

# Network Centrality and Funding Rates in the e-MID Interbank Market\*

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## Abstract

The paper empirically investigates the role of banks' network centrality in the interbank market on their funding rates. Specifically we analyze transaction data from the e-MID market, the only electronic interbank market in the Euro Area and US, over the period 2006-2009 that encompasses the global financial crisis. We show that interbank spreads are significantly affected by both local and global measures of connectedness. The effects of network centrality increased as the financial crisis evolved. Local measures show that having more links increases borrowing costs for borrowers and reduces premia for lenders. For global network centrality, borrowers receive a significant discount if they increase their intermediation activity and become more central, while lenders pay in general a premium (i.e. receive lower rates) for centrality. This provides evidence of the 'too-interconnected-to-fail' hypothesis.

*Keywords:* network centrality, interbank market, overnight loans

*JEL Classification:* G2

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# 1 Introduction

The global financial crisis of 2008 has highlighted the importance of contagion and systemic risk in financial markets and the need to go beyond the traditional micro-prudential approach to supervision. The network structure of markets has important implications for systemic risk. The actual distribution of links between market participants affect how financial distress or the disorderly failure of a financial entity could be transmitted to other financial firms and markets. When defaults occur, they can cascade throughout the network and can cause the collapse of an entire system. Three channels have been identified as primarily responsible for the contagion: bilateral-exposures in interbank markets, fire sales externalities and liquidity hoarding due to precautionary banks' behavior, with the first channel the most extensively studied. While prior to the crisis few academic papers had already investigated the importance of the interconnectedness of the economy for financial stability (Allen and Gale (2000), Freixas et al. (2000), Eisenberg and Noe (2001), Iori et al. (2006), Nier et al. (2007)) it is after the crisis that the role of the network of exposures has been brought to the fore by the wider academic community and by policymakers. Among the first, Haldane and May (2011) has called for a better understanding of how individually complex institutions connect to one another in a complex network of counterparty exposures, in order to design policy measures that can more effectively manage financial stability.

Network analysis of the degree of interconnectedness in the financial system can inform policymakers on optimal bank resolutions mechanisms and how regulation can help to reduce instability. Empirical networks have been used for (deterministic) stress test exercises (see Upper (2011) for a comprehensive review). Of critical importance in macro prudential policy is the identification of key players in the financial network, which according to the International Monetary Fund (IMF), the Bank for International Settlements (BIS) and the Financial Stability Board (FSB) should be determined in terms of their size, connectedness and substitutability. Network centrality measures, developed to assess centrality in other contexts and adapted to the context of financial networks, can guide national authorities in their assessment of the systemic importance of financial and non-financial institutions. In the financial economic literature network analysis has mostly been applied to payment systems, interbank lending markets, and more recently extended to capture the mutual exposure of financial institutions to other asset classes, including derivatives contracts, in a multilayer networks framework ( Bargigli et al. (2015), Leon et al. (2014), Molina-Borboa et

al. (2015) and Aldasoro and Alves (2015)).

In this paper we focus on interbank lending networks on the e-MID overnight (O/N) interbank market, an electronic platform, based in Italy, that offers a fully transparent trading systems with ‘buy’ and ‘sell’ proposals (prices and volumes) available on screens of the participating banks, along with the identity of the banks quoting them. Information on the terms (prices and amounts) of executed trades are available to banks in real time. Search frictions, thus, should not affect the matching process in the e-MID market. Furthermore lack of information on rates offered by alternative lenders cannot be responsible for the observed cross sectional dispersion of O/N rates in this market. Our paper contributes to the recent literature that investigates the determinants of banks’ borrowing costs in unsecured money markets and how network characteristics of interbank market participants affect their funding rates. Network positioning could affect banks’ interest rates by different mechanisms. First, in line with Acemoglu et al. (2015), dense interconnections serve as a mechanism for the propagation of shocks, leading to a more fragile financial system. As such, banks that are more connected may be perceived by the market as fragile. Second, the same banks can be perceived as ‘too-interconnected-to-fail’ such that rather than fragile, those banks are perceived as more likely to be bailout. This is similar to the too-big-to-fail effect observed in other interbank markets. Third, as argued by Booth et al. (2014), financial institutions with more extensive and strategic financial networks, can more efficiently acquire and process information due to their better access to order flows. Fourth, as stressed by Gabrieli and Georg (2014), banks with higher centrality within the network have better access to liquidity and are able to charge larger intermediation spreads. Previous empirical evidence ( Angelini et al. (2011), Gabrieli (2011), Gabbi (2012), Bech and Atalay (2010) , Akram and Christophersen (2010) and Gabrieli (2012)) suggests that being systemically more important, in term of size or connectedness, can explain part of the cross-sectional variation in banks’ borrowing costs before and during the global financial crisis. The centrality indicators used in the analysis are constructed from measures of distance of a bank from the other banks in the network, where distance is expressed in terms of: (1) paths of length one, i.e. the number of incoming or outgoing links, for degree centrality; (2) geodesics (shortest) paths (no vertex is visited more than once), for closeness and betweenness; walks (vertices and edges can be visited/traversed multiple times) for eigenvector centrality, pagerank and sinkrank. We evaluate each measure in a quarterly panel data regression set-up of bank pairs, i.e. lender and borrower match, for the period 2006-2009 and separately

for three sub-periods that encompass the latest 2007-2008 financial crisis: phase I (01 January 2006-30 June 2007, using the key date of the Two Bear Stearns' hedge fund bankruptcy was 31 July 2007), phase II (01 July 2007-30 September 2008, using the key date of Lehman Brothers collapse was 15-Sep-2008) and phase III (01 October 2008-31 December 2009).

Our results show that network measures are significant determinants of funding rates in the e-MID O/N market. Local measures show that having more links increases borrowing costs for borrowers and reduces premia for lenders. However, for global measures of network centrality borrowers receive a significant discount if they increase their intermediation activity and become more central, while lenders pay in general a premium (i.e. receive lower rates) for centrality, thus providing some evidence about the 'too-interconnected-to-fail' hypothesis. That is, banks perceived to be better inter-connected could borrow at discount rates. This effect is higher in phase II when systemic risk was the highest. Lenders do not benefit from network centrality, and as such, it could be that the market perception about their network positioning (i.e. fragility) dominates their strategic location for intermediation (as in Gabrieli and Georg, 2014). The regression analysis also highlights that there is heterogeneity across different measures of network centrality on how they affect interbank spreads.

The remainder of this article is organized as follows. Section 2 discusses previous findings in the literature and how they relate to our paper. Section 3 describes the data and variables. Section 4 provides methodology of the empirical analysis. In section 5, we present and discuss the results of the regression analysis. Section 6 discusses the results and concludes.

## **2 Network centrality and financial markets**

A number of papers have investigated the interplay between financial distress and topological characteristic of interbank networks, focusing on the network resilience to different kinds of shocks (Iori et al. (2006); Nier et al. (2007), Gai et al. (2011), Battiston et al. (2012); Anand et al. (2012), Lenzu and Tedeschi (2012); Georg (2013); Roukny et al. (2013), Acemoglu et al. (2015)). While some authors have argued that a more interconnected architecture could enhance the resilience of the system to failure of a individual bank, because credit risk is shared among more creditors, others have suggested that a higher density of connections may function as a destabilizing force, facilitating financial distress to spread further through the banking system. The overall picture

that emerges from this body of work is that the density of linkages has a non monotonous impact on systemic stability and its effect varies with the nature of the shock, the heterogeneity of the players and the state of the economy. Thus no optimal network structure, that is more resilient under all circumstances, can be identified (see Chinazzi and Fagiolo (2013) for a recent survey on systemic risk and financial contagion).

The structure of interbank networks has been mapped for several countries. Examples include Boss et al. (2004) for the Austrian interbank market, Soramaki et al. (2007) and Bech and Atalay (2010) for the US Federal funds market, De Masi et al. (2006), Iori et al. (2008) and Fricke and Lux (2015) for the Italian based e-MID, Degryse and Nguyen (2007) for Belgium, Craig and Von Peter (2014) for the German interbank market, Langfield et al. (2014) for the UK and in 't Veld and van Lelyveld (2014) for the Dutch market. These authors have explored the topology of these interbank markets and identified stylized facts and regularities. The most common findings reported in this literature are: (i) interbank networks are sparse, with only a minority of all possible links that do actually exist; (ii) degree distributions and transaction volumes distribution are fat tailed, revealing very heterogeneous players characteristics; (iii) the networks show disassortative mixing with respect to the bank size, so small banks tend to trade with large banks and vice versa; (iv) clustering coefficients are usually quite small; (v) interbank networks satisfy the small-world property<sup>1</sup>; (vi) interbank networks have a tiering structure with a tightly connected core of money-center banks to which all other periphery banks connect.

In particular for the e-MID market, while early studies (Iori et al. (2008)) have revealed a fairly random network at the daily scale, a non-random structure has been uncovered for longer aggregation periods. Monthly and quarterly aggregated data show that since the 1990s a high degree of bank concentration occurred (Iazzetta and Manna (2009)), with fewer banks acting as global hubs for the whole network. The hubs tend to cluster together and a significant core-periphery structure has been observed (Finger et al. (2013)). Hatzopoulos et al. (2015) have investigated the matching mechanism between lenders and borrowers in the e-MID market and its evolution over time. They show that, when controlling for bank heterogeneity, the matching mechanism is fairly random. Even though matches that occur more often than those consistent with a random null model (over expressed links) exist and increase in number during the crisis,

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<sup>1</sup>A network is small-world if the mean geodesic distance between pairs of nodes is small relative to the total number of nodes in the network, that is, this distance grows no faster than logarithmically as the number of nodes tends to infinity

neither lenders nor borrowers systematically present several over expressed links at the same time. The picture that emerges from their study is that banks are more likely to be chosen as trading partners because they trade more often and not because they are more attractive in some dimension (such as their financial healthiness or because they charge lower rates).

Fricke and Lux (2015) and Squartini et al. (2013) have investigated if the topology of interbank networks, respectively for the e-MID market and the Dutch market, underwent major structural change as the subprime crisis unfolded, in an attempt to identify early-warning signals of the approaching crisis. In both markets at the onset of the crisis the dynamic evolution of the network seemed completely uninformative as the networks only display an abrupt topological change in 2008, providing a clear, but unpredictable, signature of the crisis. Nonetheless, when controlling for the banks' connectivity heterogeneity, Squartini et al. (2013) show that higher-order topological properties (such as dyadic and triadic motifs) revealed a gradual transition into the crisis, starting already in 2005. Although these results provide some evidence of early warning topological precursors, at least for the Dutch interbank market, the authors cannot explain the economic rationale for the observed patterns.

In addition to the abrupt topological change after Lehman defaults, that mostly appear to be driven by precautionary liquidity hoarding, Cocco et al. (2009), Affinito (2012), Brauning and Fecht (2012) and Temizsoy et al. (2015) have shown that banks relied more extensively on relationship lending during the crisis, with both lenders and borrowers benefiting from close relationship both in terms to access to liquidity and funding rates. Relationship lending thus plays a positive role for financial stability and provides a measure of the level of financial substitutability of banks in the interbank market. Furthermore these results show that interbank exposures is used as a peer-monitoring device (Rochet and Tirole (1996)) and can help policymakers to assess market discipline. Finally, reliance on relationship lending is an indicator of trust evaporation in the banking system. Thus, monitoring how stable relations affect spreads and volumes over time may act as an early warning indicator of a financial turmoil.

Bech and Atalay (2008) analyze the topology of the Federal Funds market by looking at overnight transactions from 1997 to 2006. They show that reciprocity and centrality measures are useful predictors of interest rates, with banks gaining from their centrality. Akram and Christophersen (2010) studies the Norwegian interbank market over the period 2006-2009. He

observes large variations in interest rates across banks, with systemically more important banks, in terms of size and connectedness receiving more favorable terms. Gabrieli (2012) tests whether measures of centrality can help explaining heterogeneous patterns in the interest rates paid to borrow unsecured funds in the e-MID market, once bank size and other bank and market factors are controlled for. This paper shows that the effect of interconnectedness on interbank borrowing costs is very different before versus after August 2007; and that banks of different size profit from different forms of centrality before the crisis and lose from different forms after the crisis.

