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Abstract

What influences banks' borrowing costs in the unsecured money market? The objective of this paper is to test whether measures of *centrality*, quantifying network effects due to interactions among banks in the market, can help explain heterogeneous patterns in the interest rates paid to borrow unsecured funds once bank size and other bank and market factors that affect the overnight segment are controlled for. Preliminary evidence shows that large banks borrow on average at better rates compared to smaller institutions, both before and after the start of the financial crisis. Nonetheless, controlling for size, centrality measures can capture part of the cross-sectional variation in overnight rates. More specifically: (1) Before the start of the crisis all the banks, independently of their size, profit from different forms of interconnectedness, but the economic size of the effect is small. Bank reputation and perceived credit riskiness are the most relevant factors to reduce average daily interest rates. Foreign banks borrow at a discount over Italian ones. (2) After August 2007 the impact of banks' interconnectedness becomes larger but changes sign: the "reward" stemming from a higher centrality becomes a "punishment", which possibly reflects market discipline. Bank reputation becomes even more important. (3) After Lehman's bankruptcy the effect of centrality on the spread maintains the same sign as after August 2007, but the magnitude increases remarkably. Foreign banks borrow at a relevant premium over Italian ones; reputation becomes outstandingly more important than in normal times.

Keywords*:* Network centrality; Interbank market; Financial crisis; Money market integration; Macro-prudential analysis
JEL classification*:* C23, D85, G01, G21, G28

Résumé

Quels facteurs influencent les taux d'emprunt des banques dans le marché monétaire en blanc? L'objectif de ce papier est de tester si des indicateurs de *centralité*, mesurant les effets de réseau dû aux interactions entre banques sur le marché, peuvent expliquer l'hétérogénéité des taux d'intérêt payés pour emprunter des fonds en blanc après avoir pris en compte la taille et d'autres caractéristiques des banques et du marché qui influencent le segment des prêts au jour-le-jour. Des résultats préliminaires montrent que les grandes banques empruntent en moyenne à des taux moins élevés par rapport aux institutions plus petites, avant comme après le début de la crise financière. Toutefois, en contrôlant par la taille, les mesures de centralité capturent une partie de la variation des taux interbancaires au jour-le-jour. Plus particulièrement: (1) Avant le début de la crise toutes les banques, indépendamment de leur taille, profitent d'une forme d'interconnectivité, mais l'effet est économiquement peu significatif. La réputation d'une banque et la perception de son risque de crédit sont les facteurs les plus importants pour expliquer des taux moyens journaliers plus bas. Les banques étrangères empruntent à un taux réduit par rapport aux banques Italiennes. (2) Après août 2007 l'impact de l'interconnectivité des banques devient plus fort mais il change de sens: la «récompense» liée à une centralité plus élevée devient une «punition», ce qui pourrait représenter un effet accru de la discipline de marché. La réputation devient encore plus importante. (3) Après la faillite de Lehman l'effet de la centralité sur le taux d'intérêt garde le même sens qu'après août 2007, mais il devient beaucoup plus fort. Les banques étrangères empruntent à un taux significativement plus élevé par rapport aux banques Italiennes; la réputation joue un rôle bien plus important qu'avant la crise.

Mots-clés*:* Centralité et théorie de réseau; Marché Interbancaire; Crise financière; Intégration du marché monétaire; Analyse macro-prudentielle
Classification JEL*:* C23, D85, G01, G21, G28

1. Introduction

Banks in general, and systemically important institutions in particular, are at the core of the process currently underway to reshape the global financial system. The need to craft special treatment for institutions that are possibly systemically relevant because of the repercussions of their bankruptcy on other financial institutions has long been a concern for regulators. However, before the 2007-2008 financial crisis the special risks posed by these institutions due to the potentially large negative externalities that their failure or their bailout by public authorities might impose to the entire system were partly ignored. In those instances of regulation and supervision where the challenge of identifying "systemically important" or "critical" institutions was tackled by regulators, the size of these institutions' balance sheet was the criterion usually applied. The importance of a high level of connectedness was certainly recognized, but financial regulators used to identify connectedness with size: the largest the balance sheet of a supervised credit institution, the stronger the potential for its failure to be contagious.

The recent financial crisis has shaken this conviction. "Given the fragile condition of the financial markets at the time, the prominent position of Bear Stearns in those markets, and the expected contagion that would result from the immediate failure of Bear Stearns, the best alternative available was to provide temporary emergency financing", state the minutes of the Fed's governors meeting on 14 March 2008. In other words, Bear Stearns was saved because of its position in the market, taking into account the ripple effects that would have resulted in already weak financial markets had it been allowed to fail.

Acknowledging the importance of interconnections means to recognize that in modern financial systems the consequences of an institution's troubles cannot be considered by looking at that institution in isolation; its position in the web of overall financial exposures might reveal as important as its size, or as the size of the problem loss it is witnessing. Such acknowledgement is even more relevant at times of generalised financial distress when uncertainty, mistrust and asymmetric information grow exponentially.

This has been recognized a long time ago, for instance, by sociologists interested in identifying the "star", i.e. the central agent in a network of social interactions; in the 1990s it gained prominence in the corporate governance literature. Very recently, the study of interconnections by means of indicators and models developed in network analysis has attracted a great deal of interest among financial regulators and international institutions.[1] This paper provides evidence in support of this new stance, according to which the study of the structure of the links between financial institutions in a particular market (i.e. the topology of the

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[1] *"There is general agreement that since size, substitutability and interconnectedness are the main drivers of systemic importance, then network analysis is the area where we face the most serious challenges in accessing the data and doing the necessary modelling"* says Maarten Gelderman, head of macro-prudential analysis at De Nederlandsche Bank (Risk Magazine, June 2010). Among the policy-makers who have recently pointed out the strong potential of network analysis as a tool to better understand financial markets and to model and assess systemic risk see e.g., G. Tumpel-Gugerell, in her introductory remarks at the ECB workshop on "Recent advances in modelling systemic risk using network analysis", Frankfurt am Main, October 2009; A.G. Haldane, in "Rethinking the financial network", speech delivered at the Financial Student Association, Amsterdam, April 2009; and D. Strauss-Kahn, in "An IMF for the 21st Century", speech held at the Bretton Woods Committee Annual Meeting, Washington D.C., February 2010.

market) and of the specific characteristics of each institution based on its interactions with other market players have the potential to represent a new and valuable tool for the macro-prudential analysis of financial markets and interactions.

I perform a panel data analysis to investigate whether *network centrality* can capture part of the cross-sectional variation in banks' borrowing costs in the overnight (O/N) unsecured euro money market before and during the recent financial crisis. Centrality measures are a set of concepts, and corresponding mathematical indicators, by which the nodes of a network may be deemed important in it. In the interbank market banks are the nodes of the networks; O/N unsecured loans form the links connecting the nodes. The centrality indicators used in the analysis define a bank as central or well-connected if: (1) it has a high number of incident links (hence, weighting the links by the value transferred upon them, it is a large borrower of O/N liquidity) or a high number of outgoing links (that is, in its weighted version, it is a large lender); (2) it is at a short distance from all other banks in the network, hence it is "close" to all other banks; (3) it belongs to several shortest paths connecting other banks, (4) no matter how many incident or outgoing links it has, the banks to which it is linked are themselves central.

Although the theory of network formation has been successfully applied to several economic fields, few attempts have been made, until recently, to use this theory to understand the workings of financial systems (see Allen and Babus, 2009 for a recent survey). In particular, notwithstanding the importance of such a key concept of network analysis as centrality there are no theoretical explanations, at least to my knowledge, as of how and why centrality should affect banks' terms of trade in a financial network. Social network analysis – the field where most centrality indicators have been developed – suggests that more connected agents could profit from "network externalities", i.e. from social (or non-market) spillovers due to their interactions with other agents in the network. Thus, in an unsecured interbank market more connected banks could enjoy better funding due to an implicit government guarantee similar to that enjoyed by banks that are deemed too-big-to-fail (TBTF); or, more plausibly, banks could profit from their links to highly interconnected or TBTF banks.

While the very existence of an effect of centrality on O/N rates is not certain ex ante, the analysis reveals that measures of interconnectedness, quantifying the extent of network interactions among banks, can capture part of the cross-sectional variation in interbank rates. This is the case controlling for bank size and unobserved heterogeneity, and for a large set of bank and market factors that affect the O/N money market. Interestingly, the estimated relationship between O/N rates and bank centrality reverses after the breakout of financial tensions in August 2007.

Daily interbank networks and the corresponding banks' centrality measures are computed based on transaction level data on O/N unsecured loans traded in e-MID in the period from January 2006 until November 2008.[2]

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[2] e-MID SIM S.p.A. is a screen-based electronic market where almost 200 participants exchange unsecured interbank deposits. e-MID represents, together with direct bilateral trading and voice brokering, one of the three modes of trading interbank liquidity in the euro money market. From the end of 2006 until mid-2008 the share of transactions executed via e-MID in the unsecured segment of the market has remained roughly unchanged at 17%. See *Euro money market study 2008* (ECB, February 2009).

The results discussed in the paper show that the relationship between O/N interest rates and centrality has gone through three different phases. (1) Before the start of the crisis large banks profit from the higher frequency with which they receive O/N liquidity during the day, and medium/small and very small banks profit from being lenders to important institutions. But the economic effect of these measures of connectedness is relatively small. Foreign banks borrow on average at a relevant discount over Italian ones; banks perceived as better credit risks in 2006 continue to borrow at better rates in the first half of 2007 (and viceversa for banks perceived as worse credit risks); bank reputation, measured by the share of loans obtained after the borrower's bids, is the most relevant factor to reduce average daily interest rates. (2) After August 2007 large banks' advantage from being "closer" to all the other banks disappears, while they borrow at higher rates the higher the number of counterparties to which they lend their surplus liquidity. Medium/small as well as very small banks are not "rewarded" any longer from being lenders to central market players; on the contrary, they are "punished" for such form of interconnectedness. At the same time, medium-sized banks must be perceived by the market as better credit risks compared to their larger neighbours, so that they manage to enjoy lower borrowing costs for larger daily borrowed volumes. Foreign banks' price-benefit disappears, and bank reputation becomes even more important to obtain lower rates. (3) After the bankruptcy of Lehman Brothers, on 14 September 2008, the effects of centrality measures on banks' spreads maintain the same sign as after August 2007 but their magnitude increases remarkably. Medium/small and very small banks continue to borrow at relatively higher rates the more important the banks they are connected to. That is, a prominent position in the network seems to yield a punishment – which is possibly evidence of market discipline imposed via peer monitoring. The only exception, in this respect, are medium-sized banks that continue to profit from the "influence" they can exert on other institutions by lending liquidity. Finally, the ceteris paribus positive effect on the spread related to banks' foreign nationality becomes negative (the spread paid by foreign banks is on average 11 bps higher compared to Italian banks in the last 2.5 months of the sample) and bank reputation becomes outstandingly more important than in normal times for all the banks.

The rest of the paper is structured as follows. The next section reviews some related literature. Section 3 provides a synthetic non-technical description of centrality measures. Furthermore, it offers some preliminary evidence on the time series of O/N prices averaged across "Large", "Medium/small", and "Very small" banks, and on the time series of the various centrality indicators used for the econometric analysis. Section 4 introduces the baseline specification and the methodology of the empirical analysis. Section 5 discusses some methodological issues related to the structure of the data. Section 6 presents the results. Section 7 concludes.

2. Related literature

Although economic activity is social in nature, the importance of its embeddedness in social settings was largely ignored by economists until 20 years ago. Traditionally, economics has been biased towards the notion of a spaceless marketplace ruled by the walrasian auctioneer, where interactions are anonymous. This has gradually changed after the recognition that "Many puzzling market situations can easily be understood if we take into account their embeddedness in a social structure".[3] Since then, network studies have literally exploded in the field of social network analysis and economics, but also in computer science, physics, organization theory and business strategy, medicine and biology, applied mathematics.[4] From the perspective of analysing the financial system perhaps the most relevant adjacent fields where research on networks is advanced are sociology and statistical physics. Social network analysis has brought forth a number of important findings related, for instance, to the contagiousness of habits and behaviours and to the concept of centrality in a network. The approach in physics has been to focus more on the statistical properties – topology and dynamics – of networks, the resilience of different structures, how networks grow over time and exhibit the complex non-random structure that has been uncovered for many empirical networks.[5] The high complexity and connectedness of the financial system, and its potential for the contagious spread of rare and systemic events – as revealed by the recent crisis – has pointed to a "natural" candidate for the application of tools and results obtained in the study of complex systems in other research fields.

For instance, the study of the structure of liquidity flows in interbank and payment networks is a relatively established tool of analysis to date, employed by central bankers to better understand the functioning of payment and financial systems and, in particular, to assess their systemic (in)stability.[6] On the other hand, even if the theory of network formation has been successfully applied to several economic fields, few attempts have been made to use this theory to understand the workings of financial systems. More recently economists have started to argue that a network approach to financial systems can be instrumental in capturing the externalities that the risk associated with a single institution may create for the entire system (see Allen and Babus, 2009 for a recent survey). Many have started to model financial networks and systemic risk using an explicit network perspective, hence looking at a number of structural properties besides the degree of completeness of the network (which is at the core of the seminal paper by Allen and Gale, 2000).[7]

The use of centrality indicators to explain an economic outcome of interest is relatively new and unexplored in the financial economics literature. In particular, as regards the study of the determinants of O/N rates in the unsecured money market the literature has until recently ignored banks' position in the market, hence overlooking the degree of interconnectedness generated by cross-holdings of interbank deposits.

3 M. Granovetter (1985).

4 For a comprehensive synthesis of several strands of network science, see Jackson, *Social and Economic Networks*, 2008.

5 See, among others, Albert and Barabási (2002) and Newman (2003).

6 Among others, Soramäki et al. (2007) study the topology of Fedwire, the US real-time gross settlement system; Becher et al. (2008) study the topology of CHAPS, the UK Large Value Payment System (LVPS); Embree and Roberts (2009) the Canadian LVPS. As regards the O/N money market, Atalay and Bech (2008) have studied the topology of the Fed Funds market; Iori et al. (2008) of the Italian interbank deposits market.

7 Leitner (2005) and Babus (2007) provide the earliest models of endogenous financial network formation, where banks form links in order to reduce the risk of contagion. More recently, Battiston et al. (2009) model the endogenous emergence of systemic risk in a credit network and the evolution of the network over time; Lippert and Spagnolo (2010) model a strategic network game that applies to – and is in fact motivated by – financial networks; Babus (2010) applies Lippert and Spagnolo's idea of networks of relations to OTC markets; Allen et al. (2010) investigate the efficiency and stability of clustered versus un-clustered networks.

