

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

where

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

having that $r_{ij,n}$ and $v_{ij,n}$ are 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, n refers to the transaction, where $i \neq j$ at period t. Finally, r_m^{-d} is the daily average-weighted interest rate over all transactions carried out by all bank pairs.

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 where institution j is the borrower and institution i is the lender. As 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

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

There are also the in and out adjacency matrices A^{+} and A^{-}, defined in analogy to W^{+} and W^{-}, which implies $A = A^{+} + A^{-}$ and $A^{+} = (A^{-})^{T}$. On this basis, the network measures we consider in our study are calculated as described in Section 1 of the supplementary information. For a complete 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: transaction ratio, capital ratio, delinquency ratio, and 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 panel, 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 assets to debt, and is a measure that shows the amount of losses that can be supported by the assets of each bank,

$$\text{Regulatory capital ratio} = \frac{\text{Tier 1 capital}}{\text{Risk-Weighted assets}} \tag{4}$$

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

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

If the ratio has a negative value, it means that the number of transactions arranged after one o'clock in the afternoon was 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. The formula used for its calculation is

$$\text{Delinquency ratio} = \frac{\text{Amount of past-due loans}}{\text{Total amount of current loans}} \tag{6}$$

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. Following this, we present the various models. This paper presents only the results from regularization techniques, GLM (Ridge, Lasso, and Elastic Net); however, many models were estimated for the sake of robust results.

3.3. Econometric modeling

We carried out the correlation analysis, Variance Inflation Factor (VIF) tests, different specifications of the GMM model, and estimation through regularization techniques in GLM; these are: Ridge, Lasso (least absolute shrinkage and selection operator) and Elastic Net. GLM with machine learning provided the training of the model, thus we present the results from those models in this section along with more details.

The advantage of estimating GLMs with machine learning is that it makes it possible to: i) obtain robust models; ii) treat the multicollinearity issue (as we need to select the centrality metrics that best explain the interest rate spread in the interbank market), and thereby obtain better models for the predictions; and, principally, iii) use training data and test data to find the main explicative variables to avoid overidentification in the model. There is research with respect to these models in the econometrics literature that tests the statistical properties of estimators (consistency, efficiency and, in general, asymptotic issues).

The purpose of this paper is not theoretical, to save space here, readers can see more statistical details in Zou and Hastie (2005) and Zou and Zhang (2009). However, we present the generic formulation of the regularized models to describe the estimated model. Consider the following definition $\hat{\beta} = \arg\min_{\beta}\{\sum_{i=1}^{n}(y_i - \beta_0 - \sum_{j=1}^{p}\beta_j X_{ij}) + \delta_\lambda(\beta)\}$; where, $\beta = (\beta_1, \ldots, \beta_p)$, $\lambda \geq 0$ and $\delta_\lambda(\beta) = \lambda\sum_{j=1}^{p}\delta_j(|\beta_j|)$, this is the increasing function of penalty β, and it 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 to avoid collinearity by Hoerl and Kennard (1970). 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 $\hat{\beta}^{ridge} = \arg\min_{\beta}\{\sum_{i=1}^{n}(y_i - \beta_0 - \sum_{j=1}^{p}\beta_j X_{ij})^2\}$ 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 $\hat{\beta}^{ridge} = \sum_{i=1}^{n}(y_i - \beta_0 - \sum_{j=1}^{p}\beta_j X_{ij})^2 + \lambda\sum_{j=1}^{p}\beta_j^2, where \lambda \geq 0$, λ is determined after the estimation of the coefficients. When 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 to zero and in the end there is no selection of variables; that is why Tibshirani (1996) developed the least absolute shrinkage and selection operator ("Lasso") method $\hat{\beta}^{lasso} = \arg\min_{\beta}\{\sum_{i=1}^{n}(y_i - \beta_0 - \sum_{j=1}^{p}\beta_j X_{ij})^2\}$ s.t. $\sum_{j=1}^{p}|\beta_j| \leq \kappa$. Rewriting the above expression, we have $\hat{\beta}^{ridge} = \sum_{i=1}^{n}(y_i - \beta_0 - \sum_{j=1}^{p}\beta_j X_{ij})^2 + \lambda\sum_{j=1}^{p}|\beta_j|, where \lambda \geq 0$, 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 innovative technique of regularization and selection, introduced by Zou and Hastie (2005), automatically selects variables and 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 $\hat{\beta}^{ene} = \arg\min_{\beta}|y - X\beta|^2$ s.t. $\alpha|\beta|_1 + (1-\alpha)|\beta|^2 \leq \kappa$ 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" $\hat{\beta}^{ene} = \arg\min_{\beta} L(\lambda_1, \lambda_2, \beta) = |y - X\beta|^2 + \lambda_2|\beta|^2 + \lambda_1|\beta|_1$, where $|\beta|^2 = \sum_{j=1}^{p}\beta_j^2$, $|\beta|_1 = \sum_{j=1}^{p}|\beta_j|$, $|y - X\beta|^2$ and $\alpha = \frac{\lambda_2}{\lambda_1 + \alpha_2}$.