Similar to Gabrieli (2012), we also study the e-MID market and implement a number of centrality measures in our analysis. The main difference with Gabrieli paper is that, like Akram and Christophersen (2010), she perform the analysis on daily networks while we compute centrality measures on quarterly aggregated transaction networks. This choice is motivated by the analysis of Finger et al. (2012) who show that the e-MID networks appear to be random at the daily level, but contain significant non-random structure for longer aggregation periods. While the use of daily networks is justified by the fact that the underlying loans are O/N the daily networks are not representative for the underlying ‘latent’ network. Daily transactions are rather random draws from the true underlying network with the realizations depending on current liquidity need. A much higher degree of structural stability is achieved for longer aggregation periods, monthly or quarterly. At the daily scale several banks act exclusively as lenders or borrowers, and liquidity flows over short paths resulting in very small values of centrality according to most measures, which is not the case at longer aggregation scales. In addition we perform the regression analysis not per bank but per pair, assessing simultaneously the role of lender and borrower centrality in a transaction on the interest rates.

### **3 Data and variables definition**

We use tick-by-tick data of the Italian e-MID from 01 January 2006 to 31 December 2009. We have detailed information about each transaction; time, volume of trade, maturity, interest rate, the side of the transaction (buy/sell) and the code of the banks acting as quoter and aggressor, country of origin and size of both parties. The interest rate is expressed as annual rate and the volume of the transaction is provided in millions of Euros. The e-MID market includes contracts with maturities varying from one day to one year. We restrict our analysis to overnight (O/N)

and the overnight long (ONL<sup>2</sup>), which consists of more than 90% of all e-MID transactions as the interbank market is mainly a market for short-term trades. If loans with longer maturities were included in the dataset, it would be difficult to derive a representative interest rate for the market as longer term loans tend to be infrequent.

### 3.1 Interest Rate Spread

In this study, the unit of analysis is not an individual bank but a pair of banks, that is, lender and borrower in order to control counterparty specific characteristics. We calculate the quarterly volume weighted average interbank interest rate for each bank pair  $ij$  as

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

where  $r_{ij,n}$  and  $V_{ij,n}$  are the transaction level interest rate outstanding and volume of 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  $\bar{r}_m^d$  is the daily volume weighted average rate over all transactions carried out by the bank pairs and calculated as

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

where  $r_{ij,n}$  and  $V_{ij,n}$  are defined same as spread formula above and  $N_{ij,d}$  is number of transactions for the bank pair  $ij$  where  $i \neq j$  at day  $d$ .

In our study, we only include banks that actively participate in the interbank overnight market for all sub-periods phase I, II and III of the financial crisis of 2007-08 in order to avoid potential selection bias in our analysis. The aim of this approach is to exclude banks that go bankrupt or drop out of the market for any reason or banks that enter the market during sixteen quarters from January 2006 through to December 2009. As a result of this data trimming for entering and exiting banks, the number of banks during the period analyzed decreases from 200 to 140. Further details about the sample are in Temizsoy, Iori, and Montes-Rojas (2015). We also consider three sub-samples according to the evolution of the financial crisis:

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<sup>2</sup>ONL refers to contracts when there is more than one day between two consecutive business days.



Period	Description	Key date	No. of Quarters
1-Jan-06 - 30-Jun-07	Phase I	Two Bear Stearns' hedge fund bankruptcy (31-Jul-07)	6
1-Jul-07 - 30-Sep-08	Phase II	Lehman Brother's collapse (15-Sep-08)	5
1-Oct-08 - 31-Dec-09	Phase III	-	5

### 3.2 Network Centrality Measures

Centrality is a concept developed in sociology to assess who occupies critical positions in a network, and to identify important, or powerful, individuals. Importance can be interpreted in different ways and this has led to different definitions of centrality. The most popular centralities measures used in the financial economics literature all reflect the involvement of a node in the cohesiveness of the network but differ on how cohesiveness is measured, that is in terms of how walks between nodes are defined and counted. The measures described in this paper span from walks of length one (degree centrality) to infinite walks (eigenvalue centrality). In simple structures these different measures tend to covary but in more complex and larger networks, nodes can be more important respect to some centrality measure and less important respect to others.

The network perspective emphasizes that power is not an individual attribute but is inherently relational. Power may arise from occupying advantageous positions in networks of relations, such as by being closer to others. For our analysis we represent the market as a network consisting of nodes (banks) and a time-varying number of, weighted and directed, links between them (representing interbank loans). The direction of the links follow the flow of money (from lenders to borrowers). Two banks can be connected by two links, one in each direction, if they both act as lenders and borrowers. Thus, network centrality directed measures provide different values of the bank's interconnectedness, focusing separately on the role of a bank as lender or as a borrow.

Let  $A$  be an adjacency matrix where  $a_{ij}$  means that  $i$  contributes to  $j$ 's status and  $n$  is the number of nodes in the network. We compute a directed adjacency matrices where  $a_{ij} = 1$  if bank  $i$  lends to bank  $j$ , and 0 otherwise.

Nodes with more ties to other nodes have alternative ways to satisfy their needs, in our contest they have greater opportunities to exchange liquidity. Choice makes these nodes less dependent on other nodes, and in this sense more powerful, such as in bargaining better rates. Thus a simple measure of a node centrality is its degree. When links are directed, it is common to distinguish

centrality based on in-degree from centrality based on out-degree. Nodes that receive many ties are said to be prominent, or to have high prestige or trust. Nodes who have high out-degree are said to be influential. Formally indegree and outdegree centrality are defined as

$$IndegreeCentrality(i) = \frac{\sum_j a_{ji}}{n-1},$$

$$OutdegreeCentrality(i) = \frac{\sum_j a_{ij}}{n-1},$$

where  $A$  is the adjacency matrix and  $n$  is the number of nodes in the network.

Degree centrality only takes into account the immediate ties that a node has. A node might be tied to a large number of others, but those others might be disconnected from the network as a whole. In a case like this, the node could be central, according to degree centrality, but only in a local neighborhood. So degree is a measure of *local* centrality.

Closeness and betweenness centrality focuses on the distance of a node to all the other nodes in the network, and in this sense they are measures of *global* centrality. In connected graphs there is a natural distance metric between all pairs of nodes, defined by the length of their shortest paths. When defining Betweenness and Closeness we consider two alternative choices of directed paths: the one that follows the flow of money lent, that is paths go from lenders to borrowers (along outgoing links), and the one that follows the direction of repayments to be made, that is paths go from borrowers to lenders (along incoming links). We name these two measures as OutBetweenness, OutCloseness, InBetweenness, and InCloseness, respectively.

Betweenness centrality, introduced by Freeman (1979), is based on the idea that nodes have positional advantage if they lay in between other pairs of nodes. The intuition is that nodes who are “between” other nodes will be able to translate their broker role into power. Betweenness centrality is computed, for each node, by adding up the proportion of times a node fall on the shortest (geodesic) pathway between other pairs of nodes and is normalized by expressing it as a percentage of the maximum possible betweenness that a node could have:

$$InBetweenness(k) = \frac{1}{(n-1)(n-2)} \sum_{i,j} \frac{\sigma^{in}(i,j|k)}{\sigma^{in}(i,j)},$$

$$OutBetweenness(k) = \frac{1}{(n-1)(n-2)} \sum_{i,j} \frac{\sigma^{out}(i,j|k)}{\sigma^{out}(i,j)},$$

where  $\sigma^{in(out)}(i,j)$  is the number of shortest in (out) paths from node  $i$  to  $j$  and  $\sigma^{in(out)}(i,j|k)$  is the number of such in (out) paths passing through the bank  $k$ . While Gabrieli (2012) reports that this measure is very small and often zero in daily networks, confirming the limited extent of intermediary trading in the e-MID market at daily aggregation scale, we find that in quarterly networks, very few nodes exclusively lend or borrow (on average about 5% of the banks only lend or only borrow in a given quarter but the proportion increases up to 10% for borrower in Phase III) and values of betweenness are over 10 times larger than the one reported by Gabrieli both for the directed and non directed version of the centrality indicator.

Closeness centrality is calculated as the inverse of the average of the shortest (geodesic paths) from a node to each other node in the network.

$$InCloseness(i) = \frac{1}{n-1} \sum_{j \neq i} \frac{1}{l^{in}(i,j)},$$

$$OutCloseness(i) = \frac{1}{n-1} \sum_{j \neq i} \frac{1}{l^{out}(i,j)},$$

where  $l^{in}(i,j)$   $l^{out}(i,j)$  represent respectively the length of the shortest in and out paths.

Bonacich (1972, 1987) and Katz (1953) proposed a modification of the degree centrality based on the idea that the centrality of a node depends on the centrality of the nodes that link to it, InEigenvector centrality, or on the centrality of the nodes it links to, OutEigenvector centrality. These measures are defined as

$$InEigenvector(i) = \sum_j a_{ji} InEigenvector(j),$$

$$OutEigenvector(i) = \sum_j a_{ij} OutEigenvector(j).$$

In matrix form, this can be expressed as

$$InEigenvector = A^T InEigenvector,$$

$$OutEigenvector = A OutEigenvector,$$

where InEigenvector and OutEigenvector are vectors of centrality scores<sup>3</sup>. Thus the centralities are given by the elements of the eigenvector of  $A$  or  $A^T$  corresponding to an eigenvalue of 1, which in general has no non-zero solution. One way to make the equations solvable is to normalize the rows (columns) so that each adds up to 1 and  $A$  and  $A^T$  become a stochastic matrix. The other way, first suggested by Bonacich (1972), is to assume that each individual's status is proportional (not necessarily equal) to the weighted sum of the individuals to whom she is connected, in which case the equation can be rewritten as

$$InBonacich(i) = 1/\lambda \sum_j a_{ji} InBonacich(j),$$

$$OutBonacich(i) = 1/\lambda \sum_j a_{ij} OutBonacich(j),$$

so that the centrality measure is given by the eigenvector associated to the largest eigenvalue of  $A^T$ . If the graph is strongly connected the Perron-Frobenius theorem guarantees that there is unique and positive eigenvector. Bonacich is the eigenvector centrality measure computed for our regression analysis.

A practical problem with eigenvector centrality is that it works well only if the graph is (strongly) connected, i.e. if each node is reachable from every other node in the network. Real undirected networks typically have a large connected component. However, real directed networks do not. If a directed network is not strongly connected, only vertices that are in strongly connected components or in the out-component and in-component<sup>4</sup> of the strongly connected components can have non-zero eigenvector centrality. This happens because nodes with no incoming edges have, by definition, a null InEigenvector centrality score, and so have nodes that are pointed to only by nodes with a null InEigenvector centrality score (and the analogous for the OutEigenvector centrality). Thus, when a node is in a directed acyclic graph, centrality becomes zero, even though the node can have many edges connected to it. A way to work around this problem is to give each node a small amount of centrality for free, regardless of the position of the vertex in the network,

$$C = \alpha A^T C + \beta \mathbf{1}$$

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<sup>3</sup>In undirected networks  $A^T = A$  and the two measures coincide.

<sup>4</sup>The in-component of a node is the set of vertices from which that node can be reached; the out component is the set of vertices that can be reached from that node.

which has the solution  $C = (I - \alpha A^T)^{-1} \cdot \beta \mathbf{1}$ . This measure of centrality is equivalent to a measure proposed by Katz (1953) who suggested that influence could be measured by a weighted sum of all the powers of the adjacency matrix  $A$  (or  $A^T$ ). Powers of  $A$  (or  $A^T$ ) give the number of directed walks of length given by that power. Giving higher powers of  $A$  less weight would index the attenuation of influence through longer paths

$$InKatz = \sum_{l=1}^{\infty} (\alpha A^T)^l.$$

$$OutKatz = \sum_{l=1}^{\infty} (\alpha A)^l.$$

The infinite sum converges, so for example  $InKatz = (I - \alpha A^T)^{-1} \cdot \mathbf{1}$  as long as  $\alpha < 1/\lambda_1$ , where  $\lambda_1$  is the maximum value of an eigenvalue of  $A^T$ . As a result, eigenvector centrality can be interpreted as a distance between nodes measured by unrestricted walks of any length, rather than by paths or geodesics.

