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JFS-500; No. of Pages 20

ARTICLE IN PRESS

Journal of Financial Stability xxx (2016) xxx–xxx

Contents lists available at ScienceDirect

Journal of Financial Stability

journal homepage: www.elsevier.com/locate/jfstabil

Network centrality and funding rates in the e-MID interbank market☆

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ARTICLE INFO

Article history:
Received 2 December 2015
Received in revised form 2 November 2016
Accepted 10 November 2016
Available online xxx

JEL classification:
G2

Keywords:
Network centrality
Interbank market
Overnight loans

ABSTRACT

This 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.

1. Introduction

Network positioning could affect interbank 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 (see for instance Battiston et al. (2012a,b)). Third, as argued by Booth et al. (2014), financial institutions with more extensive and strategic financial networks acquire and process information more efficiently 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 (see Angelini et al. (2011), Gabrieli (2011), Gabbi et al. (2012), Bech and Atalay (2008), Akram and Christophersen (2010) and Gabrieli (2012)) suggests that being systemically more important, in term of size or connectedness, explains part of the cross-sectional variation in banks' borrowing costs before and during the 2008 global financial crisis. 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. In particular, we empirically study bank network centrality measures as determinants of interbank interest rates.

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 betweenness; (3) walks (vertices and edges can be visited/traversed multiple times) for eigenvector centrality, Pagerank, Sinkrank and Katz. We evaluate each measure in a quarterly panel data regression set-up of bank pairs, i.e. lender and borrower, fixed-effects for the period 2006–2009 and separately for three sub-periods that encompass the latest 2007–2008 financial crisis: phase I (1 January 2006–30 June 2007, using the key date of the Bear Stearns hedge fund bankruptcy was 31 July 2007), phase

☆ We are grateful to the Editor, Dr. Iftekhar Hasan, to two anonymous referees and to participants at the FEBS 2015 conference for helpful comments and suggestions for improving this article. The research leading to these results has received funding from the European Union, Seventh Framework Programme FP7/2007-2013 under Grant agreements FET Open Project FOC, Nr. 255987, and ICT Project CRISIS, Nr. 288501.

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http://dx.doi.org/10.1016/j.jfs.2016.11.003
1572-3089/

Please cite this article in press as: Temizsoy, A., et al., Network centrality and funding rates in the e-MID interbank market. J. Financial Stability (2016), http://dx.doi.org/10.1016/j.jfs.2016.11.003

II (1 July 2007–30 September 2008, using the key date of Lehman Brothers collapse was 15 September 2008) and phase III (01 October 2008–31 December 2009).

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 system with 'buy' and 'sell' proposals 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 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.

Our findings have implications for systemic risk assessment. 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, the Bank for International Settlements and the Financial Stability Board, 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. Our results show that borrowers that are more central benefit from lower funding rates. We argue that this effect could be driven by the market perception that more central banks will be bailed out if in distress, because 'too-connected-to-fail'. However, the expectation of implicit subsidies could create moral hazard and provide incentives for banks to become systemically important, exacerbating system fragility. While we do not demonstrate in the paper that banks actively try to occupy a central position in the network by strategically forming links with each other, we do believe that monitoring how funding cost advantages evolve over time can act as an effective early warning indicator of systemic risk and provide a way to measure the effectiveness of regulatory policy to reduce the market perception that systemically important institutions will not be allowed to default.

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 interbank markets

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), Aldasoro and Alves (2015), Poledna et al. (2015)).

A number of papers investigate 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. (2012a,b), Anand et al. (2012), Lenzu and Tedeschi (2012), Georg (2013), Roukny et al. (2013), Acemoglu et al. (2015)). While some authors argue that a more interconnected architecture enhances the resilience of the system to failure of an individual bank because credit risk is shared among more creditors, others suggest that a higher density of connections may function as a destabilizing force, facilitating financial distress to spread 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, the topology of interbank markets has been characterized and the stylized facts and regularities have been identified. Examples include Boss et al. (2004) for the Austrian interbank market, Soramaki et al. (2007) and Bech and Atalay (2008) 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. Poledna et al. (2015) studied the multi-layer network of exposure among Mexican banks including interbank credit, securities, foreign exchange and derivative markets. Billio et al. (2012) studies the time-series properties of interconnectedness measures in financial markets. The most common findings reported in this literature are: (i) interbank networks are sparse; (ii) degree and transaction volume distributions are fat tailed, revealing 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[1]; (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 among lenders and borrowers and its evolution over

[1] 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.

Table 1
Phases of the financial crisis and subsamples.

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

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, 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) investigate 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, mostly 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 are 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 O/N 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) study the Norwegian interbank market over the period 2006–2009. They observe 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 explain 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 different before and after August 2007.

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's 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. (2013) who show that the e-MID network appears to be random at the daily level, but contain significant non-random structure for longer aggregation periods. 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.

3. Data and variables definition

3.1. Data

We use tick-by-tick data of the Italian e-MID from 1 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), 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[2]), 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.

In order to construct representative measures of network centrality we use quarterly data. We also consider three sub-samples according to the evolution of the financial crisis as described in Table 1.

3.2. Interest rate spreads

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 at quarter t 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 and volume of trade, respectively, for each pair of banks ij where $i \neq j$, $N_{ij,t}$ is the number of transactions for the bank pair ij at period t, and

[2] ONL refers to contracts when there is more than one day between two consecutive business days.

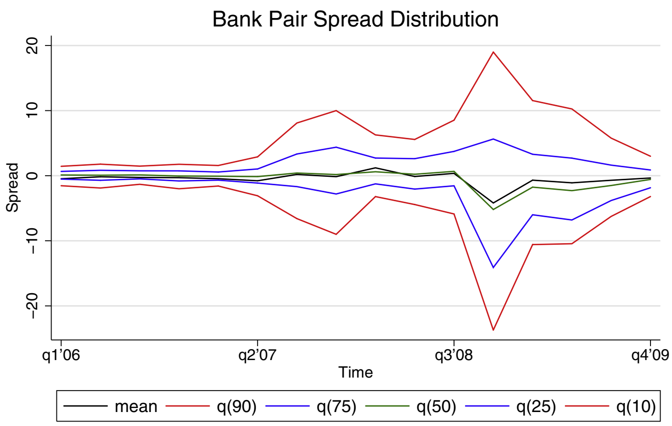

Fig. 1. Bank pair spread over time. Note: All figures shown in graphs are averaged to quarterly values.

$\bar{r}_m^d$ 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 as above and $N_{ij,d}$ is the number of transactions for the bank pair *ij* at day *d*.

In our study we only include banks that actively participate in the interbank O/N market for all sub-periods of the financial crisis of 2007–2008 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 et al. (2015).

Fig. 1 plots the evolution of spreads in our sample. A particular feature is the increase in dispersion during the financial crisis.

3.3. *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 leads to different definitions of centrality. The most popular centrality 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 (eigenvector centrality). In simple structures these different measures tend to covary but in more complex and larger networks, nodes can be more important with respect to some centrality measure and less important with 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 close 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 borrower.

Nodes with more ties to other nodes have alternative ways to satisfy their needs, that is, 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 (see Appendix A for a mathematical definition of degree and other centrality measures). 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, i.e. high in-degree, are said to be prominent, or to have high prestige or trust. Nodes with high out-degree are said to be influential.

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.

Betweenness centrality, introduced by Freeman (1979), focuses on the distance of a node to all the other nodes in the network, and in this sense is a measure of *global* centrality. It is based on the idea that nodes have positional advantage if they lay in between other pairs of nodes. The intuition is that nodes that are "between" other nodes will be able to translate their broker role into power. In connected graphs there is a natural distance metric between all pairs of nodes, defined by the length of their shortest paths (geodesic paths). Betweenness centrality measures the proportion of times a node fall on the shortest pathway between other pairs of nodes.

When defining betweenness, as well as other centrality measures, we consider two alternative choices of directed paths: the one that follows the flow of money lent, that is paths that go from lenders to borrowers (along outgoing links), and the one that follows the direction of repayments to be made, that is paths that go from borrowers to lenders (along incoming links). We name these two measures as OutBetweenness and InBetweenness, respectively. While Gabrieli (2012) reports that betweenness 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.

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, for InCentrality, or on the centrality of the nodes it links to, for OutCentrality. Katz 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). 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 neighbor gets a fraction of the source node's centrality. Pagerank can be interpreted as the fraction of time that a random walk(er) will spend at a node over an infinite time horizon.