We present the results of the GLM models with regularization techniques, in different periods of financial stress. We separate the results of this section into two subsections: in the first, we discuss the results for the whole sample period, while in the second, we discuss the results for different sub-periods. We based the selection of periods on a stress index[3] computed at the Mexican central bank. 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). Figure 4 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 line with the 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. This is to observe if there is evidence of systemic risk, connectivity, and/or relations between banks that explains the interest rates between lenders and borrowers. This is because if we know the behavior of the Mexican interbank markets, we can provide economic policy recommendations and regulations to improve their financial stability. In this section we present the results for the estimated shrinkage methods (Ridge, Lasso and Elastic Net).

4.1. Results of the estimated models for the full period

For the full sample, we can see that the Ridge method gives the minimum mean squared error, this shows the average squared difference between the estimated interest rate spread and the real interest rate spread value, also known as precision error.

[3]We are grateful to our colleagues from the Financial Stability Directorate who shared the stress index time series with us. In particular, we would like to thank Yair López Chuken for his kind support.

Table 1: **Secured Market_Full period**. Comparison between models with different alpha values (Best lambda and MSE).
This table shows the comparison through the Mean Squared Error (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 lambda 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 lambda, for all the methods, by period and markets.
Source: Authors, with data from Central Bank of Mexico.

Method	MSE	Lambda 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
Minimum MSE	**0.017209**	

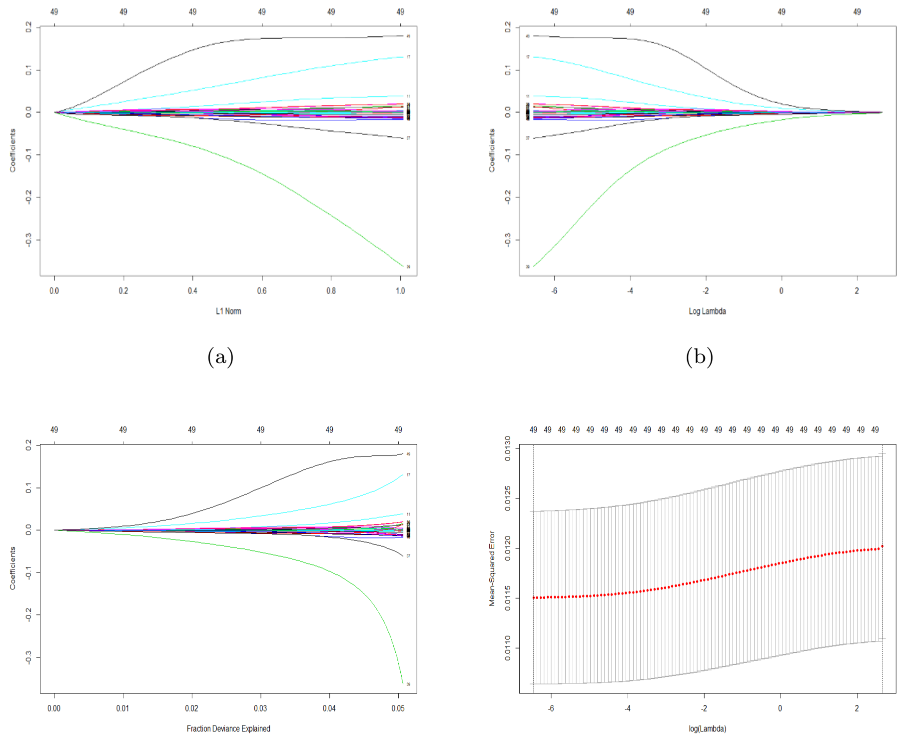
The Table 1 shows the Mean Square Error (MSE) that occurs with the regression containing the best lambda; and the last column shows the value of that lambda. Tables with estimated results, according to periods and markets, are found in Section 5 of the supplementary information.

For the secured market the Ridge method gives the best model with a minimum MSE, except for the European crisis period where the Lasso is better. For the unsecured market the best method is different for different periods, and in Table 2 we present the Elastic Net method with $\alpha = 0.75$.

The shrinkage methods, penalized or regularized, establish penalties in variables to reduce them progressively to zero; only important coefficients are found with the minimum model variance. For the secured market, the best regression is that using the Ridge method with the penalty parameter “L”. Figure 2 shows for the full period using the Ridge method: a) the dynamics of the coefficients (with different lambda values) against the L1-norm; b) the regression coefficients as λ grows from $0 \rightarrow \infty$; c) the deviation percentage explained by training data; and, d) the cross-validation curve. The figures by sub-samples and methods for both the secured and unsecured market are found in Section 6 of the supplementary information.

We can see in Figure 2 that the curves represent the centrality measures 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 λ, we can therefore observe that the majority of the variables are close to zero, and 5 variables significantly affect the variability of the interest rate spread in the full sample in the secured market. We can detect from Figure 2 panel b) that when the penalty is high (λ grows from $0 \rightarrow \infty$), the coefficients will be zero or close to zero.

We distinguish from Figure 2 panel c) that the deviation of the fraction explained by the variables, and panel d) shows the evolution of the test error (MSE) by lambda; the red dotted curve is the cross-validation curve, with upper and lower standard deviation; and the λs 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, those are close to the selection of real variables.



(a) (b)

(c) (d)

Figure 2: 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 as λ grows from $0 \to \infty$, c) Here, we can see the percentage of deviation explained by training data. d) This plot shows the evolution of the error against every λ. Section 6 of the supplementary information shows these plots for all the methods according to the market.
Source: Authors, with data from Central Bank of Mexico.