A popular commercialization of eigenvector centrality is Google's PageRank algorithm (Page et al., 1999), which also can be computed for asymmetric networks. Unlike Katz's centrality, where a node passes all its centrality to its out-links, or inherit all the centrality from its incoming links, with PageRank each connected neighbour gets a fraction of the source node's centrality

$$InPagerank(i) = \frac{1 - \beta}{N} + \beta \sum_j a_{ji} \frac{InPagerank(j)}{OutDegree(j)},$$

$$OutPagerank(i) = \frac{1 - \beta}{N} + \beta \sum_j a_{ij} \frac{OutPagerank(j)}{InDegree(j)},$$

where  $\beta$  the damping factor (that is the parting of PageRank that is transferred by a node). For  $\beta = 1$  page rank converges to eigenvector centrality (normally  $\beta = 0.85$  is used). *Pagerank* can be reformulated in matrix format as  $InPagerank(j) = (I - \beta A^T D^{-1})^{-1} \cdot \delta \mathbf{1}$  where  $D$  is a diagonal matrix of out-degrees and  $\delta = (1 - \beta)/n$ . As a result of Markov theory, it can be shown that PageRank is the steady state probability distribution of a random walk with a restart probability  $\delta$ . Thus PageRank can be interpreted as the fraction of time that a random walk(er) will spend at a node over an infinite time horizon. The restart probability allows the random process out of dead-ends (dangling nodes). PageRank (as well as SinkRank below) can be generalized to weighted

networks by replacing the adjacency matrix with the weights matrix and the nodes' degrees with their strengths.

For all the centrality measured considered so far, the *in* version capture the importance of a bank as a lender and the *out* version captures the importance of a bank as a borrower. If we are interested in systemic risk it is the *in* centrality version of the centrality measures that is more relevant. A borrower can be systemically important only if their lenders are also systemically important borrowers as in this case distress can propagate through the network. On the contrary banks characterized by a high out-centrality measure can be important liquidity providers as, by lending to other central lenders, they contribute to the overall market liquidity.

Two recently-developed centrality measures are Acemoglu et al. (2015) harmonic distance and Soramaki (2013) SinkRank.

The harmonic distance from bank  $i$  to bank  $j$  is defined as

$$Harmonic(i, j) = \theta_i + \sum_{k \neq j} (y_{ik}/y_i) C_H(k, j)$$

where  $y_{ik}$  represents the value of the loans borrowed by bank  $k$  from bank  $i$  and  $y_i$  all loans given by bank  $i$ . The centrality of the node can then be measured by the increase of the sum of the harmonic distance of a node from all other nodes in the network<sup>5</sup>. Acemoglu et al. (2015) shows that the matrix  $Q$ , whose elements are  $q_{ij} = y_{ij}/y_i$ , is a stochastic matrix and hence can be interpreted as the transition probability matrix of a Markov chain. For this Markov chain, one can define the mean hitting time from  $i$  to  $j$  as the expected number of time steps it takes the chain to hit state  $j$  conditional on starting from state  $i$ . Acemoglu et al. (2015, p.588) show that the harmonic distance from bank  $i$  to  $j$  is equal to the mean hitting time of the Markov chain from state  $i$  to state  $j$ . Acemoglu et al. (2015) argues that “various off-the-shelf (and popular) measures of network centrality (such as eigenvector or Bonacich centralities) may not be the right notions for identifying systemically important financial institutions. Rather, if the interbank interactions exhibit non-linearities similar to those induced by the presence of unsecured debt contracts, then it is the bank closest to all others according to our harmonic distance measure that may be ‘too-interconnected-to-fail.’ ” (pp. 566-567) Similar to Acemoglu et al. (2015)

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<sup>5</sup>Acemoglu's Harmonic distance is, in our terminology an *out – centrality* measure, and the corresponding *in* version could also be defined.

measure Soramaki's SinkRank is based on absorbing Markov chains. SinkRank is defined as

$$\text{Sinkrank} = \frac{n - m}{\sum_i \sum_j q_{ij}}$$

where  $m$  is the number of absorbing states and  $n - m$  the number of non absorbing states and  $q_{ij}$  the element of the matrix  $Q = (I - S)^{-1}$  and  $S$  is the matrix of transition probability for non-absorbing states.  $Q$  is a matrix whose elements give the number of times, starting in state  $i$  a process is expected to visit state  $j$  before absorption, that is the total number of visits a process is expected to make to all the non-absorbing states. Sink distance can only be calculated when a directed path exists between the absorbing node and the non-absorbing node being considered, thus it is most useful as a centrality metric for networks that are strongly connected. It can be generalized to networks that are not strongly connected by adding a small constant to the zero elements of the transition matrix, equivalent to the random jump probability used in the PageRank algorithm, in which case the transition probabilities become  $p_{ij} = \beta \frac{s_{ij}}{\sum_j s_{ij}} + \frac{1-\beta}{n}$ . We compute both the *in* and *out* versions of the Sinkrank centrality, where, as for the other centrality measures, the *in* version is obtained from the transpose of the connectivity matrix, and is also known as Sourcerank. While Sinkrank identify liquidity sinks, Sourcerank identifies liquidity providers.

Table 1 shows the summary statistics for the network centrality variables used in the regression models below.

Figure 2 illustrate the average and quantiles of indegree of borrower and outdegree of lender for three phases of 2007-2008 financial turmoil. Both variables show a higher inter-quantile range before Lehman's collapse than after. There is, however, a sharp decrease in the upper quantile of both measures during the second phase.

Figure 3 shows the average and quantiles of closeness and betweenness centrality over the time. Although there is no clear pattern in the betweenness centrality of banks, closeness decreases during the second and third phase of the 2007-2008 financial turmoil, a trend that is similar to the local degree centrality measures. Figure 4 shows no clear trend in the quantiles of the eigenvector-based centrality measures but some of the distributions appear to become more right skewed towards the end of the analyzed period.

Figures 5-7 show the distribution of centrality measures for the entire sample and for the three

different subsamples, phases I-III. We discuss these figures in more details in the Results section.

Global centrality measures tend to correlate with local centrality measures as, by construction, high degree can lead to high centrality. To quantify the importance of this effect, we regress the nodes global InCentrality (OutCentrality) versus their Indegre (Outdegree) and plot the coefficients of the pooled OLS regressions, for each quarter separately, in Figure 8. The plots show interesting dynamics: while correlations decrease over time for pagerank, they increase for closeness and have a non monotonous behavior for betweenness. We do not explore in this paper what consequences such dynamic change may have in terms of the banking system stability, but we do control for these correlations when assessing the effect of global centrality on interbank spreads.

### 3.3 Other control variables

In our analysis, in addition to centrality measures, we also control for a other variables that may affect interest rate spreads.

The identity of the banks trading in the e-MID is unknown to us and replaced by a unique identifier in our dataset. This makes it impossible to match e-MID trading data with balance sheet or other banks' specific data. Other studies (see Angelini et al., 2011) have shown that banks characteristics such as credit ratings, capital ratios, or profitability remained roughly unchanged during the precrisis and crisis period. Neither borrower and lender liquidity nor their shortage of capital correlate with e-MID market spreads in Angelini et al. (2011) study. Of course, since credit ratings lost credibility as the crisis unfolded we do not know if banks used rating agencies' scores to inform their choices of counterparty. Neither we know what other private or public information was available to banks. For this reason we also include time varying measures of aggregate volumes of O/N trading by both the lender and borrower as a proxy of banks' characteristics. The intuition is that participation in terms of volume captures all unobserved factors that may be relevant to explain banks' spreads. We also include transaction concentration, Transaction Ratio (%), that measures the ratio of the number of transactions between each pair to all transactions that takes place in the same period. This variable captures the overall importance of the pair within the network structure.

Another key determinant of O/N rates is the time of a transaction. While Angelini (2000)



using hourly e-MID data shows no intraday pattern of interest rates, Baglioni and Monticini (2008) and Gabbi et al. (2012) find a decreasing trend in the O/N rate as the trading day progresses. The intraday slope becomes more pronounced with the financial crisis and, in particular, after the Lehman Brothers collapse. The intraday term structure of interest rate is due to the maturity of O/N deposits which are expected to be reimbursed at 9 am of the day following the trade. The increase in the slope of the yield curve after the default of Lehman apparently creates a risk-free profit opportunity. Baglioni and Monticini (2008) suggest that this opportunity is not arbitrated away for two main reasons: uncertainty about availability of liquidity late in the afternoon and an increase in the implicit cost of collaterals. Similar to Baglioni and Monticini (2008), we also examine the effect of the time interval of the transaction performed. Instead of dividing the day into hourly segments, we use only two slots: morning (8 am - 1 pm) and afternoon (1 pm - 6 pm). Morning-Afternoon (AM/PM Ratio) is the fraction of the difference between number of transactions that occur during morning and afternoon to all transaction of each pair at a given period. In the interbank market, participants must repay the loans at 9 am on the next trading day of transaction. Hence, morning interest rates have a premium to account for the longer maturity period than those transactions in the afternoon.

While the e-MID market is not affected by search frictions and lack of transparency, trading in the electronic segment of the interbank market is affected by its own specific micro-structure features. Gabbi et al. (2012) and Temizsoy et al. (2015) have shown that due to a bid-ask spread effect, better rates are obtained, both by lenders and borrowers, when they act as quoters rather than as aggressors. A credit institution that first comes to the market with a proposal to lend or borrow is called quoter, while the bank that picks a quote and exercises a proposal is called aggressor. Aggressors, by choosing their counterparts, may have more power than quoters in a pair relationship. Thus we control for variations in rates that are explained by the bid-ask spread effect by separately studying quoters and aggressors. Then we control for the ratio of the difference between number of transactions of a pair that occurs when lender is a quoter and when a lender is aggressor, divided by all transactions of the pair at a given quarter (Quot/Agg Ratio).

## 4 Econometric Model

In order to investigate the effect of network characteristics on the interbank market we consider the following econometric model. Let

$$S_{ij,t} = \beta_0 + \beta_1 A_{ij,t} + \beta_2 B_{i,t} + \beta_3 C_{j,t} + u_{ij,t}$$
$$u_{ij,t} = \mu_{ij} + \delta_t + e_{ij,t}.$$

where  $i, j$  denotes bank pairs (bank  $i$  lends to  $j$ ),  $t$  indexes time,  $S_{ij,t}$  is the spread,  $A_{ij,t}$ ,  $B_{i,t}$  and  $C_{j,t}$  represent pair, lender, and borrower related variables, respectively,  $\mu_{ij}$  is the pair-specific effect,  $\delta_t$  a time-specific effect, and  $e_{ij,t}$  is the unobserved residual. We estimate the model above using fixed-effects (FE) at bank pair level and time dummies. We also compute robust standard errors clustered at the bank pair level which allows us to control for the time-varying bank heterogeneity. Since we want to allow different effect of variables on spread, we run the same model for three time spans, phase I, phase II, phase III of the latest financial turmoil, and for all pooled periods.

All analyses are done conditional on bank pair  $ij$  fixed-effects, and therefore, the effect of the variables should be interpreted as conditional on the existence of that particular link  $i \rightarrow j$ . We cannot claim that network characteristics cause spreads. Feedback effects between network positioning and prices are possible, with network characteristics leading to better prices and more favorable prices reinforcing network effects. This feedback loop makes it difficult to establish the causality of the effect. Temizsoy et al. (2015) shows that such feedback effects are small. Spreads do not determine survival of a bank pair into the following months once relationship indexes are controlled for, while relationship lending has an effect on spreads. Previous studies (see Hatzopoulos et al., 2015) have also shown that, when controlling for banks heterogeneity in trading activity, the matching process in the e-MID market is fairly random. This suggests that links are not preferentially formed with banks that offer lower rates or that are more trustworthy. Rather banks appear to be more likely to selected as trading partners because they trade more often. This points to a causal effect of relationship on prices rather than the other way around. In this paper we do not model the entry and exit decisions of banks and their matching patterns. What we show is that network variables, once formed, possibly at random, persists and are important for explaining prices and can play an important role also within a transparent market such as the

e-MID.

Network variables are introduced one at a time in different specifications, together for both lender and borrower. The reason is that while they are intended to describe different features of the network they are very correlated with each other. For global measures, we consider specifications both with and without controlling for the local network counterparts. Network variables are considered in logarithm form, and as such, regression coefficients should be interpreted as the effect of doubling network centrality on spreads, in basis points.