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

Table 2
Summary statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
Bank pair spread	37,872	−.434	8.422	−114.934	82.004
Indegree of L	37,872	20.076	22.968	0	108
Outdegree of L	37,872	30.361	15.18	1	89
Indegree of B	37,872	43.775	23.78	1	108
Outdegree of B	37,872	20.365	15.931	0	89
OutBetweenness of L	37,872	.01	.018	0	.14
InBetweenness of L	37,872	.01	.01	.001	.066
OutBetweenness of B	37,872	.013	.019	0	.14
InBetweenness of B	37,872	.006	.008	.001	.066
OutPagerank of L	37,872	.009	.006	.002	.039
InPagerank of L	37,872	.006	.007	.001	.147
OutPagerank of B	37,872	.007	.005	.001	.039
InPagerank of B	37,872	.013	.012	.001	.147
OutSinkrank of L	37,872	.004	.003	.001	.022
InSinkrank of L	37,872	.005	.005	.001	.056
OutSinkrank of B	37,872	.003	.003	.001	.022
InSinkrank of B	37,872	.01	.007	.001	.056
OutKatz of L	37,872	.087	.012	.058	.127
InKatz of L	37,872	.078	.018	.057	.146
OutKatz of B	37,872	.079	.012	.058	.127
InKatz of B	37,872	.097	.019	.057	.146
Reciprocity ratio	37,872	.566	3.842	0	422
AM/PM ratio	37,872	.036	.81	−1	1
Quot/Agg ratio	37,872	−.537	.714	−1	1
Transaction ratio	37,872	.034	.066	.004	6.44
ON Trading Amount of Lender	37,872	14.471	18.901	.007	154.421
ON Trading Amount of Borrower	37,872	20.029	22.487	.002	154.421
Logarithmic form of network measures					
ln(Indegree of L)	30,052	2.644	1.272	0	4.682
ln(Outdegree of L)	37,872	3.263	.608	0	4.489
ln(Indegree of B)	37,872	3.575	.739	0	4.682
ln(Outdegree of B)	36,094	2.687	1.02	0	4.489
ln(OutBetweenness of L)	29,960	−5.577	1.859	−13.341	−1.967
ln(InBetweenness of L)	37,872	−5.012	.825	−6.574	−2.723
ln(OutBetweenness of B)	36,056	−5.244	1.611	−13.341	−1.967
ln(InBetweenness of B)	37,872	−5.453	.797	−6.578	−2.723
ln(OutPagerank of L)	37,872	−4.844	.581	−6.447	−3.232
ln(InPagerank of L)	37,872	−5.586	.967	−6.957	−1.916
ln(OutPagerank of B)	37,872	−5.24	.65	−6.515	−3.232
ln(InPagerank of B)	37,872	−4.566	.729	−6.938	−1.916
ln(OutSinkrank of L)	37,872	−5.59	.574	−7.014	−3.811
ln(InSinkrank of L)	37,872	−5.834	.974	−7.033	−2.886
ln(OutSinkrank of B)	37,872	−5.987	.653	−7.033	−3.811
ln(InSinkrank of B)	37,872	−4.819	.726	−7.014	−2.886
OutKatz of L	37,872	−2.447	.142	−2.842	−2.067
InKatz of L	37,872	−2.575	.213	−2.871	−1.926
OutKatz of B	37,872	−2.547	.153	−2.852	−2.067
InKatz of B	37,872	−2.356	.195	−2.861	−1.926

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 the harmonic distance measure that may be 'too-interconnected-to-fail.' " (pp. 566–567). Similar to Acemoglu et al. (2015) Soramaki's Sinkrank measure is based on absorbing Markov chains. We compute both the *in* and *out* versions of the Sinkrank centrality, where the *in* version is known as Sourcerank. While Sinkrank identify liquidity sinks, Sourcerank identifies liquidity providers.[3]

Local and global centrality measures can be generalized to weighted measures by replacing the adjacency matrix with the weights matrix. In the empirical analysis we consider both the unweighted and weighted versions of the centrality measures described above (see Appendix A for the mathematical definitions of all these measures). In all cases centrality is a directed measure.

Tables 2 and 3 show the summary statistics for the network centrality variables used in the regression models below.

Fig. 2 illustrates the average and quantiles of indegree of borrower and outdegree of lender for three phases of 2007–2008

[3] Another novel measure of systemic importance inspired by centrality is Debtrank, introduced by Battiston et al. (2012b). Since our dataset that does not include banks' balance sheet information, we cannot compute this measure. Other popular measures of centrality that we considered but did not include in the analysis are closeness, eigenvector centrality and Bonacich centrality. These measures were not included because they are better suited to fully connected network and directed cyclic graphs which is not always the case in the e-Mid interbank networks (see discussion in Appendix A).

Table 3
Summary statistics (cont.).

Variable	Obs	Mean	Std. Dev.	Min	Max
Weighted Indegree of L	37,872	.746	1.561	0	18.424
Weighted Outdegree of L	37,872	1.43	1.657	0	9.953
Weighted Indegree of B	37,872	2.445	2.834	0	18.424
Weighted Outdegree of B	37,872	.807	1.29	0	9.953
Weighted OutBetweenness of L	37,872	.019	.037	0	.307
Weighted InBetweenness of L	37,872	.03	.054	0	.444
Weighted OutBetweenness of B	37,872	.038	.052	0	.307
Weighted InBetweenness of B	37,872	.026	.048	0	.444
Weighted OutPagerank of L	37,872	.01	.01	.001	.066
Weighted InPagerank of L	37,872	.005	.01	.001	.17
Weighted OutPagerank of B	37,872	.006	.008	.001	.066
Weighted InPagerank of B	37,872	.014	.022	.001	.17
Weighted OutSinkrank of L	37,872	.005	.005	.001	.037
Weighted InSinkrank of L	37,872	.003	.006	.001	.07
Weighted OutSinkrank of B	37,872	.003	.004	.001	.037
Weighted InSinkrank of B	37,872	.009	.011	.001	.07
Weighted OutKatz of L	37,872	.084	.014	.07	.153
Weighted InKatz of L	37,872	.076	.012	.068	.235
Weighted OutKatz of B	37,872	.079	.011	.07	.147
Weighted InKatz of B	37,872	.089	.023	.068	.235
Logarithmic form of weighted network measures					
ln(Weighted Indegree of L)	30,052	−1.841	2.454	−11.258	2.914
ln(Weighted Outdegree of L)	37,872	−.342	1.377	−10.064	2.298
ln(Weighted Indegree of B)	37,872	.095	1.552	−11.258	2.914
ln(Weighted Outdegree of B)	36,094	−1.416	1.991	−10.064	2.298
ln(Weighted OutBetweenness of L)	20,358	−4.357	1.819	−10.254	−1.181
ln(Weighted InBetweenness of L)	25,481	−4.182	1.857	−10.254	−.812
ln(Weighted OutBetweenness of B)	31,477	−4.011	1.79	−10.254	−1.181
ln(Weighted InBetweenness of B)	26,995	−4.443	1.883	−10.254	−.812
ln(Weighted OutPagerank of L)	37,872	−5.012	.825	−6.574	−2.723
ln(Weighted InPagerank of L)	37,872	−5.954	.927	−6.99	−1.775
ln(Weighted OutPagerank of B)	37,872	−5.453	.797	−6.578	−2.723
ln(Weighted InPagerank of B)	37,872	−4.939	1.104	−6.99	−1.775
ln(Weighted OutSinkrank of L)	37,872	−5.739	.806	−7.033	−3.306
ln(Weighted InSinkrank of L)	37,872	−6.268	.905	−7.033	−2.653
ln(Weighted OutSinkrank of B)	37,872	−6.181	.778	−7.033	−3.306
ln(Weighted InSinkrank of B)	37,872	−5.274	1.056	−7.033	−2.653
ln(Weighted OutKatz of L)	37,872	−2.493	.146	−2.663	−1.874
ln(Weighted InKatz of L)	37,872	−2.585	.134	−2.687	−1.447
ln(Weighted OutKatz of B)	37,872	−2.55	.12	−2.663	−1.917
ln(Weighted InKatz of B)	37,872	−2.441	.218	−2.687	−1.447

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. Fig. 3 shows the average and quantiles betweenness centrality over the time. Betweenness centrality of banks decreases during the second and third phase of the 2007–2008 financial turmoil, a trend that is similar to the local degree centrality measures. Fig. 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.

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 Indegree (Outdegree) and plot the coefficients of the pooled OLS regressions, for each quarter separately, in Fig. 5. The plots show interesting dynamics: while correlations decrease over time for Pagerank, they 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.

3.4. Other control variables

In our analysis, in addition to centrality measures, we also control for 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 or 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