The estimated models can learn the complex patterns of the variables, with the penalization mechanism reducing overfitting; this gives us a robust model. The main variables for the full sample in the secured market are: PageRank_B, this means that the interest rate spread is determined according to the importance of the banks that are connected to the borrowers, although borrowers face a higher average market interest rate and are thus affected by systemic risk, they obtain a better spread if they are connected to important banks; PageRank_L, it implies that lenders assume importance in line with the importance of banks connected to their network; the importance of the banks has a positive effect on spread, and banks charge a higher interest rate; Katz_cent_B, this involves the number of borrowers connected through a credit position decreases the spread, thus the borrowers pay a lower interest rate to the banks they are connected with, against a higher interest rate in the market, this shows signs of a concentration of transactions; the participation of lenders and borrowers has a positive effect on the spread, while the stress index and transition ratio are significant control variables. In both markets, we especially observe that the relationships between banks, that is, the number of operations between each pair of banks with respect to the total operations in the secured market, is relevant.

Table 2 and Figure 3 show the dynamics in the unsecured market to the full sample. The minimum MSE is found in the Elastic Net method ($\alpha = 0.75$). The non-zero coefficients for this market by Elastic Net regression ($\alpha = 0.75$) are: Eigenvector_L, Accessibility_B and PageRank_B, those are plotted versus L-norm in a) Figure 3 panel a). We thus observe that PageRank is an important measure of the financial network for both interbank markets, this means that the banks have a better interest rate spread if they connect with major banks in the network.

While Figure 3 panel b) shows the log λ value against the coefficients, we can observe how the penalty increases when λ grows from $0 \to \infty$. 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. This is because the effect on the spread due to connectivity is contrary to that analyzed in the secured market for the full sample and because the estimation is being made by periods. We can observe that the effect of connectivity on the interest rate spread is different depending on the period, with financial stress periods occurring when there is a bigger systemic risk in the unsecured market. The details are discussed in the section according to period.

In this market, the transition ratio is a relevant control variable. Lastly, Figure 3 panel c) the percentage of deviation that is explained by the training data, and panel d) shows the cross-validation curve with standard deviation curves along the lambda sequence (error bars). We can thus observe that regularization of L forces the parameters to be close to zero and that the larger penalty gives a robust model.

Table 2: **Unsecured Market_Full period**. Comparison between models with different alpha values. (Best lambda and MSE).
This table shows the comparison through Mean Squared Error (MSE) of the econometric methods, as Ordinary Least Squares (OLS) and penalized regression methods or regularized regressions, with different alpha values. We also present the lambda with the lowest precision error, in this case, for the full period in the unsecured market. The method using Elastic Net with alpha equal to 0.75 has the minimum MSE. Section 5 of the supplementary information shows the MSE and lambda for all the methods by period and markets.
Source: Source: Authors, with data from Central Bank of Mexico.

Method	MSE	Lambda 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
Minimum	0.005679	

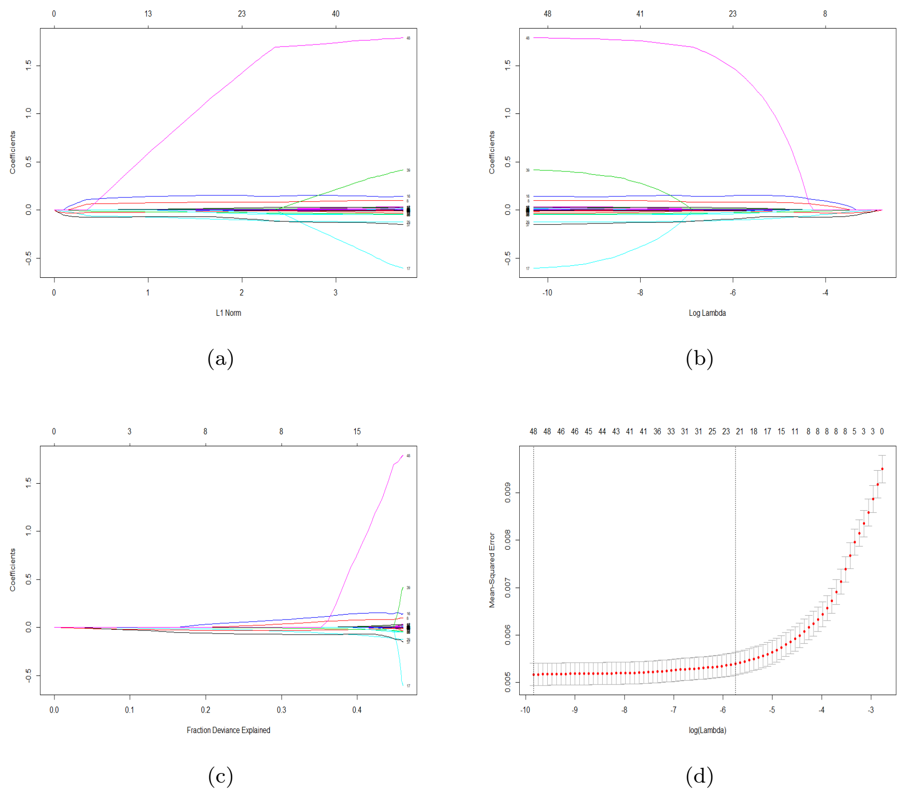


Figure 3: Unsecured market: Outputs from Elastic Net ($\alpha = 0.75$) method. These graphs show the outputs from Elastic Net ($\alpha = 0.75$) method, the method with the lower MSE for the full period in the unsecured market. a) This graph shows the estimated coefficients with different lambda values against the L1-norm. b) This plot indicates the regression coefficients as λ grows from $0 \rightarrow \infty$, c) Here, we can see the percentage of deviation explained by training data. d) This plot shows the evolution of the error against every lambda. Section 6 of the supplementary information shows these plots for all the methods by market.
Source: Authors, with data from Central Bank of Mexico.