All specifications include a set of baseline covariates given by Transaction Ratio(%), AM/PM Ratio, Quot/Agg Ratio, Reciprocity Ratio, O/N Trading Amount of Lender, O/N Trading Amount of Borrower, described in section 3.3. The inclusion of these covariates is to isolate the effect of network characteristics on transaction spreads from bank- and pair-specific variables that contribute to spreads (see Temizsoy et al., 2015, for a description of the effect of these variables on spreads).

## 5 Results

### 5.1 Local network measures

As a first approximation to the effect of network centrality on the interbank market we evaluate the effect of local centrality measures (in logs) on spreads. Table 2 shows the effect of degree centrality on interbank spreads. Columns (1)-(4) presents a specification with lenders (L) and borrowers (B), indegree and outdegree. The results show that B with high indegree pay higher spreads, and this effect increases in magnitude as the financial crisis evolves. The pooled effect determines that doubling borrowing links (i.e. increasing the logarithm of the indegree centrality measure by 1 unit) increases interest rate by 1.437 basis points in all pooled periods, which corresponds to 0.653, 0.929, and 3.849 in phases I, II and III, respectively. That is, B pay a premium to be able to get more partners in the interbank network, and this increases when systemic risk increases. We might thus speculate that financial uncertainty directs banks towards looking for better connections within the established network structure and they paid a premium for the number of links.

L have no clear pattern regarding outdegree network centrality measures. L outdegree has a

non-significant effect for all pooled periods (column (1)), positive for phases I and II (columns (2) and (3)), and negative (although not significant) for phase III (column (4)). This shows that L were able to obtain better rates for having more links within the network before Lehman's collapse, but the effect reverses after it. L thus pay a price for diversification when systemic risk increases. Possibly this suggests that in the presence of systemic risks, banks diversify their transactions, and incur in worse interest rates. Diversification may in turn increase uncertainty as well established information flows with a few partners are reduced (see Temizsoy et al., 2015).

The results show that L (B) who engage in a well connected borrowing (lending) activity benefit by obtaining better rates. Overall this suggests that network effects depend on the joint lending and borrowing activities of the banks. In order to explore this further we add the interaction terms indegree by outdegree, separately for L and B, to the previous specification (columns (5)-(8)). Considering all pooled periods, L obtain higher rates and B lower rates when they engage in both lending and borrowing activities. The same effects appear in phase I, although they are not present in phases II and III.

Figure 5, first row, shows the bivariate kernel density estimation for lenders (L) outdegree and borrowers (B) indegree, for the all periods together, phase I, phase II and phase III. The graphs show a differentiated behavior for lenders and B. L outdegree has lower dispersion in phase I than in Phases II and III, thus indicating increasing heterogeneity in L as the financial crisis evolves. B indegree, on the other hand, has decreasing dispersion across phases. In fact the phase I plot indicates the existence of B with many lenders, which eventually disappear in the following phases.

Figure 5, second row, shows the bivariate kernel density estimation for outdegree and indegree of L, while the third row does it for outdegree and indegree of B, for the all periods together, phase I, phase II and phase III. The second row also shows that, from the point of view of L, banks borrow from less counterparts overtime, while outdegree becomes bimodal in phase III. The graphs in the third row indicate an overall reduction in the amount of incoming and outgoing links, in this case from the point of view of B.

Two potential situations should be mentioned for systemic risk. The first case corresponds to banks who lend to few counterparties (small outdegree of L) that in turn borrow from many (large indegree of B). The lenders in this case are highly exposed to the B (as lenders do not diversify) and if these borrowers default they may spread the distress to several lenders. Note that while

the proportion of L with few counterparties increased, B had less and less counterparties. This indicates that this case has not been observed in our sample. The second case corresponds to banks who lend to many counterparties (large outdegree of L) who in turn borrow from few banks (small indegree of B). If such lender exits the market or default they may generate a liquidity crisis as their borrowers may find it difficult to satisfy their liquidity needs unless they create new links in the market, i.e. substitutability. The e-MID interbank market seems to be very prone to this second kind of systemic risk, provided that the overall outdegree of B reduces while there appear to be some lenders that attract many links to themselves.

## 5.2 Global network measures

Global network measures show the positioning of a bank and its relationship to the interbank system. In contrast to local measures, these variables tend to identify if the bank is located in a particular position with a particular flow of money going through it. Moreover, while local measures can be affected by individual banks' decisions, and thus regression coefficients cannot be interpreted as causal effects, global measures are less affected by individual decisions, as they depend on collective actions, and then they could be considered as exogenous variables in regression models.

Consider first the effect of betweenness in table 3. Recall that betweenness measures a bank's access to the interbank liquidity. When all pooled periods are considered, InBetweenness has a negative effect for both L and B, and OutBetweenness has a positive significant effect for B. For B, the effects increase in absolute value as the financial crisis evolves (i.e. the largest effect is in phase III). When local centrality is controlled for, only OutBetweenness remains significant. For L, the largest effect appear in phase III, where InBetweenness has a large negative effect while OutBetweenness is positive and significant. When both *in* and *out* measures are interacted B obtain a negative effect, which is significant for all pooled periods and for phase II. The fact that L coefficients are not significant suggests that the effect is not driven by market power, as otherwise both L and B would benefit from it, but by a 'too-interconnected-to-fail' perception of the B that benefit of lower spreads because the market participants believe highly connected borrowers will be bailout in case of default to avoid systemic effects. Then network interconnectedness were perceived as an asset for B during the crisis (i.e. phase II), and this vanishes after Lehman's

collapse.

Now consider the effect of closeness in table 4. Closeness is the inverse of the average shortest distance of a bank from all banks that are reachable from it, and thus, a bank with higher closeness is connected to more banks. For B, InCloseness has a large positive and significant effect for all periods and subperiods, except for phase II when local centrality is controlled for. For L, OutCloseness is negative, and statistical significant. These results suggests that both B and L pay a premium for being interconnected to the network, and this increases when systemic risk is high. Note that in this case the interaction for B of *in* and *out* has a positive coefficient for all pooled periods but not significant for subperiods.

Figures 6-7 plot betweenness of L and B bivariate density estimates. The figures clearly reveal two features producing an L-shaped density in betweenness. First, the existence of a large number of L for which betweenness is either zero or close to zero, possibly L who do not borrow. Second, there is also a big proportion of B that also have zero or small betweenness. For closeness, figure 6 also reveals two types of borrowers, some with positive closeness and some with close to zero closeness. The latter group increases as a proportion of the total amount of borrowers in phase III.

Tables 5-7 present the coefficient estimates of different global network variables using eigenvector centrality measures. All specifications include the same control variables as described in section 3.3, although they are not reported.

Eigenvector type centrality measures how well connected the nodes to which that bank is connected to. It does not only measure how a bank is connected to the network, but it also indicates connectedness of its neighbors. Three different measures are used in the regression models (see the definitions above): Bonacich's eigenvector, pagerank and sinkrank. In each case, the centrality measure can be constructed by using the adjacency matrix  $A$  or its transpose. The former is the *out* definition and corresponds to the centrality of a bank as a lender. The latter is the *in* definition and corresponds to the centrality of a bank as a borrower. For each pair of banks and a particular direction, we can consider the *in* and *out* centrality of both L and B in different specifications.

The eigenvector network variables have similar and consistent effects across measures. They show that for all pooled periods L receive lower rates for higher outcentrality (doubling *out*-centrality

reduces spreads by 0.65 basis points) while B pay higher rates for higher in-centrality (doubling *in*-centrality increases funding rates by 0.9 basis points). These effects increase in absolute value across the financial crisis, with the pooled effect driven by phase III for B (where the effect increases up to 3 basis points) and by phase II or III for L. The coefficient estimates have, in general, the same sign with and without controlling for local measures. Overall, controlling for local network degree, the effect is marginally reduced. Note that Bonacich measure has in general smaller (and less significant) effects than pagerank and sinkrank. Such differences are due to the nature of the e-MID sample as not strongly connected. This produces a significant amount of nodes with zero centrality even though they are connected nodes. Pagerank and sinkrank do not suffer from this and these are our preferred global centrality measures.

The opposite edge measures, i.e. *out* for B and *in* for L, have an overall non statistically significant effect. The exception is the *out*-centrality measures for B that appear with a negative and significant effect in phase II. That is, B who have a high global centrality in lending obtain lower rates for their borrowing. In order to explore this further, we consider the *in*- and *out*-centrality interaction. B obtain a significant discount on their funding rates, suggesting that B receive better (i.e. lower) rates when engage in both lending and borrowing. L, however, have a non statistically significant effect for all pooled periods. The largest interaction effects appear in phase II for B, and in phase III for L, the latter with a negative effect.

## 6 Discussion and concluding remarks

Local and global measures of centrality are used to identify different features of how the network characteristics affect the interbank market funding rates. Local measures show that having more links increases borrowing costs for borrowers and reduces premia for lenders. We interpret this effect as a premium paid by lenders to diversify counterparty risk, and by borrowers to reduce funding risk. Our constructed global eigenvector-based measures of centrality are in general in line with the local measures of centrality when looked at in isolation. That is, for banks being central is a cost. Note that, in general, the highest effect in absolute value corresponds to either phases II or III. In fact, the coefficient sign for all pooled periods is either dominated by that of phase II or phase III. The higher spreads paid by both lenders and borrowers with high in-centrality measures suggests the market associates InEigenvalue centrality with higher credit risk.

To disentangle the role of local factors (degree) on global centrality measures in the analysis, we control for local degree in our global centrality regressions. The fact that global effects remain statistically significant after controlling for the local network effects, suggests that overall global and local network effects operate on a different level in the e-MID market.

A node is important from a global network perspective if it is pointed by other important nodes. In our case, borrowers are important if their lenders are important borrowers as well. As such, importance, given through borrowing, is the potential to propagate distress and generate systemic risk. Eigenvalue-based centrality measures may be dominated by the degree of the nodes as, by construction, high indegree produces high InEigenvector centrality. InEigenvector centrality can be large for banks that are liquidity sinks, that is, banks that borrow from many (and borrow a lot), but that are rather peripheral to the network and as such do not spread distress beyond their direct creditors. A visual inspection of local vs. global measures indeed confirms this fact, that is, there is a high correlation between local and global measures, but several banks stand out as being characterised by high centrality and low degree. These are the banks that inherit their centrality from their lenders and are the potential spreader of systemic risk. (See the Appendix for correlation figures between local and global centrality measures.)

Betweenness, on the other hand, is high, and different from zero, for banks that both lend and borrow, and it increases as the intermediation role of banks increase. This measure is thus probably large for the banks in the core and small for those in the periphery. The negative coefficient for InBetweenness for both lenders and borrowers suggest the market participants perceive borrowers who are central according to this measure as too connected to fail, likely to be bailout in case of default to avoid systemic effects, and as such offer them a discount.

This interpretation is confirmed by the negative coefficient observed for borrowers when the *in* and *out* Pagerank and Sinkrank centrality measures are interacted, indicating again that large borrowers that are central in both directions obtain lower funding rates. However, lenders do not benefit from high betweenness or the joint *in* and *out* global network centrality. The fact that only borrowers, and not lenders, benefit from joint centrality point to a ‘too-interconnected-to-fail’ hypothesis rather to a broker or intermediation effect. As such, these borrowers get better deals for funding in the interbank markets, and this is probably due to the market perception of their network positioning. This effect is the largest in phase II, when banks became affected and/or



aware of systemic risk. For lenders, the market perception about their network positioning (i.e. fragility) dominates their strategic location for intermediation (as in Gabrieli and Georg, 2014).

From a policy perspective monitoring how funding cost advantages, associated to the perceived systemically importance of financial institutions, can be an important tool to assess the effectiveness of the regulatory reforms. Banks perceived as more likely to receive taxpayer support may benefit from lower funding costs. These implicit subsidy this can create moral hazard and provide an incentive to take on additional risk, exacerbating system fragility. Regulators thus have the objective to eliminate the perception that some financial institutions are too big to fail or, in our case, ‘too-interconnected-to-fail’. Monitoring how funding cost advantages evolve over time may provide a way to measure the effectiveness on regulatory policy to reduce systemic risk on one side and act as an early warning indicator of systemic risk on the other.

