The Effects of Crisis on the Interbank Markets and Sovereign Risk: Empirical Investigations

Asena Temizsoy

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Asena Temizsoy

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Abstract

The 2007-2008 global financial turmoil is the most severe crisis since the Great Depression. Starting with the sub-prime defaults in the United States, it quickly spills over into other markets leading to the collapses of many financial institutions, worldwide banks bailouts, downturns in asset prices and also to sovereign debt crises. The aim of this thesis is to empirically investigate the repercussions of this financial crisis on interbank market and sovereign risk.

In Chapter one, we empirically explore the effect of bank lending relationships in the interbank market. We use data from the e-MID market that represents the only transparent electronic platform in Europe and the United States, unaffected by search costs and other fictions. We show that stable relationships exist and that they play a significant role during the 2007-2008 financial crisis. Trading with preferred counterparts is associated with more favorable rates for both lenders and borrowers, and carries larger trading volumes. The results point to a peer monitoring role of relationship lending, which contributes, at a time of financial distress, to a smooth liquidity redistribution among banks. Relationship lending thus plays an important positive role for financial stability.

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

Chapter three draws attention to the effect of monetary policies and international linkages on European countries sovereign risks. Using a Global VAR method that allows for interdependencies across individual variables within and across units, we model government bond credit default swaps (CDS) relative to Germany by domestic, global, monetary and weighted foreign variables, where weights are calculated based on the countries' fiscal positions. We find evidence of positive correlation between sovereign bond CDS and risk aversion for almost all countries in the eurozone. When the European Central Bank (ECB) increases the refinancing rate, we observe an increase in risk of sovereign bonds of all countries due to negative environment in Euro area. A decline in money aggregate (M3) leads to all countries becoming more fragile, hence increasing sovereign risk. The shocks that stem from monetary policy changes (i.e. an increase in ECB refinancing rate) causes a rise in sovereign risk due to sensitivity to crisis and uncertainty in Euro area. In contrast, monetary policies have an opposite impact on Greece due to its relative worse performance.

Chapter 1

Introduction

1.1 Introduction

2007-2008 was a turning point in the history of capital markets with one of the most impactful turmoils affecting governments, regulators, financial institutions, investors and others. Originating in the United States (US) with the downward spiral in the real estate linked instruments, it quickly spread into all segments of financial markets. Consequent events gradually impacted on all economic activities and opened the gateway to global recession as well as European debt crisis, especially in Portugal, Ireland and Greece. This uncertainty caused significant disruptions and continued to threat foundational and stable pillars of the financial ecosystem.

Macro factors, financial factors and banking misapplications are the main factors that led to the 2007-2008 financial crisis. Firstly, macro factors consist of three primary drivers including monetary expansion and the housing boom in the US market, banks offering loans to high risk borrowers and high indebtedness of the US households. Secondly, financial factors included the introduction of new structured finance instruments, insufficient capabilities and regulations in credit risk assessment and increase in the number of hedge funds. Finally, banking misapplications contributed to the crisis with two main drivers. One of them was that banks followed an "Originate and Distribute" model which allowed them to repackage collateral and associated risk to other investors, not assuming any liability on the bank's balance sheets. The other driver was that financing loans with short-term maturities leading to maturity misalignment and eventually funding liquidity risk (Brunnermeier, 2009).

These common factors initially lead to defaults in subprime mortgages in early 2007, followed by a steep decrease in the mortgage credit default swap index. By the middle of 2007, two highly exposed hedge funds of Bear Sterns took a hit from subprime mortgage backed securities and confronted large margin calls. In the following months, high leverage of financial institutions along with a decline in house prices led the markets to asset price booms and a credit bubble.

Unsuprisingly, vulnerabilities quickly spread and spilt over into other asset types. Commercial banks also realized their share of impact along with mortgage lenders and investment banks. Through this period, the impact on the financial industry was observed on three critical points in August 2007, December 2007 and then in March 2008. Soon after, the elevated credit risk transformed into counterparty and liquidity risk. Especially following the white flag from Lehman Brothers in September 2008, counterparty risk continued to climb and all market participants were under pressure with significant liquidity concerns.

Until the start of events leading to global crisis in the US, Eurozone money markets demonstrated strong performance with stable interest rates. The markets in Eurozone were highly liquid and characterized with low volatility and associated risk premiums. However, the 2007-2008 financial crisis had significant implications for the European interbank market. By the end of September 2008, spreads surged to unforeseen levels with high volume of funds sitting idle at the European Central

Bank (ECB). With Lehman Brothers collapse leading to further lack of trust in the markets, financial institutions deposited and aimed to secure large sums at ECB, despite the lending opportunities and business growth potential in the interbank market. In the last quarter of 2008, asymmetric data on counterparty risk along with the rise in liquidity risk adversely affected the functioning of interbank market. Even the unprecedented increase in the liquidity provision from central banks did not help the situation. Consequently, the relationship between the banks and the banks' position in the interbank network emerged as a key determinants of borrowing cost, attracting wide interest in the topic.

The domino effect continued within Europe and the 2007-2008 financial crisis eventually lead to global recession and causing the Greece debt crisis. In 2012, sovereign credit default swaps (CDS) markets experienced high levels of disruptions causing a major concern to the stability of government risks. The debt crisis in Greece drew attention to the sovereign bond spreads and interdependence of each country's risk in Eurozone.

The aim of this thesis is to investigate the repercussions of the 2007-2008 crisis on the interbank market and 2012 Greece debt crisis on European sovereign risk, and to provide empirical evidence on the changes in the pricing of interbank deposits and government CDS before, during and after respective crisis.

1.2 Research Objectives

This research has the following objectives

- To examine the effect and evolution of lending relationship on the interbank interest rate before, during and after 2007-2008 financial crisis.
- To analyze the stability of relationship during this period.

- To explore how interbank market rates are affected by the position of both bank and counterparty in the network.

- To offer an analysis on whether local and global network centralities have different impact on funding rates.

- To extend the literature by exploring effect of position of bank in the trade (aggressor/quoter) on borrowing cost.

- To analyze the effect of ECB monetary shocks on the CDS markets controlling by local factors (fiscal fundamentals and growth), global world factors (market's appetite for risk) in order to model contagion of country risk on the Euro area.

1.3 Structure of the Thesis

This introductory chapter gives background information about the relevant topics of the thesis and marks the importance of this thesis. Chapter 2 investigates the effect of bank lending relationship in the interbank market before, during and after the 2007-2008 financial crisis with the aim of detecting early warning indicators of distress in the financial sector. Chapter 3 examines the importance of bank's position in the network in the interbank market and their funding rates. Chapter 4 focuses on European Sovereign risk in order to detect international linkage and interdependence of country risk during Greece debt crisis. The last chapter presents the main conclusions of this study as well as some suggestions for future research.

Chapter 2

The role of bank relationships in the interbank market

2.1 Introduction

Financial markets have been under extreme pressure since the start of the financial crisis late in 2007. Many components of the global economy and financial structure, from bond and share prices to money markets and foreign exchanges were affected by the market conditions following the turmoil. Among the areas affected, the money market stands out as a crucial element as it supports the implementation of monetary policy and stable borrowing conditions for the financial sector, other corporations and individuals. Within the interbank market, which covers maturities from one day to one year, the overnight (O/N) segment is of particular interest because the O/N interest rates are directly affected by rules and practices governing the refinancing operations run by the European Central Bank (ECB). This is the segment of the money market where credit institutions look to mitigate any risk that may emerge from short-term liquidity shocks and to ensure the trading day is closed with healthy liquidity positions. The interbank market is a significant element due to the fact that the O/N rates are determined in this market. Furthermore, interbank markets are central hubs for complex institutional networks, connecting all financial organizations in the banking industry (Iori et al., 2008; Fricke and Lux, 2015a, 2015b).

During the crisis, increased uncertainty about counterparty credit risk led banks to hoard liquidity rather than making it available in the interbank market. Money markets in most developed countries almost came to a freeze and banks were forced to borrow from Central Banks. Nonetheless there is growing empirical evidence that banks that had established long term interbank relationships had better access to liquidity, both before and during the crisis (Furfine, 2001; Cocco et al., 2009; Affinito, 2012; Liedorp et al. 2010, and Brauning and Fecht, 2012). Overall, these studies have shown that banks build stable relationships over time and benefit from more favorable rates when trading with their preferred counterparties. This evidence suggests that, particularly at a time of deteriorating trust towards credit rating agencies, private information acquired through repeated transactions plays an important role in mitigating asymmetric information about a borrower's creditworthiness and can ease liquidity redistribution among banks. The markets analyzed in the above studies have a distinct over-the-counter (OTC) structure (Furfine, 1999, looked at the U.S. interbank market, Cocco et al., 2009, at the Portuguese, Affinito, 2012, at the Italian, Liedorp et al., 2010, at the Dutch, and Brauning and Fecht, 2012, at the German ones). Traders in OTC markets actively search for counterparties. When counterparties meet, they negotiate terms privately, often ignoring prices available from other potential counterparties and with limited knowledge about trades recently negotiated elsewhere in the market. As suggested by Duffie et al. (2005) banks may form relationships in OTC markets to avoid costly counterparty search under asymmetric information about the liquidity shocks of other banks. Brauning and Fecht (2012) for example reports that in the run-up to the 2007-2008 financial crisis relationship lenders charged higher interest rates to their borrowers. The liquidity insurance premium paid for the relationship supports, at this time, the argument of Duffie et al. (2005).

The main goal of our paper is to explore the existence of stable trading relationships, before, during and after the 2007-2008 financial crisis, in an electronic and transparent venue such as the e-MID. The e-MID stands out as the only fully transparent trading system in Europe and the USA, with 'buy' and 'sell' proposals available on screens of the trading platform, along with the identity of the banks quoting them. Information on the terms (prices and amounts) of executed trades are available to banks in real time. Search frictions, thus, should not affect the matching process in the e-MID market. Furthermore lack of information on rates offered by alternative lenders cannot be responsible for the observed cross sectional dispersion of O/N rates in this market. In a perfectly transparent market there is little scope for relationship lending, unless private information, acquired through repeated transactions, is valuable in mitigating asymmetric information about a counterpart creditworthiness. Our objective is thus to disentangle search frictions from information effects as the determinant of relationship lending in the interbank market.

For our analysis we represent the market as a network consisting of nodes (banks) and a time-varying number of, weighted and directed, links between them (representing interbank loans). The direction of the links follow the flow of money (from lenders to borrowers) and the weights are given by the number of loans exchanged by each pair, over a given period of time. Two banks can be connected by two links, one in each direction, if they both act as lenders and borrowers. As a proxy of strength for a pair relationship we use, as detailed in section 4.4, a measure of concentration of lending and borrowing activity. Our main two relationship variables, defined as LPI and BPI for lending and borrowing preference indexes, respectively, are constructed within this network framework. We evaluate if changes in these relationship measures within a given bank-pair, across time, affects spreads and volumes.

Banks can engage in liquidity trades in other OTC market, but these transactions are not observed in the e-MID data set. In this sense, our LPI and BPI are local measures, they capture lending and borrowing relationships within the e-MID market only, and not a global measure, as they do not take into account lending and borrowing transactions happening simultaneously in the OTC market. However, we do not claim that relationships are only built within the e-MID market or that these "cause" spreads or volumes. Feedback effects between relationships and prices are possible, with relationships leading to better prices and more favorable prices reinforcing relationships. This feedback loop makes it difficult to establish the causality of the effect. We find nonetheless weak evidence showing that such feedback effects are small and they may not be the main drivers of our relationship effects. Spreads do not determine survival of a bank pair into the following months once relationship indexes are controlled for, while relationship lending has an effect on spreads (and volumes) that is robust to potential survivorship bias. Previous studies (see Hatzopoulos et al., 2015) have show that, when controlling for banks heterogeneity in trading activity, the matching process in the e-MID market is fairly random. This suggests that links are not preferentially formed with banks that offer lower rates or that are more trustworthy. Rather banks appear to be more likely to selected as trading partners because they trade more often. This points to a causal effect of relationship on prices rather than the other way around. In this paper we do not model the entry and exit decisions of banks and their matching patterns. What we show is that relationships, once formed, possibly at random, persists and are important for explaining spreads and volumes and can play an important role also within a transparent market such as the e-MID.

The identity of the banks trading in the e-MID is unknown to us and replaced by a unique identifier in our dataset. This makes it impossible to match e-MID trading data with balance sheet or other banks' specific data. Other studies (see Angelini et al., 2011) have shown that banks characteristics such as credit ratings, capital ratios, or profitability remained roughly unchanged during the pre-crisis and crisis period. Neither borrower and lender liquidity nor their shortage of capital correlate with e-MID market spreads in Angelini et al. (2011) study. Of course, since credit ratings lost credibility as the crisis unfolded we do not know if banks used rating agencies' scores to inform their choices of counterparty. Neither we know what other private or public information was available to banks. For this reason in our analysis we use a panel data model with fixed-effects at the pair-level. Therefore, unobserved characteristics of pairs, as long as they remain "fixed" for all periods are controlled for by pair-level dummy variables.

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

Our analysis show that trust, reflected both by strong preferential relationships and existence of long maturity exposures, facilitated the trade of large O/N volumes after the crisis and the redistribution of liquidity. Stable relationships were formed in the e-MID market and survived throughout the financial crisis. Relationship lending is associated with better interest rates for both lenders and borrowers, and carries larger volumes. The effect is stronger when the lender is the aggressor, as one would expect given that the lenders are exposed to credit risk. Thus information acquired through repeated interaction is valuable in the e-MID platform and, given the absence of search costs in this venue, points to a peer monitoring role of relationship lending. We also show that the existence of long term maturity trading between banks increases willingness of building relationship and is positively correlated with the amount of a transaction, during and after the crisis, but also positively correlated with spreads after Lehman's default. Overall this picture suggests that a borrower who has long term exposure to a lender benefits from being able to access larger volumes in the O/N market, but pays a premium for O/N transactions after the Lehman's bankruptcy, as the lender can exploit its position of power over the borrower at this time.