In this market, the results also show Katz_cent_B and Katz_cent_L are statistically significant (where borrowers have lower spreads and lender have higher spreads) and Debt_rank_L, this suggests that lenders are important in the system and have a higher spread. In sum, for the secured and unsecured market, we see evidence of the "too interconnected to fail" hypothesis with the effect on the interest rate spread depending on the systemic risk in the market and differing according to period, this is analyzed in the next section.

4.2. Results of the estimated models for different sub-periods

In general, several measures of centrality are statistically significant and have persistence in each of the markets, this allows us to identify the financial measures that would help to analyze financial stability and systemic risk in specific periods. We explain this in detail in this section on the interpretation of results by periods and markets. Instead of focusing only on a pre-crisis, crisis, and post-crisis, we decided to split the sample into several periods by taking into account a number of events that lead to higher stress in the financial system, as indicated by the stress index used at the Mexican Central Bank.

We chose the different periods based on the stress index test and found statistical evidence, both economic and financial, that supports the split. As the stress index shows (Figure 4), there are episodes where there was an increase in financial stress and the periods following Lehman's default are by no means homogeneous. We statistically tested the periods through the Chow breakpoint 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 tested dates are breakpoints (Table 3).

Table 3: The table shows the results from the Chow Breakpoint 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 percent confidence and for the given sample. Thus, we need to split the study periods to model it properly.
Source: Authors, with data from Central Bank of Mexico.

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

Figure 4 shows the selected periods based on the statistical test to detect breakpoints. This was performed on the Stress Index that allows us to know the periods of marked stress.

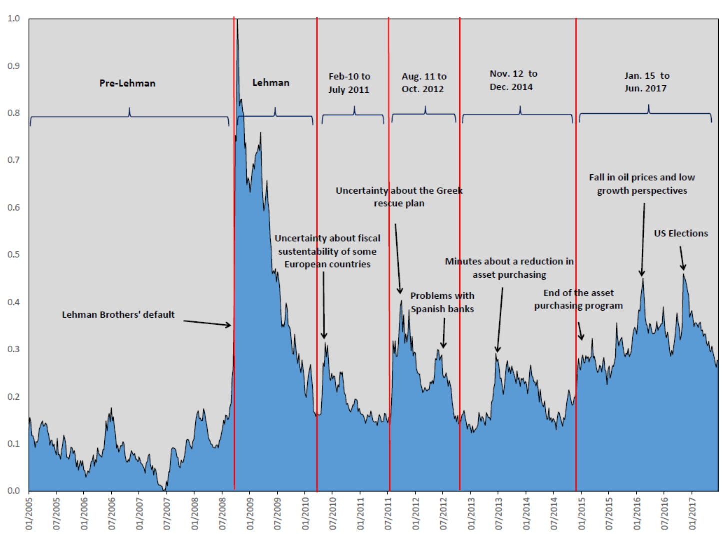


Figure 4: This graph shows the tested breakpoints in Table 3, those are analyzed as subsamples in the next section.
Source: Authors, with data from Central Bank of Mexico.

The next section shows the results of all periods using the Ridge method, the best method found for analyzing the secured market, except for during the European crisis period, where the Lasso method proved better. Section 7 of the supplementary information, we present all the results (main determinants of the interest rate spread by periods) for other methods (Elastic Net for different values of alpha).

4.3. Results for the secured market by periods

For the secured market, the results show that around eight centrality measures are statistically significant by periods (see Figure 5). During the first three periods, most of those eight metrics of centrality are highly significant. 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 measures that determined the interest rate spread were: PageRank_B (-), PageRank_L (+); Katz_cent_B (-); Katz_cen_L (+); part_B and part_L (+); HHI_B_B (-); EEC_B (+); DR_Vul_B (+); DR_Vul_L (-); DebtRank_B (+); DebtRank_L (-); Clustering_B and Clustering_L (+); Eigenvector_L (-); EEC_L and EEC_B (+); core_periphery_B and core_periphery_L (-); and, ExpectForce_B (-). The results in PageRank and Katz are the most relevant financial metrics for explaining the interest rate spread, this supports the TITF hypothesis. We observe that in this period if a bank is systemically important, it has a defined behavior in the spread.

In the crisis period, the highly significant centrality metric is the same as in the pre-crisis period. Thus, the metrics of the borrowing and lending network compatible with the TITF hypothesis are shown with the effect of PageRank and Katz. In particular, we find that EEC_L (the influence of a lender in the network), Clustering_L (the density of the connections) and Part_L (the amount of money that passed through a lender) indicate that the lender charges higher rates. Since, the effect of all those metrics on the interest rate spread is positive. We also observe that the concentration that the banks have in the counterparts of their funding transactions (HHI_B) explains the lower cost of financing in this market.