Also due to the over-the-counter (OTC) nature of interbank trades, before the start of the crisis the academic literature has documented relatively limited information regarding interbank borrowing costs. Relevant exceptions have been Stigum (1990) and Furfine (2001) for the Federal Funds market, and Cocco et al. (2009) for the Portuguese market. In particular, Stigum (1990) discusses tiering in the Funds market, by which large institutions generally get better terms than smaller institutions. Furfine (2001) shows that bank size and counterparty relationships, beyond differences in credit risk across borrowers, may also be important determinants of the price of a Federal Funds transaction. Cocco et al. (2009) document that lending relationships are an important determinant of Portuguese banks' ability to access interbank liquidity. Concerning the euro money market, important anecdotal and analytical evidence has been collected by the European System of Central Banks (ESCB) since 1999 with the Euro Money Market Survey.[8]

In the wake of the recent financial crisis a renewed interest in the determinants of interbank rates has emerged. In particular, the literature has tried to identify the drivers of the dramatic increase of interbank rates on 3-month unsecured deposits (which have been at the core of financial markets turbulence) and to distinguish the role of credit and liquidity factors. However, the lack of data on interbank transactions has somehow limited this strand of policy-oriented research, often criticized for the use of quotes rather than actual transaction prices (with the former allegedly non-representative of the latter, especially during the crisis).[9] An exception is Angelini et al. (2009), who study price developments in the term segments of the unsecured money market using actual transaction data. They find evidence that bank size and credit rating matter among a large set of bank-specific explanatory variables, with the largest banks generally able to enjoy better funding conditions compared to small and very small banks. They conclude that this is most likely related to large banks' capacity to address alternative sources of funds in the market, and to the government guarantee implicit in the interest rate paid for an unsecured loan. Consistent with these findings is the evidence documented in Gabrieli (2011a) about the major role of bank reputation in explaining the price of O/N unsecured loans and, in crisis times, about the benefit enjoyed by the banks with the highest volumes of business in the market.

The panel analysis of Angelini et al. (2009) is very close to this paper for two reasons. First, we both use e-MID data, although they study interbank prices in the term segments of the market (from 1 week to 1 year), while I look at the O/N maturity; second, we are both interested in testing whether there has been a general change in money market patterns after the breakout of the financial crisis. However, while the focus of their paper is testing which bank-specific variables drive the estimated relationship disregarding measures derived from network links among banks, my paper focuses exactly on the potential explanatory power of measures of bank centrality derived from those links.

[8] The Euro Money Market Survey, which refers to the second quarter of each year, has been conducted since 1999 on an annual basis by experts from the ESCB. A complete study based on survey data is published by the ECB every second year. For the most recent available study see *Euro Money Market Study – December 2010* (ECB, 2010).

[9] See for instance Michaud and Upper (2008) and Schwarz (2010).

Relevant recent exceptions featuring the application of network indicators to financial and interbank networks are Bech et al. (2010), Cohen-Cole et al. (2010) and Akram and Christophersen (2010). The first paper employs a centrality measure to produce a ranking of participants in the Canadian Large Value Transfer System in terms of their daily liquidity holdings. The second paper estimates that network spillovers, as measured based on the precise topology of transactions, explain as much as 90% of the individual variation in returns both in the Dow and the S&P 500 mini futures markets. According to their analysis a gain of USD 1 for a trader leads to an average of USD 20 in gains for all traders and much more for those who are directly connected to him. The third paper focuses on the determinants of interbank rates paid by banks in Norway over the period 2006-2009. The authors find that variation in O/N rates is partly attributable to differences in banks' relative size and connectedness. These papers use a variation of the measure known as eigenvector centrality (Bonacich, 1972), according to which banks obtain a higher centrality score not only if they are highly central but also if they are counterparties to other important banks. In particular, Bech et al. use an algorithm which is similar to Google's PageRank, while the other two papers use the centrality measure proposed by Bonacich (1987). Differently from these papers, I consider various measures of a bank prominence in the network, stemming both from its market activity and from its position in the graph.

3. Centrality measures and interbank prices: preliminary evidence

Centrality is one of the most studied concepts in social network analysis. Numerous indicators have been developed, providing various angles by which a market player may be deemed prominent in a network of financial liaisons.

As Borgatti (2005) importantly points out, the formulas for the different measures make implicit assumptions about the manner in which things flow in a network.[10] Therefore, the canonical interpretations we give to these measures are valid to the extent that traffic flows in certain ways. Following Borgatti's classification of network processes, I identified the centrality measures that might be suitable for application to interbank networks given the characteristics of the liquidity-exchange process that occurs via O/N loans and taking into account the specific characteristics of the e-MID. These are: (1) degree centrality and its weighted version ("strength"), (2) closeness, (3) betweenness and (4) Bonacich or eigenvector centrality (or better, a version of it called "PageRank"). These measures define a node as central if: (1) it has a high number of incident links (hence, valuing the links with the money transferred upon them, it has a high "borrowing strength") or a high number of outgoing links (or, valuing the links, a high "lending strength"); (2) it is at a short distance from all other nodes in the network, hence it is "close" to all other nodes; (3) it lies on several shortest paths "between" other nodes, (4) no matter how many incident or outgoing links it has, the nodes to which is linked are themselves central. Table 1 provides a non-technical summary of the various measures used as regressors,

[10] S. P. Borgatti (2005), "Centrality and network flow", *Social Networks*.

describing them in the specific context of interbank networks (mathematical formulas used for the computation are reported in Appendix A).[11]

All these measures are compatible with a node-to-node transmission mechanism of *transfer* type. Measures defined under concepts (1), (2) and (3) are solely based on the geometry of the network and are classified as *path*-based because the process flows in the network via paths, i.e. via restricted sequences where neither links nor nodes can be repeated more than once. Specifically, the degree and the strength of a node are known as measures of "local centrality", since they take into account only a node's direct contacts, hence its prominence in the local neighbourhood. On the other hand, closeness and betweenness centrality value also a node's indirect contacts, with a view to capture its strategic prominence in the overall structure of the network. This is why they are also known as measures of "global centrality". Eigenvector-based indicators are also classified as measures of global centrality; however, while closeness and betweenness are based on paths, eigenvector centrality assumes that the process is allowed to flow across the network via *walks*, i.e. without any restrictions on the number of times that a node or a link belong to the sequence connecting two nodes (so that a loan might flow from A to B, from B to C, and then back from C to B and from B to A). According to eigenvector and other related centrality concepts the importance of a node depends on how central or influential are its neighbours. This is why someone refers to them as influence measures. The intuition behind is that even if a node is linked and "influences" just one other node, if the latter subsequently influences many other nodes (who in turn might influence still more others), then the very first node in that chain is highly influential. At the same time, eigenvector centrality can be interpreted as providing a model of nodal risk such that a node's long-term equilibrium risk of receiving flow is a function of the risk level of its contacts.[12]

Figure 1 shows the time series of degree centrality and strength, respectively on the left and on the right side, for the top 20, the smallest 50, and the remaining (medium/small) banks operating in e-MID. Developments over time of each measure are looked at by averaging the indicators across banks that belong to one of the three categories. The latter have been defined on the basis of pre-crisis volumes of business in the market (both on the borrowing and on the lending side), reliable proxy for bank size.[13] (Please note that this classification is used here for the sake of convenience, but does not correspond to the classification of Large, Medium/small and Very small banks used in the main analysis of the paper, as explained in the following).

[11] Banks' centrality measures are determined out of the links that each bank sets up with the other banks in a business day in the e-MID market. For a discussion about the optimal sampling frequency to construct O/N interbank networks see Gabrieli (2011c).

[12] For instance, a person A in a sexual network may have sex with just one person, but if that person is having sex with many others, the risk of infection to A remains high.

[13] This analysis is taken from Gabrieli (2011c).

Table 1: Centrality measures relevant when the process flowing in the network consists of interbank loans[*]

Centrality measure	**Transmission mechanism**	**Kind of trajectories[14]**	**Definition**	**Description**
Indegree (Bavelas, 1950; Nieminen, 1974)	*Transfer* is the most suitable method of spread for O/N interbank loans: liquidity flows from the lender to the borrower so that the former loses it the moment the borrower receives it. Furthermore, liquidity flows to a specified target (i.e. the borrowing bank)	Shortest paths or *geodesics*	Number of links incident upon a node – hence number of counterparties from which a bank receives O/N liquidity	In social network analysis, it is interpreted as a measure of prestige due to the *support* received from a node's direct contacts
Outdegree (Bavelas, 1950; Nieminen, 1974)		Shortest paths or *geodesics*	Number of links outgoing from a node – hence number of counterparties to which a bank lends O/N liquidity	In social network analysis, it is interpreted as a measure of the *influence* that a node exerts on its direct contacts
Weighted in-degree (or *borrowing strength*)		Shortest paths or *geodesics*	Sum of the weights of all incoming links	Total amount borrowed from a bank's direct contacts
Weighted out-degree (or *lending strength*)		Shortest paths or *geodesics*	Sum of the weights of all outgoing links	Total amount lent to a bank's direct contacts
Closeness (Sabidussi, 1966)		Shortest paths or *geodesics*	Inverse of the average shortest distance of a node from all the nodes that are reachable from it. (The graph theoretic distance between two nodes is the length – in links – of the shortest path connecting them)	In statistical mechanics, it is interpreted as an index of the expected time until arrival of something flowing through the network. The higher the score, the lower the distance separating a node from the others, hence the lower the waiting time elapsing before the flow (e.g. O/N liquidity) reaches that node
Betwenness (Freeman, 1979)		Shortest paths or *geodesics*	The number of geodesics between any originating and any terminating nodes that passes through the node or, equivalently, the share of all paths between pairs that use that node	The betweenness of a bank A connecting pairs of nodes in the network is a measure of the dependence of these other banks from A to transfer the loans. Thus, betweenness provides an indication of the *exclusivity* of the position of a node in the network, of the 'control' that a certain node can exert on what is flowing across the nodes

[14] As described in Appendix A, there may be several sequences of links connecting two nodes, i.e. several different paths. A *geodesic* is a shortest path between two nodes. Path-based centrality implicitly assumes that whatever is flowing through the network is flowing along shortest paths. In general, this is not a realistic assumption for the money exchange process, since the node transferring money on cannot select the final/target destination of the flow. However, the assumption that loans travel (mostly) along shortest paths is suitable for interbank loans traded via e-MID because the traffic flowing from a node has usually a precise target (the bank to which the loan is granted), and the extent of intermediary trading in e-MID is very limited (Iori et al. 2008, and Gabrieli, 2011c find evidence that money flows directly from lenders to borrowers on the platform, without dealer intermediaries).

Eigenvector (Bonacich, 1972, 1987)	*Transfer* is the most suitable method of spread for O/N interbank loans: liquidity flows from the lender to the borrower so that the former loses it the moment the borrower receives it	Unrestricted paths or *walks*	The eigenvector centrality of a node is defined as the fraction of time that a random walk(er) will spend at that node over an infinite time horizon	It is also known as an 'influence' measure. A node with a high score is one that is adjacent to nodes that are themselves high scorers. Basically, eigenvector centrality is an iterative version of degree centrality: a node's centrality depends iteratively on the centralities of its neighbours
PageRank (Brin and Page, 1996)		Unrestricted paths or *walks*	PageRank is an eigenvector-based algorithm. The score for a given node may be thought of as the fraction of time spent "visiting" that node in a random walk over the vertices (following outgoing arcs from each vertex). PageRank modifies this random walk by adding to the model a probability of jumping to any other vertex that acts as a sort of score smoothing parameter. Moreover, the transition probabilities across outgoing arcs differ depending on the weights of the arcs	Similarly to eigenvector centrality, this indicator provides a measure of the influence of a node in a network. Its algorithm is behind Google's PageRank score used to assess the relevance of search results. (In that case, pages that are linked to pages with a high PageRank get in turn a higher PageRank). In our interbank context, a bank gets a higher score the more central are the banks to whom it lends

[*] Interbank networks are directed, weighted, and built at a daily frequency. Correspondingly, centrality measures are all computed at a daily frequency.

Before the onset of the crisis the 20 largest banks are the most prominent in terms of liquidity support received from their direct contacts (highest indegree and borrowing strength) and sell the largest amounts of liquidity; medium and small banks are the most influent in terms of number of counterparties they lend to (highest outdegree); the 50 smallest banks have the lowest number of incoming links and an outdegree comparable to that of the largest banks, although the liquidity they move in the system is much lower. Clearly, the time series of most of the measures witness some kind of break after August 2007 (vertical pink line). The most significant time developments concern (i) the number of incoming links and the borrowing strength of the largest banks, which decrease remarkably; (ii) the increase of medium and small banks' indegree above outdegree from August 2007 (so that these banks become the most supported until the end of the sample) and the contemporaneous sizable decrease in their lending strength; (iii) the increasing trend displayed by indegree and outdegree centrality, as well as by borrowing and lending strength, of the smallest 50 banks. While evidence about the top banks does not allow for a univocal interpretation (not least because of their chance to get higher amounts of liquidity via the ECB's repo auctions during the crisis)[15], evidence about medium/small

15 Besides the increased provision of liquidity by the Eurosystem, the strong "loss" of strength of the top 20 e-MID participants after end-July 2007 could stem both from (i) a rationing of credit in the market coupled with higher liquidity uncertainty, or (ii) the availability of alternative funding opportunities OTC rather than in e-MID. The first alternative would find support in the significant reduction, after end-July 2007, of the amounts lent by the medium-sized banks (typically lenders to large e-MID participants), in the

and very small banks seems less ambiguous. Medium-sized banks, on average, must have faced higher liquidity and credit uncertainty, which induced them to refrain from lending in the market as much as they used to do before the crisis. At the same time while some very small banks faced more stringent liquidity needs during the crisis, some others had possibly an incentive to redistribute their surplus liquidity more actively compared to normal times in order to increase their influence in the network.

Figure 2 shows closeness (left side) and betweenness (right side) centralities;

Figure 3 eigenvector (left) and PageRank (right). Also in this case a break is clearly visible. Until August 2007, the largest banks are (on average) the less distant from all the other nodes in the network; occupy the positions that allow the greater "control" over the liquidity flowing from all possible origins to all possible targets of the networks; are visibly the most influent due to their outgoing links to other influent banks. The situation becomes less clear cut after the start of the crisis. The most notable changes concern (i) the reduction in the average distance separating a bank of any of the three groups from the others, and the fact that the contemporaneous decrease in betweenness affects only the top 20 banks; (ii) the peak of eigenvector and PageRank in October 2008.