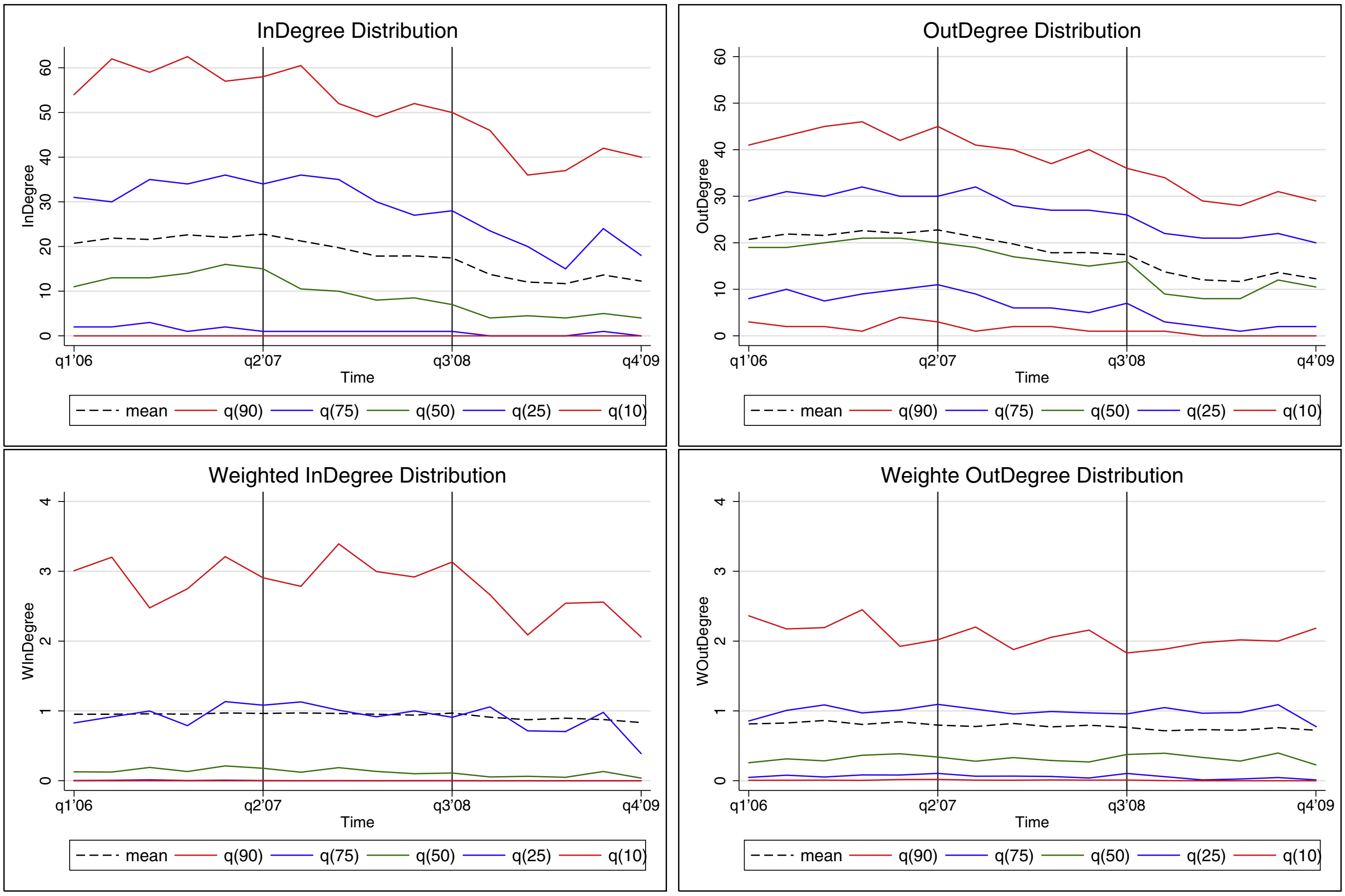

Fig. 2. Quantile analysis of degree. Note: All figures shown in graphs are averaged to quarterly values.

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 arbitraged 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 by 9 am the next trading day of the 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

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

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, μ_{ij} is the pair-specific effect, δ_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. 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.

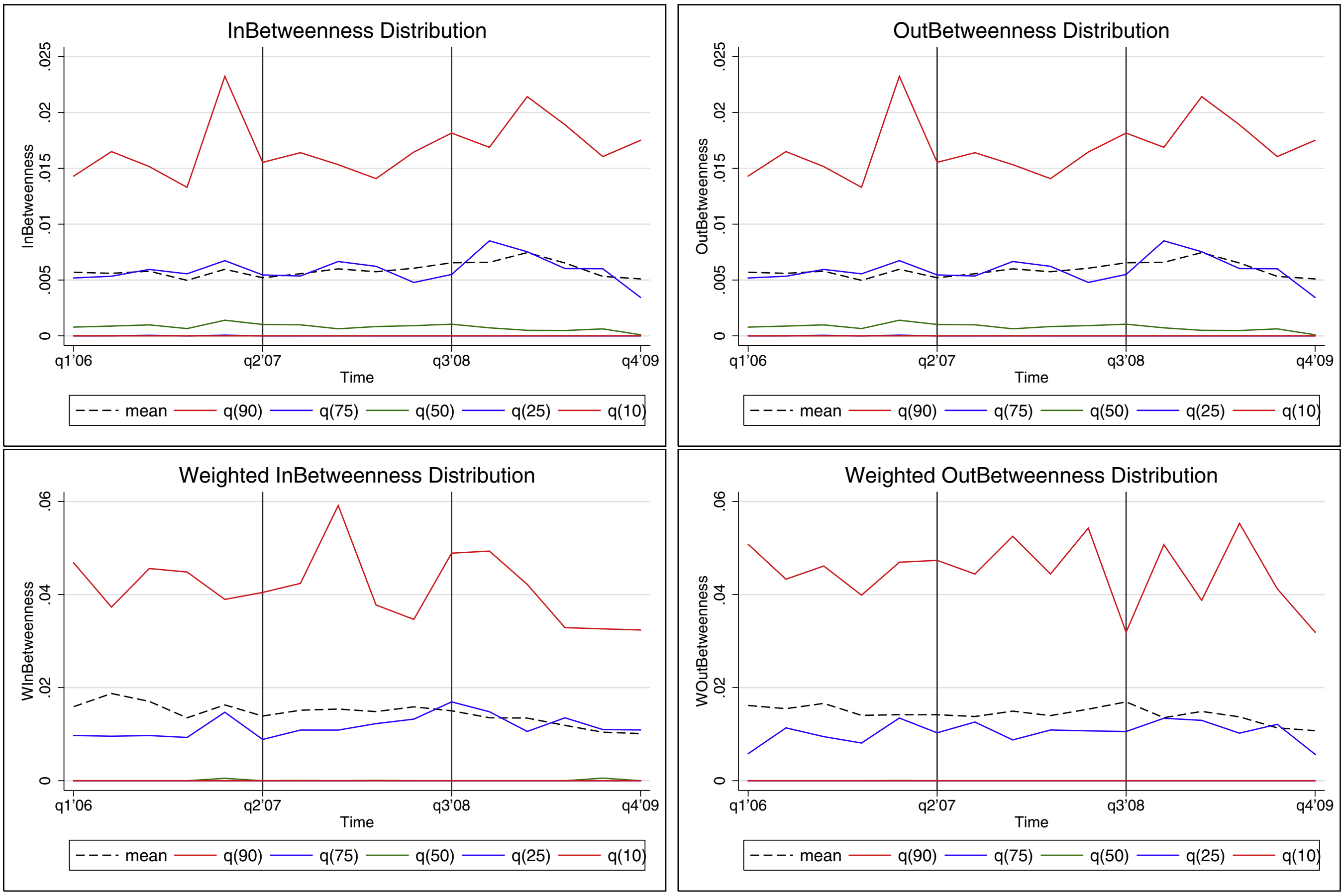

Fig. 3. Quantile analysis of betweenness. Note: All figures shown in graphs are averaged to quarterly values.

All analyses are done conditional on bank pair *ij* FE, 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 highly correlated with each other. For global measures, we consider all specifications controlling for the local network counterparts (local unweighted centrality in all cases) because local and global measures are correlated (see Fig. 5). 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. Finally, we report a set of regressions using unweighted and another using weighted measures of centrality.

For each centrality measure we consider two specifications. First, we include the *in* and *out* measures for both lenders and borrowers. Second, we add to the previous model the interactions $in \times out$ separately for both lenders and borrowers. In this case we only report the coefficients of the interaction and omit the coefficients of the free standing variables.

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 3.4. 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 4 shows the effect of degree centrality on interbank spreads. The model present 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