The remainder of this article is organized as follows. Section 3.2 covers key notes in literature. Section 2.3 explains how the interbank market operates with specific focus on the e-MID platform. Section 4.4 describes the data and methodology. Section 3.5 presents and discusses regression analysis. Section 3.6 concludes.

2.2 Literature review

One of the first papers studying the relationship driven behavior amongst market participants is Petersen and Rajan (1994) who show that borrowers benefit by maintaining a relationship with a single or small number of banks. Early papers on interbank markets focus on the existence of lending relationships in the US Federal Funds markets (Furfine, 1999, 2001). Furfine (1999) shows that larger institutions tend to have a high number of counterparties and Furfine (2001) finds that banking relationships have important effects on borrowing costs and longer relationship decreases the interest rate in the funds market. Cocco et al. (2009) analyze bank pairs loans using quarterly data from the Portuguese interbank market over the period 1997-2001. This article shows that small banks acting as borrowers are more likely to rely on lending relationship than larger banks. The authors interpret this finding as an indication that small banks try to avoid in this way the cost of peer-monitoring. They also show that both lenders and borrowers achieve more favorable rates when they establish strong relationship with their counterparts. Affinito (2012) uses monthly data from Italy, over 11 years, to analyze interbank customer relationships. His findings are that stable relationships exist and remained strong during the financial crisis. Liedorp et al. (2010) examine bank to bank relationships in the Dutch interbank market to test whether market participants affect each other riskiness through such connections. They show that larger dependence on interbank market increases risk, but banks can reduce their risk by borrowing from stable neighbors. Brauning and Fecht (2012) use Furfine algorithm to identify and extract O/N loans from the German TARGET payment system. They show that lenders anticipated the financial crisis by charging higher interest rates in the run-up to the crisis. By contrast, when the sub-prime crisis kicked in, lenders gave a discount to their close borrowers, thus pointing to a peer monitoring role of relationship lending in the German market.

There is a wide range of studies in the interbank market literature that investigate how the cross sectional dispersion in borrowing rates may relate, in addition to relationship lending, to bank specific characteristics such as their size. Allen and Saunders (1986) and Furfine (2001) show that interest rates and tiering in the US Federal Funds market favor big banks as opposed to smaller ones. Angelini et al. (2011) and Gabrieli (2011, 2012) work with e-MID transactions data to analyze the effect of the latest financial crisis on key determinants of interest rate spreads. The study of Angelini et al. (2011) focuses on maturities from one week to one year and finds that the biggest banks have access to more favorable funding conditions than smaller participants of the interbank market. A different conclusion, for the O/N segment, is found in Gabrieli (2011, 2012) whose findings, for the period following Lehman's bankruptcy, indicate that foreign banks borrowed at higher rates than Italian banks, and that small/medium banks (mostly Italian) benefited from a discount after the Lehman's collapse. While these two papers are similar to ours, in scope and dataset employed, neither of the two has looked at the role of relationship lending as a determinant of cross-sectional spreads.

Another key determinant of O/N rates is the time of a transaction. While Angelini (2000) using hourly e-MID data shows no intraday pattern of interest rates, Baglioni and Monticini (2008) and Gabbi et al. (2012) find a decreasing trend in the O/N rate as the trading day progresses. The intraday slope becomes more pronounced with the financial crisis and, in particular, after the Lehman Brother collapse. The intraday term structure of interest rate is due to the maturity of O/N deposits which are expected to be reimbursed at 9 am of the day following the trade. The increase in the slope of the yield curve after the default of Lehman apparently creates a risk-free profit opportunity. Baglioni and Monticini (2008) suggest that this opportunity is not arbitraged away for two main reasons: uncertainty about availability of liquidity late in the afternoon and an increase in the implicit cost of collaterals.

Hatzopoulos et al. (2015) have investigated the matching mechanism between lenders and borrowers in the e-MID market and its evolution over time. They show that, when controlling for bank heterogeneity, the matching mechanism is fairly random. Specifically, when taking a lender who makes l transactions over a given period of time and a borrower who makes b transaction over the same period, and such that they have m trades in common over that period, Hatzopoulos et al. (2015) show that m is consistent with a random matching hypothesis for almost all lender/borrower pairs. Even though matches that occur more often than those consistent with a random null model (which they call over expressed links) exist and increase in number during the crisis, neither lenders nor borrowers systematically present several over expressed links at the same time. The picture that emerges from their study is that banks are more likely to be chosen as trading partners because they trade more often and not because they are more attractive in some dimension (such as their financial healthiness).

A potential issue when working with e-MID data is that of a selection bias following the drop in the number of trading banks after the collapse of Lehman Brothers. Since the e-MID is a transparent platform, banks may decide not to post any bid on the e-MID market to avoid a reputation effect (i.e. a borrower posting the urgent need for funds). More specifically, it might be the case that after the occurrence of the financial crisis only banks with sound financial conditions would remain trading in the e-MID market, whereas troubled banks would search for alternative ways of obtaining financing in more opaque OTC markets. Other authors, such as Heider, Hoerova, and Holthausen (2015), have suggested that the bias may affect interbank lending in the opposite direction, that is, with the more creditworthy participants leaving the market and the remaining banks facing higher interbank rates due to adverse selection. Empirical evidence does not support the existence of this potential bias in either direction. Angelini et al. (2011) show that banks characteristic such as credit ratings, capital ratios, or profitability remained roughly unchanged during the pre-crisis and crisis periods or improved slightly. Neither borrower and lender liquidity nor their shortage of capital correlated with spreads in their study. They address the potential self-selection problem on longer maturity loans in the e-MID market but conclude that these type of distortions did not influence their empirical findings. More recently, Iori, Kapar and Olmo (2015b) reject an overwhelming presence of survivorship bias in their analysis of the overnight segment of the e-MID market. While they find some effect during the early periods of the financial crisis (where banks that dropped had obtained, in the preceding periods, higher borrowing rates than those banks that remained in the market) they do not find statistically significant differences in funding rates between dropping and surviving banks after the collapse of Lehman Brothers.

2.3 Interbank market and e-MID

Credit institutions have two main alternatives to deal with liquidity shocks and meet their liquidity needs in the short term. The first option is recurring to the Central Bank refinancing operations against posting of collaterals. This channel usually provides banks with the majority of the liquidity they require. In addition credit institutions can access unsecured money market to meet their short-term liquidity needs and to ensure that the trading day is closed with a balanced position. According to a 2007 ECB survey, the overnight segment accounts for about 70% the unsecured money market.

The O/N market is directly affected by the Eurosystem's operational framework, which is enforced by the ECB for the implementation of its monetary policy. The operational framework of the Eurosystem consists of the following set of instruments: open market operations, standing facilities and minimum reserve requirements for credit institutions. With the help of its open market operations, the Eurosystem controls interest rates and manages liquidity in the money market. These include the main refinancing operations, longer-term refinancing operations as well as finetuning and structural operations. Standing facilities aim to provide and absorb O/N liquidity. Two standing facilities, administered in a decentralised way by national Central Banks, are available to eligible counterparties: marginal lending facility and deposit facility. The interest rate on the marginal lending facility normally provides a ceiling for the O/N market interest rate while the interest rate on the deposit facility normally provides a floor. Credit institutions are required to hold minimum reserves over a specific period of time which allows the operational framework to stabilize money market interest rates and create a structural liquidity storage. This period of time in which credit institutions have to comply with the minimum reserve requirements is called the reserve maintenance period, and is usually equivalent to one calendar month.

The largest proportion of unsecured credit transactions takes place OTC and data of the trades can only be inferred from the payment system such as in Furfine (1999). Nonetheless two benchmarks for the money and capital markets in the Euro zone have been introduced. One is the Euro O/N Index Average (Eonia) computed, by the ECB, as the weighted average of all uncollateralized O/N lending transactions in the interbank market in Euros undertaken by a panel of banks, and published, through Thomson Reuters, every day before 7pm CET. The panel of contributing banks currently consists of 35 contributors. The other is Euribor, the rate at which Euro interbank term deposits are offered by one prime bank to another prime bank within the EMU zone. As of 1 June 2013, the Eonia and Euribor respective panels of contributing banks have been differentiated.

The e-MID market represents the only exception to OTC trading in Europe and USA, by providing an electronic platform for interbank deposits. Founded in 1990 for Italian Lira transactions it became denominated in Euros in 1999. The e-MID currently facilitates transactions in multiple currencies including Euro, US

Dollar and GBP. Participation of foreign banks fast increased since the opening of the market and just before the crisis the foreign banks shared, almost equally, the market with the Italian banks. In 2007 there were 246 participants from 16 EU countries: Austria, Belgium, Switzerland, Germany, Denmark, Spain, France, United Kingdom, Greece, Ireland, Italy, Luxembourg, Netherlands, Norway, Poland, and Portugal. According to the ECB the e-MID accounted, before the crisis, for 17% of total turnover in unsecured money market in the Euro area.

The e-MID provides a transparent platform where all parties can monitor in real time the evolution of traded rates. Trades are public in terms of maturity, rate, volume, and time. A credit institution that comes to the market first with a proposal to lend or borrow is called the quoter. Quotes are visible to all market participants on their terminal screens. Banks can choose which quote to accept. A bank that picks a quote and exercise a proposal is called the aggressor. While the identity of the quoting bank is also usually public (the quoter can choose to post a trade anonymously but this option is rarely used) the identity of the aggressor can only be disclosed by a quoter during the negotiation phase. Within a trade, both aggressor and quoter have the right to negotiate volume and rate and the right to reject a trade after knowing the identity of the counterpart.

An important advantage of the e-MID is that interest rates reflect actual transactions, and therefore they are isolated from distortions impacting offered rates, such as Libor and Euribor. Also, the limited number of data points captured by the Eonia makes it unsuitable for studies on relationship lending. On the other side, entry or exit of banks from the e-MID platform is driven by endogenous decisions and may lead to a self selection bias (see Gabbi et al., 2012, for a recent analysis of this point). For this reason we limit the analysis to the banks that traded actively on the electronic platform in the period under study.

2.4 Data and econometric modelling

2.4.1 Data

The dataset used for this paper includes tick-by-tick data of the e-MID from 5 June 2006 to 7 December 2009. Our time structure consists of maintenance periods, usually four weeks. These periods correspond to a specific component of a regulatory framework where ECB mandates a bank to maintain a certain amount of its short term liabilities on its central bank account. We have 42 maintenance periods.[1] We also consider three sub-samples according to the evolution of the financial crisis:

Period	Description	Key date	Maintenance periods
5-Jun-06 - 7-Aug-07	Before Crisis	Two Bear Stearns' hedge fund bankruptcy (31-Jul-07)	14
8-Aug-07 - 7-Oct-08	During Crisis	Lehman Brother's collapse (15-Sep-08)	14
8-Oct-08 - 7-Dec-09	After Crisis	-	14

We have detailed information about each transaction; time, trading volume, maturity, interest rate, the side of the transaction (buy/sell) and the code (but not the identity) of the banks acting as quoter and aggressor, country of origin and size of both parties (for the Italian banks only). The interest rate is expressed as annual rate and the volume of the transaction is provided in millions of Euros. The e-MID market includes contracts with maturities varying from one day to one year. We restrict our analysis to O/N and O/N long[2], which consists of more than 90% of all e-MID transactions as the interbank market is mainly a market for short-term

[1]Besides the mandate to meet reserve requirements, banks are also required to avoid negative balance on any day. Therefore the market activity increases towards the last days of the reserve maintenance period with noticeable rise in the number of transactions, bank pairs and volatility of the interest rates. As a consequence, the interbank market is mostly dominated by reserve management activities of banks (Gaspar et al., 2008; Cassola et al., 2010).

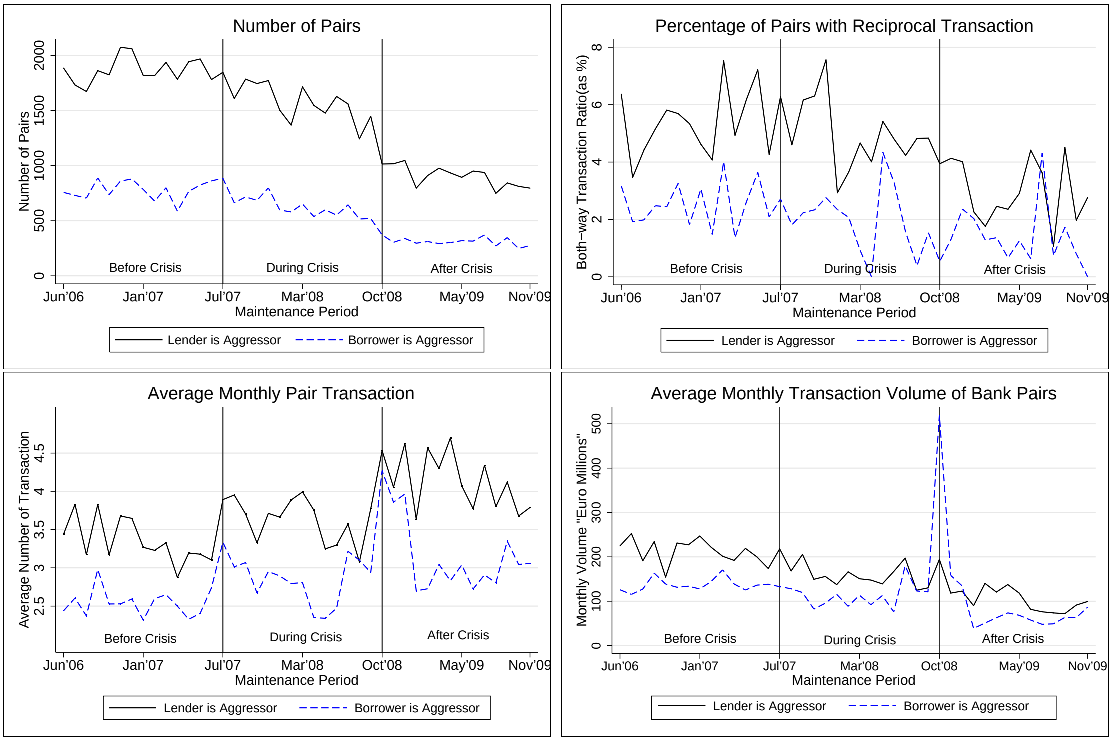
[2]This refers to contracts when there is more than one day between two consecutive business days.

trades. If loans with longer maturities were included in the dataset, it would be difficult to derive a representative interest rate for the market as longer term loans tend to be infrequent.