Favorable rates obtained by more central banks do not necessarily reflect lower credit risk owing to any implicit government guarantee against default. It could also reflect higher bargaining power and/or lower credit risk through more diversified portfolios. Disentangling these effects is difficult in the case of OTC markets where market participants actively search for counterparties. When counterparties meet, they negotiate terms privately, often ignoring prices available from other potential counterparties and with limited knowledge about trades recently negotiated elsewhere in the market. Thus better connected banks may have better access to liquidity and benefit from better rates in compensation of their intermediation role. But the e-MID is a fully transparent trading platform. There is little scope for intermediation in this market. Search frictions and lack of information on rates offered by alternative lenders cannot be responsible for the observed cross-sectional dispersion of O/N rates in this market.

Nonetheless our analysis does not allow to identify why centrality affect banks terms of trade in a financial network. Some banks probably choose to create more local links or have to because they cannot satisfy their needs trading with fewer counterparties. Some may choose to act as intermediaries. While in a fixed network one can expect centrality to deliver positive effects to both lenders and borrowers, either because information or market power effects, in the case of endogenous and dynamic networks this is less obvious. The theoretical literature does not help us in this respect. While several theoretical papers have analyzed how the incentives of single agents to form linkages affect the resulting network topology (Goyal and Vega-Redondo (2007), Babus

(2011), Babus (2013), van der Leij and Kovarik (2012)) leading in some cases to a core-periphery structure (in 't Veld et al. (2014), Lux and Farboodi (2013)) they do not provide any insights on the benefit of centrality in terms of prices. Our empirical results thus indicate that further theoretical work should be done to explore this issue.

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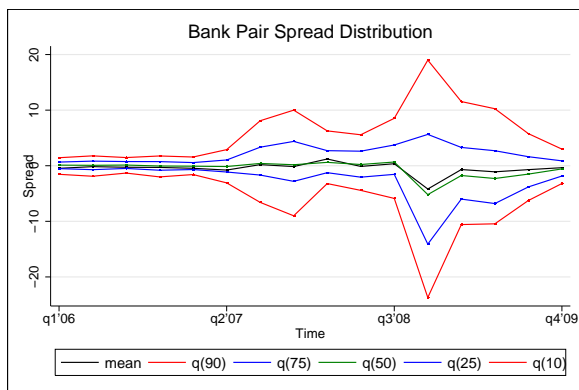
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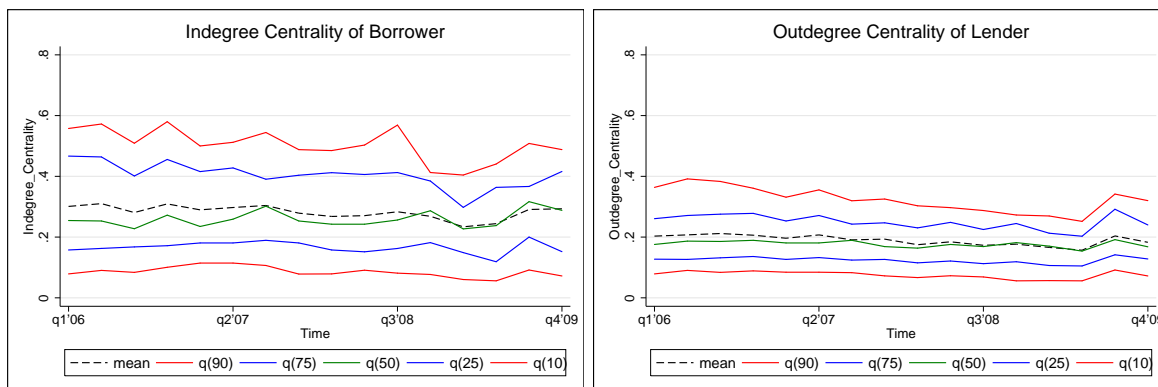
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Figure 1: Bank Pair Spread over Time



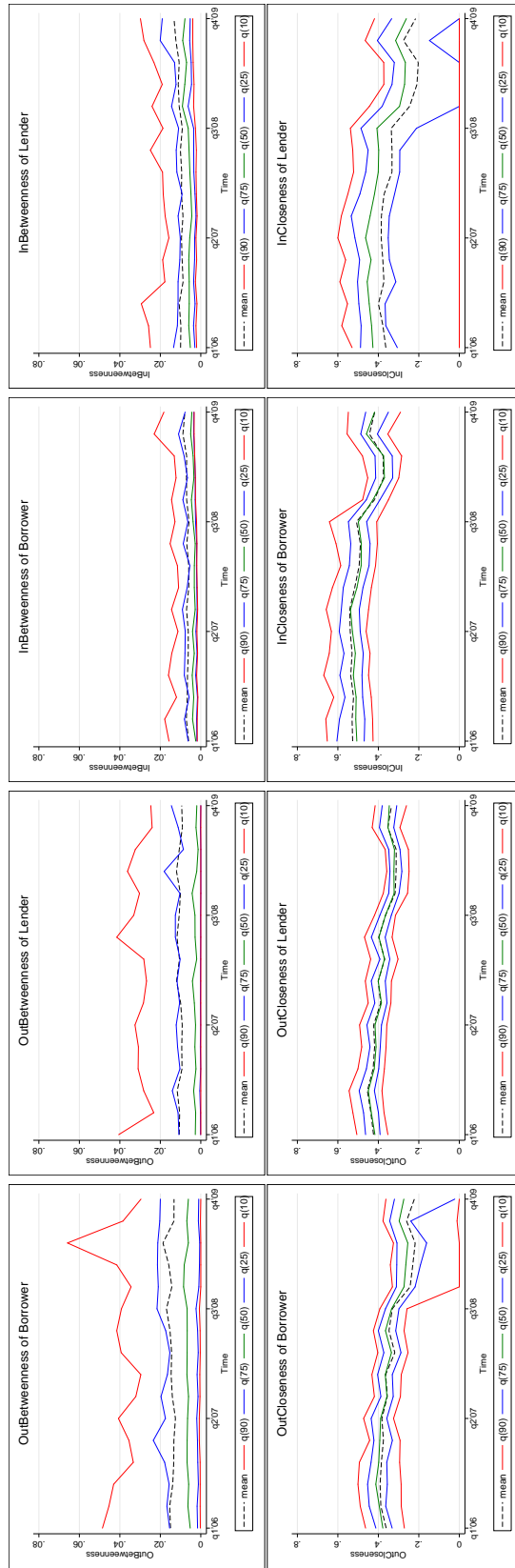
Note: All figures shown in graphs above are averaged to quarterly values.

Figure 2: Quantile Analysis Degree Centrality



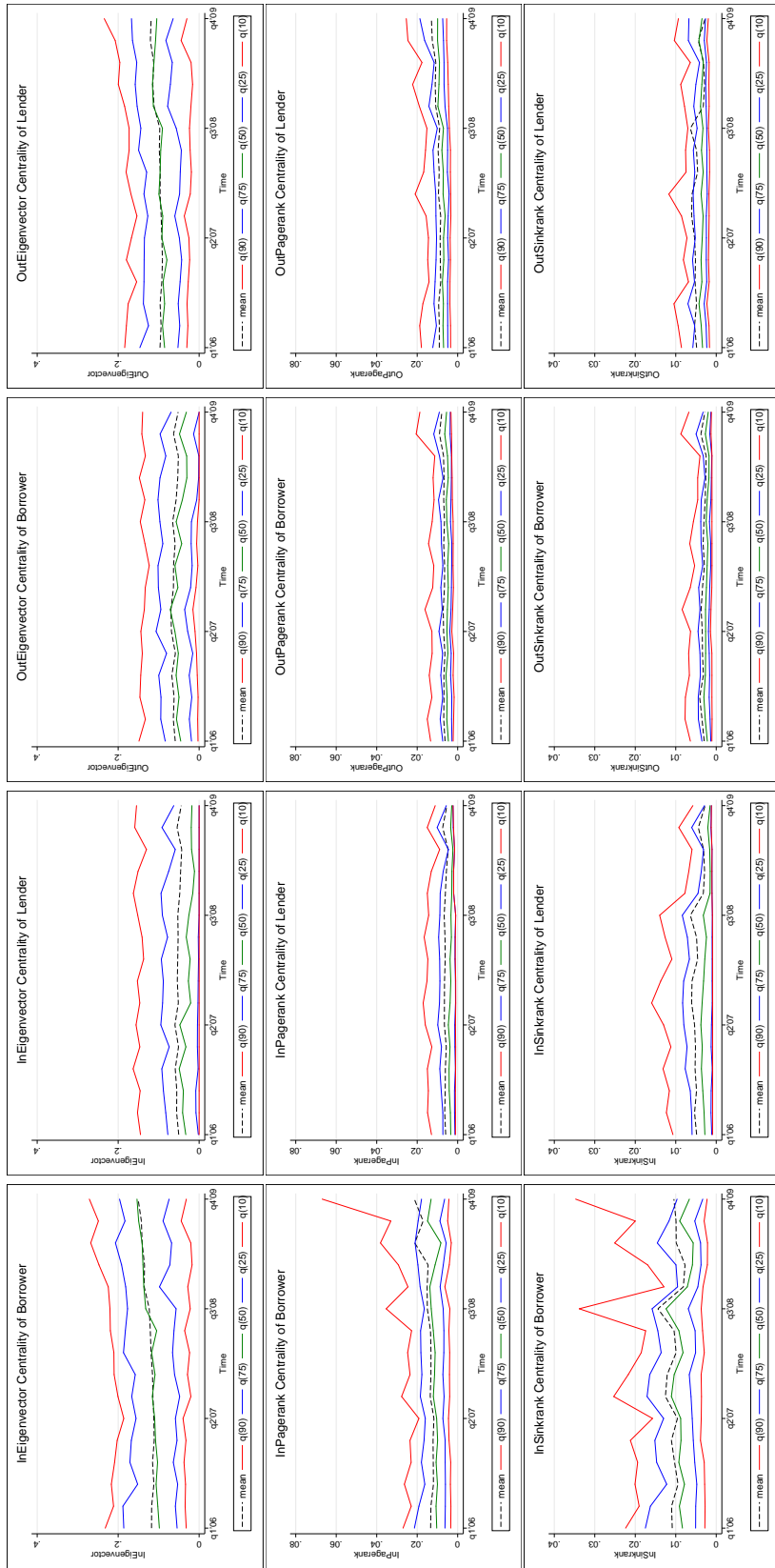
Note: All figures shown in graphs above are averaged to quarterly values.

Figure 3: Quantile Analysis of Betweenness & Closeness



Note: All figures shown in graphs above are averaged to quarterly values.

Figure 4: Quantile Analysis of Eigenvector, Pagerank, Sinkrank



Note: All figures shown in graphs above are averaged to quarterly values.