Two things are worthy of remark in the specific case at hand. First, the betweenness scores are on average very small for e-MID banks, and sometimes they are zero. This confirms the limited extent of intermediary trading in this market, which is then reflected in the minimal economic impact of betweenness on the spreads in the econometric analysis. Second, although eigenvector-based measures are probably the most adequate for networks in which the thing transferred among agents is money, a caveat is necessary in the interbank networks at stake. In fact, eigenvector-based scores assume that the underlying network is strongly connected, i.e. that each node is reachable from every other node in the network and that all links are reciprocal (so that for each loan transferred from bank A to bank B, another loan is also transferred back from B to A in the same day). This is a limit situation which is not verified in e-MID nor in other real money market networks in general, where the graph is internally connected but links are very rarely reciprocal. Thus, these indicators would provide in the econometric analysis a sort of benchmark indication about the impact of interconnectedness on the price paid for interbank loans. The PageRank score is preferred, because it allows for different probabilities that the random walk follows any outgoing arcs depending on the weight of the arc.

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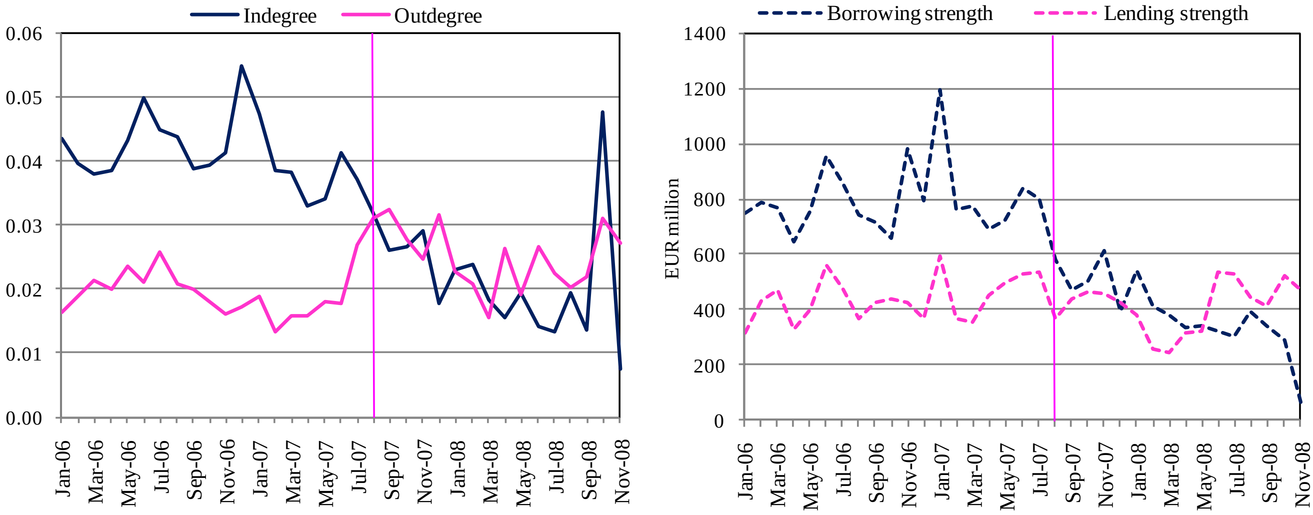
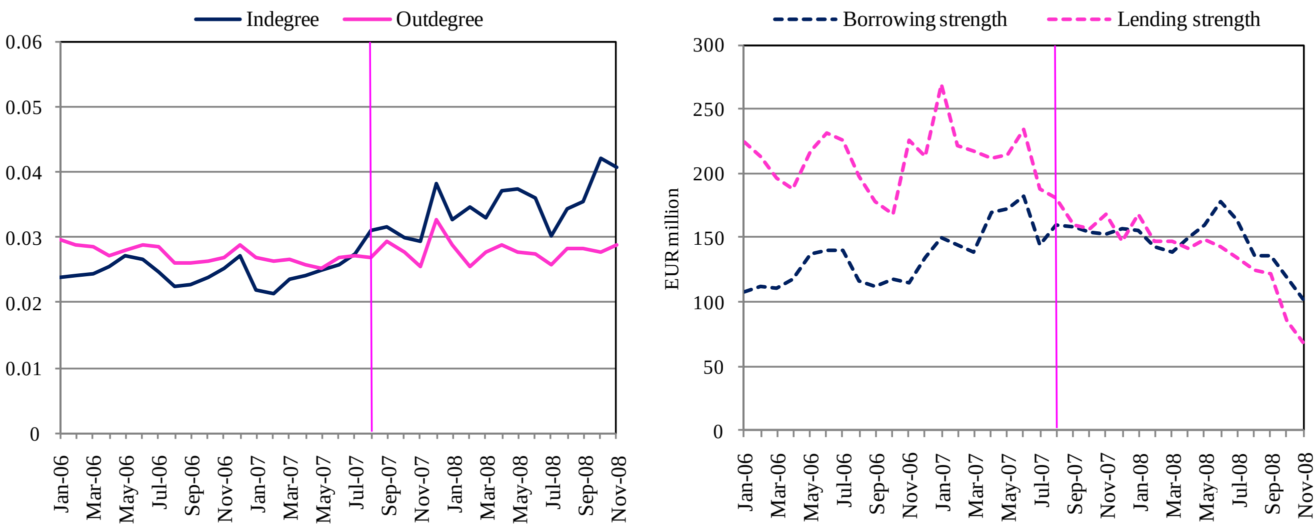
documented increased importance of bank reputation to obtain lower rates in e-MID after the start of the turmoil (Gabrieli, 2011a), and in the fact that large international banks experienced larger financial losses at the start of subprime-related distress. However, the second alternative seems more likely, and finds support in the increase of the volumes traded by the 44 banks with the highest volumes of business in the euro zone (forming the EONIA panel) in the period after August 2007 (and until end-September 2008), which could signal the shift of large banks' deals from e-MID to OTC trading. On the other hand, the interpretation of the time series of centrality measures for medium and very small banks is less ambiguous also due to the fact that many of them are Italian, hence with a long-lasting tradition of activity in the platform. (See also the discussion of the robustness check reported in Appendix C).

Figure 1: Normalised *in* and *out*degree centrality (left side) and borrowing and lending strength (right side)

Top 20 banks



Medium and small banks



Smallest 50 banks

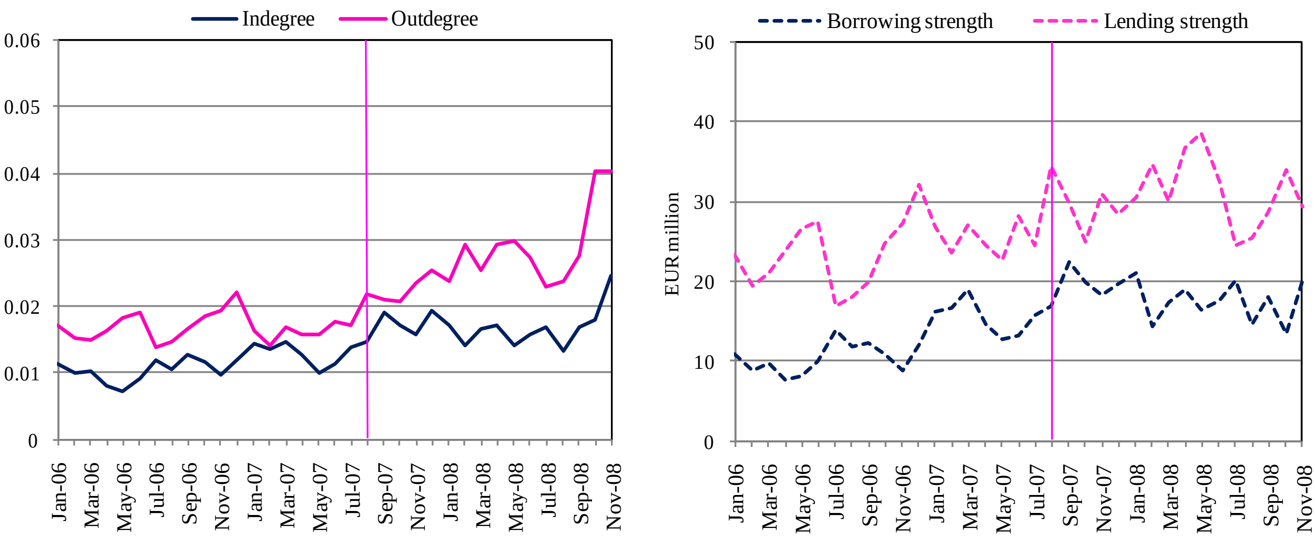
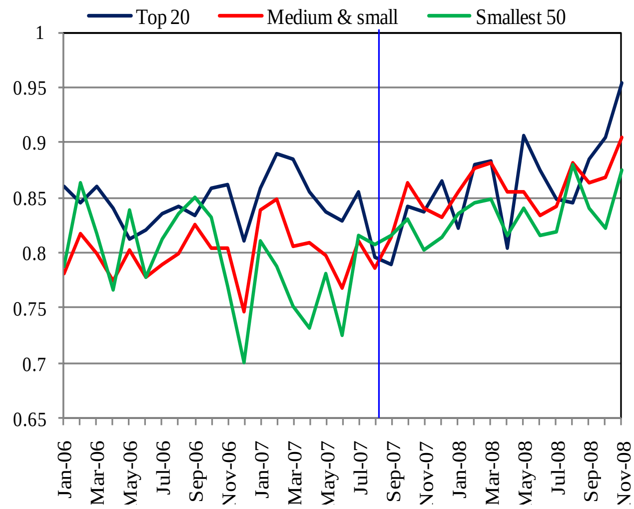


Figure 2: Closeness (left side) and betweenness (right side) centrality



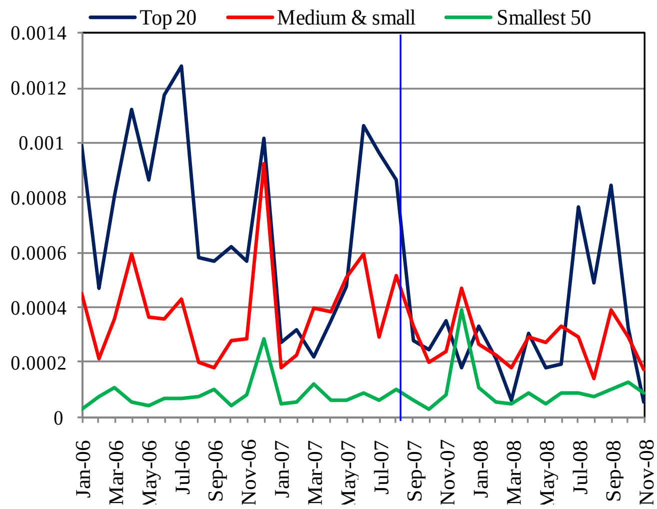
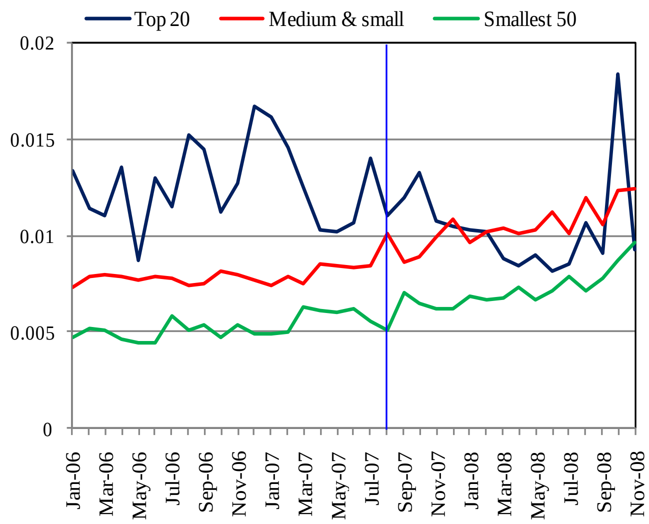
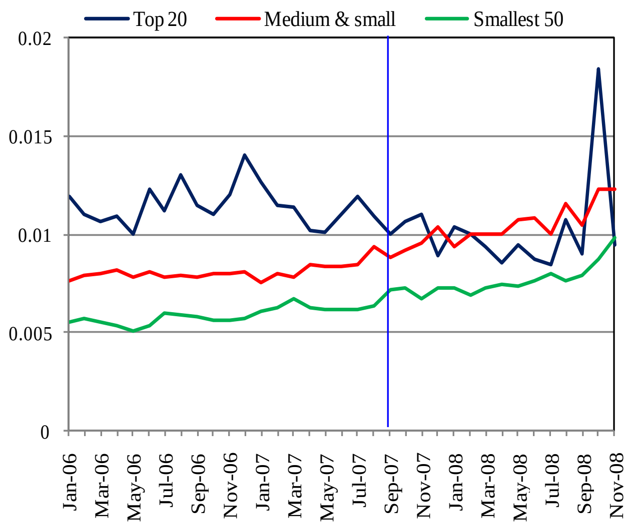


Figure 3: Eigenvector (left side) and PageRank (right side) centrality





Finally, Figure 4 plots the time series of the average daily spreads between O/N rates and the policy rate set by the ECB (i.e. the minimum bid rate in the Eurosystem's main refinancing operations). Each time series is obtained by averaging daily spreads across banks of different size, i.e. across large (L), medium/small (M) and very small (S) banks.[16] In formulae, the average spread paid in day t by bank i (where bank i belongs to group $g = L, M$ or S depending on its size) is computed as:

$$s_{it}^{g} = \frac{\sum_{j=1}^{J} (p_{jit} - r_t) w_{jit}}{\sum_{j=1}^{J} w_{jit}}$$

16 This classification is based on banks' average daily strength, i.e. on the sum of bank borrowing and lending volumes. In each year, a bank is classified as *large* if it trades an average daily amount above the 75th percentile of the distribution; it is *medium/small* if it trades an average daily amount larger than the 25th percentile but lower than the 75th; it is a very small bank if in that year trades an average daily amount below the 25th percentile of the distribution. Approximately the same number of banks belongs to each group.

where p_{jit} denotes the interest rate paid by bank i on loan j in day t ; r_t denotes the policy rate; w_{jit} is the amount borrowed via the j^{th} loan, and J denotes the total number of loans exchanged by bank i in day t.