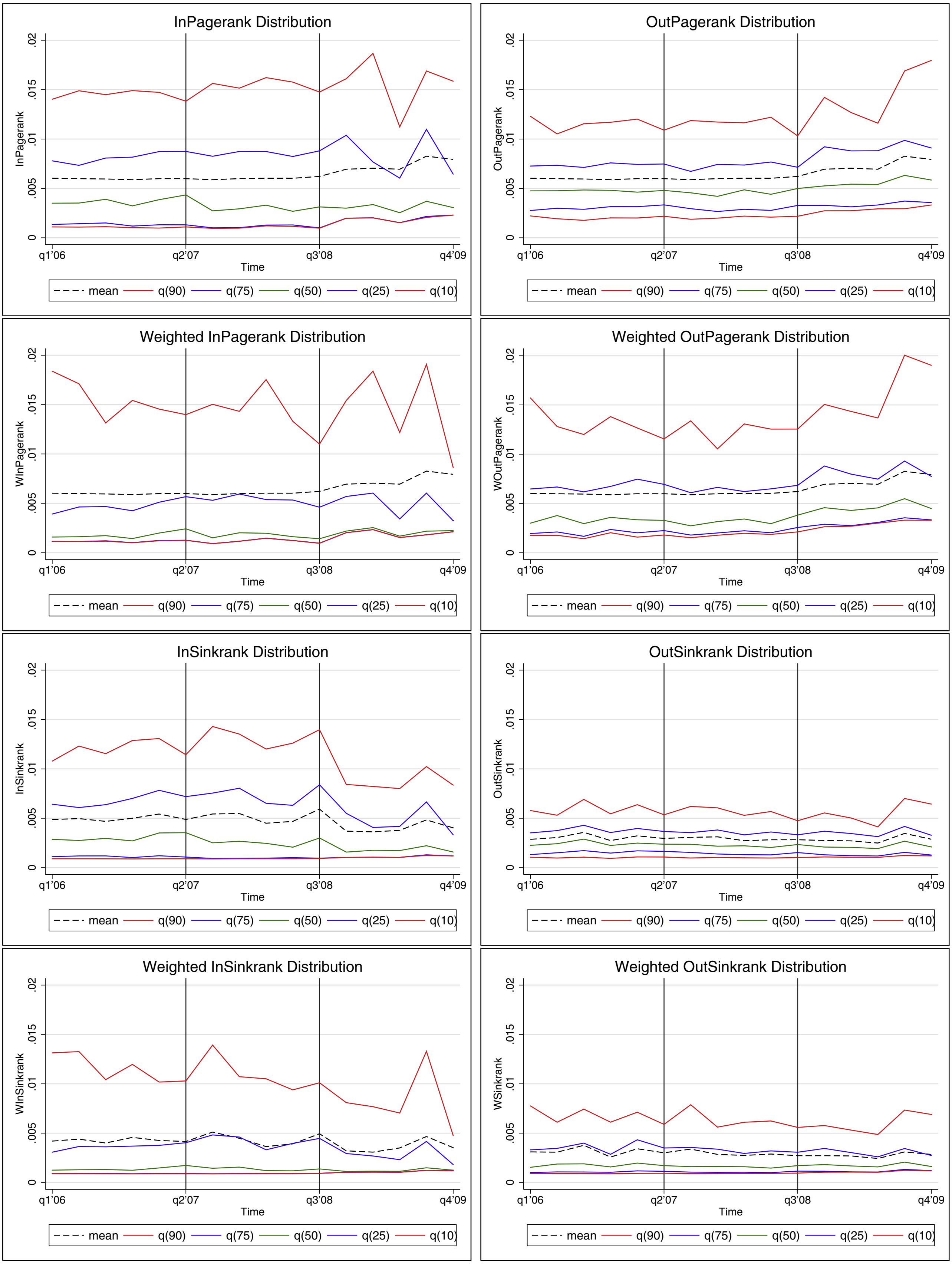

Fig. 4. Quantile analysis of Pagerank, Sinkrank, Katz. Note: All figures shown in graphs are averaged to quarterly values.

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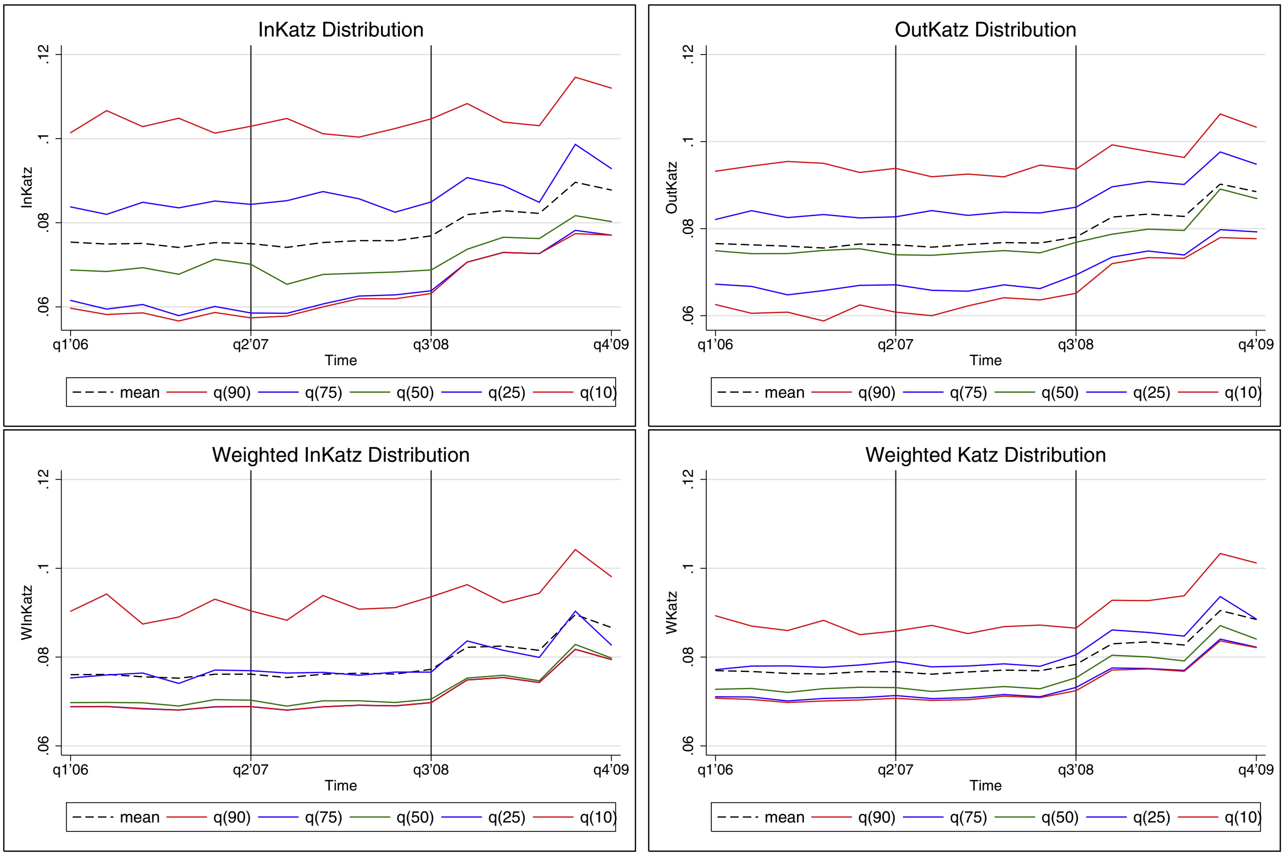

Fig. 4. (*Continued*)

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, for the unweighted measures. Results for the weighted measures are smaller but have the same sign and statistical significance. 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, positive for phases I and II, and negative (although not significant) for phase III. 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).

Table 4
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
	FE							
	Unweighted				Weighted			
Outdegree(L)	−0.000	0.731**	0.766	−0.773	0.078	0.282**	0.274	−0.032
	(0.235)	(0.329)	(0.528)	(0.732)	(0.096)	(0.133)	(0.184)	(0.275)
Indegree(B)	1.437***	0.653***	0.929	3.849***	0.739***	0.336***	0.689***	2.036***
	(0.235)	(0.217)	(0.718)	(0.684)	(0.092)	(0.077)	(0.242)	(0.267)
Indegree(L)	0.171**	−0.114	−0.218	0.604***	0.068*	−0.056	−0.086	0.499***
	(0.078)	(0.096)	(0.150)	(0.190)	(0.041)	(0.048)	(0.077)	(0.119)
Outdegree(B)	−0.107	0.065	−0.726***	−0.363	−0.002	0.033	−0.216***	0.070
	(0.085)	(0.088)	(0.184)	(0.247)	(0.038)	(0.042)	(0.080)	(0.096)
Degree(L)(in*out)	0.212*	0.322*	0.438	−0.936*	0.014	0.108***	0.041	−0.301***
	(0.124)	(0.170)	(0.267)	(0.568)	(0.028)	(0.036)	(0.047)	(0.093)
Degree(B)(in*out)	−0.279**	−0.299*	−0.121	−0.645	−0.139***	−0.003	−0.048	−0.150*
	(0.134)	(0.173)	(0.387)	(0.484)	(0.031)	(0.023)	(0.076)	(0.087)