Figure 5: Bivariate Kernel Density - Local Network Measures (*Graph Type; Directed: Yes, Weight: None*)

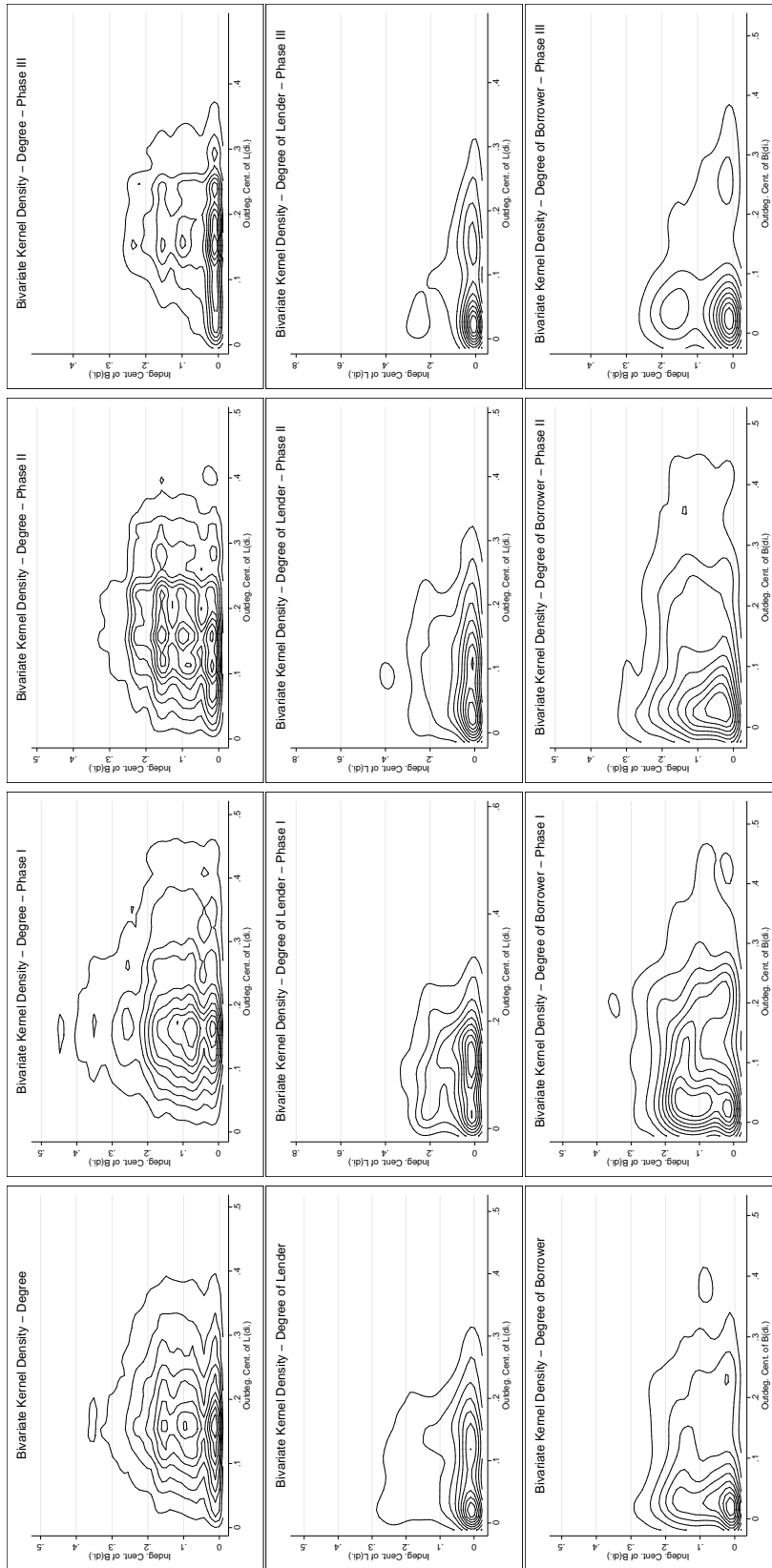


Figure 6: Bivariate Kernel Density - Global Network Measures(In) (*Graph Type: Directed; Weight: None*)

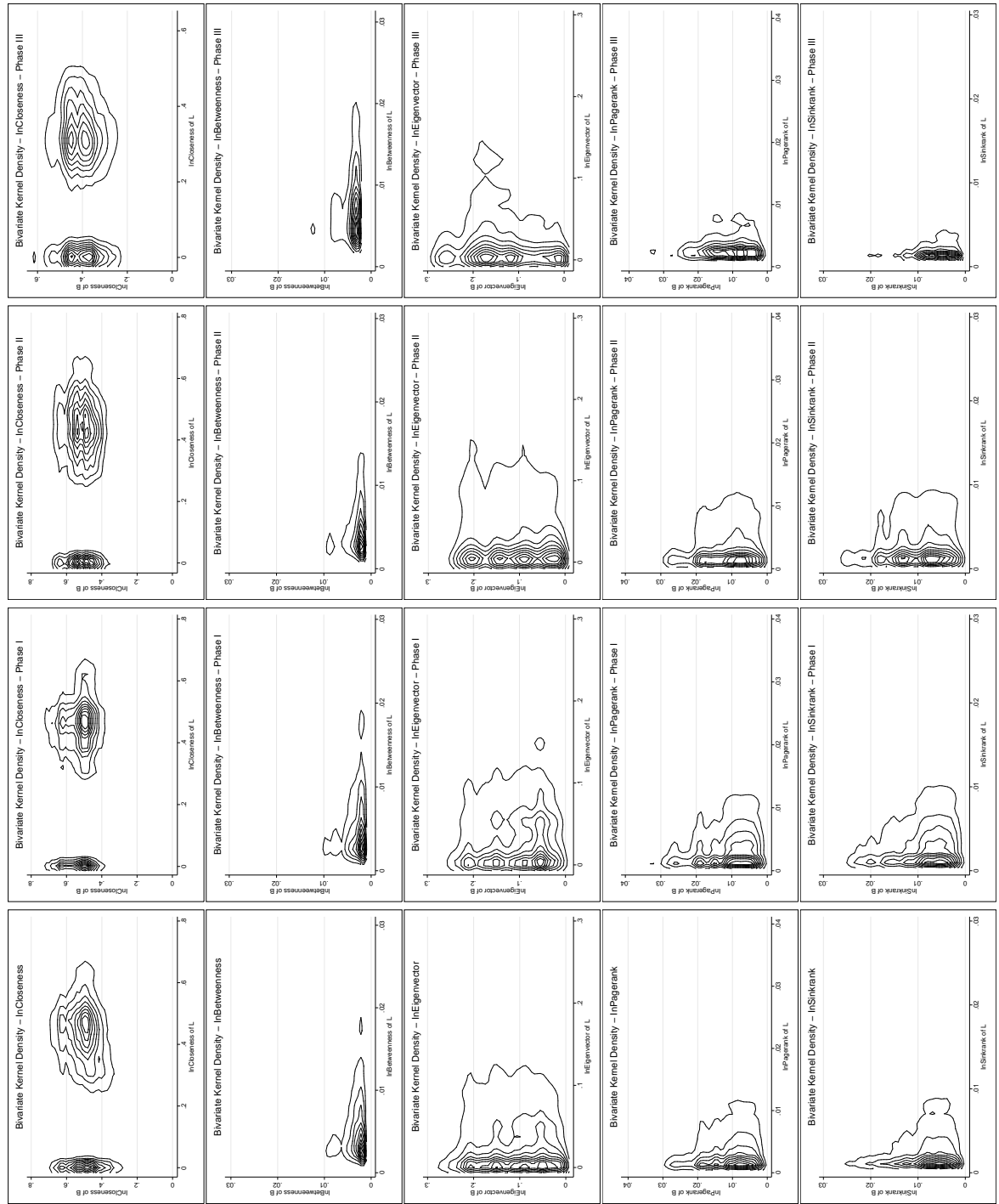


Figure 7: Bivariate Kernel Density - Global Network Measures(Out) ( Graph Type; Directed:Yes, Weight:None)

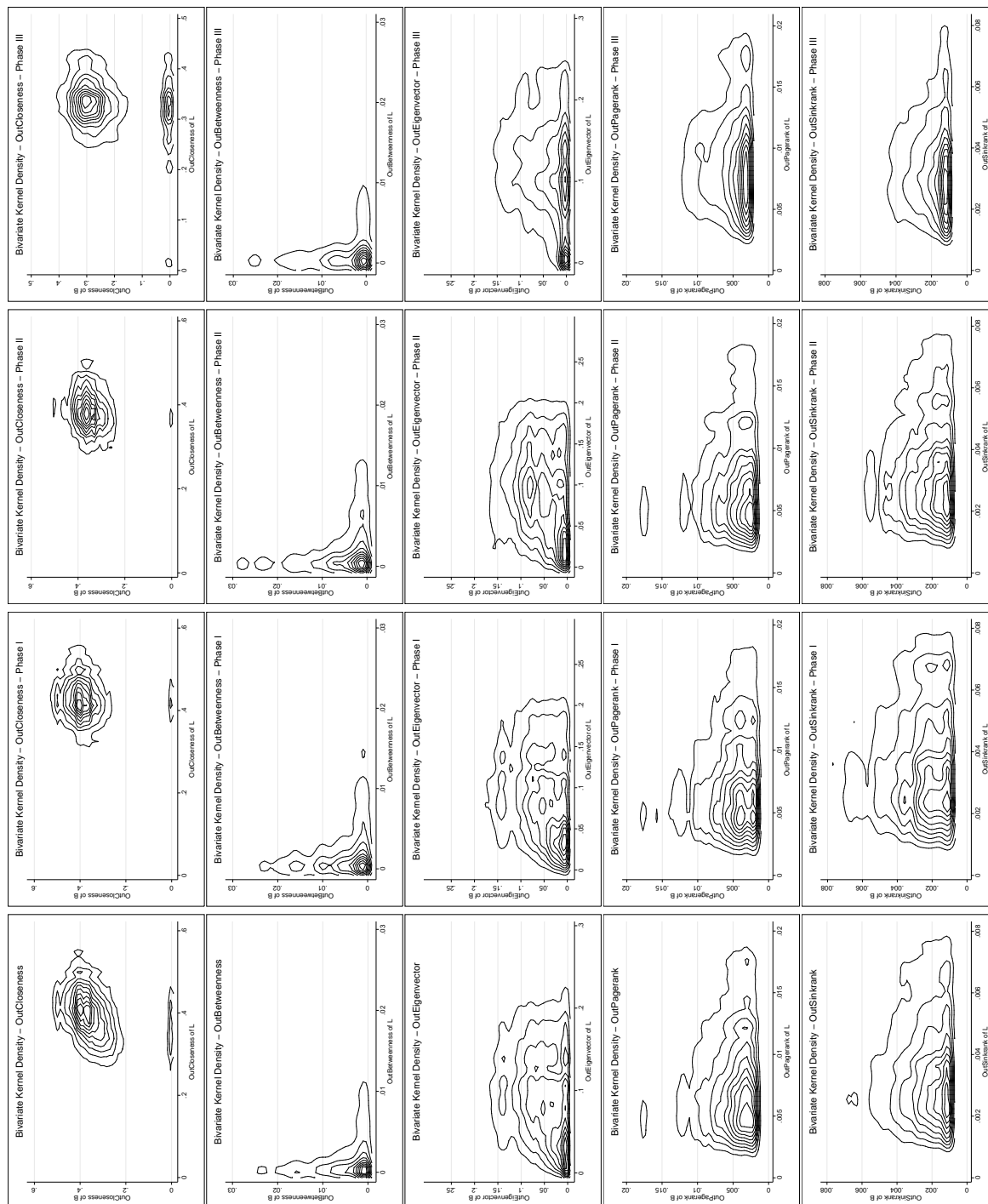
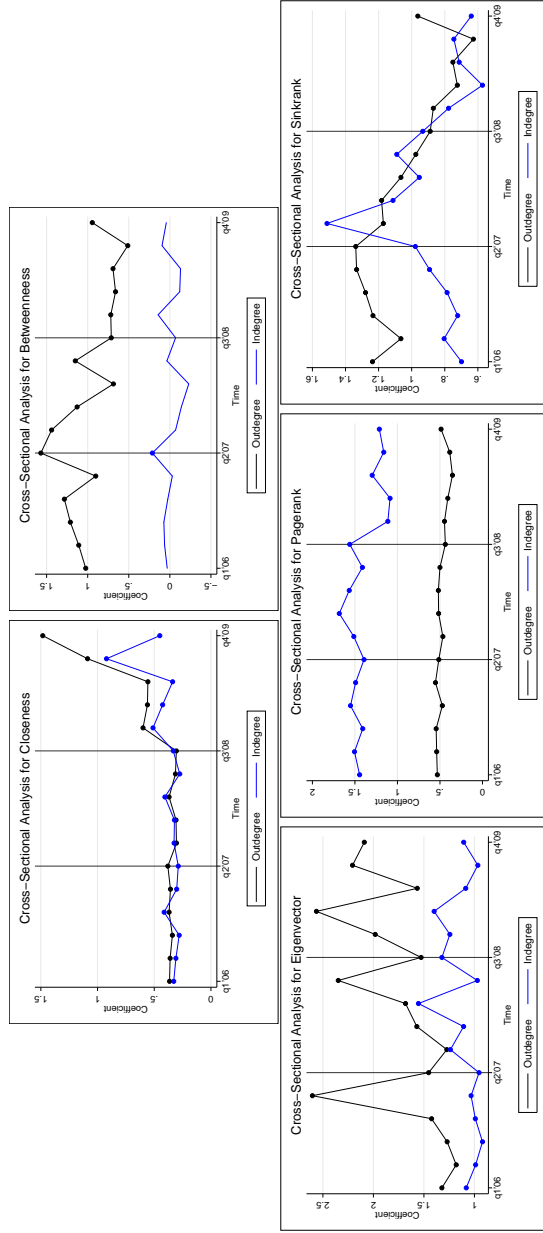


Figure 8: Global InCentrality (OutCentrality) vs their Indegre (Outdegree)



Note: Bold data points reflect coefficients significant at 10% significance level. All global and degree measures are in logarithmic form.