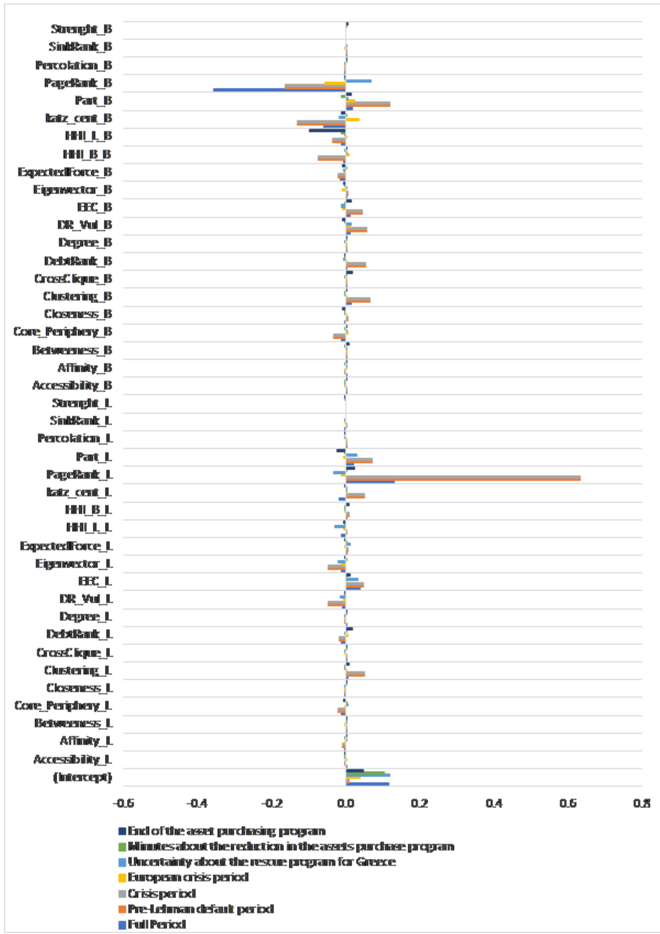


Figure 5: Results by periods for the secured interbank market Ridge ($\alpha = 0$) model. This graph shows the centrality networks from the Ridge method, the method with the lowest MSE in the secured market according to periods. The periods are: full period (navy blue), pre-Lehman default period (orange), crisis period (gray), European crisis period (yellow), uncertainty about the rescue program for Greece (blue), Minutes period in 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 through the other methods.
Source: Authors, with data from Central Bank of Mexico.

For the European crisis period, PageRank_B is one of the most important metrics relating to the spread. From the side of the lender, we find that DebtRank_L (this implies systematically important lenders) and EEC_L (it suggests influence of the lender in the interbank market) are also related to the spread. Interestingly, Katz and Part have coefficients with positive signs, this means a 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. This period can thus also be classified as a period of high financial stress. In comparison with previous periods, there are fewer statistically significant centrality measures; however, there is still evidence that supports the TITF hypothesis. The results of the model show that lenders with market influence (due to the positive effect from EEC_L and Part_L on the spread) could charge higher rates during this period. The influence of the borrowers (EEC_B and ExpectedForce_B) and the large number of the connections in a network (Katzcent_B) show that borrowers were allowed to obtain a lower financing cost. However, the importance of the institutions connected to the borrower generated systemic risk and a higher financing cost was observed.

This period labeled "Minutes" can also be classified as a period of high financial stress, but the statistically significant variables supporting the TITF hypothesis, for borrowers means that there is a major borrower in the network (either because of their concentration (HHI_B), the amount of the money in its transactions (Part_B) or its influence in the market (EEC_L)) implying a lower funding cost, while from the lender's side, there is a small near-zero effect of all the centrality measures in the spread.

The last period, DebtRank_L (systemic relevance of the lender), EEC_L (influence of the lender in the market), HHI_L (concentration of the loans offered), PageRank PageRank involved charging higher interest rates and therefore positive spreads; whereas, HHI_B (concentration of the loans received), ExpectedForce_B (measuring influence), DR_Vul_B (systemic relevance of the borrower) and Katz_cent_B (number of borrowers connected in a transaction) support the TITF hypothesis for the borrowers in this period 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, then it can charge high interest rates and fund itself at a lower interest rate. This involves an important economic policy recommendation, the regulations need to focus beyond the size of the bank, those should consider the connections that a bank has and the number of transactions it conducts. In terms of the centrality network measures, we found ExpectedForce, PageRank, and Katzcent to be significant in several periods.

4.4. Results for the unsecured market by periods

The results for the unsecured market are represented graphically in Figure 6. There are around five types of centrality measure that have an effect on the interest rate spread in this market. For the pre-Lehman period, DebtRank_L and Eigenvector_L have a positive effect on spread, this means that a bank with influence of systemic relevance in transactions charges high interest rates and is financed at lower interest rates. However, 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. There are some statistically significant variables that support the TCTF hypothesis on the borrower side: DebtRank_B, EEC_B, Eigenvector_B, Katz_cent_B and Part_B. Those metrics indicate that a borrower with connections, systemic relevance, influence, and numerous financial transactions per day can have lower financing cost during this period. Under financial stress, 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.