Notes: Standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

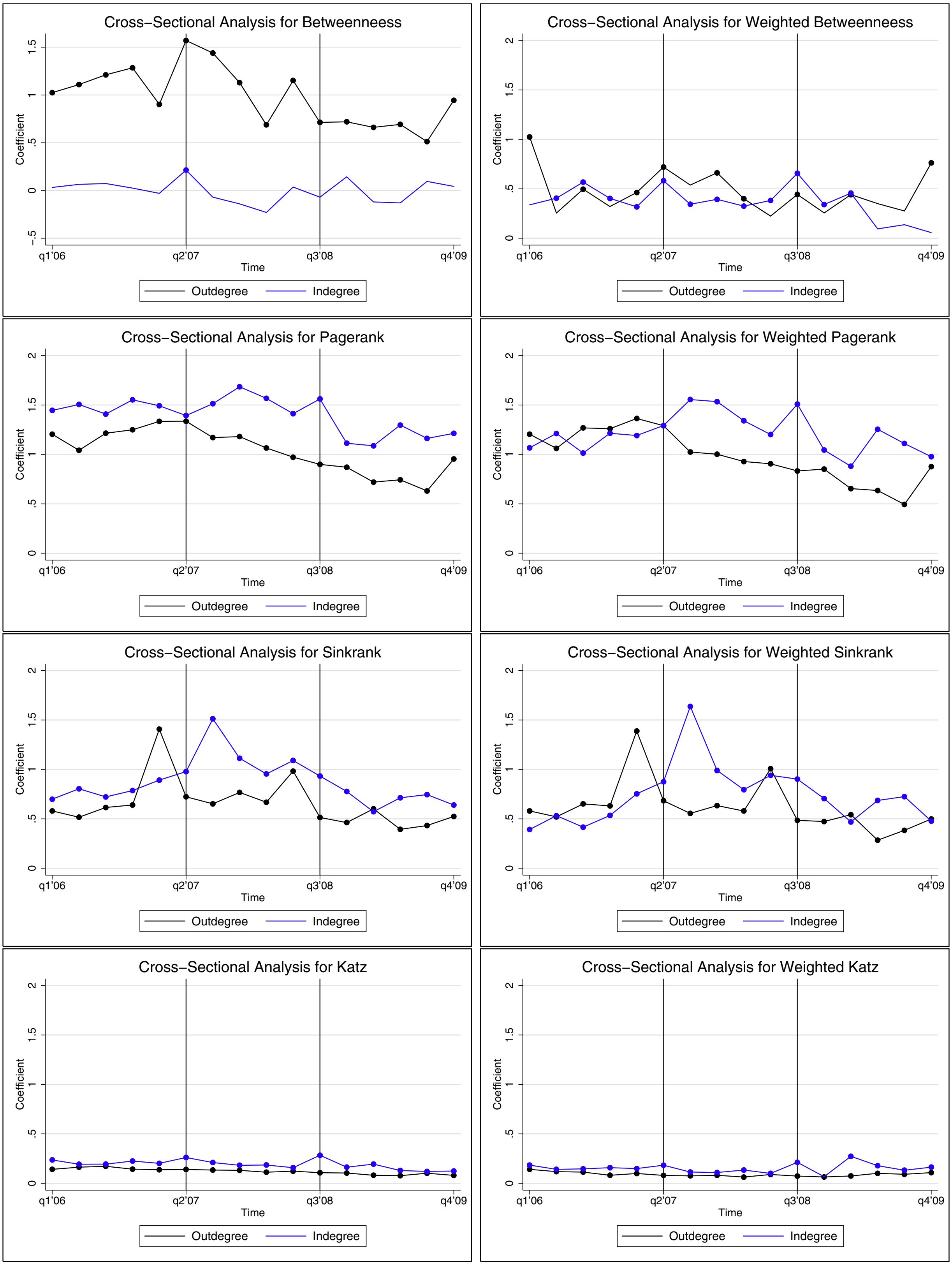

Fig. 5. Global InCentrality (OutCentrality) vs. their Indegree (Outdegree). Note: Bold data points reflect coefficients significant at 10% significance level. All global and degree measures are in logarithmic form.

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 (as stated above we only report the regression coefficients of the interactions). Considering all pooled periods, L obtain higher rates and B lower rates when they

Table 5
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
	FE							
	Unweighted				Weighted			
InBetweenness(L)	−0.639***	0.079	−0.858***	−1.444***	−0.122	0.018	−0.557***	−0.960***
	(0.161)	(0.133)	(0.293)	(0.436)	(0.088)	(0.135)	(0.189)	(0.312)
InBetweenness(B)	−0.148	−0.156	−0.410	−0.152	−0.038	−0.140*	−0.222	0.405**
	(0.126)	(0.153	(0.253)	(0.405)	(0.070)	(0.074)	(0.161)	(0.182)
OutBetweenness(L)	0.012	−0.131	0.196	0.413**	−0.027	−0.122	0.245	0.056
	(0.066)	(0.081)	(0.124)	(0.184)	(0.064)	(0.081)	(0.157)	(0.221)
OutBetweenness(B)	0.332***	0.011	0.233	0.424**	0.007	0.001	−0.058	−0.021
	(0.095)	(0.095)	(0.230)	(0.169)	(0.071)	(0.093)	(0.162)	(0.172)
Betweenness(L)(in*out)	0.024	−0.018	0.209*	−0.565***	0.009	0.013	0.032	0.044
	(0.045)	(0.050)	(0.114)	(0.195)	(0.028)	(0.036)	(0.081)	(0.102)
Betweenness(B)(in*out)	−0.313***	−0.179**	−0.354*	−0.031	−0.011	−0.037	0.100	−0.012
	(0.062)	(0.084)	(0.198)	(0.275)	(0.027)	(0.028)	(0.128)	(0.056)

Notes: Standard errors in parentheses. ***$p<0.01$, **$p<0.05$, *$p<0.1$.

engage in both lending and borrowing activities. The same effects appear in phase I, although they are not present in phases II and III.

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). L in this case are highly exposed to the B (as L do not diversify) and if these B default they may spread the distress to several L. 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 L 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.

For all the centrality measures considered, the *in* version capture the importance of a bank as a borrower and the *out* version captures the importance of a bank as a lender. If we are interested in systemic risk it is the InCentrality version of the centrality measures that is more relevant. B are likely to be systemically more important if their L are also systemically important B as in this case distress can propagate farther through the network. On the contrary banks characterized by a high OutCentrality are likely to be important liquidity providers as, by lending to other central L, they can contribute more effectively to the overall liquidity of the market.

Our choice of weights for weighted centrality measures captures the relative importance of a borrower for a lender, for InCentrality, and of a lender for a borrower, for OutCentrality. The reason is that InCentrality is transmitted via lending and OutCentrality is transmitted via borrowing. This is because if a lender is also a potentially systemic borrower (as measured by its high InCentrality), its main B, by defaulting, may trigger this lender default and, as such, become systemically important themselves (inheriting a larger proportion of their lender InCentrality). Similarly if a borrower is also a central lender (as measured by its high OutCentrality), its own main L become important liquidity providers themselves (inheriting a larger proportion of their borrower OutCentrality).

Consider first the effect of betweenness in Table 5. Recall that betweenness measures a bank's access to the interbank liquidity. For the unweighted measures, when all pooled periods are considered, InBetweenness has a negative effect for both L and B, and

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
	FE							
	Unweighted				Weighted			
OutPagerank(L)	−0.629***	−0.425*	−0.409	−1.264**	−0.622***	−0.111	−0.636**	−1.169**
	(0.217)	(0.255)	(0.382)	(0.575)	(0.156)	(0.174)	(0.284)	(0.459)
OutPagerank(B)	0.309*	−0.054	−0.085	0.479	0.006	−0.236	−0.239	0.479
	(0.160)	(0.192)	(0.297)	(0.477)	(0.252)	(0.202)	(0.403)	(0.746)
InPagerank(L)	−0.166	−0.160	0.322	1.024**	−0.219*	−0.100	0.014	−0.073
	(0.152)	(0.185)	(0.316)	(0.452)	(0.118)	(0.140)	(0.208)	(0.369)
InPagerank(B)	0.871***	0.536**	0.156	3.317***	0.659***	0.244	0.140	2.681***
	(0.213)	(0.242)	(0.520)	(0.530)	(0.169)	(0.179)	(0.405)	(0.406)
Pagerank(L)(in*out)	−0.007	0.376**	−0.110	−1.934***	−0.190	0.236	0.154	0.266
	(0.140)	(0.154)	(0.243)	(0.480)	(0.207)	(0.256)	(0.405)	(0.578)
Pagerank(B)(in*out)	−0.866***	−0.137	−1.177**	−0.666	0.427*	−1.034***	0.062	−1.382***
	(0.175)	(0.187)	(0.462)	(0.462)	(0.220)	(0.265)	(0.511)	(0.532)

Notes: Standard errors in parentheses. ***$p<0.01$, **$p<0.05$, *$p<0.1$.

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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
	FE							
	Unweighted				Weighted			
OutSinkrank(L)	−0.645***	−0.443*	−0.414	−1.298**	−0.663***	0.007	−0.700**	−1.374***
	(0.226)	(0.262)	(0.408)	(0.592)	(0.158)	(0.133)	(0.294)	(0.473)
OutSinkrank(B)	0.310*	−0.058	−0.095	0.476	0.070	−0.123	−0.226	−0.258
	(0.161)	(0.194)	(0.301)	(0.486)	(0.121)	(0.143)	(0.234)	(0.412)
InSinkrank(L)	−0.178	−0.171	0.326	1.037**	−0.135	−0.120	0.191	0.925**
	(0.153)	(0.187)	(0.319)	(0.461)	(0.111)	(0.149)	(0.231)	(0.363)
InSinkrank(B)	0.915***	0.539**	0.167	3.311***	0.805***	0.312**	0.930***	2.519***
	(0.233)	(0.250)	(0.534)	(0.570)	(0.134)	(0.134)	(0.302)	(0.418)
Sinkrank (L)(in*out)	−0.177	0.382**	−0.102	−1.778***	0.041	0.272***	−0.348*	−0.897**
	(0.156)	(0.158)	(0.266)	(0.465)	(0.096)	(0.097)	(0.188)	(0.349)
Sinkrank (B)(in*out)	−0.674***	−0.123	−1.621***	−0.896*	−0.577***	−0.060	−0.686***	−0.634**
	(0.173)	(0.178)	(0.453)	(0.480)	(0.087)	(0.083)	(0.220)	(0.304)

Notes: Standard errors in parentheses. ***$p<0.01$, **$p<0.05$, *$p<0.1$.

Table 8
All O/N loans – global network measures as determinants of interest rate spread (Katz).