Table 1: Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Bank Pair Spread	37872	-.434	8.422	-114.934	82.004
Indegree of L	37872	20.076	22.968	0	108
Indegree Centrality of L	37872	.125	.141	0	.645
Outdegree of L	37872	30.361	15.18	1	89
Outdegree Centrality of L	37872	.19	.092	.006	.533
Indegree of B	37872	43.775	23.78	1	108
Indegree Centrality of B	37872	.274	.146	.006	.645
Outdegree of B	37872	20.365	15.931	0	89
Outdegree Centrality of B	37872	.126	.097	0	.533
OutBetweenness of L	37872	.01	.018	0	.14
InBetweenness of L	37872	.01	.01	.001	.066
OutBetweenness of B	37872	.013	.019	0	.14
InBetweenness of B	37872	.006	.008	.001	.066
OutCloseness of L	37872	.391	.066	.006	.606
InCloseness of L	37872	.337	.196	0	.716
OutCloseness of B	37872	.336	.11	0	.606
InCloseness of B	37872	.493	.088	.006	.716
OutBonacich of L	37872	.098	.056	0	.262
InBonacich of L	37872	.052	.059	0	.346
OutBonacich of B	37872	.061	.05	0	.241
InBonacich of B	37872	.118	.069	0	.346
OutPagerank of L	37872	.009	.006	.002	.039
InPagerank of L	37872	.006	.007	.001	.147
OutPagerank of B	37872	.007	.005	.001	.039
InPagerank of B	37872	.013	.012	.001	.147
OutSinkrank of L	37872	.004	.003	.001	.022
InSinkrank of L	37872	.005	.005	.001	.056
OutSinkrank of B	37872	.003	.003	.001	.022
InSinkrank of B	37872	.01	.007	.001	.056
Reciprocity Ratio	37872	.566	3.842	0	422
AM/PM Ratio	37872	.036	.81	-1	1
Quot/Agg Ratio	37872	-.537	.714	-1	1
Transaction Ratio	37872	.034	.066	.004	6.44
ON Trading Amount of Lender	37872	14.471	18.901	.007	154.421
ON Trading Amount of Borrower	37872	20.029	22.487	.002	154.421
<i>Logarithmic Form of Network Measures</i>					
ln(Indegree of L)	30052	2.644	1.272	0	4.682
ln(Indegree Centrality of L)	30052	-2.429	1.264	-5.13	-.439
ln(Outdegree of L)	37872	3.263	.608	0	4.489
ln(Outdegree Centrality of L)	37872	-1.805	.596	-5.13	-.629
ln(Indegree of B)	37872	3.575	.739	0	4.682
ln(Indegree Centrality of B)	37872	-1.493	.731	-5.13	-.439
ln(Outdegree of B)	36094	2.687	1.02	0	4.489
ln(Outdegree of B)	36094	-2.385	1.004	-5.13	-.629
ln(OutBetweenness of L)	29960	-5.577	1.859	-13.341	-1.967
ln(InBetweenness of L)	37872	-5.012	.825	-6.574	-2.723
ln(OutBetweenness of B)	36056	-5.244	1.611	-13.341	-1.967
ln(InBetweenness of B)	37872	-5.453	.797	-6.578	-2.723
ln(OutCloseness of L)	37872	-.957	.228	-5.106	-.501
ln(InCloseness of L)	30052	-.92	.505	-5.13	-.334
ln(OutCloseness of B)	36094	-1.099	.462	-5.106	-.501
ln(InCloseness of B)	37872	-.729	.238	-5.13	-.334
ln(OutBonacich of L)	37838	-2.605	1.226	-25.999	-1.341
ln(InBonacich of L)	29686	-3.393	1.692	-32.993	-1.061
ln(OutBonacich of B)	36022	-3.513	2.712	-25.999	-1.424
ln(InBonacich of B)	37813	-2.405	.933	-32.993	-1.061
ln(OutPagerank of L)	37872	-4.844	.581	-6.447	-3.232
ln(InPagerank of L)	37872	-5.586	.967	-6.957	-1.916
ln(OutPagerank of B)	37872	-5.24	.65	-6.515	-3.232
ln(InPagerank of B)	37872	-4.566	.729	-6.938	-1.916
ln(OutSinkrank of L)	37872	-5.59	.574	-7.014	-3.811
ln(InSinkrank of L)	37872	-5.834	.974	-7.033	-2.886
ln(OutSinkrank of B)	37872	-5.987	.653	-7.033	-3.811
ln(InSinkrank of B)	37872	-4.819	.726	-7.014	-2.886

Table 2: All O/N Loans - Local Network Measures as Determinants of Interest Rate Spread

VARIABLES	(1) All	(2) Phase I	(3) Phase II	(4) Phase III	(5) All	(6) Phase I	(7) Phase II	(8) Phase III
OutdegreeCentrality (L)	-0.000 (0.235)	0.731** (0.329)	0.766 (0.528)	-0.773 (0.732)	0.059 (0.246)	0.783** (0.340)	0.835 (0.551)	-0.866 (0.724)
IndegreeCentrality (B)	1.437*** (0.235)	0.653*** (0.217)	0.929 (0.718)	3.849*** (0.684)	1.338*** (0.248)	0.575*** (0.215)	0.896 (0.773)	3.756*** (0.679)
IndegreeCentrality (L)	0.171** (0.078)	-0.114 (0.096)	-0.218 (0.150)	0.604*** (0.190)	0.175** (0.078)	-0.094 (0.097)	-0.219 (0.150)	0.941*** (0.337)
OutdegreeCentrality (B)	-0.107 (0.085)	0.065 (0.088)	-0.726*** (0.184)	-0.363 (0.247)	-0.000 (0.096)	0.103 (0.088)	-0.675*** (0.201)	0.133 (0.457)
DegreeCentrality (L) (in*out)					0.212* (0.124)	0.322* (0.170)	0.438 (0.267)	-0.936* (0.568)
DegreeCentrality (B) (in*out)					-0.279** (0.134)	-0.299* (0.173)	-0.121 (0.387)	-0.645 (0.484)
Transaction Ratio	4.932** (2.318)	0.800 (1.532)	0.137 (1.889)	17.800*** (2.642)	4.884** (2.301)	0.720 (1.539)	0.237 (1.899)	16.626*** (2.679)
AM/PM Ratio	2.270*** (0.093)	1.155*** (0.098)	3.247*** (0.197)	1.638*** (0.246)	2.273*** (0.093)	1.158*** (0.098)	3.241*** (0.196)	1.680*** (0.246)
Quot/Agg Ratio	1.606*** (0.119)	0.872*** (0.137)	1.794*** (0.255)	3.125*** (0.364)	1.614*** (0.119)	0.873*** (0.137)	1.793*** (0.255)	3.163*** (0.361)
Reciprocity Ratio	-0.070*** (0.020)	0.027 (0.039)	-0.040 (0.029)	-0.031 (0.175)	-0.069*** (0.019)	0.029 (0.039)	-0.037 (0.029)	-0.062 (0.179)
ON Trading Amount of Lender	-0.009* (0.005)	-0.012** (0.006)	-0.027** (0.013)	-0.066 (0.054)	-0.007 (0.005)	-0.010* (0.006)	-0.022* (0.012)	-0.081 (0.055)
ON Trading Amount of Borrower	0.012** (0.006)	-0.001 (0.005)	0.010 (0.014)	-0.071** (0.028)	0.009 (0.006)	-0.004 (0.005)	0.008 (0.015)	-0.081*** (0.031)
Observations	28,690	12,886	10,996	4,808	28,690	12,886	10,996	4,808
R-squared	0.084	0.037	0.082	0.174	0.085	0.038	0.083	0.178
Number of pair_id	6,214	4,710	4,565	2,360	6,214	4,710	4,565	2,360

All network measures are in logarithmic form. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. Robust standard errors in parentheses. ON Trading Volume is used as proxy for bank size.

Table 3: All O/N Loans - Global Network Measures as Determinants of Interest Rate Spread (Betweenness)

VARIABLES	(1) All	(2) Phase I	(3) Phase II	(4) Phase III	(5) All	(6) Phase I	(7) Phase II	(8) Phase III
InBetweenness (L)	-0.531*** (0.131)	0.321*** (0.123)	-0.301 (0.224)	-2.038*** (0.393)	-0.535** (0.245)	0.155 (0.276)	-0.345 (0.529)	-4.368*** (0.945)
InBetweenness (B)	-0.608*** (0.125)	-0.238* (0.130)	-0.639*** (0.245)	-0.918** (0.405)	-1.138*** (0.281)	-0.714* (0.419)	-0.951 (0.711)	0.487 (1.033)
OutBetweenness (L)	0.057 (0.052)	-0.089 (0.059)	0.055 (0.104)	0.390*** (0.129)	0.071 (0.226)	-0.261 (0.259)	0.020 (0.553)	-1.996** (0.856)
OutBetweenness (B)	0.330*** (0.066)	0.104* (0.062)	-0.109 (0.124)	0.444*** (0.150)	-0.440 (0.376)	-0.580 (0.499)	-0.589 (1.137)	2.672* (1.506)
Betweenness (L)(in*out)					0.003 (0.044)	-0.032 (0.052)	-0.007 (0.102)	-0.496*** (0.186)
Betweenness (B)(in*out)					-0.130** (0.061)	-0.111 (0.081)	-0.078 (0.180)	0.395 (0.263)
R-squared	0.081	0.036	0.079	0.159	0.081	0.036	0.079	0.164
<i>Controlling for Local Measures</i>								
InBetweenness (L)	-0.639*** (0.161)	0.079 (0.133)	-0.858*** (0.293)	-1.444*** (0.436)	-0.565** (0.251)	-0.012 (0.294)	-0.047 (0.521)	-3.917*** (0.937)
InBetweenness (B)	-0.148 (0.126)	-0.156 (0.153)	-0.410 (0.253)	-0.152 (0.405)	-1.338*** (0.278)	-0.868** (0.419)	-1.718** (0.749)	-0.324 (1.039)
OutBetweenness (L)	0.012 (0.066)	-0.131 (0.081)	0.196 (0.124)	0.413** (0.184)	0.151 (0.248)	-0.234 (0.265)	1.351** (0.640)	-2.372** (0.943)
OutBetweenness (B)	0.332*** (0.095)	0.011 (0.095)	0.233 (0.230)	0.424** (0.169)	-1.562*** (0.389)	-1.107** (0.535)	-1.937 (1.278)	0.256 (1.584)
Betweenness (L)(in*out)					0.024 (0.045)	-0.018 (0.050)	0.209* (0.114)	-0.565*** (0.195)
Betweenness (B)(in*out)					-0.313*** (0.062)	-0.179** (0.084)	-0.354* (0.198)	-0.031 (0.275)
R-squared	0.084	0.038	0.084	0.178	0.085	0.038	0.085	0.182

All network measures are in logarithmic form. In all models, we control for same variables used in the analysis of local network measures in table 2; transaction ratio, AM/PM ratio, quoter/aggressor ratio and ON trading volume. ON Trading Volume is used as proxy for bank size. In the second set of results, we also control for indegree and outdegree of both lender and borrower. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. Robust standard errors in parentheses.