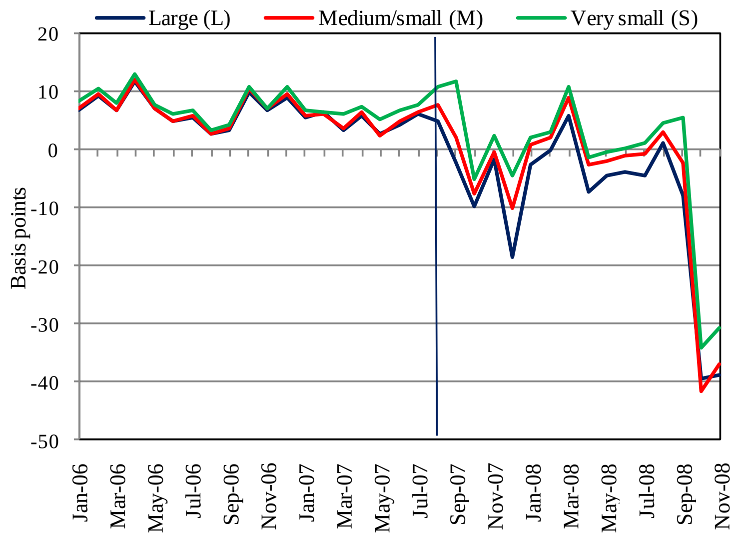
The average spread plotted in Figure 4 is then computed as

$$s_t^g = \frac{\sum_{i \in g} s_{it}^g}{G}$$

where g denotes either L, M or S banks (respectively represented by the blue, red and green lines), and G the total number of L, M or S banks trading in the market in day t.

Clearly, before the start of the crisis the dispersion of interest rates in the cross-section is minimal, although I find that large banks enjoy on average slightly better rates compared to smaller institutions. Moreover, banks borrow on average above the policy rate, which reflects that the system is liquidity-short. Starting from August 2007 (vertical blue line) the cross-sectional dispersion in banks' cost of funding increases remarkably, with large banks enjoying far better rates compared to medium/small and very small banks. The system is now liquidity-long as a consequence of the supplementary amounts of liquidity provided by the ECB to ease tensions in the money market and restart its regular functioning; thus, banks can borrow below the policy rate for extended periods of time. The evidence that large European banks borrow on average at better rates compared to smaller banks is consistent with what has been observed e.g. for the US Federal Funds market. Discussing the results in Section 6 we will see that, even controlling for bank size and other bank and market variables, indicators of interconnectedness do matter to explain heterogeneous interbank funding costs.

Figure 4: Average daily spread between the O/N e-MID rate and the policy rate (across banks of different size)



4. Baseline specification

To estimate the impact of centrality indicators on banks' borrowing rates I use daily data from January 2006 to November 2008.[17] I estimate the following equation:

$$s_{it} = \alpha + \beta^{L\prime}C_{it} + \beta^{M\prime}C_{it} + \beta^{S\prime}C_{it} + \gamma' X_{it} + \eta' Z_t + \delta^{L\prime}C_{it}D_t + \delta^{M\prime}C_{it}D_t + \delta^{S\prime}C_{it}D_t + \epsilon_{it} \qquad (1)$$

where s_{it} is the interest rate spread paid by bank i in day t over the policy rate; C_{it} is a vector of bank centrality measures including (normalized) indegree and outdegree, borrowing and lending strength, closeness and (normalised) betwenness centrality and PageRank[18]; X_{it} is a vector of additional bank-specific variables; Z_t includes time-varying factors that affect interbank rates; D_t is a dummy taking value one in the period after 1 August 2007 and zero otherwise. In fact, I estimate equation (1) first by excluding the post-Lehman subsample (i.e. considering only data until 14 September 2008). Afterwards, I use the whole sample and include two sets of interacted variables: I interact bank centrality measures (C_{it}) both with $D_{t,pre\text{-}Lehman}$, taking value one from 1 August 2007 until 14 September 2008, and with $D_{t,post\text{-}Lehman}$ taking value one after 15 September 2008. This allows to distinguish the additional impact of Lehman Brothers's default on the spread.

The spread is computed as described in Section 3, i.e. as a weighted average of the interest rate differences between the prices paid by bank i on each loan obtained in day t and the policy rate set by the ECB. Each intraday spread is weighted by the amount borrowed through the corresponding loan (interest rates outside the corridor determined by the Eurosystem's standing facilities have been filtered out).

The specification of equation (1) allows the coefficients of interest – the elements of vectors β^L, β^M, β^S and δ^L, δ^M, δ^S representing the marginal impact of centrality measures on the spread – to differ across banks of different size, i.e. across large (L), medium/small (M) and very small (S) borrowers classified as explained in the previous section when showing preliminary evidence on the spreads (see footnote 16). The vector X_{it} includes bank nationality, perceived riskiness in normal times, daily level of clustering and bank reputation. Z_t insures the consistency of OLS and within estimators by including time-varying variables that affect the interbank market in general and the O/N segment in particular. Among the former stands a measure of counterparty credit risk in the euro zone (the iTraxx Europe Senior Financials Index) and a proxy for aggregate market liquidity conditions (the volumes traded by the EONIA panel banks). Among the latter stand the aggregate amount of liquidity ideally available in the market (i.e., the total amount of refinancing provided by the ECB) and measures of the tightness/looseness of individual banks' liquidity needs (i.e., institutions'

17 This sample choice aims at reducing the market microstructure noise related to the impact of changes in the Eurosystem's operational framework on the O/N segment of the money market. The current operational framework for the implementation of monetary policy became effective on 10 March 2004. However, the loose liquidity policy that the ECB was regularly using until the start of the crisis (by which the ECB allots liquidity in excess of its forecasts of the liquidity needs of the system) started to be ran from 12 October 2005. Considering the possible lags with which financial market operators have adjusted to the new rules and procedures, I decided to choose as starting date for the analysis 2 January 2006.

18 Measures such as closeness and PageRank have been computed on the basis of outgoing arcs. Therefore, these measures are null for the days when a given bank does not have any outgoing arcs. PageRank is used rather than eigenvector centrality due to the non-appropriate assumption on which the latter algorithm relies (see the previous section). See Table 1 for a non-technical summary of centrality measures used as regressors, and Appendix A for the technical details.

recourse to the Eurosystem's standing facilities, and the spread between the marginal and the minimum bid rate at the ECB's Main Refinancing Operations). Furthermore, Z_t includes a set of daily dummies to control for the influence of the Eurosystem's operational framework (e.g. dummies taking value one in the days of allotment of Fine Tuning Operations, FTOs, and of Main and Long Term Refinancing Operations, MROs and LTROs, respectively), as well as for seasonal and calendar-related movements that affect the O/N money market and the e-MID.[19] All these variables are described in detail in Table 2. Summary statistics of the regressors and of the e-MID networks are reported in Appendix B.

I perform OLS regressions as well as fixed effects estimations. In both cases, due to the structure of the data, I cluster standard errors at borrower level in order to account for serial correlation in the residuals of each cluster (i.e. each bank). Further detail about the methodology and estimation issues are discussed in the next section. The results are discussed in Section 6.

Table 2: Additional controls, and bank and market factors included in the baseline specification

Right-hand side variables		**Description**
Bank-specific factors	$\boldsymbol{X_{it}}$	
- Time-constant	$Nationality_i$	Dummy variable taking value one for foreign and zero for Italian banks
	$Risk_i$	Average spread (relative to policy rate, in bps) paid by bank *i* for O/N loans before the start of the crisis (proxy for a bank's riskiness in normal times)[20]
- Time-varying	$Clustering_{it}$	Daily clustering coefficient of bank *i*
	$Reputation_{it}$	Ratio of contracts initiated via a bid quote to the total number of contracts that bank *i* trades in day *t*, proxy for bank reputation (like centrality measures this variable differs for Large, Medium and Small banks)[21]
	$dqty_{it}$	Dummy taking value one when the average size of the loans traded by bank *i* in day *t* is above the median size of all the transactions and zero otherwise
Market-wide factors affecting in general interbank rates	$\boldsymbol{Z_t}$	
	$iTraxx_t$	The iTraxx Europe Senior Financials Index (5 years maturity) is based on a basket of CDS of 25 members headquartered in Europe
	$Eoniavol_t$	Daily volumes of O/N loans traded by the 44 banks with the highest volumes of business in the euro zone (forming the EONIA panel) (EUR million)

19 Since 9 August 2007 the ECB started to allot "supplementary" FTOs and LTROs. Correspondingly, I use different dummies to distinguish the impact on O/N rates of regular versus supplementary operations. According to the Eurosystem's operational framework, MROs and LTROs are regularly implemented based on an indicative calendar (published on the ECB website). FTOs are not allotted according to a calendar, but regularly take place on the last days of reserve maintenance periods to counter the liquidity imbalance showed in the ECB's forecasts. For further details about the Eurosystem's operational framework see ECB, 2006.

20 The average spread is computed as a yearly average using 2006 data for banks operating in e-MID already in 2006. For banks that started to operate in e-MID in 2007 $Risk_i$ is instead the average spread computed over the first half of 2007.

21 In e-MID banks can borrow either by posting a bid quote, hence demanding a certain amount of liquidity at a given price, or by accepting an offer (price and quantity) from a willing lender. The rates of bid-initiated loans are typically significantly lower, both for the O/N and for longer term maturities. This suggests the importance of bank reputation on the platform. The transparency of e-MID allows banks to exploit the funding capacity of their reputation while minimising search and borrowing costs.

Market-specific factors affecting the O/N segment	$\boldsymbol{Z_t}$	
	$totref_t$	Total amounts of Eurosystem's refinancing outstanding (EUR million)
	mlf_t	Recourse to marginal lending facility (EUR million)
	df_t	Recourse to deposit facility (EUR million)
	fto_t	Amount allotted at FTOs (EUR million)
	$margmbr_t$	Spread between the marginal tender rate in MRO auctions and the minimum bid rate set by the ECB (basis points)
	$dendRMP_t$	Dummy taking value one in the last day of the Reserve Maintenance Period and zero otherwise
Time-dummies to control for seasonal and calendar-related movements[22]	$endm_t$	Dummy taking value one in the last 5 days of each month (and hence quarters and years) and zero otherwise
	$target_t$	Dummy taking value one in the day immediately before and the day immediately after a TARGET holiday and zero otherwise
	$nathol_t$	Dummy taking value one in the day immediately before and the day immediately after Italian national holidays and zero otherwise
	$regFTO_t$	Dummy taking value one in the days when FTOs have been regularly implemented before the start of the financial crisis and zero otherwise
	$supplFTO_t$	Dummy taking value one in the days when supplementary FTOs have been implemented starting from 9 August 2007 and zero otherwise
	MRO_t	Dummy taking value one in the days of allotment of weekly MROs and zero otherwise
	$regLTRO_t$	Dummy taking value one in the days of allotment of regular 3-months LTROs before the start of the financial crisis and zero otherwise
	$supplLTRO_t$	Dummy taking value one in the days of allotment of supplementary 3 and 6-months LTROs, allotted starting from 22 August 2007 and zero otherwise[23]
	ecb_t	Dummy taking value one in the Thursdays of ECB's press conferences after the start of the crisis and in the days of ECB's crisis-related interventions other than supplementary liquidity injections, e.g. the announcement that the ECB would start offering USD (12 Dec 07), or subsequent changes to EUR-USD swap operations; the coordinated interest rate cut (8 Oct 08); the changes to the implementation framework (switch to a fixed rate-full allotment auction procedure & narrowing of the corridor on 9 Oct 08); the broadening of the list of eligible collateral for refinancing ops (15 Oct 08)

22 These time-dummies allow to control for all those days in which a higher intraday variability and downward/upward spikes of interest rates are regular and predictable (see Beaupain and Durré, 2008).

23 Alternatively, the dates of the announcement of MROs and LTROs have been used. However, the analysis confirms that it is the date of implementation/allotment, i.e. of effective availability of liquidity, that matters for the O/N segment of the money market.

5. Methodological issues

The estimation strategy has been chosen based on (i) economic intuition about the likely presence of unobserved time-varying bank effects that enter the residuals (causing OLS standard errors to be biased), and (ii) evidence obtained following the insights provided by Peterson (2009) as regards the different approaches to estimating standard errors in finance panel data sets. Concerning the economic intuition, the daily liquidity needs of the bank, its risk aversion or the managerial ability at the bank, represent the so called bank heterogeneity. Such heterogeneity is partly fixed and partly time-varying (for instance, liquidity conditions change day-by-day) and likely affects the dependent, hence implying a (downward) bias of OLS White standard errors. Following Peterson's paper I studied the structure of the dataset at hand and, therefore, the serial correlation of estimated standard errors. In particular, I compared heteroskedasticity-robust standard errors with (a) robust errors clustered at bank level and (b) robust errors clustered by time. The estimates confirm the intuition that there is a significant bank effect in the data. On the other hand, the time effect seems to be negligible (i.e. White standard errors are almost equal to standard errors clustered by time). This is most likely due to the availability on the right-hand side of the estimated equations of a large number of daily-dummies and regressors that allow to control for the dependence in the cross-section, i.e. for those unobserved time effects that cause the residuals of each day *t* to be correlated across different banks. Furthermore, both interbank spreads and centrality measures show a high degree of persistence, a kind of data structure where bias in OLS/White and also Fama-MacBeth standard errors is most likely. Finally, the structure of the data is such that the bank effects are clearly non constant.

This analysis points to the use of clustered standard errors both in the OLS and in the within estimation. In fact, this methodology has been shown to produce correctly sized confidence intervals independently of whether the bank effect is permanent or temporary.

A crucial methodological issue of the analysis concerns the attrition present in the data. Especially during the financial crisis, it is reasonable to argue that banks' selection into the sample of e-MID borrowers was probably non-random, but determined by unobserved individual banks' characteristics that are non-fixed – e.g. increased risk aversion/risk perception in crisis times, reputational concerns, or individual liquidity needs. A sample selection problem is crucial for the analysis because it would affect the consistency and asymptotic normality of the OLS and of the within estimator. In order to address this issue I drop out of the sample the banks that traded only very rarely in the period under analysis (in less than the 10th percentile of the business days in each of the 3 years, i.e. in less than 14 days in 2006-07 and in less than 13 days in 2008).[24]

I perform various checks on the robustness of the results of the baseline specification. The most important consists in re-running the analysis by restricting the sample to those banks that traded in at least the median number of business days in each of the 3 years under analysis, i.e. in at least 127 out of 254 business days in

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24 The data set covers the period until 28 November 2008, this is why the number of business days considered for 2008 is lower.

2006 and 2007, and in at least 117 business days in 2008. While this reduces significantly the number of units in the cross section and, consequently, the number of observations available, it allows to significantly reduce also the potential for sample selection bias – i.e., the possibility that the results be in fact driven by unobserved factors included in the error term that in turn drive banks' selection into the sample in any given day. The results are overall confirmed in the period before the crisis. However, in the period after August 2007 the sign and size of the coefficients of interest are overall confirmed only for medium-sized and very small banks, while most effects on the centrality of large borrowers lose statistical significance. This seems to confirm the intuition that the largest banks are those that self-selected out of the sample after the start of the crisis. (See footnote 15 and the results reported in Appendix C).[25]

Moreover, I check the robustness of including/excluding one or more controls in the baseline specification. In particular, I am keen on testing that the interacted terms do not introduce collinearity among the regressors. (For instance, the dummy controlling for the liquidity strains that emerge in the last day of reserve maintenance periods is perfectly collinear with the dummy taking value one in the dates of allotment of regular FTOs, since FTOs regularly take place exactly on the last day of the RMP to counter liquidity imbalance showed in ECB's forecasts).