For the crisis period (October 2008 to February 2010), see Figure 6, there is strong evidence for lenders and borrowers of the benefits of being important. In particular, DebtRank_L, EEC_L, Part_L, Katzcent_L, PageRank_L determine the spread (fundamentally the last two metrics), while DebtRank_B, EEC_B, HHI_B_B Katzcent_B and Part_B support the TCTF hypothesis. This is because borrowers have a lower funding cost and lenders have a positive spread. However, the density of the connections (Clustering_B), the relevance of the banks connected to them (PageRank_B), and the concentration of the loans received (HHI_L_B) indicate a higher financing cost, this is reasonable in a period of financial uncertainty, for a market with more risk because there is no collateral. For the Lehman period, there is strong evidence of the benefits of being central for lenders and borrowers, and of systemic risk affecting the spread.

The European crisis period is strong evidence supporting the TCTF, namely, that being central can be beneficial for lenders and borrowers. From the borrower side, the PageRank_B, Part_B, Katz_cent_B, HHI_B_B, EEC_B, DebtRank_B and Clustering_B indicate that borrowers with systemic relevance, influence, and connections have a lower funding cost, while Katz_cent_L, PageRank_L, HHI_B_L, DebtRank_L and Clustering_L have a positive effect on interest rate spread. This means that lenders with systemic relevance, important connections due to the relevance of their counterparts and the density in their connections, can charge higher interest rate and obtain finance at a lower interest rate.

There is a similar dynamic to the above, in the period we called uncertainty about the rescue program for Greece. However, an important difference is in the opposite effect of Clustering_B and DR_Vul_B on spread. This indicates that the density of the connections between the borrowers and the vulnerability have a positive effect on the spread. This means that borrowers faced higher financing cost due to the uncertainty in a market with higher systemic risk than the secured interbank market. The Greece period was characterized by uncertainty about the rescue plans for Greece, and by serious problems in Spanish banks.

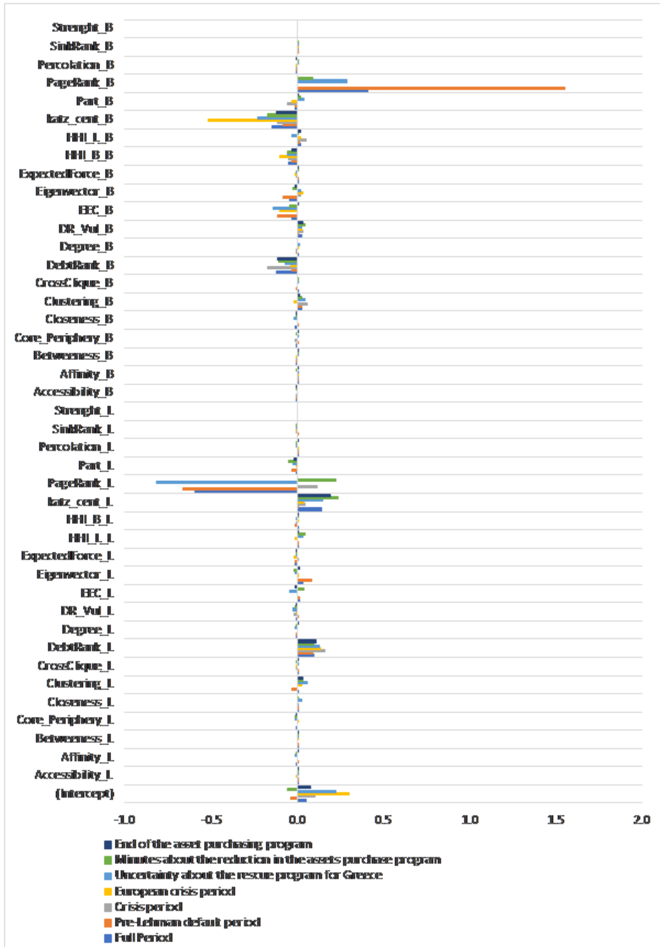


Figure 6: Results by periods, for the unsecured interbank market Elastic Net ($\alpha = 0.75$) model. This graph shows the centrality networks from the Elastic net ($\alpha = 0.75$) method, the method with the lowest MSE in the unsecured market according to periods. The periods are: full period (navy blue), pre-Lehman default period (orange), crisis period (gray), European crisis period (yellow), uncertainty about the rescue program for Greece (blue), Minutes period in 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 through the other methods.

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

The fifth period can be considered a less stressed period, we called it a Minutes period. This has various structural metrics that are statistically significant. 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, it can charge a higher interest rate. HHI_L_L, EEC_L and Clustering_L also support the TCTF. From DebtRank_B, Katz_cent_B, HHI_B_B, Eigenvector_B and EEC_B indicate that a relevant borrower can find lower funding cost with their counterparts.

For the last period (Figure 6), the main centrality measures that explain the higher lending rates are: Katz_cent_L, PageRank_L, DebtRank_L and Clustering_L. The lower funding cost is explained for DebtRank_B, Katz-cent_B, HHI_B_B and Eigenvector_L. For lenders and borrowers, the systemic relevance is fundamental.