In our study, we restrict our analysis to banks that actively participate in the interbank O/N market for all periods before, during and after the financial crisis of 2008. This is done for avoiding potential selection bias in our analysis, although at the price that our results are only valid conditional on active participation. With this approach we aim to exclude banks that leave the market for any reason, as well as banks that enter the market within the same period. Then we only consider banks that have at least one transaction in each sub-period (i.e. before, during and after crisis). As a result of this data trimming for entering and exiting banks, the number of banks during the period analyzed decreases from 200 to 140.

Our unit of analysis is not the individual bank but a pair of banks, that is, lender and borrower. We consider pairs when lender and borrower have more than one transaction in a given period. Finally, we construct two subsamples of bank pairs depending on the nature of the e-MID transaction. These are when lender is aggressor (LiA) and when borrower is aggressor (BiA). As shown in figure 2.1, the number of bank pairs in a month range from 1000 to 2000 when lender is aggressor, but the number decreases to a range between 400 and 1000 when borrower is aggressor. The same pattern (approx. 1:2.5) is also observed for the number of transactions. This is expected because borrowers are those in need of funds, hence their quotes dominate the market activity on most days. Although there is a remarkable decrease in the number of pairs after Lehman's bankruptcy, the average number of transaction for pairs increased for active pairs where lenders participate as aggressors. Average volume for each transaction of pair decreases from June 2006 through to December 2009 with a sharp fall in the last quarter of 2008.

Figure 2.1: Descriptive analysis for bank pairs



2.4.2 Variable definitions

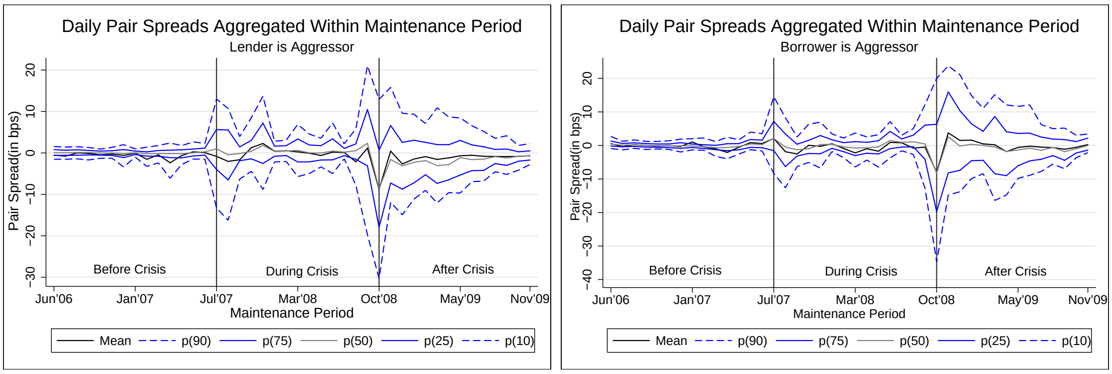
2.4.2.1 Interbank rate spread and trading volume

In this study we calculate the monthly volume weighted average rate for each bank pair considering the reserve maintenance period announced by ECB. Consider banks i and j. The spread for each ij pair of banks for period t is calculated as

$$S_{ij,t} = \frac{1}{\sum_{n=1}^{N_{ij,t}} V_{ij,n}} \sum_{n=1}^{N_{ij,t}} (r_{ij,n} - \bar{r}_m^d) \times V_{ij,n}, \tag{2.1}$$

where $r_{ij,n}$ and $V_{ij,n}$ are the transaction level interest rate and volume, respectively, of transaction n for pair ij, $i \neq j$, $N_{ij,t}$ is the number of transactions for the bank pair ij at maintenance period t, and $\bar{r}_m^d$ is the daily volume weighted average rate over all transactions carried out by the bank pairs in a given day the transaction n

Figure 2.2: Daily O/N spread aggregated within maintenance periods



corresponds to, which is calculated as

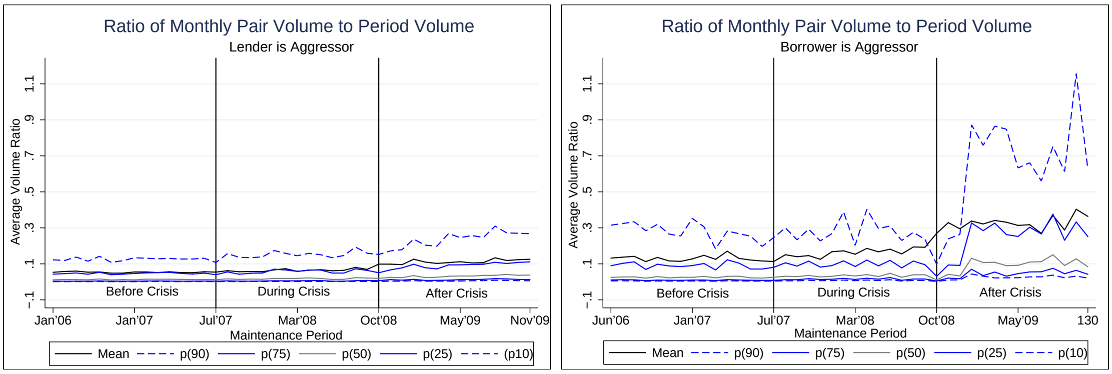
$$\bar{r}_m^d = \frac{\sum_{j=1}\sum_{i=1}\sum_{n=1}^{N_{ij,d}} r_{ij,n} \times V_{ij,n}}{\sum_{j=1}\sum_{i=1}\sum_{n=1}^{N_{ij,d}} V_{ij,n}}, \tag{2.2}$$

where $N_{ij,d}$ is the number of transactions for the bank pair ij at day d.

As shown in figure 2.2, the variation in the spread increases during crisis and has its peak when Lehman Brothers collapsed. Being a quoter is more beneficial for both lender and borrowers. We also run t-tests to compare the mean spread for both datasets, for each sub-period and for all pooled periods, and the results show significant differences for aggressors and quoters. We believe that the reason is that the quoter bank is the one which defines the volume/amount and interest rate of transactions in the first place, and therefore, they have more power than the aggressor in determining the interbank rate, although both parties have a right to negotiate.

We also investigate the determinants of trading volume, which is a key determinant of liquidity in the interbank market. In order to make total trading volume of transactions for a given pair comparable across periods, we divide aggregated pair volume within a period by total transaction volume in that period. This variable is defined as VN (for volume-normalized) and allows us to capture the importance of

Figure 2.3: Aggregated trading volume-normalized within maintenance periods



bank pair for flow of funds in the interbank market. This is calculated as

$$VN_{ij,t} = \frac{\sum_{n=1}^{N_{ij,t}} V_{ij,n}}{\sum_{h=1} \sum_{k=1} \sum_{n=1}^{N_{hk,t}} V_{hk,n}}. \tag{2.3}$$

Figure 2.3 presents average and percentiles of monthly transaction normalized volume for both datasets. There are three interesting facts to highlight. First, there is an increasing trend in both datasets. Second, the variation in volume-normalized increases after the 2008 financial turmoil. Third, the average market share of pair is higher when lender is quoter. The reason behind this might be that borrowers are reluctant to quote a loan in the market in high volumes as there is a potential reputation and credit risk effects.

2.4.2.2 Lending relationship variables

With the 2007 crisis, banks struggled to re-built a trust environment within the interbank market. Our hypothesis is that, while banks were able to screen their potential counterparts on the e-MID system, they were reluctant to have an extra cost for intelligence on each peer's credit profile. In such environment of uncertainty, with increased level of concern on the validity of opinions from credit rating agencies, we explore if participants of the e-MID interbank market moved into a relationship driven funding approach. This behavior would allow each participant to better understand each other's credit risk profile with closer relationships.

Our proxies for interbank relationships are given in terms of concentration of lending and borrowing activity. Unlike Furfine (2001) who defines pair relationship in terms of number of days that the bank pair has transactions, but similar to Cocco et al. (2009), Affinito (2012) and Brauning and Fecht (2012), we use lender and borrower preference indexes as relationship measures. We introduce a new versions of preference indexes and use the number of transactions, rather then the volume, as a measure of the strength of a relationship. Our choice is motivated by the fact that banks are heteregeneous. We do not want to bias the results toward the large banks that trade more volumes with each other simply because they are bigger. Moreover, our main interest is in estimating if building a relationship with a counterpart is important in the interbank market because of its information content. Our working hypothesis is that information flows with a transaction, regardless of the amount or volume of each transaction[3].

We compute the lender preference index ($\mathrm{LPI}_{ij,t}$) as the ratio between the *number* of loans that i lends to j for a given period t and average *number* of lending transactions of lender i. We define the average number of lending transactions as the ratio between the number of loans that bank i lends to any bank in the interbank market and the outdegree of lender i, defined as the number of counterparties (i.e. banks) to which a bank lends in the interbank market. Therefore lender preference index is computed as:

[3]The literature has used both types of weights to measure the strength of a relationship. Volume, or "money flow", is generally used when the focus is on measuring market liquidity, or the potential for interbank contagion. Number of transactions, or "information flow" is used when the focus is on understanding the network formation mechanism such as in Hatzopoulos et al. (2015) and Iori et al. (2015a).

$$LPI_{ij,t} = \frac{\sum_{n=1}^{N_t} y_n^{i \to j}}{\sum_{n=1}^{N_t} y_n^{i \to any} / outdegree_{i,t}}, \tag{2.4}$$

where $n = 1, 2, ..., N_t$ refers to all loans in the market at time t, $y_n^{i \to j}$ is an indicator for each loan n that bank i lends to bank j, $y_n^{i \to any}$ is an indicator for each loan n that bank i lends to any bank, and $outdegree_{i,t}$ is the outdegree of lender i at time t.

Similarly we define the borrower preference index (BPI$_{ij,t}$) as the ratio of the number of transactions that bank j borrows from bank i to the average number of borrowing transactions of borrower j:

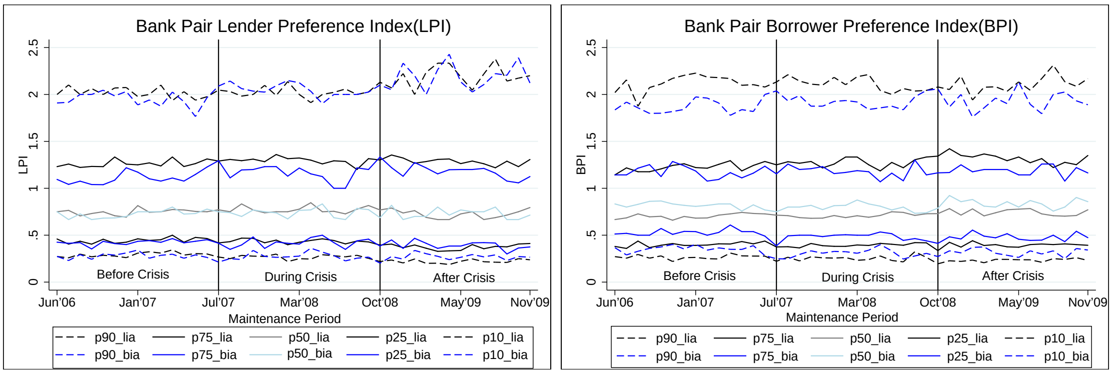
$$BPI_{ij,t} = \frac{\sum_{n=1}^{N_t} y_n^{i \to j}}{\sum_{n=1}^{N_t} y_n^{any \to j} / indegree_{j,t}}, \tag{2.5}$$

where $y_n^{any \to j}$ is an indicator for each loan n that any bank lends to bank j, and $indegree_{j,t}$ is the indegree of borrower j at time t, defined as the number of banks from which a borrower take loans.

Since the denominator of LPI (BPI) is the average number of lending (borrowing) transactions, when LPI (BPI) is 1, it means that the number of transactions with the borrower j (lender i) equals to the average number of lending (borrowing) transactions, and therefore the preference of lender (borrower) for that borrower (lender) is neutral. If $LPI > 1$ ($BPI > 1$), then the lender i (borrower j) prefers trading with bank j (i) more compared with the rest of the market. The opposite occurs when $LPI < 1$ ($BPI < 1$).

We estimate LPI and BPI for each month (i.e. maintenance period), $t = 1, 2, ..., T$. We also calculate the average of the last four months of the relationship measures in order to distinguish short and long term relationship measures. Both lending preference index and borrowing preference index are calculated using

Figure 2.4: Bank pairs preference indexes



only the aggressor dataset in order to find out the effect of counter-party selection as an aggressor. To have enhanced precision for the effect of the preference index, only the pairs where both lender and borrower have more than one transaction are included in the empirical study.

Figure 2.4 plots percentiles of monthly time series of preference index of market for our two subsamples, that is, LiA and BiA. Based on our calculation of preference indexes, the value of 1 reflects that the bank is neutral to the counterparty, therefore the trend in higher percentiles shows us the importance of change in establishing relationship over time. There is a slight increase in trend for upper percentiles of preference indexes. Banks rely more on lending relationship after Lehman's collapse in September 2008. This can be attributed to deteriorated level of trust in market perception of credit profiles (mostly through credit rating agencies) and bank's tendency to work with preferred peers becoming a pattern.