Variables	(1) All	(2) Phase I	(3) Phase II	(4) Phase III	(5) All	(6) Phase I	(7) Phase II	(8) Phase III
	FE							
	Unweighted				Weighted			
OutKatz(L)	−6.082***	−2.367	−1.642	−2.117	−2.707***	−1.918**	−1.533	−6.650***
	(2.179)	(3.285)	(4.801)	(8.415)	(0.822)	(0.861)	(1.533)	(2.571)
OutKatz(B)	5.091***	−1.449	−5.999**	−2.083	−0.838	−1.719	−1.599	7.809***
	(1.101)	(1.489)	(2.749)	(5.436)	(0.860)	(1.213)	(1.816)	(3.002)
InKatz(L)	−2.074**	−0.053	1.680	10.446***	−0.784	−0.504	0.907	6.760**
	(0.992)	(1.164)	(2.428)	(3.593)	(1.010)	(1.765)	(2.097)	(3.380)
InKatz(B)	11.440***	5.734***	1.794	20.817***	2.027***	1.287	4.016***	20.323***
	(1.685)	(1.829)	(4.158)	(7.224)	(0.748)	(0.848)	(1.539)	(2.160)
Katz (L)(in*out)	2.171	5.585	2.994	−72.430***	6.273*	10.190	−9.404	−44.933***
	(3.107)	(3.600)	(7.642)	(18.962)	(3.700)	(6.308)	(7.337)	(13.359)
Katz (B)(in*out)	−21.570***	−9.325***	−18.767**	17.921	−33.118***	−10.485**	−28.942***	18.829*
	(3.375)	(3.347)	(9.541)	(17.987)	(5.098)	(4.706)	(10.205)	(10.166)

Notes: Standard errors in parentheses. ***$p<0.01$, **$p<0.05$, *$p<0.1$.

OutBetweenness has a positive significant effect for B. Weighted measures have in general the same sign but with less statistical significance. Calculations for betweenness with weighted paths result in unstable measures, and we believe this is the cause of the lack of statistical significance in our regression models, and we prefer the unweighted measures. For B, the effects increase in absolute value as the financial crisis evolves (i.e. the largest effect is in phase III). For L, the largest effect appear in phase III, where InBetweenness has a large negative effect while OutBetweenness is positive and significant (significant only for unweighted). 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

Table 9
IV-FE – 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
	IV-FE							
	Unweighted				Weighted			
Outdegree(L)	−0.338	−0.103	−1.295	4.102	0.063	0.188	−0.215	0.686
	(1.100)	(1.248)	(1.951)	(3.903)	(0.327)	(0.372)	(0.551)	(1.097)
Indegree(B)	0.694	−2.322***	1.370	7.596**	0.143	−0.581*	0.022	3.745**
	(1.205)	(0.883)	(2.592)	(3.451)	(0.464)	(0.342)	(0.907)	(1.636)
Indegree(L)	0.309	0.265	−0.054	0.408	0.187	0.083	0.142	−0.044
	(0.232)	(0.256)	(0.480)	(0.407)	(0.127)	(0.152)	(0.211)	(0.364)
Outdegree(B)	0.272	0.331	0.587	−0.686	−0.138	0.241**	−0.040	−0.839**
	(0.222)	(0.233)	(0.382)	(0.739)	(0.088)	(0.103)	(0.139)	(0.344)
Degree(L)(in*out)	−0.522	0.480	−1.863	0.083	−0.195**	0.126	−0.306**	−0.450**
	(0.586)	(0.516)	(1.284)	(1.111)	(0.083)	(0.097)	(0.149)	(0.229)
Degree(B)(in*out)	−1.318**	−0.561	−0.927	−1.834	−0.036	−0.086	0.051	0.007
	(0.563)	(0.406)	(1.602)	(1.281)	(0.099)	(0.110)	(0.164)	(0.416)

Notes: Standard errors in parentheses. ***$p<0.01$, **$p<0.05$, *$p<0.1$.

Please cite this article in press as: Temizsoy, A., et al., Network centrality and funding rates in the e-MID interbank market. J. Financial Stability (2016), http://dx.doi.org/10.1016/j.jfs.2016.11.003

Table 10
IV-FE – 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
	IV-FE							
	Unweighted				Weighted			
InBetweenness(L)	−0.752	−0.611	−1.226	−0.682	−0.454	0.025	−1.992***	2.047
	(0.535)	(0.592)	(0.908)	(2.064)	(0.389)	(0.449)	(0.764)	(1.456)
InBetweenness(B)	−0.553	0.196	−0.296	−6.941***	0.046	0.088	0.408	−1.013
	(0.365)	(0.306)	(0.628)	(2.160)	(0.291)	(0.368)	(0.539)	(1.265)
OutBetweenness(L)	0.022	−0.100	0.180	−0.165	0.143	−0.312	1.351*	−0.068
	(0.189)	(0.211)	(0.350)	(0.548)	(0.287)	(0.331)	(0.726)	(0.598)
OutBetweenness(B)	0.371	0.216	0.753	1.697***	−0.726***	−0.399	−1.434**	0.177
	(0.227)	(0.209)	(0.672)	(0.558)	(0.280)	(0.378)	(0.617)	(0.689)
Betweenness(L)(in*out)	−0.214	−0.109	−0.174	−0.548	0.030	0.045	−0.046	−0.035
	(0.157)	(0.144)	(0.325)	(0.503)	(0.130)	(0.214)	(0.282)	(0.287)
Betweenness(B)(in*out)	−0.355	−0.391**	−0.313	1.371	−0.147	−0.081	−0.367	−0.146
	(0.218)	(0.189)	(0.521)	(0.889)	(0.102)	(0.143)	(0.231)	(0.266)

Notes: Standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 11
IV-FE – 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
	IV-FE							
	Unweighted				Weighted			
OutPagerank(L)	−0.460	−0.380	0.287	−1.784*	−0.355	−0.585	0.191	−0.896
	(0.388)	(0.419)	(0.715)	(0.919)	(0.328)	(0.398)	(0.501)	(0.889)
OutPagerank(B)	−0.137	0.156	0.425	−3.290***	0.658***	0.140	1.351***	0.480
	(0.258)	(0.235)	(0.398)	(1.002)	(0.252)	(0.202)	(0.403)	(0.746)
InPagerank(L)	0.070	−0.070	0.523	−1.106*	−0.154	−0.179	0.252	−1.020**
	(0.232)	(0.270)	(0.357)	(0.598)	(0.143)	(0.159)	(0.211)	(0.440)
InPagerank(B)	−0.191	−0.744**	−0.290	1.338	0.058	0.056	−0.232	−0.323
	(0.379)	(0.368)	(0.717)	(1.013)	(0.327)	(0.362)	(0.721)	(0.673)
Pagerank(L)(in*out)	−0.384	0.707**	−1.836***	−0.200	−0.577**	0.919***	−1.066***	−0.992*
	(0.275)	(0.327)	(0.465)	(0.832)	(0.245)	(0.331)	(0.395)	(0.590)
Pagerank(B)(in*out)	−0.345	−0.125	−1.014	−0.021	−0.035	0.665	−0.957	0.246
	(0.401)	(0.357)	(0.874)	(0.915)	(0.376)	(0.475)	(0.835)	(0.686)

Notes: Standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

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.

Eigenvector type centrality measures how well connected the nodes to which that bank is connected to. It does not only measure

Table 12
IV-FE – 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
	IV-FE							
	Unweighted				Weighted			
OutSinkrank(L)	−0.425	−0.380	0.317	−1.593*	−0.716**	−0.485	−0.136	−2.087**
	(0.392)	(0.416)	(0.727)	(0.963)	(0.325)	(0.367)	(0.511)	(0.963)
OutSinkrank(B)	−0.161	0.156	0.446	−3.652***	−0.224	0.302	0.068	−4.790***
	(0.259)	(0.237)	(0.401)	(1.024)	(0.232)	(0.227)	(0.324)	(1.277)
InSinkrank(L)	0.088	−0.067	0.540	−1.083*	0.024	−0.143	1.303**	−1.847***
	(0.234)	(0.273)	(0.360)	(0.604)	(0.290)	(0.326)	(0.533)	(0.618)
InSinkrank(B)	−0.231	−0.749**	−0.292	1.888	−0.005	−0.351	−0.657	2.767***
	(0.390)	(0.367)	(0.711)	(1.217)	(0.299)	(0.307)	(0.599)	(0.757)
Sinkrank (L)(in*out)	−0.455	0.475	−1.747***	−1.222	0.737	2.170	−0.396	2.529
	(0.395)	(0.451)	(0.188)	(1.349)	(0.877)	(9.100)	(1.477)	(1.828)
Sinkrank (B)(in*out)	0.173	0.071	−1.484*	1.505*	−0.774	−1.386	0.627	−0.895
	(0.371)	(0.327)	(0.797)	(0.885)	(0.681)	(1.659)	(0.825)	(1.257)

Notes: Standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 13
IV-FE – global network measures as determinants of interest rate spread (Katz).