5. Conclusions

We explored the structural properties of the Mexican secured and unsecured 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, panel models with fixed effects, with and without control variables, GMMs, and GLMs with machine learning fundamentals. Due to space issues, we present only the results of the latter model in this paper. It's important pointing 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.

Our work has the follow innovations: 1) The period investigated is wider than in previous studies, this allows different sub-samples to be investigated under different financial stress periods; 2) We study two important interbank markets using the same approaches. 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 what financial network measures are important in an unsecured market; 3) We included new network metrics and observed that for the secured market, the Expect Force (a centrality measure that quantifies node spreading power, from the epidemiological viewpoint) can explain part of the dynamics of the interest rate spread for several periods. This is a measure of influence and contagion that indicates the expected value of the force of failure (infection), generated by a bank (node), after two transmissions.

In general, there are eight types of centrality measure that explain the interest rate spread for the secured market and five for the unsecured market from around 20 different types of network measures. Moreover, the coefficients indicate that higher centrality implies lower rates for borrowers and eventually higher rates for lenders. It is supporting the TCTF hypothesis, with PageRank and Katz_cent explaining the interest rate spread in almost all the periods and markets. Those measures show, respectively, that the importance of a bank is due to the importance of its connections and a number of banks that can be connected in a path. This in line with the result for PageRank found in Temizsoy et al. (2017).

There are important effects of banks on the interest rate spread. These are dependent on the 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 were higher than before it.

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 (belonging to an important connection) obtain lower rates as borrowers and charge higher rates as lenders. All of the above support the argument of being TCTF or also know "too interconnected to fail" (TITF), because a bank that is central or systemic can charge higher rates and fund itself at lower rates.

The results for different time periods indicate that banks do 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 that has systemic risk because there is no collateral in their transactions. For the unsecured market, PageRank, Katz_cent and DebtRank explain the spread in greater amount, while PageRank, Katz_cent and the Participation explain the spread in the secured market. In addition, in pre-crisis and crisis periods, the network measures mentioned above explain the spread of the interest rate to a greater extent. It is important to note that Percolation, for the unsecured market, is a consistent financial measure that considerably explains the interest rate spread across different time periods.

A future extension of this study could be to consider other relevant variables, like macroeconomic or financial variables, or variables related to the collateral used in secured transactions. An extension of this work is to use the same approach to include more intermediaries (for example, pension funds, investment funds, and brokerage firms), those 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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References

Afonso, G., Kovner, A., Schoar, A., 2013. Trading Partners in the Interbank Lending Market. Staff Reports 620. Federal Reserve Bank of New York.

Afonso, G., Lagos, R., 2015. Trade dynamics in the market for federal funds. Econometrica 83, 263–313. URL: https://onlinelibrary.wiley.com/doi/abs/10.3982/ECTA10586, doi:10.3982/ECTA10586, arXiv:https://onlinelibrary.wiley.com/doi/pdf/10.3982/ECTA10586.

Arellano, M., Bond, S., 1991. Some tests of specification for panel data: Monte carlo evidence and an application to employment equations. The Review of Economic Studies 58, 277–297. URL: http://dx.doi.org/10.2307/2297968, doi:10.2307/2297968.

Babus, A., 2016. The formation of financial networks. The RAND Journal of Economics 47, 239–272. URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/1756-2171.12126, doi:10.1111/1756-2171.12126, arXiv:https://onlinelibrary.wiley.com/doi/pdf/10.1111/1756-2171.12126.

Baglioni, A., Monticini, A., 2008. The intraday price of money: Evidence from the e-mid interbank market. Journal of Money, Credit and Banking 40, 1533–1540. URL: http://www.jstor.org/stable/25096322.

Barucca, P., Lillo, F., 2016. Disentangling bipartite and core-periphery structure in financial networks. Chaos, Solitons & Fractals 88, 244 – 253. URL: http://sciencedirect.com/science/article/pii/S0960077916300352, doi:https://doi.org/10.1016/j.chaos.2016.02.004. complexity in Quantitative Finance and Economics.

Bech, M., Atalay, E., 2010. The topology of the federal funds market. Physica A: Statistical Mechanics and its Applications 389, 5223–

5246. URL: https://EconPapers.repec.org/RePEc:eee:phsmap:v:389:y:2010:i:22:p:5223-5246.

Bonacich, P., 1987. Power and centrality: A family of measures. American Journal of Sociology 92, 1170–1182. URL: http://www.jstor.org/stable/2780000.

Boss, M., Elsinger, H., Summer, M., Thurner, S., 2004. The network topology of the interbank market. Quantitative Finance 4, 677–684.

Bräuning, F., Fecht, F., 2017. Relationship lending in the interbank market and the price of liquidity. Review of Finance 21, 33–75. URL: https://EconPapers.repec.org/RePEc:oup:revfin:v:21:y:2017:i:1:p:33-75.

Craig, B., von Peter, G., 2014. Interbank tiering and money center banks. Journal of Financial Intermediation 23, 322 – 347. URL: http://www.sciencedirect.com/science/article/pii/S1042957314000126, doi:https://doi.org/10.1016/j.jfi.2014.02.003.

Craig, B.R., Fecht, F., Tümer-Alkan, G., 2015. The role of interbank relationships and liquidity needs. Journal of Banking & Finance 53, 99 – 111. URL: http://www.sciencedirect.com/science/article/pii/S0378426614004038, doi:https://doi.org/10.1016/j.jbankfin.2014.12.022.