2.4.2.3 Other control variables

We also control for a set of pair- and bank-specific variables that affect interest rate spread and volume. Transaction concentration (Transaction Ratio in %) measures the ratio of the number of transactions between each pair to all transactions taken place in the same period within the market. Similar to Baglioni and Monticini (2008), we also examine the effect of the time interval of the transaction performed. Instead of dividing the day into hourly segments, we use only two slots: morning (8 am - 1 pm) and afternoon (1 pm - 6 pm). Morning-Afternoon (AM/PM Ratio) is the fraction of the difference between number of transactions that occur during morning and afternoon to all transaction of each pair at a given period. In the interbank market, participants must repay the loans at 9 am on the next trading day of transaction. Hence, morning interest rates have a premium to account for the longer maturity period than those transactions in the afternoon.

Since we work with bank pairs, it is important to explore inverse relationships between them. In order to capture the effect of bilateral relations on the interbank rate, we introduce a variable (Reciprocity Ratio) which is defined as the number of counter-way transactions divided by the number of transaction of a pair at a given period. We expect a negative effect on spreads for this variable since a lending bank would charge less interest rate to its counter-party from which it also borrows.

Besides activity, timing and pair related variables, we also examine two indicators that represent the sizes of lender and borrower as defined by e-MID based on total assets of each institution. Size is a widely referred item in the literature and it has been identified as an important variable in the financial crisis. However empirical analysis regarding the effect of bank size also contradict with each other in terms of the way it affects the rates (Furfine, 2001; Angelini et al., 2011; Gabrieli, 2011, 2012). Therefore we believe it is important to include size of both borrowing and lending banks in order to identify the effect on the e-MID rate of bank pairs.

The identity of the lender and borrower is not known, and therefore we cannot observe the bank's size. We are only able to observe a categorical variable with categories: Foreign, Major, Big, Medium, Small and Minor. Since we use fixed-effects panel model at the level of bank pairs for our estimations, we need a proxy for the size information that we have in tick-by-tick data. Our initial analysis on the e-MID data confirms that larger banks make transactions with larger volumes. Therefore, *total amount* is used as a proxy for size in section 2.5.2 where we present estimation results for determinants of preference indexes. We also construct an index taking value of 5 for Foreign or Major (all foreign banks in the Italian market are large compared to national ones), and in descending order to 1 for Minor. A high number of the index thus reflects a large size.

In order to measure the effect of long-term maturity relationship on the spread for overnight rates, we use a variable (LT Maturity) which reflects the number of transactions with longer term maturity for a given pair at a given time. The percentages of the observations with deals for longer terms maturities is similar for both datasets. The existence of loans with LT maturity are 7% and 10% of the observations when lender is aggressor and when lender is quoter, respectively.

We also introduce two new variables to examine the volume ratio of inverse transactions. The variable for Lender (Lender's B/L Ratio) of a pair is measured as the borrowing amount of the bank from any other bank divided by its lending amount to any other bank at a given period. Same ratio is also included for borrowing bank (Borrower's L/B Ratio).[4]

Since our dataset is separated for lenders only as aggressors and borrowers only as aggressors, all variables used in the analysis are calculated within each group. Table 2.1 and 2.2 provide summary statics of all variables and number of banks in each subsample used in the empirical analysis. A detailed description of the variables appear in the Appendix.

[4]For lender: Assuming bank A is the lender of a pair, this variable is the bank A's borrowing amount from any other bank divided by its lending amount to any other bank at a given period. For borrower: Assuming bank B is the borrower of a pair, this variable is the bank B's lending amount to any other bank divided by its borrowing amount from any other bank at a given period

2.4.3 Econometric modeling

We estimate a set of regression models to shed light on the impact of the preference relationship index variables defined in the previous section on the existence of a bank pair in the following months (i.e. survival), the interbank rate spread and volume. All analyses are done conditional on bank pair ij fixed-effects, and therefore, the effect of the variables should be interpreted as conditional on the existence of that particular link $i \rightarrow j$ (bank i lends to j). Let t index time for which we also construct time-specific fixed-effects. In all models we compute robust standard errors with clusters at the bank pair level. Since we want to explore for differences across the phases of the latest financial crisis, we run the models for four time spans: all pooled periods and before, during, and after crisis.

We evaluate first the suitability of the proposed preference indexes to measure the stability of bank relationships. Our unit of analysis is the bank pair relationship, which is only observed if there was any trade between the banks in the pair. We thus explore the hypothesis that having stronger relationship with a counterparty, as measured by LPI and BPI, increase the probability of having transactions with the same counterparty in the next month. The dependent variable survival is a binary variable, $Survival_{ij,t}$, which takes the value of 1 if trade happens between pair ij in t and 0 if the pair is not active in t. We thus run a logit model of $Survival_{ij,t+1}$ on a set of covariates of interest evaluated at t, $[S_{ij,t}, LPI_{ij,t}, BPI_{ij,t}]$, and dummy variables for bank-pairs and time periods. Bank-pair dummies (i.e. fixed-effects by pair) are intendend to capture unobserved characteristics of the pair that determine their probability of being active in any particular month. Time dummies capture changes in market conditions over time. We also use $Survival_{ij,t+1} \times Survival_{ij,t+2}$ and $Survival_{ij,t+1} \times Survival_{ij,t+2} \times Survival_{ij,t+3}$ as alternative dependent variables in the logit model in order to explore the effect of having relationships on the probability of occurring trade for the same pair the following two consecutive months and following three consecutive months, respectively.

We then consider a fixed-effects model in order to investigate what causes lending relationship and how the effect of these changes over the three subperiods of analysis:

$$LPI_{ij,t}(orBPI_{ij,t}) = \beta_0 + \beta_1 A_{ij,t} + \beta_2 B_{i,t} + \beta_3 C_{j,t} + u^{(1)}_{ij,t},\ u^{(1)}_{ij,t} = \mu^{(1)}_{ij} + \delta^{(1)}_t + e^{(1)}_{ij,t}, \tag{2.6}$$

where A, B and C represent pair, lender and borrower specific variables, respectively, and $u^{(1)}_{ij,t}$ is the residual term with bank-pair ($\mu^{(1)}_{ij}$) and time-specific effects ($\delta^{(1)}_t$), and $e^{(1)}_{ij,t}$ corresponds to uncorrelated shocks. The bank-pair effects captures banks unobserved characteristics such as ownership and long-term pair relationships. The time fixed-effects captures the evolution of the market across time and common shocks that affect all banks.

The most important analysis in this paper correspond to the questions:

1. What is the effect of relationship on pricing?
2. What is the effect of relationship on volume? We therefore construct the following models.

Regarding the first question we consider the following panel data fixed-effects model of the interbank spread:

$$S_{ij,t} = \gamma_0 + \gamma_1 LPI_{ij,t} + \gamma_2 BPI_{ij,t} + \gamma_3 A_{ij,t} + \gamma_4 B_{i,t} + \gamma_5 C_{j,t} + u^{(2)}_{ij,t},\ u^{(2)}_{ij,t} = \mu^{(2)}_{ij} + \delta^{(2)}_t + e^{(2)}_{ij,t}. \tag{2.7}$$

Regarding the second question we use the following panel data fixed-effects model of volume normalized:

$$VN_{ij,t} = \eta_0 + \eta_1 LPI_{ij,t} + \eta_2 BPI_{ij,t} + \eta_3 A_{ij,t} + \eta_4 B_{i,t} + \eta_5 C_{j,t} + u^{(3)}_{ij,t},\ u^{(3)}_{ij,t} = \mu^{(3)}_{ij} + \delta^{(3)}_t + e^{(3)}_{ij,t}. \tag{2.8}$$

Here A, B and C also represent pair, lender and borrower specific variables, respectively, u corresponds to unobserved determinants of spreads and volumes, with the corresponding bank-pair- (μ), time-specific (δ) and shocks (e).

2.5 Results

2.5.1 Stability of relationship

We first study the suitability of the preference indexes described above to predict a bank pair survival. Tables 2.3 and 2.4 present the survival analysis for the subsamples of lender is agressor (LiA) and borrower is agressor (BiA), respectively, using logit models. Each table reports the marginal effect of selected variables on the probability of a pair being active the next month, next two months and next three months, and for the all/before/during/after crisis time intervals separately.

The results show that the interbank spread is in general not statistically significant or have a small effect on the probability of survival for the three time spans considered and for both subsamples. On the other hand, the preference indexes, LPI and BPI, are statistically significant to explain the likelihood of the pair being active in the following months. The effects of both LPI and BPI are positive meaning that the preference index captures features that are correlated with the stability of the relationship. Moreover, the effects decrease in magnitude with respect to the number of consecutive months that we evaluate the survival of the pair. Both tables show that the preference indexes have a larger effect on the subsample of pairs that are active in all time intervals, again showing that LPI and BPI capture inherent characteristics of a pair that correspond to stability. The effect of LPI is the largest after the financial crisis for LiA subsample, while BPI has the largest effect during the crisis (for one and two months survival only). Similar results, although weaker in terms of statistical significance and magnitude, are observed in Table 2.4 for the BiA subsample.

2.5.2 Lending relationship

After studying the stability of relationships, we next study banks' characteristics that are correlated with the preference indexes. Table 2.5 and 2.6 estimate the determinants of lending relationships LPI and BPI for LiA and BiA subsamples, respectively, using least-squares pairwise FE estimates. For the former subsample, a higher number of transactions between two banks lead to higher preference indexes, although this effect decreases over time and has the smallest effect after Lehman's collapse. This might be an indicator for the banks' tendency to concentrate lending (borrowing) activities on less risky borrowers (lenders) as a result of market shocks. For the latter subsample, however, there is a significant effect of Transaction Ratio only for the during crisis time interval. Thus LPI and BPI capture the pair's specificity when lender is aggressor, but there is no clear association when borrower is.

Controlling all other variables, bank size becomes more important over time to establish relationship in the LiA subsample. In line with Cocco et al. (2009), our results show that smaller banks tend to establish and build relationships with large counterparties. Since the bank's strategies are different for the two subsamples, we observe significant differences. When lender is aggressor, smaller banks try to strengthen existing funding channels and create new ones with other banks in order to benefit from more favorable rates, especially during and after crisis. When the borrower is aggressor we do not observe the effect of size as strong as when lender is aggressor. Lender's size has significant effect on LPI only after crisis, however there is no effect of borrower's size on BPI. Although bank's own bilateral transaction and counterparty's bilateral transaction ratio has positive and negative effect respectively for both datasets, the magnitude is almost zero for all scenarios, therefore borrowing/lending ratio does not have any effect on preference indexes.

When the borrower is aggressor (BiA subsample), loans with long term maturity in the same month increases its willingness of building closer relationship after the crisis. However, when the lender is aggressor, loans with long term maturity have no clear effect on LPI and BPI. This suggest that lenders have no incentive to be be exposed to the same borrowers both at short and long maturity, while borrowers interpret the willingness of a lender to provide long term funding as an indication they are trusted counterparties and thus are encouraged to establish stable relationships on the O/N market. To the best of our knowledge, no paper has yet exploited the multilayer structure of the interbank network and investigated whether the co-existence of the different maturity layers strengthen the role of relationship lending or if the two layers are independent from one another (see Boccaletti et al. (2014) for a recent review on multilayer networks).

2.5.3 Interest rate spread

We now study the main subject of our paper, that is, the effect of preference indexes on interest rates. This analysis answers the question: 'Do banks' preferences for trade partners have an effect on interest rates?' If lending relationship builds trust among banks, then lenders and borrowers in a pair with high values of the relationship measure indexes should get a better rate compared with pairs with low index values. Tables 2.7 and 2.8 show least-squares pairwise FE estimates for the determinants of interest rate spreads and how lending relationship affects the market before/during/after crisis, for the LiA and BiA subsamples, respectively.

When lender is aggressor (LiA subsample), we come up with several important results regarding the effect of preference indexes on interest rate spread. Our estimates suggest that both borrowing and lending banks benefit from having relationship with other participants in the market. LPI has a positive effect on spread while BPI has a negative effect. Therefore, while borrowers have a discount on interest rates, lenders have more favorable rates when there is a high preference for a counterparty.

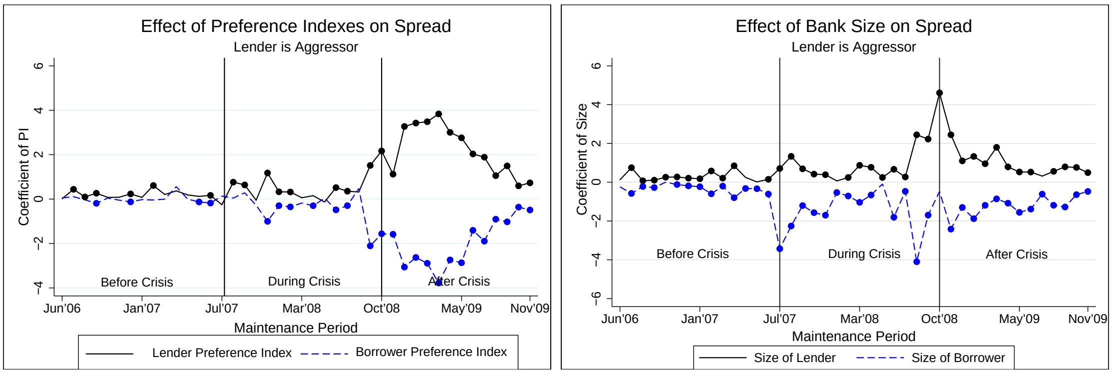
This result suggests that when a borrower is exposed predominantly to one lender, the lender can observe the behaviour of the borrower on most of its borrowing transactions and better assess its credit worthiness. Nonetheless, the borrower, by concentrating all its trading with a single lender, exposes itself to funding risk, in case its preferential lender decides to hoard liquidity and stop rolling over credit in the future. The lender thus is willing to offer a discount to compensate the borrower for taking funding risk, as a price to improve its monitoring opportunity. On the other side, when a lender concentrates its lending activity with a single borrower, it exposes itself to counterparty risk by not diversifying its loan portfolio. The lender can monitor the reliability of the borrower only on their pairwise transactions but cannot observe the behaviour of the borrower when trading with other counterparties. The lender in this case does not fully benefit from an informational advantage on the quality of the borrower. The borrower on its side benefits from the preferential relationship as it represents a stable source of funding. The borrower thus is willing to pay a premium, to compensate the lender for non diversification risk, as a price for preferential access to liquidity.