Finally, I test the methodology used for the analysis (i) by augmenting the bank-fixed effects specification with time-effects, and (ii) by estimating the model using random effects GLS estimator. In the first case the results do not differ significantly from those of the baseline specification. As regards the random effects GLS estimator, this is discarded against the within estimator on the basis of the Hausman's specification test.

6. Results

Table 3 reports the results of OLS and within estimations of equation (1) (in columns (a)-(a)' and (b)-(b)', respectively). In both estimation strategies standard errors are adjusted for borrower-clusters, and I distinguish the marginal impact of centrality measures on the spread before the crisis from the additional impact during the crisis. In particular, the additional effects in crisis times are reported separately for the period before the default of Lehman Brothers and afterward. (The integral results of the estimations, i.e. including the coefficients on market variables, are available upon request).[26]

Before discussing the results in detail, it is worth emphasizing that the interpretation of the economic significance of the coefficients needs to take into account the (very) different order of magnitude of each centrality variable. Keeping in mind Figures 1, 2 and 3, I consider the following unitary increases for each

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25 A related issue concerns the degree to which the sample of banks operating in e-MID is representative of the overall population of European banks after the start of the crisis, given the strong reduction of the turnover of e-MID and of the number of banks that continued to use the platform on a regular basis (see Gabrieli, 2011a). In this respect, any generalisation of the results to the whole population of European banks needs to be considered with caution.

26 The coefficient estimates on the market control variables are discussed in footnotes 27 and 28.

measure: 0.01 for normalized indegree and outdegree; 0.1 for closeness; 0.0001 for betwenness; 0.001 for PageRank. As regards borrowing and lending strength, given the high heterogeneity in the size of loans traded in e-MID by the biggest versus the smallest banks, it is meaningful to consider a EUR 100 million increase in the daily amount borrowed/lent by large and medium banks, while a EUR 1 million increase is more adequate for very small banks.

6.1 Impact of centrality measures before the crisis

Large borrowers

Before August 2007, large borrowers (L-banks) pay relatively more the "stronger" they are in terms of inflows of liquidity obtained from other banks. However, the economic size of the coefficients on the borrowing strength is very small: a EUR 100 million increase in daily borrowed funds is associated with a 0.042/0.05 bps increase in the spread. More relevant in economic terms is the benefit enjoyed by L-banks due to a lower distance from all the other banks in the network, i.e. from a higher frequency with which L-banks receive O/N liquidity in the market during the day. Thus, the largest banks have on average the highest scores in closeness before the crisis (see left panel of Fig. 2) and gain a 0.10 bps discount for each 0.1 increase in the score.

Medium/small borrowers

Medium/small borrowers (M-banks) must be perceived as less creditworthy in the unsecured money market compared to L-banks, so that a EUR 100 million increase in daily borrowed funds corresponds to a 0.17/0.23 bps increase in the spread they pay. Interestingly, there seems to be a negative relationship between the PageRank and betweenness of these banks and the average daily spread on O/N loans. The estimates show that a 0.0001 increase in betweenness determines a 0.01 bps decrease in the spread, while a 0.001 increase in PageRank determines a spread reduction of 0.03 bps. Noteworthy is also the negative coefficient on M-banks' lending strength (significant, however, only in the absence of bank fixed-effects), which suggests a positive reward for these banks' role as large liquidity providers.

Very small borrowers

Also the smallest banks (S-banks) profit from their connections to central counterparties (the coefficients on PageRank are more than double compared to M-banks, independently of whether bank fixed effects are included or not in the estimation). At the same time, however, a higher betweenness seems to be associated with a higher cost of borrowing for the very small banks. The same holds true for indegree centrality: a 0.01 increase of indegree (which, considering the average number of trading banks in pre-crisis e-MID networks, corresponds to 1.27 additional incoming links), determines a relatively high 0.17 bps increase in the spread.

As regards the coefficients on the other bank-specific factors it is worth to remark the positive impact on the cost of unsecured funding of a stronger reputation, as measured by the proportion of loans that a banks manages to obtain at the price (and for the quantity) it demands. Interestingly, this holds true for all the banks, suggesting that before the crisis reputation was an important element of banks' contracting power in this market. Loans whose average size is above the median are traded at a higher price (almost 1 extra basis point).

Finally, note the negative and positive sign, respectively, of the coefficients on the dummy for foreign banks and on the proxy for banks' pre-crisis riskiness: foreign banks used to borrow at more than a half basis point discount compared to Italian ones; banks perceived as riskier in 2006 continued to pay almost 1 bps more for their funds in the first half of 2007. All in all, these estimates confirm existing evidence on the functioning of the market and on its efficiency. Measures of interconnectedness are statistically significant, but their economic size is much lower compared to other bank and market features.[27]

6.2 Impact of centrality measures during the crisis – before Lehman's bankruptcy

Large borrowers

The marginal effect of receiving a higher amount of liquidity becomes economically larger – increasing from 0.042/0.05 bps to 0.1bps for a EUR 100 million increase in daily borrowed funds. Moreover, a higher number of outgoing arcs – i.e. a higher number of counterparties to which a L-bank lends O/N liquidity – increases the cost of borrowing. I interpret this result (robust to the extension of the sample to include Lehman's default) as evidence that those banks that became more interconnected after the start of the crisis, maybe to exploit some market power by lending surplus liquidity, were in fact "punished" in their borrowing rates because of the consequent greater exposure to potential financial losses (whose precise extent remained unclear to market participants for months after August 2007). Interestingly, these effects are not statistically significant in the results of the robustness check reported in Appendix C, which suggests that such a punishment did not occur for the large banks that continued to trade O/N deposits in e-MID on a regular basis.

Medium/small borrowers

The same interpretation can be given to the sudden change of sign of the coefficient on M-banks' PageRank: while being lenders to other central market players implies a benefit in normal times, it now becomes a significant cost. Equivalently, a higher betweenness determines now a worsening of the spread more than 3 times larger than the reduction it used to imply before the crisis. (A 0.0001 increase in betweenness was associated to a 0.01 bps decrease in the spread until August 2007; it determined a 0.04 bps increase afterwards). On the other hand, larger borrowed amounts now correspond to a significantly lower spread.

[27] Most of the coefficients on the market variables are significant at 1% level before the crisis and have the expected sign. That is, interest rate spreads rise during the last days of a calendar month/quarter/year (of about 4 bps) and even more in the days immediately before and after TARGET holidays (of almost 8 bps). The spread increases slightly also in the days before and after Italian national holidays. A unit increase in the iTraxx index makes the spread 0.044 bps higher before August 2007; each additional EUR billion traded by EONIA panel banks is related to a 0.1 bp lower spread paid by banks in e-MID. More ample liquidity in the market via larger amounts of ECB's refinancing is associated to lower spreads; the same holds true for a higher recourse to the deposit facility. On the other hand, a higher recourse to marginal lending reflects tighter conditions in the money market, hence is associated to higher spreads in e-MID. The implementation of regular FTOs before the crisis achieves on average the intended effect of easing liquidity tensions that materialise at the end of the reserve maintenance period. As expected, the allotment of regular 3-months LTROs does not have an immediate impact on the O/N spread.

Such positive effect could signal that after the start of financial distress M-borrowers were recognised by the market as better risks compared to bigger banks.

Very small borrowers

Like M-banks, also very small banks witness a significant deterioration of their funding costs, worse the higher their connectedness in terms of having links outgoing towards other highly central nodes. However, differently from M-banks, S-banks face higher prices for O/N funds also the stronger their liquidity needs (for each extra million borrowed in the market the spread increases of 0.02/0.03 bps).

Finally, the price-benefit enjoyed by foreign banks compared to Italian ones disappears, while the benefit from reputation remains highly significant and is in fact much larger (more than double for M and S-banks, almost three times as high for L-borrowers). Loans above the median size are still significantly more expensive than loans below the median; the extra cost is now more than double compared to normal times.

To summarize, the borrowing costs of large and very small banks get worse the larger the daily amounts of liquidity borrowed in the market. On the contrary, medium-sized borrowers seem to be perceived as better credit risks, so that they profit from a larger borrowing strength. Noteworthy is the change in the sign of the effect of PageRank on the spread paid by M and S-banks compared to normal times: a higher centrality in the graph due to more central connections yields no longer a “reward” but results in a higher cost of liquidity. A similar worsening occurs on average for M-banks that increase the control they can exert upon the liquidity flowing across the network. L-banks too are “punished” for a higher connectedness: they pay more the higher the number of banks to which they are exposed because of their lending activity. The economic magnitude of the coefficients, although not so large, is in general at least double compared to normal times (and up to 4 times as high for certain measures).[28]

6.3 Impact of centrality measures during the crisis – after Lehman’s bankruptcy

Large borrowers

After 15 September 2008 the negative impact on the spread due to a higher borrowing strength disappears, but this is most likely driven by the very small amounts traded by L-banks in the market in the last 2 months of the sample. The negative impact due to banks’ higher connectedness as liquidity providers is confirmed (although the significant coefficient is now on PageRank rather than on outdegree centrality).

[28] After August 2007, the time-dummies for the allotment of supplementary 3 and 6-months LTROs capture a 2.5 bps increase in overnight rates over the policy rate (possibly a spurious effect), while in the dates of implementation of supplementary FTOs the spread increases of almost 5 bps. This could reflect different degrees of liquidity imbalance of e-MID borrowers and/or the exploitation of some market power by banks that managed to borrow at those supplementary auctions. However, the strongest increase in the spreads is captured by the ecb_t dummy, taking value one in the Thursdays of ECB’s press conferences and of announcements of specific interventions during the crisis. More ample aggregate liquidity conditions in the market, as reflected in larger EONIA volumes, are still associated to a lower spread. The increase in e-MID overnight spreads associated to a higher recourse to marginal lending is now 6 times higher than before the crisis. To summarise, the market-specific controls confirm the tensions that have plagued also the shortest maturity of the unsecured money market since August 2007.

Table 3: Results of the baseline specification in equation (1)[29]

	Dependent variable: unsecured O/N spread over policy rate (in bps)											
	(a)			(b)			(a)'			(b)'		
Right-hand side variables	Before the start of the financial crisis (Jan 2, 2006 – July 31, 2007)											
Centrality measures												
Large borrowers												
Borrowing strength	0.0004	***	(.0001)	0.0005	***	(.0001)	0.0004	***	(.0001)	0.0005	***	(.0001)
Lending strength	-0.0001		(.0003)	0.0004		(.0003)	-0.0001		(.0004)	0.0005		(.0003)
Indegree	0.75		(4.40)	-0.96		(4.24)	1.06		(4.66)	-1.36	**	(4.57)
Outdegree	4.68		(4.44)	-8.32	*	(4.87)	5.91		(4.36)	-8.03		(5.20)
Closeness	-1.03	**	(0.43)	-0.89	**	(0.35)	-1.10	**	(0.45)	-0.93		(0.38)
Betweenness	-6.24		(50.23)	8.54		(50.36)	-2.40		(53.71)	12.32		(55.39)
PageRank	6.65		(23.35)	-8.89		(11.59)	2.89		(24.52	-11.00		(11.25)
Medium/small borrowers												
Borrowing strength	0.0017	***	(.0005)	0.0023	***	(.0004)	0.0019	***	(.0005)	0.0024	***	(.0004)
Lending strength	-0.0016	**	(.0007)	-0.0004		(.0007)	-0.0017	**	(.0007)	-0.0005		(.0008)
Indegree	4.50	*	(2.48)	0.94		(3.06)	4.47	*	(2.61)	3.34		(3.31)
Outdegree	11.52	*	(5.37)	-0.48		(6.90)	11.03	*	(5.62)	1.40		(7.23)
Closeness	-0.15		(0.23)	-0.20		(0.23)	-0.14		(0.23)	-0.15		(0.25)
Betweenness	-104.97	*	(60.37)	-96.33	*	(49.27)	-111.30	*	(62.81)	-109.68	**	(53.87)
PageRank	-30.80	***	(9.76)	-25.76	**	(12.63)	-34.86	***	(9.97)	-26.71	**	(13.23)
Very small borrowers												
Borrowing strength	-0.0007		(.0028)	0.0027		(.0021)	-0.0003		(.0028)	0.0040	*	(.0022)
Lending strength	-0.0018		(.0018)	0.0037	**	(.0018)	-0.0023		(.0016)	0.0037	**	(.0018)
Indegree	17.25	***	(6.30)	15.56	***	(4.80)	16.40	**	(6.28)	12.21	**	(4.95)
Outdegree	-8.64		(9.40)	-23.28	**	(9.84)	-5.02		(8.95)	-18.61	*	(10.07)
Closeness	0.07		(0.22)	-0.02		(0.25)	-0.015		(0.23)	-0.13		(0.25)
Betweenness	266.34	***	(59.86)	277.22	***	(58.40)	274.96	***	(61.08)	282.33	***	(61.05)
PageRank	-68.59	***	(14.36)	-87.85	***	(14.59)	-72.83	***	(14.55)	-97.95	***	(15.26)
Other bank-specific factors												
$Nationality_i$	-0.66	***	(0.23)	-			-0.67	***	(0.24)	-		
$Risk_i$	0.81	***	(0.17)	-			0.79	***	(0.17)	-		
Large borrowers												
$Clustering_{it}$	-0.32		(1.54)	0.36		(2.23)	-0.55		(1.61)	0.43		(2.29)
$Reputation_{it}$	-2.17	***	(0.30)	-0.96	***	(0.33)	-2.28	***	(0.30)	-0.79	***	(0.36)
Medium and small borrowers												
$Clustering_{it}$	-0.49		(2.79)	-0.58		(3.07)	0.13		(2.83)	0.008		(3.16)
$Reputation_{it}$	-2.20	***	(0.26)	-2.05	***	(0.24)	-2.32	***	(0.28)	-2.09	***	(0.25)
Very small borrowers												
$Clustering_{it}$	-0.50		(2.26)	-0.66		(2.88)	-0.55		(2.16)	-0.50		(2.68)
$Reputation_{it}$	-1.67	***	(0.26)	-2.46	***	(0.22)	-1.79	***	(0.26)	-2.50	***	(0.22)

[29] Columns (a) and (a)' show the results of OLS regressions. Columns (b) and (b)' show the results of within regressions. Heteroskedasticity-robust standard errors adjusted for 147 clusters are reported in parenthesis to the right of each coefficient. The analysis is based on daily data, from January 2006 until November 2008. Columns (a) and (b) exclude the crisis sub-period after Lehman's bankruptcy (i.e. after 15 September 2008), while columns (a)' and (b)' are based on the whole sample. One, two and three asterisks denote statistical significance at 10, 5 and 1 percent level, respectively.