Ductor, L., Fafchamps, M., Goyal, S., van der Leij, M.J., 2014. Social networks and research output. Review of Economics and Statistics 96, 936–948.

Finger, K., Fricke, D., Lux, T., 2013. Network analysis of the e-mid overnight money market: the informational value of different aggregation levels for intrinsic dynamic processes. Computational Management Science 10, 187–211. URL: https://EconPapers.repec.org/RePEc:spr:comgts:v:10:y:2013:i:2:p:187-211.

Freeman, L.C., 1978. Centrality in social networks conceptual clarification. Social Networks 1, 215 – 239. URL: http://www.sciencedirect.

com/science/article/pii/0378873378900217, doi:https://doi.org/10.1016/0378-8733(78)90021-7.

Gabrieli, S., 2012. Too-connected versus too-big-to-fail: Banks' Network Centrality and Overnight Interest Rates. Working Paper 398. Banque de France.

Han, S., Nikolaou, K., 2016. Trading Relationships in the OTC Market for Secured Claims: Evidence from Triparty Repos. Finance and Economics Discussion Series 2016-064. Board of Governors of the Federal Reserve System (U.S.). URL: https://EconPapers.repec.org/RePEc:fip:fedgfe:2016-64.

Hoerl, A.E., Kennard, R.W., 1970. Ridge regression: Biased estimation for nonorthogonal problems. Technometrics 12, 55–67. URL: https://www.tandfonline.com/doi/abs/10.1080/00401706.1970.10488634, doi:10.1080/00401706.1970.10488634, arXiv:https://www.tandfonline.com/doi/pdf/10.1080/00401706.1970.10488634.

Iori, G., De Masi, G., Precup, O.V., Gabbi, G., Caldarelli, G., 2008. A network analysis of the italian overnight money market. Journal of Economic Dynamics and Control 32, 259–278. URL: https://EconPapers.repec.org/RePEc:eee:dyncon:v:32:y:2008:i:1:p:259-278.

Iori, G., Gabbi, G., Germano, G., Hatzopoulos, V., Kapar, B., Politi, M., 2014. Market microstructure, banks' behaviour, and interbank spreads. URL: http://openaccess.city.ac.uk/3950/. "".

López, M.U., Martínez-Jaramillo, S., Dey, F.L.G., 2017. The repo market in mexico: Empirics and stylized facts. Neurocomputing 264, 2 – 19. URL: http://www.sciencedirect.com/science/article/pii/S0925231217311050, doi:https://doi.org/10.1016/j.neucom.2016.10.102. machine learning in finance.

Martinez-Jaramillo, S., Alexandrova-Kabadjova, B., Bravo-Benitez, B., Solorzano-Margain, J.P., 2014. An empirical study of the mexican banking system's network and its implications for systemic risk. Journal of Economic Dynamics & Control 40, 242–265.

Nowicki, K., Snijders, T.A.B., 2001. Estimation and prediction for stochastic blockstructures. Journal of the American Statistical Association 96, 1077 – 1087. URL: http://doi.org/10.1198/016214501753208735, doi:10.1198/016214501753208735.

Poledna, S., Martínez-Jaramillo, S., Caccioli, F., Thurner, S., 2018. Quantification of systemic risk from overlapping portfolios in the financial system. arXiv preprint arXiv:1802.00311 .

Poledna, S., Molina-Borboa, J., Martinez-Jaramillo, S., van der Leij, M., Thurner, S., 2015. The multi-layer network nature of systemic risk and its implications for the costs of financial crises. Journal of Financial Stability 20, 70–81. URL: http://pure.iiasa.ac.at/id/eprint/11393/, doi:10.1016/j.jfs.2015.08.001.

Silva, T.C., de Souza, S.R.S., Tabak, B.M., 2016. Network structure analysis of the Brazilian interbank market. Emerging Markets Review 26, 130–152. URL: https://ideas.repec.org/a/eee/ememar/v26y2016icp130-152.html, doi:10.1016/j.ememar.2015.12.

Temizsoy, A., Iori, G., Montes-Rojas, G., 2015. The role of bank relationships in the interbank market. Journal of Economic Dynamics and Control 59, 118–141. URL: https://EconPapers.repec.org/RePEc:eee:dyncon:v:59:y:2015:i:c:p:118-141.

Temizsoy, A., Iori, G., Montes-Rojas, G., 2017. Network centrality and funding rates in the e-mid interbank market. Journal of Financial Stability 33, 346–365. URL: https://EconPapers.repec.org/RePEc:eee:finsta:v:33:y:2017:i:c:p:346-365.

Tibshirani, R., 1996. Regression shrinkage and selection via the lasso. Journal of the Royal Statistical Society. Series B (Methodological) 58, 267–288. URL: http://www.jstor.org/stable/2346178.

Zou, H., Hastie, T., 2005. Regularization and variable selection via the elastic net. Journal of the Royal Statistical Society. Series B (Statistical Methodology) 67, 301–320. URL: http://www.jstor.org/stable/3647580.

Zou, H., Zhang, H.H., 2009. On the adaptive elastic-net with a diverging number of parameters. The Annals of Statistics 37, 1733–1751. URL: http://www.jstor.org/stable/30243686.