Our results are consistent with Cocco et al. (2009) who examined the impact of preference indexes as a determinant of interest rate spread in the Portuguese interbank market. Moreover, the effect of the former is the largest during the financial crisis and the effect of the latter is the largest after the crisis (in line with Affinito (2012) and Brauning and Fecht (2012)). A similar pattern is observed if we replace monthly-based LPI and BPI with four months averages, thus reflecting that the monthly based preference indexes capture a longer term relationship. In contrast to results in the German interbank market by Brauning and Fecht (2012), we observe that borrowers do not pay any premium for relationship during crisis (in fact the opposite). This can be attributed to the OTC structure of the German interbank market, in contrast with the transparent e-MID platform.

When borrower is aggressor (BiA subsample), only LPI is statistically significant, and it is not significant before the crisis. In this case, if borrowers choose lenders for which they are a preferential relationship they pay a premium while they do not seem to have any advantage (or disadvantage) from trading with their own preferential counter parties. These results may arise because, when lenders quote, borrowers decision to accept a trade may be driven by prices rather than by existing relationships. Also, as shown by Gabbi et al. (2012), when borrowers act as aggressor they pay higher rates because of the bid-ask spread. Possibly any advantage from trading with preferential counter parties is diluted by this.

We also run the same specification, separately, for each individual month in order to illustrate the evolution of the effects of lending relationship measures and size of lender and borrower. As discussed above, the identity of the borrower is not known, and therefore we cannot observe the bank's size. We are only able to observe a categorical variable with categories: Foreign, Major, Big, Medium, Small and Minor. We then construct an index taking value of 5 for Foreign or Major (all

Figure 2.5: LiA - Effect of preference indexes and banks size on O/N spread

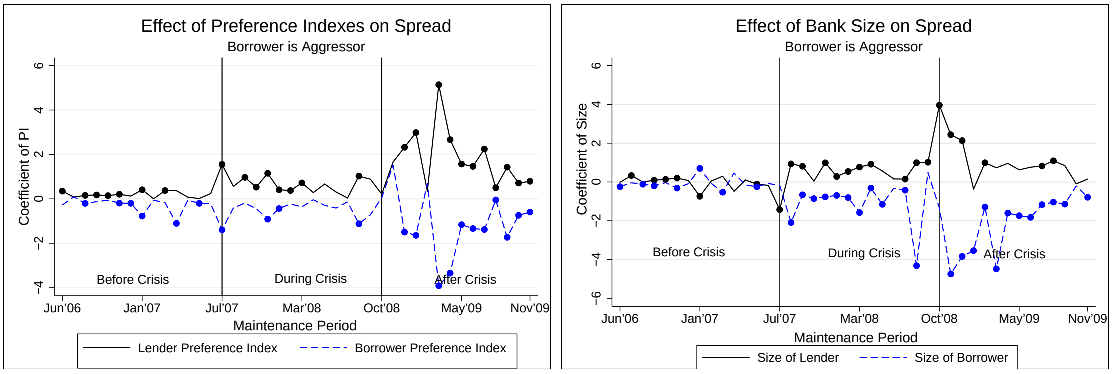


Note: Bold data points coefficients significant at 10%.

foreign banks in the e-MID market are large compared to the average Italian bank), and in descending order to 1 for Minor. A high number of the index thus reflects a large size. We also run the fixed effects specification when both LPI and BPI are interacted with both size of lender and size of borrower.

Figure 2.5 shows changes in the effect of preference indexes and size on interbank rate spread over time, controlling for all other variables, and for the LiA subsample. While the effect of LPI is positive, BPI is mostly negatively correlated with spread. There is an increased movement in the effect of lending relationships that starts early in 2007 and accelerates with the Lehman's bankruptcy. The trend changes in the Spring 2009 suggesting the ECB injection of liquidity starts easing the liquidity crisis. The effect of these variable is further reduced in June 2009 after the ECB injected almost 450 billion euro with a 1-year longer term refinancing operation and goes back to pre-Lehman level at the end of 2009. Thus, the effects of LPI and BPI described above are significant only in times of financial distress, when liquidity and credit risk becomes an issue for concern even at the shortest exposures. In this sense the evolution of the regression coefficients of these variables can provide an early warning signal of an impending financial crisis and can be used to monitor the impact of regulatory measures.

Figure 2.6: BiA - Effect of preference indexes and banks size on O/N spread



Note: Bold data points coefficients significant at 10%.

Similarly, the sizes of lender and borrower show a significant differentiation during and after the crisis. In particular, the size of lender becomes markedly positive during and after the crisis, while the size of the borrower becomes negative for the same time intervals. The fact that size has a marked effect during and after the crisis has a different interpretation for lenders and borrowers. For lenders, the positive effect tells a story of market power that favors lenders. For the borrower, it suggests that lenders choose big borrowers because they have lower risk. This could be a real reduction of risk associated with big banks or the results of the "too big too fail" assumption.

When borrower is aggressor (see figure 2.6), the effect of LPI and BPI on spreads goes in the same direction as in the LiA subsample, but the curves are more noisy (no clear pattern can be extracted from the figure), while size follows the same results of the previous figure, that is, big lenders obtain higher and big borrowers lower interest rates. In this case, the effect of size is larger for the borrower than in the LiA subsample, pointing out that big borrowers may have more flexibility to choose a better deal.

Tables 2.9 and 2.10 report coefficients of the preference indexes effect on spread, when interacted with size of the lender and borrower (using the categories Foreign, Major, Big, Medium, Small and Minor as above), for LiA and BiA subsamples, respectively. For LiA, the interactions suggest, with different degrees of statistical significance, that preference indexes have an effect for Medium and Small borrower banks that trade with Big to Small lender banks. For BiA, there is no clear statistical pattern that emerges.

Turning to the other control variables in the model, the transaction concentration for a given pair is significant in explaining interest rate spreads when lender is aggressor but it has no significant effect when borrower is aggressor. The AM/PM ratio for the time of transactions is a key determinant of a pair spread at all times before, during and after crisis, both when lenders or borrowers are aggressors. Moreover, this effect has the highest effect during the crisis for LiA, and after the crisis for BiA. The reason behind this result is that banks in need of urgent liquidity, make the deal in the morning to avoid the risk of not finding an offer in the afternoon, and for that borrowers are willing to pay a premium. Reciprocity ratio is only significant for the LiA during the crisis. We can conjecture that banks who have built a reciprocal relationship of lending and borrowing reduce the interest rate at which they trade in times of financial distress. Finally, number of loans with long term maturity has an effect only for lenders being the aggressors, with marked increasing trend over the time of analysis, suggesting that lenders require a premium for accepting both long term and short term exposure from the same borrower.

2.5.4 Trading volume

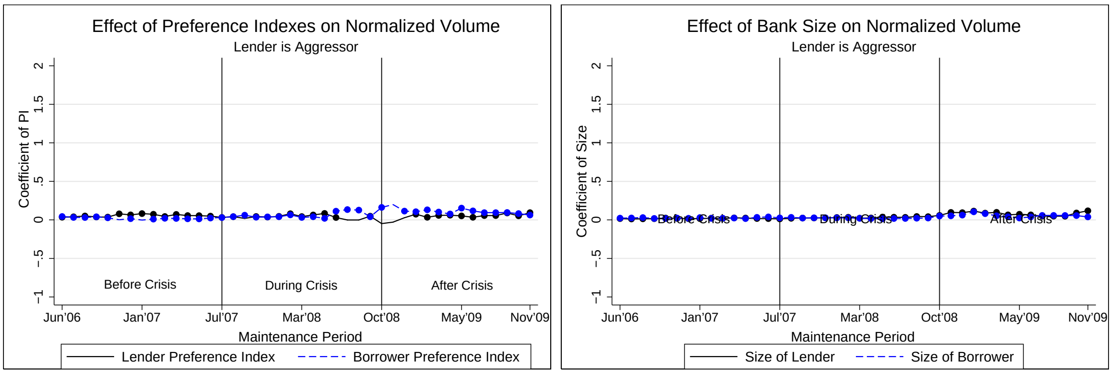
The volume of trade is an important variable because liquidity plays a central role in financial crisis. This analysis answers the question 'Do banks' preferences for trade partners have an effect on volume traded?' Tables 2.11 and 2.12 present least squares pairwise FE results for the determinants of VN (volume ratio traded by the pair to volume traded in the market) for the LiA and BiA subsamples, respectively.

LPI has a positive and significant effect on the volume ratio traded by the pair for both subsamples. BPI has a significant effect for the LiA subsample, however for the BiA subsample it is significant only in the after crisis interval. The sign is positive in all cases. Because all the analysis is conditional on the pairs' characteristics (i.e. fixed effects), this reflects that for a given pair, volume increases the more preferential relationship has been built between lender and borrower. In particular, it is the lender to whom relationship matters the most as it faces the risk of loan default.

In a similar fashion to the spread analysis, we run the same specification for each month, separately, in order to illustrate the evolution of the effects of lending relationship measures and size of lender and borrower on volume (figures 2.7 and 2.8). The effect of LPI and BPI on volume, while positive and significant, is very small in the LiA subsample. In the BiA subsample the positive role of LPI is more evident from the summer of 2007, while BPI become positive and significant only in the few months preceding the Lehman bankruptcy. The effect of relationship lending on volume decreases (but it is still positive and significant for both variables) after October 2008, when the ECB decided to carry out their weekly main refinancing operations through a fixed rate-full allotment procedures, to reduce the corridor of its standing facilities from 200 basis points to 100 basis points, to expand the list of assets eligible for collateral and to enhance the provision of liquidity through longer term refinancing operations.

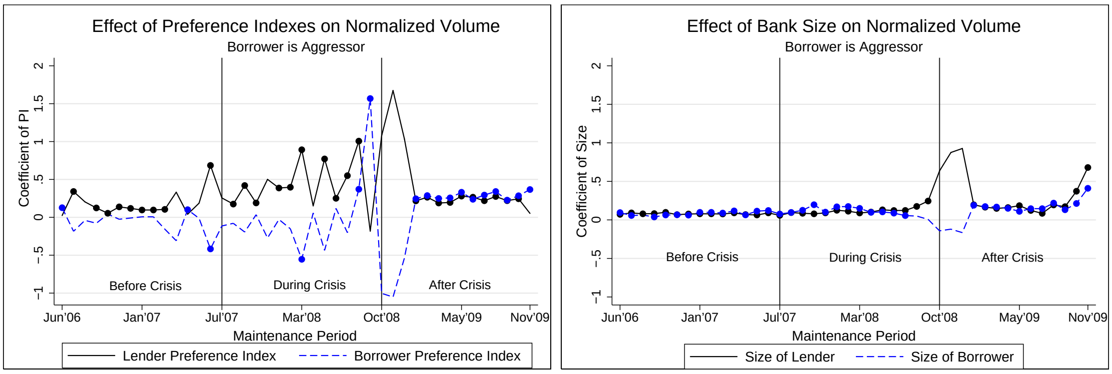
When lender is aggressor, as expected, AM/PM ratio can explain the variation in volume ratio for all time spans. The reason behind this result might be that the banks, which need liquidity urgently, make the deal in the morning since there is a chance of not finding an offer in the afternoon. However, the variable is significant

Figure 2.7: LiA - Effect of preference indexes and banks size on trading volume



Note: Bold data points coefficients significant at 10%.

Figure 2.8: BiA - Effect of preference indexes and banks size on trading volume



Note: Bold data points coefficients significant at 10%.

only after crisis for the second dataset. When lender is aggressor, lender's higher borrowing/lending ratio leads lower value of volume ratio after crisis, however there is no effect before and during crisis. We also find that having a deal in longer term maturities have negative, positive, and positive relations with the volume of ON transaction before, during and after crisis, respectively. The change in sign of this variable suggest that, during and after the crisis, trust, as reflected in this case by the existence of long term maturity trading, facilitated access to ON liquidity, even though at a premium, as seen in the previous sub-section.

2.5.5 Robustness analysis

2.5.5.1 Attrition bias

As noted by an anonymous referee, one potential concern is that of attrition bias. Figure 2.1 shows that the number of pairs fluctuates over time and thus, the effect of LPI and BPI might be biased if these are correlated with bank-pairs unobservable factors, which in turn determine the pair appearance in a given month. Moreover, the survival analysis above shows that both LPI and BPI affects the probability of survival into the following periods. In order to address this concern we run a Heckman selection-type model to the regression models for interbank spread and trading volume.

The model is implemented as follows. First, note that if a pair is not observed at a given period t, we cannot observe the pair's spread (or trading volume) and any other covariates at t, and there is no guarantee this particular pair has been observed at $t-1$. For this reason we use $Survival_{ij,t+1}$, that is, survival into the next period, as a proxy of the probability of appearance of a given pair ij at t. The key assumption is that the probability of appearance of a particular pair in t is related to the probability of appearance at $t+1$. Second, we then run a probit model where

$Survival_{ij,t+1}$ is used as dependent variable and we use all covariates considered for equations (2.7) and (2.8), respectively. That is, we model selection bias using bank-pair survival into the next month using the same covariates used in both the spread and trading volume specifications, including bank-pairs and time dummies. This corresponds to the first-step (i.e. selection equation) in a Heckman selection model. From the probit model we get $Pr(\widehat{Survival}_{ij,t+1}) \equiv \Phi(z_{ij,t})$, where $\Phi(.)$ is the normal cumulative distribution function and $z_{ij,t}$ is the implied realization of a normal random variable. Then define $\phi(z_{ij,t})$ as the normal density function evaluated at $z_{ij,t}$. Third, we then construct the inverse Mills ratio to control for attrition bias as $invMills_{ij,t} \equiv \frac{\phi(z_{ij,t})}{1-\Phi(z_{ij,t})}$. Finally, we include $invMills$ as an additional covariate in regression models (2.7) and (2.8). This last model corresponds to the second-step (i.e. outcome equation) in a Heckman selection model.