	Additional effects during the financial crisis											
	(a)			(b)			(a)’			(b)’		
	Before Lehman’s collapse (Aug 1, 2007 – Sept 14, 2008)											
Centrality measures interacted with $D_{t,pre\text{-}Lehman}$												
Large borrowers												
Borrowing strength	0.0010		(.0007)	0.0010	**	(.0004)	0.0011		(.0008)	0.0010	**	(.0005)
Lending strength	-0.0027		(.0021)	-0.0025		(.0015)	-0.0032		(.0023)	-0.0031	*	(.0017)
Indegree	-3.88		(10.62)	-3.72		(8.75)	-3.73		(12.73)	-4.20		(10.30)
Outdegree	45.58	**	(25.62)	36.51	**	(16.77)	56.50	**	(24.71)	50.75	***	(18.84)
Closeness	-1.12		(1.03)	-1.37		(0.91)	-0.82		(1.15)	-1.12		(0.99)
Betweenness	-195.64		(164.9)	-178.35		(172.5)	-365.85		(237.3)	-348.08		(236.9)
PageRank	8.21		(33.03)	17.73		(33.59)	11.17		(45.54)	22.27		(41.14)
Medium/small borrowers												
Borrowing strength	-0.0028	**	(.0014)	-0.0026	**	(.0011)	-0.0024	*	(.0014)	-0.0022	*	(.0011)
Lending strength	-0.0059		(.004)	-0.0068	**	(.003)	-0.0064		(.0043)	-0.0076	**	(.004)
Indegree	10.41		(7.26)	12.02	*	(5.63)	11.04		(7.53)	10.82	*	(6.00)
Outdegree	-46.88	***	(15.70)	-30.30		(20.21)	-37.37	**	(18.20)	-17.66		(22.50)
Closeness	0.51		(0.74)	0.54		(0.62)	0.95		(0.80)	0.99		(0.68)
Betweenness	405.18	***	(103.1)	374.80	***	(97.27)	156.81		(106.1)	126.92		(119.1)
PageRank	70.44	**	(35.14)	58.29	**	(26.60)	78.19	**	(39.02)	63.72	**	(27.99)
Very small borrowers												
Borrowing strength	0.021	**	(.011)	0.030	**	(.008)	0.024	**	(.011)	0.035	***	(.008)
Lending strength	-0.03		(.029)	-0.03		(.024)	-0.022		(.034)	-0.033		(.029)
Indegree	20.15		(15.95)	15.66		(12.38)	22.10		(15.81)	15.20		(12.64)
Outdegree	-14.57		(52.43)	1.53		(40.98)	-8.52		(58.71)	9.58		(47.76)
Closeness	1.24	*	(0.70)	0.94		(0.69)	1.48	*	(0.75)	1.12		(0.74)
Betweenness	-82.01		(230.9)	-71.36		(230.5)	-384.55	**	(188.6)	-354.88	*	(209.7)
PageRank	114.89	**	(47.35)	93.55	***	(28.71)	130.78	**	(48.18)	106.82	***	(30.54)
Other bank-specific factors interacted with $D_{t,pre\text{-}Lehman}$												
$Nationality_i$	-0.16		(0.67)	-0.57		(0.48)	-0.25		(0.70)	-0.75		(0.52)
$Risk_i$	0.10		(0.24)	1.13		(0.21)	0.11		(0.24)	1.22	***	(0.23)
Large borrowers												
$Clustering_{it}$	-12.83		(14.50)	-12.27		(13.71)	-8.15		(15.72)	-6.96		(14.78)
$Reputation_{it}$	-6.30	***	(0.83)	-4.66	***	(0.70)	-6.46	***	(0.89)	-4.73	***	(0.77)
Medium/small borrowers												
$Clustering_{it}$	-2.89		(11.04)	-1.99		(10.97)	-4.50		(10.82)	-3.78		(10.75)
$Reputation_{it}$	-4.12	***	(0.59)	-3.21	***	(0.52)	-4.41	***	(0.60)	-3.32	***	(0.55)
Very small borrowers												
$Clustering_{it}$	-3.74		(6.50)	-3.50		(7.14)	-7.14		(5.95)	-6.94		(7.65)
$Reputation_{it}$	-4.21	***	(0.62)	-3.91	***	(0.45)	-4.46	***	(0.66)	-4.18	***	(0.47)

	(a)	(b)	(a)'			(b)'		
	Additional effects after Lehman's collapse (Sept 15, 2008 – Nov 28, 2008)							
Centrality measures interacted with $D_{t,post\text{-}Lehman}$								
Large borrowers	-	-						
Borrowing strength			0.0001		(.0008)	0.0001		(.0019)
Lending strength			0.0030		(.0025)	0.0025		(.0031)
Indegree			-47.97		(52.62)	-39.76		(32.01)
Outdegree			-130.19		(163.4)	-114.85		(149.5)
Closeness			-7.66	**	(3.23)	-7.17		(4.63)
Betweenness			1429.32		(2659)	1629.57		(3952)
PageRank			548.40	**	(212.7)	554.06	***	(162.3)
Medium/small borrowers	-	-						
Borrowing strength			0.0047		(.0080)	0.0052		(.0060)
Lending strength			-0.068	***	(.010)	-0.061	***	(.010)
Indegree			-55.40		(34.81)	-32.30		(21.99)
Outdegree			-55.83		(70.08)	-63.06		(57.88)
Closeness			-3.38		(2.30)	-2.17		(2.04)
Betweenness			1068.70	*	(608.5)	1070.83	*	(574.1)
PageRank			472.01	***	(179.5)	368.05	***	(98.75)
Very small borrowers	-	-						
Borrowing strength			0.039		(.046)	0.065		(.023)
Lending strength			-0.021		(.065)	-0.023		(.052)
Indegree			-56.77		(62.52)	-76.19		(32.79)
Outdegree			-158.17		(123.3)	-143.60		(125.2)
Closeness			3.24		(2.23)	2.40		(2.46)
Betweenness			2143.57		(1476)	1904.19		(1169)
PageRank			626.79	***	(97.93)	562.21	***	(78.56)
Other bank-specific factors interacted with $D_{t,post\text{-}Lehman}$	-	-						
Nationality_i			10.72	***	(3.85)	10.98	***	(1.80)
Risk_i			1.42	*	(0.72)	3.50	***	(0.42)
Large borrowers	-	-						
Clustering_{it}			337.42	***	(120.6)	334.80		(222.6)
Reputation_{it}			-25.11	***	(3.83)	-23.51	***	(2.52)
Medium/small borrowers	-	-						
Clustering_{it}			-25.61	*	(14.10)	-20.23		(19.99)
Reputation_{it}			-12.41	***	(3.16)	-11.82	***	(1.75)
Very small borrowers	-	-						
Clustering_{it}			12.26		(7.44)	11.88		(12.93)
Reputation_{it}			-13.81	***	(3.13)	-12.35	***	(1.73)
Number of obs.	37,918	37,918	40,111			40,111		
R-squared [30]	0.33	0.33	0.49			0.51		
Number of banks	147	147	147			147		

[30] Note that the correct R^2 is reported for within regressions in columns (b) and (b)', i.e. the R^2 of the corresponding Least Squares Dummy Variable (LSDV) regression. Estimated within standard errors are already correct because of the clustering procedure.

Medium/small borrowers

On the contrary, M-banks benefit remarkably from their lending role in the market: each extra 100 million lent during the day reduce the spread by a high 6.1/6.8 bps. The punishment for being more connected to other prominent banks becomes 6 times larger than after August 2007, equalling approximately half a basis point.

Very small borrowers

The punishment is even stronger for very small banks, for which a 0.001 increase in PageRank is associated with 0.63 bps increase in the spread.

Finally, after the collapse of Lehman Brothers foreign banks borrow at a remarkably higher price compared to Italian banks (the spread is on average 11 bps higher) which adds to existing evidence pointing to a move against the integration of the money market.[31] The price-benefit stemming from a stronger reputation skyrockets for all the banks, independently of their size, and reaches 25 bps for the largest borrowers (hence becoming approximately 10 times higher than in normal times).

7. Conclusions

The application of such a key network concept as centrality is a novelty in financial economics and banking. This is partly related to the idea, traditional among economists and supervisors, that a bank's importance is proportional to the size of its balance sheet and of its volumes of business. The relevance of a bank's position in the complex and rich architecture of (direct and indirect) financial links has become apparent only after the 2007-2008 financial crisis. The latter has demonstrated the importance of interdependencies in modern financial systems, hence the limits of a merely micro-prudential approach to supervision. This has brought to the fore the potential of network centrality indicators for the ex ante identification of systemically relevant institutions or, more importantly, for enhancing the accuracy of macro-prudential analysis.

Preliminary evidence about interbank borrowing costs presented in this paper shows that large European banks borrow on average at better rates compared to smaller institutions in normal times, and even more after the start of the financial crisis. Angelini et al. (2009) and Gabrieli (2011a) document that the price of unsecured loans (at longer-term and at O/N maturity, respectively) reduces significantly for the biggest e-MID participants after the start of the crisis, which is likely evidence of a too-big-to-fail guarantee implicitly granted to the banks with the highest volumes of business in the market. Adding to this evidence, the econometric analysis in this paper reveals that, even controlling for bank size and other relevant bank and market factors, the prominence of a bank in the structure of the network can capture part of the cross-sectional variation of interbank rates. Moreover, the size of the effect of interconnectedness on interbank borrowing costs is very different before versus after August 2007; and, interestingly, banks of different size "profit" from different forms of centrality before the crisis and "lose" from different forms after the start of the crisis.

[31] See Cassola et al. (2008) and Gabrieli (2011a).

More specifically: (1) In normal times large banks profit from the higher frequency with which they receive O/N liquidity from other participants, while medium/small and very small banks profit from being lenders to central institutions. But the economic effect of these measures of interconnectedness is relatively small. Foreign banks borrow on average at a relevant discount over Italian ones; banks perceived as better credit risks in 2006 continue to borrow at better rates in the first half of 2007; bank reputation is the most relevant factor to enjoy better funding conditions. (2) After August 2007 large banks' advantage from being "closer" to all the other banks disappears, while they borrow at higher rates the higher the number of counterparties to which they lend their surplus liquidity. Medium/small and very small banks are not rewarded any longer from being lenders to central market players; on the contrary, they are "punished" for such form of interconnectedness. Foreign banks price-benefit disappears, and bank reputation becomes even more important to get more favourable rates. (3) After the bankruptcy of Lehman Brothers the effects of centrality measures on banks' spreads maintain the same sign as after August 2007 but their magnitude increases remarkably. That is, a prominent position in the network seems to yield a strong punishment, which is possibly evidence of market discipline imposed via peer monitoring. The only exception, in this respect, are medium-sized banks that continue to profit from the influence they can exert on other institutions by lending liquidity. Foreign banks pay much higher prices than Italian banks in the last 2 months of the sample, and bank reputation becomes outstandingly more important than in normal times for all the banks.

The evidence discussed in this paper supports further study of the structure of the links between financial institutions in a network perspective, and of the specific characteristics of each institution based on its interactions with other market players. Such a study will allow to better understand and monitor the conditions under which interconnections can impair the viability of an institution with ripple effects throughout the system, hence allowing an enhanced comprehension and measurement of where systemic risks might be in the financial sector. Going forward and depending on data availability such a study should extend to consider links that arise in various financial markets/instruments and, possibly, in the shadow banking sector.

Large and highly interconnected institutions are potentially large contributors to the overall level of risk of the system. This is why a substantial part of the future macro-prudential oversight will certainly concern these institutions. In this respect, I think that measures of network centrality, together with indicators of size, complexity, leverage, over-reliance on short-term or foreign wholesale funding, and more generally the riskiness of individual business models, could be used to: (i) assess the opportunity to limit institutions' exposures, (ii) set up some form of regulatory fees or capital surcharges, (iii) introduce an insurance fund financed through institution-specific insurance premia. An approach of this kind has been recently endorsed by the IMF in its Final Report for the G20.[32]

[32] The report states that an ideal levy on financial institutions *would vary according to the size of the systemic risk externality, e.g. based on a network model which would take into account all possible channels of contagion*. *In practice, however, existing models are not able to fully capture all propagation channels*. This is why the degree of systemic relevance would need to be estimated based on a series of indicators – some of which coincide with those I have listed in the text. In a speech on 16 November 2010, V. Constâncio, Vice-President of the ECB, argued that *"enhanced disclosure will allow a better understanding and measurement of where systemic*

The link found in this paper between centrality and banks' terms of trade supports the potential of centrality measures to enhance the accuracy of tools available for macro-prudential analysis and supervision. A closer interaction between micro and macro-prudential supervision has emerged as a critical feature of the new regulatory framework, at the EU and international level, exactly with a view to better assess interdependencies across individual institutions and evaluate how such interconnections, plausible channels for contagion, might lead to the materialisation of risks considered of a potentially systemic nature.

The new macro-prudential approach to supervision in the EU and around the globe rests on the concept and measurement of systemic risk. The analysis in this paper supports further investigation and modelling of systemic risk in a network perspective and a test of the predictive content of centrality measures for interbank rates/activity (both levels and dispersion), especially at times of financial distress.

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Appendix A: Networks as graphs

Basic concepts and terminology[1]

A network or graph is defined by two nonempty sets: the set $N = \{1,..., n\}$ of *nodes* or *vertices* and the set L of unordered pairs of distinct elements (i , j) called *links* or *edges* that express the connections among the nodes. A graph can be denoted by $g \equiv g(N, L)$. The *order* of g is the number of vertices (i.e. the cardinality of the set N); the *size* of g is the total number of links established in the network in a given time period. The *adjacency matrix* $G(g) = \{g_{ij}\}$ of g is the N-square matrix that keeps track of the "direct" connections in the network. That is, if a vertex i has a direct link with vertex j then $g_{ij} = 1$; $g_{ij} = 0$ otherwise.[2] If two vertices i and j are directly linked, i.e. $g_{ij} = 1$, then i and j are *neighbours* or *adjacent*.