Variables	(1) All	(2) Phase I	(3) Phase II	(4) Phase III	(5) All	(6) Phase I	(7) Phase II	(8) Phase III
	IV-FE							
	Unweighted				Weighted			
OutKatz(L)	−5.688*	−0.465	−12.223*	6.237	−4.165*	−4.983	−0.242	−3.980
	(3.103)	(2.981)	(6.752)	(11.524)	(2.507)	(3.089)	(4.017)	(6.548)
OutKatz(B)	2.138	−1.569	4.853*	−18.979**	2.956	3.578	8.938**	−50.795***
	(1.669)	(1.655)	(2.719)	(8.242)	(2.953)	(3.051)	(3.688)	(18.023)
InKatz(L)	2.064	3.274*	2.773	−6.934	−0.310	−0.956	7.090	−38.791**
	(1.901)	(1.699)	(3.718)	(4.722)	(3.532)	(3.244)	(4.999)	(17.243)
InKatz(B)	−1.023	−10.061***	−7.705	26.048***	3.684*	−0.416	−4.186	21.776***
	(2.797)	(2.929)	(4.989)	(7.138)	(2.119)	(2.083)	(3.995)	(5.133)
Katz (L)(in*out)	−17.882	3.064	−76.379**	67.812	−20.789	76.856	−100.362*	280.215
	(11.489)	(8.340)	(30.148)	(59.021)	(30.166)	(73.314)	(56.382)	(243.773)
Katz (B)(in*out)	−22.798**	−10.022	−22.419	−106.164**	−23.890	−185.303***	0.217	111.772*
	(10.295)	(8.551)	(19.404)	(53.860)	(20.074)	(64.873)	(24.436)	(61.590)

Notes: Standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

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 in Appendix A): Pagerank, Sinkrank and Katz, in Tables 6–8, respectively. 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. Moreover, we construct both unweighted and weighted centrality measures.

The eigenvector network variables have similar and consistent effects across measures. They show that for all pooled periods L receive lower rates for higher out-centrality (doubling *out*-centrality reduces spreads by 0.65 basis points for Pagerank and

Table 14
All O/N loans – network measures as determinants of interest rate spread (Lender).

Variables	(1) All	(2) Phase I	(3) Phase II	(4) Phase III	(5) All	(6) Phase I	(7) Phase II	(8) Phase III
	Lender × Quarter and Borrower FE							
	Unweighted				Weighted			
Indegree(B)	1.286***	0.610***	1.464**	3.211***	0.689***	0.423***	0.858***	1.870***
	(0.205)	(0.161)	(0.675)	(0.528)	(0.080)	(0.078)	(0.225)	(0.204)
Outdegree(B)	−0.117	0.025	−0.648***	−0.425**	0.010	0.055	−0.201***	0.148*
	(0.075)	(0.096)	(0.172)	(0.188)	(0.033)	(0.047)	(0.070)	(0.078)
Degree (B)(in*out)	−0.292**	−0.219	−0.227	−0.952***	−0.103***	−0.004	−0.024	−0.224***
	(0.114)	(0.136)	(0.362)	(0.331)	(0.025)	(0.022)	(0.078)	(0.070)
InBetweenness(B)	0.144**	−0.022	−0.273*	0.962***	−0.054	−0.102**	−0.323**	0.555***
	(0.073)	(0.069)	(0.139)	(0.118)	(0.055)	(0.048)	(0.125)	(0.125)
OutBetweenness(B)	0.285***	0.087	−0.216	1.217***	0.064	−0.024	0.163	0.018
	(0.075)	(0.070)	(0.142)	(0.126)	(0.055)	(0.045)	(0.142)	(0.096)
Betweenness(B)(in*out)	−0.099***	−0.037***	−0.083***	−0.243***	−0.043*	−0.017	0.011	−0.116***
	(0.012)	(0.012)	(0.023)	(0.039)	(0.023)	(0.019)	(0.074)	(0.036)
InPagerank(B)	0.593***	0.590***	−0.595	3.641***	0.507***	0.361***	0.235	2.541***
	(0.190)	(0.225)	(0.572)	(0.464)	(0.123)	(0.139)	(0.295)	(0.338)
OutPagerank(B)	0.304*	−0.002	0.017	0.020	0.128	−0.044	−0.023	−0.419
	(0.166)	(0.199)	(0.281)	(0.387)	(0.115)	(0.146)	(0.232)	(0.324)
Pagerank(B)(in*out)	−0.774***	−0.050	−1.094**	−0.911***	−0.656***	−0.140	−0.643***	−1.088***
	(0.156)	(0.161)	(0.426)	(0.333)	(0.084)	(0.087)	(0.217)	(0.225)
InSinkrank(B)	0.607***	0.609***	−0.594	3.670***	0.662***	0.422***	0.521	2.337***
	(0.209)	(0.231)	(0.588)	(0.491)	(0.130)	(0.142)	(0.318)	(0.346)
OutSinkrank(B)	0.303*	−0.004	0.014	−0.017	0.130	−0.044	0.014	−0.340
	(0.168)	(0.201)	(0.284)	(0.400)	(0.117)	(0.150)	(0.239)	(0.350)
Sinkrank (B)(in*out)	−0.606***	−0.028	−1.351***	−1.149***	−0.476***	−0.044	−0.608***	−0.875***
	(0.163)	(0.149)	(0.424)	(0.343)	(0.083)	(0.081)	(0.208)	(0.248)
InKatz(B)	8.825***	4.348***	−3.954	23.883***	1.771***	2.226**	1.669	17.885***
	(1.507)	(1.552)	(3.788)	(4.789)	(0.663)	(0.922)	(1.654)	(1.712)
OutKatz(B)	3.902***	−1.213	−3.249	−0.665	−1.389*	−0.937	−3.194*	5.538**
	(1.093)	(1.441)	(2.818)	(4.879)	(0.792)	(1.177)	(1.661)	(2.585)
Katz (B)(in*out)	−19.212***	−6.897**	−20.376**	−6.186	−30.248***	−8.295*	−33.790***	11.213
	(2.815)	(2.913)	(8.635)	(14.342)	(5.019)	(5.013)	(10.678)	(8.146)

Notes: Standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 15
All O/N loans – network measures as determinants of interest rate spread (Borrower).

Variables	(1) All	(2) Phase I	(3) Phase II	(4) Phase III	(5) All	(6) Phase I	(7) Phase II	(8) Phase III
	Borrower × Quarter and Lender FE							
	Unweighted				Weighted			
Indegree(L)	0.035	−0.200*	−0.045	0.396***	0.044	−0.084	0.007	0.315***
	(0.058)	(0.113)	(0.139)	(0.153)	(0.032)	(0.055)	(0.069)	(0.099)
Outdegree(L)	0.360*	0.683**	1.630***	−0.632	0.227***	0.283**	0.563***	−0.116
	(0.207)	(0.335)	(0.527)	(0.525)	(0.085)	(0.134)	(0.194)	(0.209)
Degree(L)(in*out)	0.309***	0.241	0.686***	−0.617*	0.043*	0.091**	0.070	−0.241***
	(0.102)	(0.207)	(0.257)	(0.321)	(0.023)	(0.040)	(0.046)	(0.059)
InBetweenness(L)	−0.068	−0.073	−0.084	0.129	−0.147**	−0.024	−0.414**	−0.666***
	(0.055)	(0.068)	(0.101)	(0.145)	(0.074)	(0.112)	(0.167)	(0.253)
OutBetweenness (L)	0.005	−0.116**	0.137*	0.231*	−0.075	−0.089	0.056	0.119
	(0.050)	(0.052)	(0.082)	(0.126)	(0.049)	(0.065)	(0.110)	(0.175)
Betweenness(L)(in*out)	0.007	0.004	0.020	−0.088*	0.003	0.019	0.063	0.010
	(0.013)	(0.022)	(0.031)	(0.046)	(0.025)	(0.032)	(0.087)	(0.072)
InPagerank(L)	−0.150	−0.021	0.039	0.551	−0.025	0.002	0.065	0.547*
	(0.133)	(0.182)	(0.283)	(0.397)	(0.101)	(0.139)	(0.190)	(0.313)
OutPagerank(L)	−0.539***	−0.288	−0.624*	−0.759	−0.411***	0.045	−0.796***	−0.819**
	(0.189)	(0.246)	(0.344)	(0.532)	(0.126)	(0.126)	(0.257)	(0.383)
Pagerank(L)(in*out)	0.085	0.182	0.000	−1.771***	0.142*	0.209**	−0.230	−1.242***
	(0.118)	(0.195)	(0.217)	(0.393)	(0.078)	(0.100)	(0.159)	(0.304)
InSinkrank(L)	−0.175	−0.039	0.029	0.514	−0.059	−0.044	0.090	0.583*
	(0.134)	(0.184)	(0.286)	(0.399)	(0.103)	(0.143)	(0.205)	(0.323)
OutSinkrank(L)	−0.551***	−0.314	−0.658*	−0.797	−0.431***	0.033	−0.876***	−0.941**
	(0.197)	(0.253)	(0.369)	(0.544)	(0.132)	(0.128)	(0.278)	(0.418)
Sinkrank (L)(in*out)	0.027	0.241	0.133	−1.517***	0.088	0.158*	−0.188	−1.105***
	(0.131)	(0.195)	(0.230)	(0.383)	(0.081)	(0.094)	(0.162)	(0.295)
InKatz(L)	−2.292***	0.857	2.459	2.116	0.236	0.658	0.486	0.939
	(0.790)	(1.194)	(2.119)	(3.375)	(0.860)	(1.651)	(1.875)	(2.955)
OutKatz(L)	−4.391***	−0.222	−3.298	−0.521	−1.287*	−1.099	−2.323*	−3.745*
	(1.687)	(3.097)	(4.862)	(5.796)	(0.657)	(0.896)	(1.403)	(2.079)
Katz (L)(in*out)	6.893**	5.712	8.579	−47.745***	6.669*	7.280	−8.672	−29.229***
	(2.784)	(3.995)	(7.401)	(14.125)	(3.499)	(8.233)	(7.067)	(10.246)

Notes: Standard errors in parentheses. ***$p<0.01$, **$p<0.05$, *$p<0.1$.