Regression results in tables 2.13 and 2.14, for the LiA and BiA subsamples, respectively, evaluate the effects of lending relationships on O/N spread and trading volume controlling for potential attrition bias. Overall the results show that controlling for attrition bias does not change the coefficient estimates of the relationship variables, LPI and BPI, spread and volume. That is, the coefficients in these tables are similar to the corresponding coefficients in tables 2.7 and 2.8 for O/N spreads[5], and 2.11 and 2.12 for trading volume. If any, there is a slight reduction in the coefficient estimates of both LPI and BPI, pointing out that the presence of survivorship bias may have produced upward biased results in the original estimates. The additional variable $invMills$ is in general non-statistically significant or significant at the 10% level.

[5]Although not reported, but available from the Authors upon request, similar results are found for the the 4-month average values of LPI and BPI.

2.5.5.2 Trading volume weighting

Our two key relationship variables, LPI and BPI, were constructed using number of transactions rather than trading volume (i.e. money flow) of transactions. As explained above this is done because we consider that information flows according to the number of interactions, and it is not necessarily proportional to the volume or magnitude of each interaction. As noted by an anonymous referee, this deviates from the literature (eg. Cocco et al. (2009)) where volume weighted relationship measures are used instead. In order to evaluate this we construct LPI and BPI using trading volume weights, and then run regression models (2.7) and (2.8) with the newly defined variables.

We compute the volume-weighted lender preference index ($\text{LPI\_vol}_{ij,t}$) as the ratio of total *volume* of loans from bank bank i to j for a given period t ($\sum_{n=1}^{N_t} V_{ij,n} y_n^{i \to j}$) to the average lending *volume* of lender i. Therefore volume based lender preference index is calculated as:

$$LPI\_vol_{ij,t} = \frac{\sum_{n=1}^{N_t} V_{ij,n} y_n^{i \to j}}{\sum_{n=1}^{N_t} V_{i\ any,n} y_n^{i \to any} / outdegree_{i,t}}.$$

Similarly we define the volume-weighted borrower preference index ($\text{BPI\_vol}_{ij,t}$) as the ratio of the volume of transactions of bank pairij to the average borrowing transaction volume of borrower j:

$$BPI\_vol_{ij,t} = \frac{\sum_{n=1}^{N_t} V_{ij,n} y_n^{i \to j}}{\sum_{n=1}^{N_t} V_{any\ j,n} y_n^{any \to j} / indegreej, t}.$$

These variables have the same interpretation as the number-of-transactions-weighted defined above. That is, a value of 1 correspond to lender or borrower neutrality, > 1 to a high preference towards a particular lender or borrower, and < 1 low preference towards a particular lender or borrower.

Regression results appear in Tables 2.15 and 2.16 for interbank spreads and volumes, and for the LiA and BiA subsamples, respectively. The regression results confirm that lending relationship has an effect on O/N spreads. LPI_vol is statistically significant for all pooled periods and for each subperiod separately, and for both LiA and BiA subsamples. The largest effect corresponds to the During Crisis period. BPI_vol has a negative effect for spreads in the LiA subsample, and no statistically significant effect on BiA. Regarding trading volume, both LPI_vol and BPI_vol are positive and statistically significant for the LiA subsample, and positive and with less statistical significance for the BiA subsample. The largest effect corresponds to the After Crisis period. Note that these are similar results to those in table 2.11.

2.6 Conclusion and implications for systemic risk

The aim of our study is to analyze the structure of the links between financial institutions participating in the e-MID interbank market in an attempt to establish a connection between interest rate spread and volume and the stability of bank relationships. Our data allow us to monitor the evolution of the lending patterns during the first and second phase of the financial crisis. We show that, particularly after the Lehman Brothers collapse, when liquidity became scarce, established relationships with the same bank became an important determinant of interbank spreads. Both borrowers and lenders benefited from establishing relationship throughout the crisis. Preference indexes also impacted the O/N transaction volumes with LPI and BPI indices showing both a positive and significant effects on the volume traded by pairs. The effect of BPI in particular increased as the crisis progressed.

Given the transparent nature of the e-MID platform, our results point to a peer monitoring role of relationship lending. Private information acquired through frequent transactions, supported liquidity reallocation in the e-MID market during the crisis by improving the ability of banks to assess the creditworthiness of their counterparties. Relationship lending thus plays a positive role for financial stability. If a bank, who is the preferential lender to several borrowers defaults, or stop lending, this may pose a serious funding risk for its borrowers who may find it difficult to satisfy their liquidity needs from other lenders and may be forced to accept deals at higher rates. This may eventually put them under distress and increase systemic risk in the system. Similarly if preferential borrowers exit the interbank market, such lenders may find it difficult to reallocate their liquidity surplus if they fail to find trusted counterparties. The resulting inefficient reallocation of liquidity, may in turn increase funding costs of other borrowers and again contribute to the spread of systemic risk. In this sense relationship lending provides a measure of the financial substitutability of a bank in the interbank market [6]. Thus when establishing if a bank is too connected to fail, regulators should not only look at how connected a bank is, but also at how preferentially connected it is to other players.

Furthermore, reliance on relationship lending is an indicator of trust evaporation in the banking system and monitoring the effect of stable relations on spreads and traded volume may help as an early warning indicator of a financial turmoil.

Acknowledgements

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[6] Substitutability captures the extent to which other firms could provide similar financial services in a timely manner at a similar price and quantity if a bank withdraws from a particular market. Bank's substitutabilty is one of the factor, together with bank's size, inerconnectedness, complexity and global (cross-jurisdictional) activity, identified by the Basel Committee (BCBS, 2011) to assess whether a financial institution is systemically important.

Appendix: Definition of variables

Formula	Description
$\mathrm{S}_{ij,t} = \frac{\sum_{n=1}^{N_{ij,t}} (r_{ij,n} - \bar{r}_m^d) * V_{ij,n}}{\sum_{n=1}^{N_{ij,t}} V_{ij,n}}$	Monthly volume weighted spread of bank pair ij.
$\mathrm{VN}_{ij,t} = \frac{\sum_{n=1}^{N_{ij,t}} V_{ij,n}}{\sum_{h=1} \sum_{k=1} \sum_{n=1}^{N_{hk,t}} V_{hk,n}}$	The ratio of monthly total volume of pair ij to monthly total transaction volume in the market.
$\mathrm{LPI}_{ij,t} = \frac{\sum_{n=1}^{N_t} y_n^{i \to j}}{\sum_{n=1}^{N_t} y_n^{i \to any} / outdegree_{i,t}}$	*Lender Preference Index:* The ratio of number of loans from bank i to bank j to average number of lending transactions of i.
$\mathrm{BPI}_{ij,t} = \frac{\sum_{n=1}^{N_t} y_n^{i \to j}}{\sum_{n=1}^{N_t} y_n^{any \to j} / indegree_{j,t}}$	*Borrower Preference Index:* The ratio of number of loans from bank i to bank j to average number of borrowing transactions of j.
$\text{Transaction Ratio}_{ij,t} = \frac{\sum_{n=1}^{N_t} y_n^{i \to j}}{\sum_{n=1}^{N_t} y_n^{any \to any}}$	The ratio for number of transactions between each pair to all transactions taken place at a given period.
$\text{AM/PM Ratio}_{ij,t} = \frac{\sum_{n=1}^{N_{ij,t}} y_{ij,n}^{am} - \sum_{n=1}^{N_{ij,t}} y_{ij,n}^{pm}}{\sum_{n=1}^{N_{ij,t}} y_{ij,n}}$	The ratio for the difference of number of transaction that occur during morning and afternoon to all transaction of each pair at a given period.
$\text{Reciprocity Ratio}_{ij,t} = \frac{\sum_{n=1}^{N_t} y_n^{j \to i}}{\sum_{n=1}^{N_t} y_n^{i \to j}}$	The number of counter-way transactions divided by the number of transaction of pair at a given period.
$\text{Lender's B/L Ratio}_{ij,t} = \frac{\sum_{n=1}^{N_t} V_n^{any \to i}}{\sum_{n=1}^{N_t} V_n^{i \to any}}$	Assuming bank i is the lender of a pair, this variable is the bank i's borrowing amount from any other bank divided by its lending amount to any other bank at a given period.
$\text{Borrower's L/B Ratio}_{ij,t} = \frac{\sum_{n=1}^{N_t} V_n^{j \to any}}{\sum_{n=1}^{N_t} V_n^{any \to j}}$	This variable is the bank j's lending amount to any other bank divided by its borrowing amount from any other bank.
$\text{Tot Amount of Lender}_{ij,t} = \sum_{i=1} \sum_{n=1}^{N_{ij,t}} V_{ij,n}$	Monthly total transaction volume of lender.
$\text{Tot Amount of Borrower}_{ij,t} = \sum_{j=1} \sum_{n=1}^{N_{ij,t}} V_{ij,n}$	Monthly total transaction volume of borrower.
$\text{LT Maturity}_{ij,t} = \sum_{n=1}^{N_t} L_n^{i \to j}$	Number of transactions with longer term maturity for a pair at a given period.

where $y_n^{i \to j}$, $L_n^{i \to j}$ are indicators of loans n borrowed by bank i from bank j with over-night and longer term maturities respectively. $V_{ij,n}$ is volume of transaction for each bank pair ij, and $N_{ij,t}$ is the number of transactions for the bank pair ij at time t. N_t is the total number of the transactions in the market for given time period t. $\bar{r}_m^d$ is the daily volume weighted average rate over all transactions carried out by the bank pairs.

Table 2.1: Summary statistics

Variable Name	Dataset	Mean	Std. Dev.	Min	Max
Spread (in bps)	LiA	-0.4428	8.8623	-118.0136	97.0987
	BiA	-0.0910	8.1543	-118.5429	70.1501
LPI	LiA	1	0.8185	0.03509	17.7931
	BiA	1	0.8847	0.0089	15.4636
BPI	LiA	1	0.8867	0.0385	16.7842
	BiA	1	0.7462	0.0667	15.0578
Transaction Ratio (as %)	LiA	0.0688	0.0895	0.01311	2.2314
	BiA	0.1738	0.3764	0.03389	28.4740
AM/PM Ratio	LiA	0.0529	0.8599	-1	1
	BiA	0.2926	0.8712	-1	1
Reciprocity Ratio	LiA	0.1216	1.2242	0	129
	BiA	0.0422	0.5073	0	42
Total Amount of Lender (in Billions)	LiA	5.0504	7.3391	0.0010	108.9172
	BiA	6.2366	8.6716	0.0025	108.9172
Total Amount of Borrower (in Billions)	LiA	8.2561	9.7499	0.0015	108.9172
	BiA	6.2605	8.3608	0.0020	108.9172
Lender's B/L Ratio	LiA	3.0391	40.0668	0	4085.2000
	BiA	3.1439	29.6242	0	2026.3480
Borrower's L/B Ratio	LiA	2.0141	20.9463	0	1947.4670
	BiA	5.2931	88.7491	0	10011
LT Active (in bps)	LiA	0.0697	0.2547	0	1
	BiA	0.1034	0.3045	0	1
Survival-Next Period	LiA	0.5731	0.4946	0	1
	BiA	0.44267	0.4972	0	1
Survival-Next Two Periods	LiA	0.3956	0.4890	0	1
	BiA	0.2712	0.4446	0	1
Survival-Next Three Periods	LiA	0.2957	0.4564	0	1
	BiA	0.1873	0.3901	0	1
Volume-Pair	LiA	173.5799	592.4856	0.0500	65393.0000
	BiA	123.9555	1222.1650	0.0500	158897.8000
No. of Transaction-Pair	LiA	3.8275	5.7255	1	280
	BiA	3.2502	13.5544	1	1628

Note: Number of observations in LiA and BiA datasets are 61085 and 24161, respectively.