Table 4: All O/N Loans - Global Network Measures as Determinants of Interest Rate Spread (Closeness)

VARIABLES	(1) All	(2) Phase I	(3) Phase II	(4) Phase III	(5) All	(6) Phase I	(7) Phase II	(8) Phase III
InCloseness (L)	0.068 (0.111)	-0.026 (0.080)	-0.256 (0.174)	-0.219 (0.222)	0.186 (0.960)	3.148 (2.277)	-0.039 (0.890)	3.113*** (1.168)
InCloseness (B)	5.226*** (0.909)	3.668*** (1.065)	3.628** (1.595)	19.255*** (3.243)	9.499*** (1.329)	-2.767 (4.343)	1.339 (8.942)	20.615*** (2.880)
OutCloseness (L)	-2.214*** (0.722)	3.167** (1.352)	0.474 (1.775)	-5.909*** (1.807)	-1.650 (1.090)	5.811** (2.825)	0.626 (1.952)	-0.685 (1.946)
OutCloseness (B)	0.034 (0.124)	0.441 (0.559)	-1.180*** (0.298)	-0.597** (0.262)	2.113*** (0.412)	-4.098 (3.183)	-2.628 (5.254)	-0.917 (1.003)
Closeness (L) (in*out)					0.091 (0.950)	3.585 (2.552)	0.226 (0.857)	2.814*** (1.027)
Closeness (B) (in*out)					2.941*** (0.575)	-7.051 (4.993)	-2.060 (7.473)	-0.580 (1.396)
R-squared	0.083	0.037	0.079	0.208	0.085	0.038	0.079	0.213
<i>Controlling for Local Measures</i>								
InCloseness (L)	0.056 (0.118)	0.037 (0.080)	-0.048 (0.185)	-0.664** (0.277)	-0.256 (0.994)	3.569 (2.330)	-0.313 (0.864)	2.349* (1.224)
InCloseness (B)	2.188** (1.051)	3.733** (1.731)	1.798 (1.751)	20.844*** (5.949)	6.420*** (1.721)	-3.228 (4.889)	-2.629 (8.764)	25.098*** (4.165)
OutCloseness (L)	-4.694*** (1.252)	0.766 (1.878)	-9.283*** (3.108)	-7.491*** (2.363)	-4.643*** (1.524)	3.863 (3.190)	-9.629*** (3.222)	-2.225 (2.376)
OutCloseness (B)	0.185 (0.126)	-0.167 (1.083)	-0.288 (0.285)	-0.777*** (0.287)	1.925*** (0.443)	-4.744 (3.284)	-2.921 (4.938)	-0.503 (0.985)
Closeness (L)(in*out)					-0.302 (0.980)	3.968 (2.604)	-0.265 (0.833)	2.522** (1.061)
Closeness (B)(in*out)					2.504*** (0.629)	-7.130 (5.095)	-3.741 (7.022)	0.332 (1.426)
R-squared	0.086	0.038	0.084	0.213	0.087	0.038	0.084	0.218

All network measures are in logarithmic form. In all models, we control for same variables used in the analysis of local network measures in table 2; transaction ratio, AM/PM ratio, quoter/aggressor ratio and ON trading volume. ON Trading Volume is used as proxy for bank size. In the second set of results, we also control for indegree and outdegree of both lender and borrower. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. Robust standard errors in parentheses.



Table 5: All O/N Loans - Global Network Measures as Determinants of Interest Rate Spread (Bonacich eigenvector)

VARIABLES	(1) All	(2) Phase I	(3) Phase II	(4) Phase III	(5) All	(6) Phase I	(7) Phase II	(8) Phase III
OutBonacich (L)	-0.244** (0.108)	0.711** (0.319)	0.018 (0.327)	-0.621** (0.273)	-0.092 (0.127)	0.813 (0.553)	0.059 (0.390)	-0.973* (0.546)
OutBonacich (B)	-0.012 (0.020)	0.072 (0.060)	-0.832*** (0.165)	-0.147*** (0.042)	0.167*** (0.050)	0.146 (0.325)	-0.624* (0.369)	-0.455*** (0.149)
InBonacich (L)	0.027 (0.035)	-0.076 (0.068)	-0.083** (0.039)	0.650*** (0.166)	0.170* (0.091)	0.020 (0.290)	-0.067 (0.141)	0.388 (0.318)
InBonacich (B)	0.955*** (0.183)	0.709*** (0.168)	0.401** (0.186)	2.709*** (0.517)	1.392*** (0.181)	0.804** (0.409)	0.727 (0.621)	2.169*** (0.580)
Bonacich (L)(in*out)					0.039* (0.022)	0.036 (0.097)	0.003 (0.032)	-0.123 (0.141)
Bonacich (B)(in*out)					0.110*** (0.030)	0.031 (0.137)	0.077 (0.118)	-0.208** (0.091)
R-squared	0.083	0.039	0.083	0.190	0.084	0.039	0.083	0.193
<i>Controlling for Local Measures</i>								
OutBonacich (L)	-0.531*** (0.160)	0.842 (0.626)	-2.668*** (0.645)	-0.751** (0.325)	-0.432** (0.175)	1.099 (1.017)	-2.679*** (0.668)	-1.190* (0.655)
OutBonacich (B)	0.014 (0.021)	0.106 (0.121)	-0.738** (0.374)	-0.166*** (0.047)	0.149*** (0.046)	0.262 (0.348)	-1.132* (0.648)	-0.436*** (0.153)
InBonacich (L)	0.027 (0.037)	-0.005 (0.103)	0.001 (0.046)	0.701*** (0.229)	0.130 (0.122)	0.214 (0.397)	0.043 (0.180)	0.404 (0.377)
InBonacich (B)	0.394* (0.203)	1.047*** (0.332)	0.159 (0.154)	1.520* (0.879)	0.838*** (0.216)	1.284** (0.589)	-0.366 (0.700)	1.100 (0.921)
Bonacich (L)(in*out)					0.025 (0.027)	0.072 (0.125)	0.010 (0.037)	-0.143 (0.146)
Bonacich (B)(in*out)					0.092*** (0.030)	0.064 (0.145)	-0.110 (0.130)	-0.191* (0.098)
R-squared	0.085	0.039	0.088	0.193	0.085	0.039	0.088	0.196

All network measures are in logarithmic form. In all models, we control for same variables used in the analysis of local network measures in table 2; transaction ratio, AM/PM ratio, quoter/aggressor ratio and ON trading volume. ON Trading Volume is used as proxy for bank size. In the second set of results, we also control for indegree and outdegree of both lender and borrower. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. Robust standard errors in parentheses.

Table 6: All O/N Loans - Global Network Measures as Determinants of Interest Rate Spread (Pagerank)

VARIABLES	(1) All	(2) Phase I	(3) Phase II	(4) Phase III	(5) All	(6) Phase I	(7) Phase II	(8) Phase III
OutPagerank (L)	-0.551*** (0.149)	0.170 (0.181)	0.060 (0.265)	-1.321*** (0.339)	0.403 (0.694)	1.974** (0.829)	-0.317 (1.235)	-5.832*** (1.909)
OutPagerank (B)	-0.033 (0.106)	0.046 (0.125)	-0.659*** (0.201)	-0.141 (0.288)	-2.552*** (0.642)	-0.019 (0.705)	-5.253*** (1.596)	0.155 (1.284)
InPagerank (L)	-0.157* (0.094)	-0.237** (0.117)	-0.248 (0.182)	0.683*** (0.262)	0.726 (0.583)	1.439** (0.705)	-0.573 (1.027)	-3.113** (1.491)
InPagerank (B)	1.243*** (0.125)	0.637*** (0.142)	0.507* (0.266)	3.515*** (0.277)	-1.687** (0.755)	0.567 (0.764)	-4.949** (2.003)	3.870** (1.502)
Pagerank (L)(in*out)					0.181 (0.117)	0.342** (0.141)	-0.065 (0.203)	-0.824** (0.341)
Pagerank (B)(in*out)					-0.563*** (0.142)	-0.015 (0.145)	-1.059*** (0.367)	0.070 (0.291)
R-squared	0.092	0.034	0.079	0.182	0.093	0.035	0.081	0.184
<i>Controlling for Local Measures</i>								
OutPagerank (L)	-0.629*** (0.217)	-0.425* (0.255)	-0.409 (0.382)	-1.264** (0.575)	-0.694 (0.812)	1.548* (0.930)	-1.041 (1.450)	-11.267*** (2.510)
OutPagerank (B)	0.309* (0.160)	-0.054 (0.192)	-0.085 (0.297)	0.479 (0.477)	-3.599*** (0.799)	-0.684 (0.926)	-5.196*** (2.008)	-2.488 (2.066)
InPagerank (L)	-0.167 (0.152)	-0.160 (0.185)	0.322 (0.316)	1.023** (0.452)	-0.207 (0.698)	1.677** (0.744)	-0.229 (1.259)	-7.657*** (2.074)
InPagerank (B)	0.871*** (0.213)	0.536** (0.242)	0.156 (0.520)	3.317*** (0.530)	-3.769*** (0.970)	-0.178 (1.002)	-5.993** (2.534)	-0.166 (2.376)
Pagerank (L)(in*out)					-0.007 (0.140)	0.376** (0.154)	-0.110 (0.243)	-1.934*** (0.480)
Pagerank (B)(in*out)					-0.866*** (0.175)	-0.137 (0.187)	-1.177** (0.462)	-0.665 (0.462)
R-squared	0.085	0.038	0.083	0.194	0.086	0.039	0.084	0.201

All network measures are in logarithmic form. In all models, we control for same variables used in the analysis of local network measures in table 2; transaction ratio, AM/PM ratio, quoter/aggressor ratio and ON trading volume. ON Trading Volume is used as proxy for bank size. In the second set of results, we also control for indegree and outdegree of both lender and borrower. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. Robust standard errors in parentheses.

Table 7: All O/N Loans - Global Network Measures as Determinants of Interest Rate Spread (Sinkrank)

VARIABLES	(1) All	(2) Phase I	(3) Phase II	(4) Phase III	(5) All	(6) Phase I	(7) Phase II	(8) Phase III
OutSinkrank (L)	-0.556*** (0.152)	0.167 (0.183)	0.070 (0.278)	-1.352*** (0.339)	-0.385 (0.788)	2.133** (0.834)	-0.428 (1.340)	-5.930*** (2.062)
OutSinkrank (B)	-0.037 (0.107)	0.045 (0.126)	-0.670*** (0.203)	-0.221 (0.290)	-1.660** (0.663)	0.072 (0.727)	-6.754*** (1.596)	-0.187 (1.509)
InSinkrank (L)	-0.163* (0.095)	-0.242** (0.118)	-0.246 (0.183)	0.657** (0.267)	0.013 (0.731)	1.777** (0.780)	-0.727 (1.256)	-3.499** (1.747)
InSinkrank (B)	1.294*** (0.132)	0.642*** (0.144)	0.501* (0.269)	3.543*** (0.302)	-0.754 (0.845)	0.678 (0.867)	-7.488*** (2.191)	3.588* (1.831)
Sinkrank (L)(in*out)					0.032 (0.128)	0.362*** (0.138)	-0.083 (0.218)	-0.753** (0.333)
Sinkrank (B)(in*out)					-0.344** (0.140)	0.005 (0.145)	-1.360*** (0.354)	0.010 (0.304)
R-squared	0.092	0.034	0.079	0.177	0.092	0.035	0.082	0.178
<i>Controlling for Local Measures</i>								
OutSinkrank (L)	-0.645*** (0.226)	-0.443* (0.262)	-0.414 (0.408)	-1.298** (0.592)	-1.619* (0.919)	1.612* (0.965)	-1.028 (1.575)	-11.541*** (2.689)
OutSinkrank (B)	0.310* (0.161)	-0.058 (0.194)	-0.095 (0.301)	0.476 (0.486)	-2.884*** (0.831)	-0.642 (0.904)	-7.344*** (2.036)	-4.070* (2.428)
InSinkrank (L)	-0.178 (0.153)	-0.171 (0.187)	0.326 (0.319)	1.037** (0.461)	-1.176 (0.885)	1.947** (0.867)	-0.243 (1.551)	-8.541*** (2.412)
InSinkrank (B)	0.915*** (0.233)	0.539** (0.250)	0.167 (0.534)	3.311*** (0.570)	-3.176*** (1.076)	-0.182 (1.059)	-9.438*** (2.787)	-2.058 (2.846)
Sinkrank (L)(in*out)					-0.177 (0.156)	0.382** (0.158)	-0.102 (0.266)	-1.778*** (0.465)
Sinkrank (B)(in*out)					-0.674*** (0.173)	-0.123 (0.178)	-1.621*** (0.453)	-0.896* (0.480)
R-squared	0.085	0.038	0.082	0.191	0.086	0.039	0.086	0.197

All network measures are in logarithmic form. In all models, we control for same variables used in the analysis of local network measures in table 2; transaction ratio, AM/PM ratio, quoter/aggressor ratio and ON trading volume. ON Trading Volume is used as proxy for bank size. In the second set of results, we also control for indegree and outdegree of both lender and borrower. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. Robust standard errors in parentheses.