Sinkrank) while B pay higher rates for higher in-centrality (doubling *in*-centrality increases funding rates by 0.9 basis points for Pagerank and Sinkrank). 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. Katz centrality measures show much larger effects on the same direction.

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 positive and significant effect in phase III. 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.

5.3. Robustness analysis I: instrumental variables

As argued above the regression model may not be able to capture the causal effect of centrality on rates but rather the correlation between these two provided that feedback effects cannot be ruled out. A particular concern is that banks self-select partners according to unobservable characteristics, not captured by individual effects (i.e. pair intrinsic characteristics) or the rich set of observables described in Section 3.4 (including volume transaction of both L and B). As argued by an anonymous referee this is a potential problem if network characteristics are considered as credit risk indicators, a point that we emphasize in this paper.

In order to solve this endogeneity problem we implement an instrumental variables (IV) strategy for each specification. In particular, we use centrality in $t-1$ as instrument for centrality in t. If we assume that the error term is conditionally serially uncorrelated, lagged centrality measures will be uncorrelated with error terms in t. Moreover, bank centrality is a persistent measure across time (first-stage results are available from the Authors upon request). Since all our centrality measures are potentially endogenous, we use one-period lagged values of all centrality measures as instruments for all of them. The model with interaction terms also requires to instrument the interactions, and for that we include the corresponding lagged interactions as additional instruments. The IV estimators are thus exactly identified.

The IV results appear in Tables 9–13 for each centrality measure (unweighted and weighted). The results partially confirms the results discussed above.

For local centrality (see Table 9) the IV method reduces statistical significance. This could indicate that degree centrality is correlated with the unobserved balance sheet. An interesting result is that while in-B centrality has a negative effect before the financial crisis (phase I), pointing out that borrowers with more links obtained lower rates, this becomes positive in phase III. The interaction of *in* and *out* for B also confirms that they obtain lower rates if they simultaneously engage in lending and borrowing with many partners.

For global centrality (see Tables 10–13), in general, the results corresponding to all pooled periods have a similar sign and magnitude of those of the regression models without instrumenting, although many coefficients are not robust. Of particular stability across specifications are the coefficients of out-L, confirming that lenders pay a premium for centrality. Moreover, the negative value is also large and significant for phase III. The other results that stand out are the positive effects of in-B in phase III (Sinkrank and Katz), which highlights the higher interest rates B paid after the crisis.

5.4. Robustness analysis II: bank-specific time-varying fixed-effects

Following an anonymous referee suggestion, we implement an alternative FE model with the intention of evaluating the potential effect of bank-specific time-varying latent causes of both centrality and spreads. Because our network centrality measures are bank and quarter specific we cannot simultaneously include centrality *it* or *jt* measures and *it* and *jt* FE. However, as a robustness check, we use *jt* B specific network centrality measures together with *it* L FE (Table 14), and *it* L specific network centrality measures together with *jt* B FE (Table 15). The results are similar in terms of magnitude and statistical significance to the baseline results (Table 8) for B centrality (controlling for L×quarter FE) and L centrality (controlling for B×quarter FE) when we study the effect of global centrality measures (Pagerank, Sinkrank and Katz) but there are differences in significance levels for local (i.e. degree) and betweenness measures. Overall, however, the baseline models regression coefficients show that centrality measures are robust to counterparty specific time-varying shocks.

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 InEigenvector 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, or points to, other important nodes. In our case, borrowers are important if their lenders are important borrowers as well, as this configuration is more likely to propagate distress further through the network and generate systemic risk. In turn lenders are important if their borrowers are also important lender as this configuration allows a more effective redistribution of liquidity through the network.

Eigenvector-based centrality measures may be dominated by the degree of the nodes as, by construction, high indegree produces high in-eigenvector centrality. In-eigenvector 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 peripherical 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 characterized by high centrality and low degree. These are the banks that inherits their centrality from their lenders and are the potential spreader of systemic risk.

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. The betweenness regression results, however, are not robust across specifications, while eigenvector measures show similar results for unweighted and weighted. We thus prefer eigenvector-based measures.

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. This 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 affects 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, 2015, 2016; van der Leij and Kovarik, 2012) leading in some cases to a core-periphery structure (in 't Veld and van Lelyveld, 2014), 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.

Appendix A. Mathematical definition of centrality measures

Let A be an adjacency matrix where $a_{ij}=1$ if bank i lends to bank j (in a given quarter), and 0 otherwise. We denote as A^T the transpose of the adjacency matrix. We use A to compute the out-centrality measures and A^T to compute the in-centrality measures.

Let W^{in} be a weighted & directed network whose elements are $W_{ij}^{in} = V_{ij}/V_i^l$ where V_{ij} represents the value of the loans made by bank i to bank j (over a quarter) and V_i^l is the total volume lent by bank i (over the same quarter).

Let W^{out} be a weighted & directed network whose elements are $W_{ij}^{out} = V_{ij}/V_j^b$ where V_{ij} again represents the value of the loans made by bank i to bank j (over a quarter) and V_j^b is the total volume borrowed by bank j (over the same quarter).

We will use A^T and A for unweighted in-centrality and out-centrality measures, and W^{in} and W^{out} for weighted in-centrality and out-centrality measures. Our choice of weights for weighted centrality measures captures the relative importance of a borrower for a lender, for InCentrality, and of a lender for a borrower, for OutCentrality.

Indegree and Outdegree centrality are defined as

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

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

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

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. The definition of weighted betweenness is analogous but the length of each link in a path is given by the inverse of the link's weight. We find however that weighted betweenness is not a stable measure, and this could explain the lack of statistical significance in the regression models.

Eigenvector centralities are 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. According to the original definition, Eigenvector centralities are given by

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

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

where InEigenvector and OutEigenvector are vectors of centrality scores.[4] In matrix form, this can be expressed as

$$InEigenvector = A^T \quad InEigenvector,$$

$$OutEigenvector = A \quad OutEigenvector.$$

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 definitions of the weighted eigenvector centrality measures, given our choice of weights, are

$$wInEigenvector(i) = \sum_j \frac{V_{ji}}{V^l(j)} \quad wInEigenvector(j),$$

$$wOutEigenvector(i) = \sum_j \frac{V_{ij}}{V^b(j)} \quad wOutEigenvector(j).$$

In matrix form, this can be expressed as

$$wInEigenvector(i) = (W^{in})^T \quad wInEigenvector(j),$$

$$wOutEigenvector(i) = W^{out} \quad wOutEigenvector(j).$$

An alternative definition, 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

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

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

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.

The volume weighted version of Bonacich is defined as

$$wInBonacich(i) = 1/\lambda \sum_j \frac{V_{ji}}{V^l(j)} \quad wInBonacich(j),$$

[4] In undirected networks $A^T = A$ and the two measures coincide.

Please cite this article in press as: Temizsoy, A., et al., Network centrality and funding rates in the e-MID interbank market. J. Financial Stability (2016), http://dx.doi.org/10.1016/j.jfs.2016.11.003

$$wOutBonacich(i) = 1/\lambda \sum_j \frac{V_{ij}}{V^b(j)} \quad wOutBonacich(j).$$

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 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. It can be shown that the approach above 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) provide the number of directed walks of length given by that power. 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. Giving higher powers of A less weight, via an attenuation factor α, would index the attenuation of influence through longer paths. The infinite sum over all paths converges, so for example $InKatz = (I - \alpha A^T)^{-1} \cdot \mathbf{1}$ as long as the attenuation factor $\alpha < 1/\lambda_1$, where λ_1 is the maximum value of an eigenvalue of A^T. Given this convergence Katz centrality can be expressed as

$$InKatz(i) = \alpha \sum_j a_{ji} \quad InKatz(j) + \beta,$$

$$OutKatz(i) = \alpha \sum_j a_{ij} \quad OutKatz(j) + \beta,$$

with $\beta = 1$.The volume weighted version of Katz is defined as

$$wInKatz(i) = \alpha \sum_{l=1}^{\infty} \frac{V_{ji}}{V^l(j)} \quad wInKatz(j) + \beta,$$

$$wOutkatz(i) = \alpha \sum_{l=1}^{\infty} \frac{V_{ij}}{V^b(j)} \quad wOutKatz(j) + \beta.$$

Katz centrality is the eigenvector centrality we use in our regressions.

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 neighbor gets a fraction of the source node's centrality

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

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

where β is the damping factor (that is the parting of Pagerank that is transferred by a node). For $\beta = 1$ Pagerank 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 δ. 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. The weighted versions of Pagerank are defined as

$$wInPagerank(i) = \frac{1-\beta}{N} + \beta \sum_j \frac{V_{ji}}{V^l(j)} \quad wInPagerank(j),$$

$$wOutPagerank(i) = \frac{1-\beta}{N} + \beta \sum_j \frac{V_{ij}}{V^b(j)} \quad wOutPagerank(j).$$

Two recently-developed centrality measures are Acemoglu et al. (2015) harmonic distance and Soramaki and Cook (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.[5]

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

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

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. S is defined in terms of the A matrix for the unweighted measures and in terms of the W^{in} and W^{out} matrices for the weighted measure. 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

[5] Acemoglu's harmonic distance is, in our terminology an *out-centrality* measure, and the corresponding *in* version could also be defined.

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.

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