Table 2.2: Participation of banks by bank size

Lender - LiA						
	Foreign	Minor	Small	Medium	Large	Major
Before Crisis	70	18	62	14	10	6
During Crisis	73	20	58	12	8	6
After Crisis	52	20	57	12	5	4
Borrower - LiA						
	Foreign	Major	Large	Medium	Small	Minor
Before Crisis	56	12	50	14	10	6
During Crisis	56	15	53	12	9	6
After Crisis	38	13	47	13	5	4
Lender - BiA						
	Foreign	Major	Large	Medium	Small	Minor
Before Crisis	54	13	51	14	9	6
During Crisis	57	17	55	11	8	6
After Crisis	28	17	52	9	5	4
Borrower - BiA						
	Foreign	Major	Large	Medium	Small	Minor
Before Crisis	61	14	56	15	10	6
During Crisis	55	18	55	13	9	6
After Crisis	35	17	52	13	5	4

Table 2.3: LiA - Marginal effect of survival analysis

VARIABLES	All	Before Crisis	During Crisis	After Crisis
		Survival for the next period		
Spread	0.001***	-0.001	-0.000	-0.001
	(0.000)	(0.001)	(0.000)	(0.001)
LPI	0.087***	0.037***	0.045***	0.071***
	(0.005)	(0.012)	(0.010)	(0.012)
BPI	0.071***	0.075***	0.097***	0.045***
	(0.005)	(0.011)	(0.010)	(0.012)
Observations	47,690	14,577	16,280	10,175
Number of pairs	3,866	2,330	2,459	1,563
		Survival for the next two periods		
Spread	0.001***	-0.002*	-0.000	-0.004***
	(0.000)	(0.001)	(0.001)	(0.001)
LPI	0.080***	0.027**	0.032***	0.064***
	(0.005)	(0.012)	(0.010)	(0.011)
BPI	0.055***	0.054***	0.068***	0.022*
	(0.005)	(0.011)	(0.010)	(0.011)
Observations	42,292	11,792	13,777	8,490
Number of pairs	2,780	1,553	1,709	1,058
		Survival for the next three periods		
Spread	0.002***	-0.001	0.001	-0.005***
	(0.000)	(0.001)	(0.001)	(0.001)
LPI	0.069***	0.011	0.024**	0.043***
	(0.005)	(0.012)	(0.010)	(0.012)
BPI	0.050***	0.056***	0.053***	0.013
	(0.005)	(0.011)	(0.010)	(0.012)
Observations	36,921	9,512	11,419	6,711
Number of pairs	2,100	1,113	1,257	721

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

Table 2.4: BiA - Marginal effect of survival analysis

VARIABLES	All	Before Crisis	During Crisis	After Crisis
Survival for the next period				
Spread	-0.000	-0.001	0.000	-0.001
	(0.001)	(0.002)	(0.001)	(0.001)
LPI	0.108***	0.052***	0.106***	0.067***
	(0.008)	(0.017)	(0.015)	(0.024)
BPI	0.038***	0.059***	0.019	0.032
	(0.009)	(0.018)	(0.016)	(0.024)
Observations	16,293	5,436	5,909	2,674
Number of pairs	1,810	1,057	1,045	496
Survival for the next two periods				
Spread	0.000	-0.001	0.002	-0.001
	(0.001)	(0.002)	(0.001)	(0.002)
LPI	0.093***	0.076***	0.056***	0.030
	(0.008)	(0.018)	(0.014)	(0.023)
BPI	0.033***	0.013	0.039**	0.031
	(0.009)	(0.019)	(0.016)	(0.024)
Observations	13,004	4,036	4,471	1,868
Number of pairs	1,067	620	603	251
Survival for the next three periods				
Spread	-0.001	-0.003	0.001	-0.001
	(0.001)	(0.003)	(0.002)	(0.002)
LPI	0.079***	0.071***	0.034**	-0.016
	(0.008)	(0.019)	(0.015)	(0.024)
BPI	0.031***	-0.009	0.045***	0.048*
	(0.009)	(0.022)	(0.017)	(0.026)
Observations	10,577	2,985	3,566	1,545
Number of pairs	733	397	426	180

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

Table 2.5: LiA - Determinants of LPI and BPI

	Dep.var.: LPI				Dep.var.: BPI			
VARIABLES	(1) All	(2) Before Crisis	(3) During Crisis	(4) After Crisis	(5) All	(6) Before Crisis	(7) During Crisis	(8) After Crisis
Transaction Ratio	6.279***	10.375***	7.088***	5.032***	7.016***	13.592***	8.672***	5.364***
	(0.279)	(0.438)	(0.524)	(0.264)	(0.289)	(0.409)	(0.525)	(0.197)
AM/PM Ratio	0.014***	-0.008	0.002	0.003	0.024***	0.002	0.018***	0.007
	(0.005)	(0.005)	(0.008)	(0.007)	(0.005)	(0.005)	(0.006)	(0.007)
Reciprocity Ratio	-0.016***	-0.031***	-0.012*	-0.013***	-0.015***	-0.010*	-0.022**	-0.013***
	(0.004)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.009)	(0.004)
Tot Amount of Lender	-0.014***	-0.017***	-0.021***	-0.032***	0.024***	0.011***	0.024***	0.043***
	(0.001)	(0.002)	(0.002)	(0.007)	(0.002)	(0.001)	(0.003)	(0.007)
Tot Amount of Borrower	0.020***	0.014***	0.019***	0.027***	-0.015***	-0.012***	-0.016***	-0.051***
	(0.001)	(0.001)	(0.002)	(0.003)	(0.001)	(0.001)	(0.002)	(0.003)
Lender's B/L Ratio	0.000***	0.002***	0.000***	0.000	-0.000**	-0.001***	-0.000*	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Borrower's L/B Ratio	-0.002***	-0.003***	-0.001**	-0.004***	0.002***	0.004***	0.001**	0.005***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
LT Maturity	-0.005	-0.061**	-0.033	-0.024	0.059**	-0.031	-0.009	0.001
	(0.023)	(0.029)	(0.027)	(0.027)	(0.025)	(0.023)	(0.023)	(0.022)
Observations	51,871	19,276	20,730	11,865	51,871	19,276	20,730	11,865
R-squared	0.590	0.624	0.609	0.653	0.627	0.782	0.734	0.694
Number of pairs	6,066	4,449	4,441	2,728	6,066	4,449	4,441	2,728

Notes: Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$
All models include bank-pair and maintenance period specific fixed-effects.

Table 2.6: BiA - Determinants of LPI and BPI

	Dep.var.: LPI				Dep.var.: BPI			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	All	Before Crisis	During Crisis	After Crisis	All	Before Crisis	During Crisis	After Crisis
Transaction Ratio	0.450	0.876	1.655**	0.475	0.369	1.013***	1.398***	0.438
	(0.333)	(0.652)	(0.653)	(0.326)	(0.290)	(0.333)	(0.416)	(0.308)
AM/PM Ratio	0.099***	0.056***	0.064***	0.067***	0.050***	0.028***	0.033**	0.045**
	(0.014)	(0.011)	(0.015)	(0.022)	(0.011)	(0.010)	(0.014)	(0.023)
Reciprocity Ratio	-0.021	-0.071***	-0.065*	-0.037	-0.027*	-0.043**	-0.091***	-0.060
	(0.015)	(0.026)	(0.038)	(0.043)	(0.015)	(0.021)	(0.032)	(0.097)
Tot Amount of Lender	-0.003	0.003	-0.006	-0.039***	0.014***	0.016***	0.017***	-0.001
	(0.002)	(0.003)	(0.005)	(0.013)	(0.002)	(0.002)	(0.004)	(0.009)
Tot Amount of Borrower	0.029***	0.017***	0.038***	0.055***	-0.002	0.001	-0.008	-0.011
	(0.003)	(0.004)	(0.006)	(0.011)	(0.002)	(0.002)	(0.005)	(0.011)
Lender's B/L Ratio	-0.000	-0.001*	-0.000	-0.002	-0.001*	-0.002**	-0.002***	-0.004
	(0.000)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.000)	(0.003)
Borrower's L/B Ratio	-0.001**	-0.000	-0.002***	-0.001*	0.000	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
LT Maturity	0.259***	0.107*	0.134	0.154*	0.265***	0.087	0.113**	0.151*
	(0.081)	(0.057)	(0.101)	(0.082)	(0.076)	(0.080)	(0.052)	(0.081)
Observations	19,643	7,856	8,042	3,745	19,643	7,856	8,042	3,745
R-squared	0.179	0.186	0.421	0.244	0.174	0.328	0.384	0.210
Number of pairs	3,705	2,475	2,416	1,291	3,705	2,475	2,416	1,291

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
All models include bank-pair and maintenance period specific fixed-effects.

Table 2.7: LiA - Determinants of O/N spreads

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	All	Before Crisis	During Crisis	After Crisis	All	Before Crisis	During Crisis	After Crisis
LPI	0.587***	0.055	0.699***	0.509**				
	(0.088)	(0.081)	(0.132)	(0.205)				
BPI	-0.626***	-0.200**	-0.018	-1.003***				
	(0.091)	(0.086)	(0.143)	(0.177)				
Average LPI(4M)					0.828***	0.146	0.513***	0.929***
					(0.111)	(0.129)	(0.197)	(0.210)
Average BPI(4M)					-0.492***	-0.007	-0.101	-0.820***
					(0.104)	(0.109)	(0.209)	(0.231)
Transaction Ratio	6.200***	5.101***	-0.912	5.996***	4.490***	2.332***	2.709**	3.172***
	(1.430)	(1.455)	(1.715)	(2.081)	(0.882)	(0.743)	(1.173)	(0.987)
AM/PM Ratio	2.396***	1.253***	3.458***	1.679***	2.383***	1.252***	3.450***	1.669***
	(0.064)	(0.082)	(0.123)	(0.112)	(0.064)	(0.082)	(0.123)	(0.112)
Reciprocity Ratio	-0.299**	-0.082	-0.840**	0.027	-0.296**	-0.078	-0.846**	0.034
	(0.128)	(0.157)	(0.354)	(0.073)	(0.128)	(0.157)	(0.354)	(0.073)
Lender's B/L Ratio	-0.005*	-0.010*	-0.004	-0.001*	-0.005*	-0.010*	-0.004	-0.001**
	(0.002)	(0.005)	(0.005)	(0.000)	(0.002)	(0.005)	(0.005)	(0.000)
Borrower's L/B Ratio	-0.023**	-0.035***	-0.011	-0.085***	-0.023**	-0.035***	-0.011	-0.085***
	(0.010)	(0.013)	(0.012)	(0.015)	(0.010)	(0.013)	(0.012)	(0.015)
LT Maturity	-0.033	-0.223***	0.027	0.496***	-0.060	-0.224***	-0.015	0.489***
	(0.159)	(0.077)	(0.167)	(0.187)	(0.161)	(0.074)	(0.168)	(0.187)
Observations	51,871	19,276	20,730	11,865	51,871	19,276	20,730	11,865
R-squared	0.097	0.037	0.084	0.178	0.097	0.037	0.083	0.176
Number of pairs	6,066	4,449	4,441	2,728	6,066	4,449	4,441	2,728

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
All models include bank-pair and maintenance period specific fixed-effects.

Table 2.8: BiA - Determinants of O/N spreads

VARIABLES	(1) All	(2) Before Crisis	(3) During Crisis	(4) After Crisis	(5) All	(6) Before Crisis	(7) During Crisis	(8) After Crisis
LPI	0.211**	0.044	0.256***	0.453*				
	(0.088)	(0.046)	(0.096)	(0.265)				
BPI	-0.094	0.032	-0.011	-0.060				
	(0.106)	(0.075)	(0.143)	(0.302)				
Average LPI(4M)					0.280**	0.158*	0.565***	0.257
					(0.114)	(0.082)	(0.164)	(0.516)
Average BPI(4M)					-0.220	-0.022	-0.305	-0.016
					(0.156)	(0.110)	(0.213)	(0.583)
Transaction Ratio	0.080	-0.017	0.236	0.265	0.113	-0.005	0.387	0.369*
	(0.103)	(0.068)	(0.255)	(0.177)	(0.106)	(0.058)	(0.296)	(0.204)
AM/PM Ratio	1.633***	0.669***	1.949***	2.155***	1.636***	0.665***	1.950***	2.173***
	(0.094)	(0.102)	(0.161)	(0.288)	(0.094)	(0.102)	(0.161)	(0.288)
Reciprocity Ratio	-1.003*	-0.153	-1.870	0.451	-1.005*	-0.150	-1.877	0.476
	(0.589)	(0.330)	(1.184)	(1.938)	(0.590)	(0.330)	(1.184)	(1.940)
Lender's B/L Ratio	0.001	-0.005	0.007	-0.029	0.001	-0.005	0.007	-0.030
	(0.006)	(0.007)	(0.005)	(0.031)	(0.005)	(0.007)	(0.005)	(0.031)
Borrower's L/B Ratio	0.002	-0.001	0.011	-0.036***	0.002	-0.001	0.012	-0.036***
	(0.002)	(0.001)	(0.007)	(0.010)	(0.002)	(0.001)	(0.007)	(0.010)
LT Maturity	-0.171	0.004	-0.180	0.254	-0.149	-0.003	-0.157	0.290
	(0.198)	(0.051)	(0.145)	(0.385)	(0.192)	(0.052)	(0.147)	(0.382)
Observations	19,643	7,856	8,042	3,745	19,643	7,856	8,042	3,745
R-squared	0.078	0.037	0.079	0.163	0.078	0.038	0.079	0.162
Number of pairs	3,705	2,475	2,416	1,291	3,705	2,475	2,416	1,291

Notes: Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$
All models include bank-pair and maintenance period specific fixed effects.

Table 2.9: LiA - Analysis by bank size

	Coefficient of LPI on O/N spreads					
	Size of Lender					
Size of Borrower	Foreign	Major	Big	Medium	Small	Minor
Foreign	-0.227	-3.538**	1.752	4.619*	0.729	-2.898
	(0.246)	(1.537)	(2.419)	(2.772)	(1.100)	(2.256)
Major	-1.738	-0.721	3.203	3.414	1.816***	0.348
	(1.096)	(2.340)	(3.885)	(2.849)	(0.628)	(1.488)
Big	-0.941	1.889	1.581*	0.132	0.395	1.192**
	(1.520)	(1.403)	(0.761)	(1.654)	(0.373)	(0.474)
Medium	0.890	0.319	2.753**	0.891	0.645**	-0.289
	(0.628)	(0.740)	(1.297)	(0.722)	(0.265)	(0.324)
Small	-0.345	0.175	0.673	0.404	0.751***	0.845***
	(0.518)	(0.741)	(0.413)	(0.253)	(0.136)	(0.305)
Minor	N/A	-21.77	-7.227	0.366	-0.858	-2.616
		(17.93)	(7.748)	(1.239)	(1.090)	(2.462)
	Effect of BPI on O/N spreads					
	Size of Lender					
Size of Borrower	Foreign	Major	Big	Medium	Small	Minor
Foreign	-0.146	-1.178	-1.403	1.928**	-0.486	-2.916
	(0.225)	(1.210)	(1.737)	(0.840)	(1.072)	(3.514)
Major	-1.166	-1.240	-9.906**	-0.201	-0.849**	-0.139
	(1.619)	(1.428)	(3.699)	(2.077)	(0.408)	(1.254)
Big	4.903**	-0.763	-0.648	0.505	0.116	-0.367
	(2.128)	(0.893)	(1.348)	(1.293)	(0.252)	(0.339)
Medium	-0.957	-0.799	-2.215	-2.282***	-0.494**	-0.739**
	(0.968)	(0.528)	(1.817)	(0.808)	(0.221)	(0.330)
Small	-0.935	-1.744**	-0.886	-1.045**	-0.842***	-1.418**
	(0.954)	(0.743)	(0.569)	(0.416)	(0.196)	(0.566)
Minor	N/A	29.45**	14.99**	-0.380	-0.592	5.310
		(13.31)	(5.955)	(1.412)	(0.986)	(4.140)

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
All models include bank-pair and maintenance period specific fixed effects.