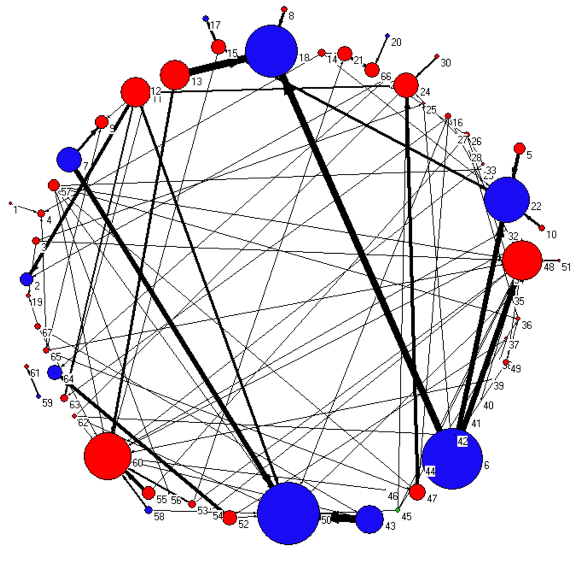
In a directed graph, a link has two distinct ends: a head (the end with an arrow) and a tail. Each end is counted separately. The sum of head endpoints terminating upon a node is called *indegree*; the sum of tail endpoints originating from a node is called *outdegree*.[3] In the interbank context they correspond to the number of banks from which i borrows and to which i lends, respectively. In formulae:

$$g_i^{in} = \sum_j g_{ji} \text{ and } g_i^{out} = \sum_j g_{ij}$$

Another key concept in graph theory is that of a *path*: two vertices i and j are connected if there is a path from i to j. A path of length k from i to j is defined as an ordered sequence of vertices $[i_0, i_1, ..., i_k]$ starting from i and terminating at j (i.e. $i_0 = i$ and $i_k = j$) such that $g_{i_s i_{s+1}} = 1$ for all $0 \leq s \leq k\text{-}1$. That is, a path is an ordered set of nodes where node i_s and node i_{s+1} are directly linked.

Figure 5 shows the core of the e-MID interbank network (92 linkages each transferring a value of at least EUR 50 million and representing 83% of the total daily turnover) on January 3, 2007.

Figure 5: Visualisation of the largest links in e-MID on 3 January 2007



Only links transferring an amount of at least EUR 50 million are included. These are 92 links and transferred 83% of the total market turnover on 3 January 2007. Legend: blue circles represent the 20 largest banks; red circles are the medium and small banks; green circles (for which only a label-number is visible in the picture) are the 50 smallest banks in the system. The size of a circle is determined by the (borrowing and lending) strength of the bank.

[1] This short introduction to the basics of graph theory relies on the course in "Empirics of Networks" held by Prof. Eleonora Patacchini.

[2] By convention $g_{ii} = 0$.

[3] The idea of a directed graph in sociology is applied, for instance, to model social networks based upon nominations. In this case $g_{ij} = 1$ if j has nominated i as his/her friend, and $g_{ij} = 0$ otherwise.

Connected sub-graphs: network components

In order to apply tools developed in graph theory we need to analyse connected networks. A network is *connected* if there is a path connecting every pair of nodes, i.e. if every pair of nodes in the network is reachable. If this is not the case, then the network is *disconnected*.

A disconnected graph can be partitioned into two or more subsets in which there are no paths between the vertices in different subsets. These connected sub-graphs or sub-networks $g^{'} \subset g$ are called *components*.[4] They form a partition of the whole graph, i.e. by definition:

$$g = \bigcup_{g^{'} \in C(g)} g^{'}$$

C(g) being the set of components of *g*.

Components are classified according to whether the vertices in the subset are reachable among them via directed or only via undirected edges. In the first case the sub-network is defined as *strongly connected* (SCC); in the second case it is *weakly connected* (WCC). Most real networks are composed by one largest WCC and one or more – much smaller – WCCs that are disconnected from the largest one. The SCCs of a graph might be subsets of the largest as well as of any of the smaller weakly connected components.

Geodesics and distance

There may be several different paths connecting two vertices. A *geodesic* is a shortest path between two nodes. The *geodesic distance* or simply *distance* (d_{ij}) is then the length of a shortest path between node *i* and node *j*. The *average shortest path* is the mean distance separating vertex *i* from all other vertices belonging to the same component, that is:

$$\overline{d_i} = \frac{\sum_{j \neq i} d_{ij}}{n-1}.$$ [5]

Clustering coefficient

A *triad* is a group of three vertices linked in the network. A triad is *transitive* if whenever *i* → *j* and *j* → *k* then also *i* → *k*. For each vertex the *clustering coefficient* is the fraction of transitive triads the vertex is involved in over the total number of triads in the network. That is, clustering measures the probability that two nodes having a common neighbour are neighbours themselves. Formally:

$$c_i = \frac{\sum_j \sum_k g_{jk}}{g_i (g_i - 1)}$$

for all *j*, *k* that are directly connected to *i*.

Centrality measures

One of the most important uses of network analysis is the identification of the most “central” nodes in a graph. Measures of centrality (or prestige, as it is called in directed social networks) define a node as central if: (1) it has a high degree; (2) it is at a short distance (in links) from other reachable nodes, hence it is “close to” other nodes; (3) it lies on several shortest paths “between” other nodes. Measures defined under concept (1), (2) and (3) are all solely based on the geometry of the network. However, measures that belong to (1) take into account only direct connections among the nodes, while measures based on (2) and (3) value also indirect connections.

Degree centrality and strength

One of the dimensions by which a player is central in a network is the number of connections it has. In the interbank context, this measure amounts to the number of counterparties a bank trades with, i.e. its *degree* (g_i). In particular, both the number of outgoing and the number of incoming arcs (i.e. g_i^{out} and g_i^{in}) are used as measures of prestige in a directed network: outdegree is a measure of the “influence” that a vertex exerts on other vertices; indegree is a measure of “support” that a vertex receives from other vertices. In order to compare the degree centrality across different networks these indicators can be normalized dividing them by the maximum number of links that a node can establish. This leads to the following statistics:

---

[4] Note that a completely isolated node that has no links is not considered a component, while a couple (*i* , *j*) sharing a reciprocal link constitutes a distinct strongly connected sub-network.

[5] In graph theory when there is no path connecting two nodes the distance between them is infinite. Therefore, *n* in the denominator of the formula refers to the order of the connected component the node belongs to (*n-1* is then the maximum possible distance between node *i* and any another node *j* in the same component).

$$g_i^{in*} = \frac{\sum_j g_{ji}}{n-1}\ ,\ g_i^{out*} = \frac{\sum_j g_{ij}}{n-1} \text{ and } g_i^{*} = \frac{g_i}{n-1} \text{ where } g_i = g_i^{in} + g_i^{out}\ .$$

Furthermore, by weighing the number of links that an agent sets up with the volume transacted upon each link it is possible to assess the centrality of a node in terms of its *strength*. In particular, we can define the *borrowing* and *lending strength* of a node as:

$$s_i^b = \sum_j w_{ij}^b \text{ and } s_i^l = \sum_j w_{ij}^l$$

where w_{ij}^b denotes the overall value exchanged between any *i* as the borrowing bank and any *j* as the lending bank, and w_{ij}^l denotes the overall value exchanged between any *i* as the lender and any *j* as the borrower.[6] Finally, the strength of a vertex can also be assessed in terms of net flows computing

$$s_i^{netflow} = \sum_j f_{ij} \text{ where } f_{ij} = w_{ij}^b - w_{ij}^l\ ,$$

or in terms of its total (borrowing plus lending) strength (i.e., $s_i = s_i^b + s_i^l$).

Closenness centrality

Another dimension by which a node is central in a graph is its proximity to all other vertices. A normalised measure of *closeness* centrality of a node is defined as the inverse of its average shortest path.[7] Being *n–1* the maximum possible distance between any two nodes in the network, the indicator:

$$cl_i^* = \frac{n-1}{\sum_{j\neq i} d_{ij}}$$

provides a normalised measure of the ease of accessibility of vertex *i* from all other vertices in the graph or, in a flow context, the expected time until arrival of something flowing through the network.

Betweenness centrality

A third dimension of centrality is the *betweenness* of a vertex. According to this measure, a player is central if it lies between other players on their geodesics: the distance from other units is not the only relevant property; more important is the number of geodesics among other units that a vertex can exert control on.[8] A normalised betweenness indicator for a directed network is computed as follows:

$$btw_i^* = \frac{\sum_{j,l} \frac{a_{jl,i}}{a_{jl}}}{(n-1)(n-2)}$$

where $a_{jl,i}$ denotes the number of geodesics between *j* and *l* through *i* and a_{jl} is the total number of shortest paths between *j* and *l* .[9]

Eigenvector centrality

Another popular measure of centrality is eigenvector centrality (Bonacich, 1972). Eigenvector centrality is defined as the principal eigenvector of the adjacency matrix defining the (internally connected) network. The defining equation of an eigenvector is

$\lambda v = G\, v$

where *G* is the adjacency matrix of the graph, λ is a constant (the eigenvalue), and $\boldsymbol{v}$ is the eigenvector. The equation lends itself to the interpretation that a node that has a high eigenvector score is one that is adjacent to nodes that are themselves high scorers. It can be shown (Bonacich, 1987, 1991) that an eigenvector is proportional to the row sums

6 Clearly, $w_{ij}^b = w_{ji}^l$.

7 This definition of closeness centrality is due to Sabidussi (1966).

8 Betweenness centrality is used in particular for communication networks, where nodes that have the highest "betweenness" have a stronger potential for control over the flow of information in the network. See Freeman (1977).

9 Dividing by (*n–1*)(*n–2*) we obtain a normalized version because this factor represents the maximum number of pairs of players not including *i*, hence the maximum value that this indicator can take.

of a matrix ***S*** formed by summing all powers of the adjacency matrix, weighted by corresponding powers of the reciprocal of the eigenvalue, as shown in the next equation.

$$S = G + \lambda^{-1}G^2 + \lambda^{-2}G^3 + \ldots$$

But another well known result in graph theory is that the cells of the matrix powers give the number of walks of length k from node i to node j. Thus the measure counts the number of walks of all lengths, weighted inversely by length, which emanate from a node. As a result, the measure assumes that traffic is able to move via unrestricted walks rather than being constrained by paths or geodesics. This requires that the network on which the indicator is computed is internally strongly connected. (The limitations of this assumption for e-MID networks are emphasized in Section 3).

PageRank centrality

PageRank is an eigenvector-based algorithm. Keeping in mind its walk-based nature, the score of a node can be thought of as the fraction of time that a random walk (following outgoing arcs) will spend at that node over an infinite time horizon. PageRank modifies the standard eigenvector algorithm by adding to the model a probability (*alpha*) of jumping to any node that acts as a sort of score smoothing parameter. Furthermore, it allows to have different probabilities that the random walk follows any outgoing arcs depending on the weight of the arcs (where the latter, meant to represent transition probabilities, are rescaled so that they sum up to one). This indicator is calculated using the JUNG PageRank measure (setting the dumping parameter *alpha* equal to 0.15).

Appendix B: Summary statistics about e-MID networks and the regressors

Normal times (2 January 2007 – 31 July 2007; 490 business days)

Variables	Mean	Standard deviation	Min	Max	25th percentile	50th percentile	75th percentile
Number of trading banks	128	8	77	146	124	128	132
Number of traded loans	393.5	46.37	196	533	362	386	416
Average spread over the policy rate	5.31	6.29	-36.19	16.86	5.86	6.78	7.69
Intraday variability of interest rates	2.62	5.77	0.55	44.07	0.92	1.17	1.69
e-MID turnover	24.04	5.45	11.63	41.11	20.30	23.22	27.31
iTraxx Europe Senior Financials Index (5 years maturity)	9.25	3.22	7.38	32.00	8.05	8.26	8.64
EONIA turnover	44.61	9.48	25.74	67.55	37.18	44.10	51.45
Amount of Eurosystem's refinancing	433.73	13.48	407.50	465.50	426	431.50	441.50
Amount of reserves deposited with the Eurosystem	183.29	8.16	152.80	205.40	178.75	183.44	188.34
Recourse to Marginal Lending Facility	0.21	0.47	0	2.50	0.001	0.009	0.17
Recourse to Deposit Facility	0.35	0.99	0.01	8.07	0.05	0.09	0.18
Amount allotted at liq. providing FTOs	2.26	0.25	2	2.5	2	2.50	2.50
Amount allotted at liq. absorbing FTOs	7.81	8	2.3	22.5	2.3	2.46	6
Amount allotted at MROs	292.72	15	271.5	330.5	281	288	301.5
Amount allotted at LTROs	141.24	11.54	120	150	130	149.99	150
Spread between marginal and minimum bid rate at MROs	5.90	1.07	3	8	5	6	7

From the start of tensions until the bailout of EU banks (31 July 2007 – 28 September 2008; 298 business days)

Variables	Mean	Standard deviation	Min	Max	25th percentile	50th percentile	75th percentile
Number of trading banks	112	9.5	48	133	108	114	119
Number of traded loans	368.33	59.16	99	553	330	369	404
Average spread over the policy rate	-0.67	13.78	-51.92	62.67	-4.88	1.47	4.57
Intraday variability of interest rates	6.07	6.77	1.14	43.40	1.95	3.04	7.39
e-MID turnover	14.51	3.39	5.39	24.35	12.15	14.07	16.78
iTraxx Europe Senior Financials Index (5 years maturity)	79.58	37.24	27.82	198.93	47.92	72.85	106.17
EONIA turnover	51.99	10.57	17.75	82..34	44.73	52.14	59.26
Amount of Eurosystem's refinancing	453.96	26.91	386	546.50	437.09	454.01	467
Amount of reserves deposited with the Eurosystem	202.74	28.29	122.99	325	189.67	201.55	217.89
Recourse to Marginal Lending Facility	0.26	0.66	0	6.80	0	0.013	0.22
Recourse to Deposit Facility	0.76	2.13	0	28.10	0.16	0.30	0.58
Amount allotted at liq. providing FTOs	37.82	25.71	7.70	94.84	15	40	47.67
Amount allotted at liq. absorbing FTOs	61.38	59.22	8	200	20	29	133.61
Amount allotted at MROs	193.15	50.37	128.50	368.61	161.50	176.50	208
Amount allotted at LTROs	265.94	39.05	150	301	265	268.50	295
Spread between marginal and minimum bid rate at MROs	15.18	6.76	3	48	11	15	18

From the bailout of EU banks until the end of November 2008 (29 September 2008 – 28 November 2008; 45 days)

Variables	Mean	Standard deviation	Min	Max	25th percentile	50th percentile	75th percentile
Number of trading banks	90	7	76	105	86	90	94
Number of traded loans	277.84	49.55	176	375	247	275	302
Average spread over the policy rate	-33.58	12.77	-72.25	-6.14	-38.44	-32.56	-28.85
Intraday variability of interest rates	18.63	7.71	10.04	39.44	12.36	15.06	24.55
e-MID turnover	8.47	1.51	4.79	11.78	7.49	8.41	9.66
iTraxx Europe Senior Financials Index (5 years maturity)	142.46	24.17	111.80	228.81	126.58	134.96	149.54
EONIA turnover	36.78	7.09	18.65	57.21	31.87	35.74	40.78
Amount of Eurosystem's refinancing	703.94	132.20	410.50	827.70	671.40	753.10	798
Amount of reserves deposited with the Eurosystem	221.80	56.90	152.40	384.90	178.40	199.40	265.50
Recourse to Marginal Lending Facility	10.98	6.71	1.2	24.60	4	12.7	15.50
Recourse to Deposit Facility	168.26	77.16	38.90	297.40	102.80	202.20	218.90
Amount allotted at liq. providing FTOs	24.70	0	24.70	24.70	24.70	24.70	24.70
Amount allotted at liq. absorbing FTOs	163.02	38.64	79.60	200	147.1	173	193.80
Amount allotted at MROs	287.26	56.54	180	338.70	250.90	311.90	335.20
Amount allotted at LTROs	44304	35.98	301	501.80	420.50	447.20	462.80
Spread between marginal and minimum bid rate at MROs	43.17	3.14	40	48	40	45	45

Appendix C: Robustness to sample selection bias

In order to tackle a possible sample selection problem in the econometric analysis, I reduce the cross section to those banks that traded in at least the median number of business days in each of the 3 years under analysis, i.e. in at least 127 out of 254 business days in 2006 and 2007, and in at least 117 business days in 2008. The sample shrinks from 147 to 78 banks.

The results are overall confirmed for the period before the crisis. However, for the period after August 2007 the results are robust only for medium/small and very small banks, while most centrality measures lose statistical significance for L-banks. In particular, by considering only the banks that continued to trade in e-MID on a regular basis, the results do not suggest any "punishment" of L-banks from being more interconnected (in terms of having a higher number of outgoing links) after August 2007. None of the interacted centrality measures is significant after the start of the crisis, while after Lehman's default L-banks gain extremely good prices for their loans when they post a bid quote and, ceteris paribus, they profit from a higher level of clustering. This network indicator, measuring the tendency of a node to connect in triplets, was never significant in the results reported in Table 3. The results reported in Table 4 show, instead, that an increased tendency of large and very small banks to form groups where ties were relatively denser resulted in better interest rates after the collapse of Lehman.

For medium-sized and very small banks all the coefficients of interest are robust to this check. All in all, this seems to suggest that the largest banks selected out of the sample after the start of the crisis. This might be explained by the fact that bigger banks can likely find alternative sources of funding more easily compared to medium and small banks. This in turn might be related also to the foreign nationality of many of the largest e-MID participants. Foreign banks are more likely to have refrained from using the platform during the crisis compared to Italian banks given that the e-MID system is based in Italy and is in fact an exception in the European landscape, where interbank trading is done mostly OTC. These two factors, coupled with increased uncertainty and information asymmetry, might have induced large banks to shift deals away from e-MID to less transparent trading environments (i.e. to OTC trading) during the crisis. The next table reports the results of OLS and within estimations of equation (1).

Table 4: Robustness to sample selection bias. Results of the specification in equation (1)[10]

	Dependent variable: unsecured O/N spread over policy rate (in bps)											
	(a)			(b)			(a)'			(b)'		
Right-hand side variables	**Before the start of the financial crisis (Jan 2, 2006 – July 31, 2007)**											
Centrality measures												
Large borrowers												
Borrowing strength	0.0005	***	(.0001)	0.0007	***	(.0001)	0.0006	***	(.0002)	0.0008	***	(.0002)
Lending strength	-0.0001		(.0007)	0.0007		(.0005)	-0.0001		(.0007)	0.0006		(.0006)
Indegree	-1.04		(4.01)	-4.83		(4.41)	-0.72		(4.33)	-3.99		(4.69)
Outdegree	1.84		(6.84)	-8.44		(8.09)	4.42		(6.58)	-2.56		(8.45)
Closeness	-1.01	**	(0.53)	-0.88	**	(0.342)	-1.07	*	(0.56)	-0.89	**	(0.45)
Betweenness	24.58		(16.68)	40.65	*	(24.50)	29.96	*	(16.44)	44.64	*	(26.58)
PageRank	10.35		(18.65)	-5.74		(11.32)	5.63		(20.35)	-6.96		(10.75)
Medium/small borrowers												
Borrowing strength	0.0015	***	(.0005)	0.0016	***	(.0005)	0.0018	**	(.0008)	0.0019	***	(.0006)
Lending strength	-0.0017		(.0012)	0.0002		(.0012)	-0.0019		(.0014)	0.0002		(.0012)
Indegree	5.48	*	(3.13)	5.67	*	(3.13)	5.30	*	(3.18)	7.19	**	(3.52)
Outdegree	11.10		(7.72)	3.30		(7.72)	11.04		(7.28)	6.03		(8.06)
Closeness	0.013		(0.24)	-0.21		(0.24)	0.03		(0.25)	-0.19		(0.25)
Betweenness	-136.36	*	(58.53)	-131.35	**	(58.53)	-146.41	*	(72.03)	-147.22	**	(63.66)
PageRank	-34.17	***	(13.30)	-33.82	**	(13.30)	-38.43	***	(11.63)	-33.09	**	(13.87)

10 Columns (a) and (a)' show the results of OLS regressions. Columns (b) and (b)' show the results of within regressions. Heteroskedasticity-robust standard errors adjusted for 78 clusters are reported in parenthesis to the right of each coefficient. The analysis is based on daily data, from January 2006 until November 2008. One, two and three asterisks denote statistical significance at 10, 5 and 1 percent level, respectively.

	(a)		(b)		(a)'		(b)'	
Very small borrowers								
Borrowing strength	-0.0024	(.0038)	0.0049 *	(.0027)	-0.0021	(.0038)	0.0090 ***	(.0029)
Lending strength	-0.0032	(.0086)	-0.0034	(.0074)	-0.0023	(.0085)	-0.0018	(.0070)
Indegree	17.25 **	(7.99)	10.27 *	(6.14)	16.70 **	(7.98)	3.87	(6.34)
Outdegree	-5.91	(18.44)	-3.42	(14.93)	-5.08	(17.89)	-1.90	(14.45)
Closeness	0.13	(0.26)	-0.24	(0.32)	0.10	(0.27)	-0.38	(0.32)
Betweenness	142.05 *	(83.01)	145.29 **	(71.43)	156.14 *	(86.76)	152.73 **	(77.61)
PageRank	-66.86 ***	(16.93)	-75.67 ***	(18.85)	-73.83 ***	(17.57)	-92.56 ***	(19.82)
Other bank-specific factors								
$Nationality_i$	-0.63 **	(0.31)	-		-0.69 ***	(0.32)	-	
$Risk_i$	0.98 ***	(0.17)	-		0.97 ***	(0.18)	-	
Large borrowers								
$Clustering_{it}$	0.37	(1.11)	1.23	(2.16)	0.13	(1.19)	1.10	(2.15)
$Reputation_{it}$	-2.14 ***	(0.43)	-0.34	(0.46)	-2.27 ***	(0.44)	-0.20 ***	(0.49)
Medium and small borrowers								
$Clustering_{it}$	0.24	(3.31)	-0.58	(3.60)	0.80	(3.37)	-0.06	(3.70)
$Reputation_{it}$	-2.16 ***	(0.38)	-2.59 ***	(0.32)	-2.31 ***	(0.40)	-2.60 ***	(0.34)
Very small borrowers								
$Clustering_{it}$	3.12	(2.49)	2.94	(3.04)	3.24	(2.42)	2.64	(3.02)
$Reputation_{it}$	-1.46 ***	(0.34)	-2.29 ***	(0.28)	-1.58 ***	(0.35)	-2.36 ***	(0.29)
	Additional effects during the financial crisis							
	(a)		(b)		(a)'		(b)'	
	Before Lehman's collapse (Aug 1, 2007 – Sept 14, 2008)							
Centrality measures interacted with $D_{t,pre\text{-}Lehman}$								
Large borrowers								
Borrowing strength	0.0001	(.0009)	0.0006 **	(.0005)	0.0002	(.0009)	0.0007	(.0006)
Lending strength	0.0023 *	(.0012)	0.0022	(.0020)	0.0020	(.0014)	0.0019	(.0021)
Indegree	13.21	(9.37)	4.33	(9.92)	14.00	(12.15)	0.97	(11.49)
Outdegree	-38.48	(25.62)	-34.66 **	(27.04)	-17.78	(33.91)	-15.99	(32.41)
Closeness	-0.22	(1.31)	-0.44	(1.23)	-0.16	(1.47)	-0.65	(1.35)
Betweenness	-301.86	(219.69)	-289.18	(206.29)	-436.56	(334.75)	-421.54	(310.3)
PageRank	-16.88	(32.48)	-0.95	(35.86)	-16.67	(47.20)	6.80	(43.29)
Medium/small borrowers								
Borrowing strength	-0.0041 **	(.0018)	-0.0037 ***	(.0014)	-0.0040 **	(.0017)	-0.0038 ***	(.0014)
Lending strength	-0.0055	(.0065)	-0.0066 *	(.0040)	-0.0066	(.0071)	-0.0085 *	(.0044)
Indegree	11.10	(8.66)	8.91	(5.96)	12.08	(8.92)	8.52	(6.33)
Outdegree	-61.06 **	(27.59)	-56.85 *	(29.91)	-62.78 *	(34.59)	-56.60	(34.62)
Closeness	0.99	(0.87)	1.12	(0.74)	1.64	(0.99)	1.81 **	(0.83)
Betweenness	342.27 ***	(95.13)	338.33 ***	(111.57)	167.28	(118.49)	164.34	(146.2)
PageRank	66.39 *	(35.85)	63.20 **	(26.43)	73.31 *	(42.12)	69.74 **	(27.91)
Very small borrowers								
Borrowing strength	0.018	(.011)	0.021 **	(.009)	0.021 *	(.012)	0.026 ***	(.009)
Lending strength	-0.02	(.032)	-0.016	(.028)	-0.021	(.039)	-0.018	(.034)
Indegree	16.83	(17.33)	20.53	(14.27)	19.43	(17.09)	23.46	(14.50)
Outdegree	-20.43	(62.40)	-20.34	(42.30)	-17.29	(64.18)	-17.78	(46.89)
Closeness	0.70	(0.84)	0.82	(0.78)	1.05	(0.88)	1.20	(0.79)
Betweenness	115.70	(209.68)	120.41	(237.47)	-120.66	(187.57)	-108.66	(222.0)
PageRank	125.38 **	(56.57)	90.94 ***	(34.01)	139.07 **	(58.30)	98.93 ***	(34.29)

Other bank-specific factors interacted with $D_{t,pre\text{-}Lehman}$								
Nationality$_i$	1.56	(0.97)	-0.08	(0.86)	1.64	(1.04)	-0.34	(0.93)
Risk$_i$	0.084	(0.29)	1.16 ***	(0.28)	0.11	(0.29)	1.23 ***	(0.29)
Large borrowers								
Clustering$_{it}$	-5.73	(14.69)	-4.97	(13.29)	-6.14	(16.10)	-4.85	(14.97)
Reputation$_{it}$	-7.65 ***	(1.29)	-5.93 ***	(0.94)	-7.64 ***	(1.42)	-5.39 ***	(1.02)
Medium and small borrowers								
Clustering$_{it}$	-8.60	(17)	-7.17	(16.70)	-8.75	(16.73)	-7.45	(16.40)
Reputation$_{it}$	-3.90 ***	(0.72)	-2.95 ***	(0.66)	-4.03 ***	(0.72)	-2.80 ***	(0.70)
Very small borrowers								
Clustering$_{it}$	-13.78 **	(6.88)	-14.01 *	(7.39)	-7.28	(10.68)	-6.86	(10.04)
Reputation$_{it}$	-4.81 ***	(0.74)	-4.55 ***	(0.55)	-5.07 ***	(0.82)	-4.81 ***	(0.58)
	After Lehman's collapse (Sept 15, 2008 – Nov 28, 2008)							
	(a)		(b)		(a)'		(b)'	
Centrality measures interacted with $D_{t,post\text{-}Lehman}$								
Large borrowers								
Borrowing strength	-	-	-	-	0.0003	(.0038)	0.0009	(.0021)
Lending strength					0.0038 **	(.0018)	0.0028	(.0037)
Indegree					-19.99	(50.60)	-37.81	(32.01)
Outdegree					-164.60 **	(64.53)	-155.22	(236.2)
Closeness					-3.24 **	(5.05)	-4.36	(5.64)
Betweenness					-3396.3 *	(1765.8)	-3179.3	(5224)
PageRank					338.07	(274.53)	397.22 **	(191.3)
Medium/small borrowers								
Borrowing strength	-	-	-	-	0.0073	(.0093)	0.0091	(.0077)
Lending strength					-0.071 ***	(.016)	-0.069 ***	(.014)
Indegree					-41.10	(33.22)	-37.40	(24.48)
Outdegree					-163.09 **	(74.15)	-149.68 *	(84.29)
Closeness					-2.16	(2.44)	-1.56	(2.33)
Betweenness					1943.43 **	(609.57)	1818.41 ***	(668.9)
PageRank					342.77 **	(139.41)	299.47 ***	(96.25)
Very small borrowers								
Borrowing strength	-	-	-	-	0.051	(.048)	0.057 ***	(.026)
Lending strength					-0.036	(.051)	-0.032	(.053)
Indegree					-61.35	(68.03)	-60.60 **	(36.07)
Outdegree					-240.39 ***	(80.71)	-243.62	(134.9)
Closeness					4.10 *	(2.18)	4.14	(2.74)
Betweenness					856.81	(791.96)	687.75	(788.1)
PageRank					574.48 ***	(99.25)	529.04 ***	(78.86)
Other bank-specific factors interacted with $D_{t,post\text{-}Lehman}$								
Nationality$_i$	-	-	-	-	21.02 ***	(4.28)	18.15 ***	(2.20)
Risk$_i$					1.25 *	(0.48)	2.75 ***	(0.45)
Large borrowers								
Clustering$_{it}$	-	-	-	-	-1516.7 ***	(164.64)	-1534.1 *	(787.7)
Reputation$_{it}$					-24.10 ***	(5.55)	-20.61 ***	(2.93)
Medium and small borrowers								
Clustering$_{it}$	-	-	-	-	-16.42	(14.01)	-14.50	(19.66)
Reputation$_{it}$					-13.36 ***	(4.13)	-12.40 ***	(1.95)
Very small borrowers								
Clustering$_{it}$	-	-	-	-	3.13	(5.14)	3.96	(10.32)
Reputation$_{it}$					-13.02 ***	(3.69)	-12.29 ***	(1.91)
Number of obs.	26,480		26,480		28,217		28,217	
R^2	0.32		0.32		0.53		0.51	
Number of banks	78		78		78		78	

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