Table 2.10: BiA - Analysis by bank size

Coefficient of LPI on O/N spreads							
		Size of Borrower					
		Foreign	Major	Big	Medium	Small	Minor
Size of Lender	Foreign	0.878*	-1.473	-0.437	-0.820	1.740	N/A
		(0.524)	(1.797)	(1.163)	(0.676)	(1.844)	
	Major	-0.122	4.223	-3.998	0.159	-0.804	N/A
		(0.404)	(5.357)	(4.651)	(0.395)	(0.672)	
	Big	N/A	N/A	3.996***	-4.792***	1.041	N/A
				(0.703)	(1.379)	(0.944)	
	Medium	4.159	-20.42	1.490	0.0676	0.0455	1.473
		(5.611)	(12.55)	(1.273)	(0.425)	(0.505)	(2.129)
	Small	0.338	2.538	1.206**	-0.181	-0.507	-1.878**
		(1.690)	(2.738)	(0.563)	(0.188)	(0.317)	(0.850)
	Minor	0	N/A	2.228***	0.884**	0.0383	0.435
		(0)		(0.768)	(0.424)	(0.408)	(1.882)
Coefficient of BPI on O/N spreads							
		Size of Borrower					
		Foreign	Major	Big	Medium	Small	Minor
Size of Lender	Foreign	-0.105	0.379	0.230	-1.278***	-3.621	N/A
		(0.504)	(1.571)	(1.387)	(0.454)	(2.926)	
	Major	0.776	-17.68***	3.270	-0.646	-0.670	N/A
		(0.742)	(5.496)	(2.772)	(0.523)	(0.561)	
	Big	N/A	N/A	-0.295	5.404	-0.301	N/A
				(0.995)	(4.795)	(0.705)	
	Medium	2.687	-54.16**	-0.790	0.324	-0.625	-1.348
		(4.768)	(24.96)	(0.654)	(0.469)	(0.498)	(1.290)
	Small	0.0511	-0.558	-1.229***	-0.504**	-0.201	-0.0118
		(0.971)	(1.547)	(0.449)	(0.249)	(0.164)	(0.997)
	Minor	-68.67***	N/A	1.716	-1.452*	-0.912*	-3.052*
		(6.664)		(1.528)	(0.828)	(0.504)	(1.615)

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
All models include bank-pair and maintenance period specific fixed effects.

Table 2.11: LiA - Determinants of trading volumes

VARIABLES	(1) All	(2) Before Crisis	(3) During Crisis	(4) After Crisis
LPI	0.042***	0.041***	0.023***	0.049***
	(0.005)	(0.005)	(0.006)	(0.009)
BPI	0.061***	0.028***	0.077***	0.103***
	(0.008)	(0.003)	(0.013)	(0.016)
AM/PM Ratio	0.009***	0.007***	0.005**	0.021***
	(0.002)	(0.001)	(0.002)	(0.006)
Reciprocity Ratio	-0.001	-0.000	0.001	0.002**
	(0.001)	(0.001)	(0.002)	(0.001)
Lender's B/L Ratio	-0.000*	-0.000	0.000	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Borrower's L/B Ratio	-0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
LT Maturity	0.036**	-0.011***	0.045**	0.032*
	(0.018)	(0.002)	(0.019)	(0.017)
Observations	51,871	19,276	20,730	11,865
R-squared	0.192	0.218	0.347	0.180
Number of pairs	6,066	4,449	4,441	2,728

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
All models include bank-pair and maintenance period specific fixed effects.

Table 2.12: BiA - Determinants of trading volumes

VARIABLES	(1) All	(2) Before Crisis	(3) During Crisis	(4) After Crisis
LPI	0.198**	0.142*	0.148	0.158***
	(0.088)	(0.086)	(0.151)	(0.033)
BPI	-0.008	-0.043	0.162	0.197***
	(0.083)	(0.093)	(0.231)	(0.045)
AM/PM Ratio	0.021*	0.006	-0.003	0.040***
	(0.011)	(0.009)	(0.021)	(0.012)
Reciprocity Ratio	0.003	0.004	0.006	0.031
	(0.006)	(0.014)	(0.025)	(0.031)
Lender's B/L Ratio	-0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.001)
Borrower's L/B Ratio	0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
LT Maturity	0.119	0.113	0.072	0.129*
	(0.077)	(0.091)	(0.066)	(0.066)
Observations	19,643	7,856	8,042	3,745
R-squared	0.055	0.119	0.099	0.268
Number of pairs	3,705	2,475	2,416	1,291

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
All models include bank-pair and maintenance period specific fixed effects.

Table 2.13: LiA - Determinants of spread and trading volume controlling for attrition bias

	Dep.var.: Spread				Dep.var.: Volume			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	All	Before Crisis	During Crisis	After Crisis	All	Before Crisis	During Crisis	After Crisis
LPI	0.593***	0.091	0.737***	0.535***	0.030***	0.030***	0.016	0.010
	(0.100)	(0.085)	(0.149)	(0.199)	(0.008)	(0.007)	(0.012)	(0.023)
BPI	-0.623***	-0.179**	0.003	-0.997***	0.052***	0.018***	0.071***	0.077***
	(0.102)	(0.088)	(0.149)	(0.179)	(0.008)	(0.007)	(0.014)	(0.016)
Transaction Ratio	6.260***	5.947***	-0.682	6.487***				
	(1.379)	(1.554)	(1.769)	(2.310)				
AM/PM Ratio	2.398***	1.276***	3.474***	1.694***	0.005	0.003	0.002	0.008
	(0.068)	(0.085)	(0.126)	(0.115)	(0.003)	(0.003)	(0.004)	(0.009)
Reciprocity Ratio	-0.300**	-0.090	-0.845**	0.021	0.000	0.001	0.001	0.006**
	(0.128)	(0.157)	(0.354)	(0.073)	(0.002)	(0.001)	(0.002)	(0.003)
Lender's B/L Ratio	-0.005*	-0.010*	-0.004	-0.001**	-0.000	-0.000	0.000	-0.000
	(0.002)	(0.005)	(0.005)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Borrower's L/B Ratio	-0.023**	-0.036***	-0.011	-0.086***	0.000	0.000	0.000	0.001**
	(0.011)	(0.013)	(0.012)	(0.015)	(0.000)	(0.000)	(0.000)	(0.000)
LT Maturity	-0.036	-0.254***	0.013	0.471**	0.039**	-0.008***	0.047**	0.045**
	(0.156)	(0.081)	(0.168)	(0.186)	(0.018)	(0.003)	(0.020)	(0.019)
invMills	-0.064	-0.529*	-0.351	-0.414	0.092*	0.086	0.056	0.302*
	(0.493)	(0.289)	(0.435)	(0.714)	(0.049)	(0.064)	(0.066)	(0.158)
Observations	51,871	19,276	20,730	11,865	51,871	19,276	20,730	11,865
R-squared	0.097	0.037	0.084	0.178	0.193	0.223	0.348	0.189
Number of pairs	6,066	4,449	4,441	2,728	6,066	4,449	4,441	2,728

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
All models include bank-pair and maintenance period specific fixed-effects.

Table 2.14: BiA - Determinants of spread and trading volume controlling for attrition bias

	Dep.var.: Spread				Dep.var.: Volume			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	All	Before Crisis	During Crisis	After Crisis	All	Before Crisis	During Crisis	After Crisis
LPI	0.449***	0.081	0.390***	0.796**	0.181***	0.112	0.024	-0.117
	(0.125)	(0.066)	(0.126)	(0.356)	(0.064)	(0.078)	(0.159)	(0.318)
BPI	-0.018	0.039	0.024	0.148	-0.014	-0.050	0.121	0.032
	(0.103)	(0.075)	(0.143)	(0.382)	(0.094)	(0.094)	(0.211)	(0.177)
Transaction Ratio	0.197**	0.019	0.324	0.458***				
	(0.081)	(0.074)	(0.294)	(0.133)				
AM/PM Ratio	1.700***	0.678***	1.986***	2.306***	0.016	-0.001	-0.034	-0.074
	(0.098)	(0.103)	(0.163)	(0.311)	(0.024)	(0.011)	(0.033)	(0.136)
Reciprocity Ratio	-1.052*	-0.159	-1.895	0.349	0.006	0.008	0.027	0.107
	(0.589)	(0.330)	(1.183)	(1.939)	(0.011)	(0.015)	(0.034)	(0.100)
Lender's B/L Ratio	0.000	-0.005	0.006	-0.032	-0.000	-0.000	0.001	0.002
	(0.005)	(0.007)	(0.005)	(0.031)	(0.000)	(0.000)	(0.000)	(0.002)
Borrower's L/B Ratio	0.001	-0.001	0.011	-0.038***	0.000	0.000	0.001*	0.002
	(0.002)	(0.001)	(0.007)	(0.010)	(0.000)	(0.000)	(0.000)	(0.002)
LT Maturity	-0.243	-0.012	-0.218	0.087	0.123	0.121	0.095	0.240
	(0.207)	(0.054)	(0.149)	(0.409)	(0.083)	(0.093)	(0.072)	(0.146)
invMills	-1.685***	-0.236	-0.919*	-3.665	0.112	0.173	0.787*	2.708
	(0.503)	(0.191)	(0.499)	(2.686)	(0.324)	(0.112)	(0.437)	(3.263)
Observations	19,643	7,856	8,042	3,745	19,643	7,856	8,042	3,745
R-squared	0.078	0.037	0.079	0.163	0.055	0.121	0.107	0.274
Number of pair_id	3,705	2,475	2,416	1,291	3,705	2,475	2,416	1,291

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
All models include bank-pair and maintenance period specific fixed-effects.

Table 2.15: LiA - Determinants of spread and trading volume, volume weighted LPI and BPI

	Dep.var.: Spread				Dep.var.: Volume			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	All	Before Crisis	During Crisis	After Crisis	All	Before Crisis	During Crisis	After Crisis
LPI_vol	0.579***	0.223***	0.907***	0.360***	0.036***	0.041***	0.022***	0.050***
	(0.062)	(0.054)	(0.110)	(0.130)	(0.004)	(0.004)	(0.004)	(0.007)
BPI_vol	-0.161***	0.005	0.064	-0.252***	0.067***	0.032***	0.076***	0.104***
	(0.050)	(0.050)	(0.068)	(0.096)	(0.006)	(0.004)	(0.008)	(0.013)
Transaction Ratio	3.020***	0.618	-3.311***	2.993**				
	(1.028)	(0.911)	(1.178)	(1.424)				
AM/PM Ratio	2.348***	1.234***	3.367***	1.676***	-0.000	-0.001	-0.004**	0.007
	(0.063)	(0.081)	(0.121)	(0.113)	(0.002)	(0.001)	(0.002)	(0.005)
Reciprocity Ratio	-0.296**	-0.073	-0.841**	0.031	-0.001	0.002**	-0.000	0.004**
	(0.126)	(0.157)	(0.343)	(0.072)	(0.001)	(0.001)	(0.002)	(0.002)
Lender's B/L Ratio	-0.005*	-0.010**	-0.004	-0.001**	0.000	-0.000	0.000	0.000
	(0.002)	(0.005)	(0.005)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Borrower's L/B Ratio	-0.023**	-0.035***	-0.011	-0.087***	-0.000**	-0.000**	-0.000***	-0.000
	(0.011)	(0.013)	(0.012)	(0.015)	(0.000)	(0.000)	(0.000)	(0.000)
LT Maturity	0.006	-0.184**	0.092	0.526***	0.027	-0.011***	0.026**	0.023
	(0.164)	(0.074)	(0.166)	(0.184)	(0.016)	(0.002)	(0.011)	(0.016)
Observations	51,871	19,276	20,730	11,865	51,871	19,276	20,730	11,865
R-squared	0.098	0.038	0.088	0.175	0.299	0.395	0.579	0.299
Number of pairs	6,066	4,449	4,441	2,728	6,066	4,449	4,441	2,728

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
All models include bank-pair and maintenance period specific fixed-effects.

Table 2.16: BiA - Determinants of spread and trading volume, volume weighted LPI and BPI

	Dep.var.: Spread				Dep.var.: Volume			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	All	Before Crisis	During Crisis	After Crisis	All	Before Crisis	During Crisis	After Crisis
LPI_vol	0.309***	0.096*	0.379***	0.369**	0.149***	0.146**	0.096	0.174***
	(0.063)	(0.057)	(0.086)	(0.184)	(0.052)	(0.063)	(0.077)	(0.024)
BPI_vol	-0.071	0.045	0.024	0.080	0.051	-0.008	0.160	0.215***
	(0.065)	(0.070)	(0.105)	(0.206)	(0.042)	(0.050)	(0.130)	(0.045)
Transaction Ratio	0.033	-0.072	0.043	0.242				
	(0.114)	(0.095)	(0.194)	(0.193)				
AM/PM Ratio	1.601***	0.655***	1.900***	2.129***	0.006	-0.005	-0.021	0.009
	(0.093)	(0.100)	(0.159)	(0.287)	(0.012)	(0.008)	(0.021)	(0.011)
Reciprocity Ratio	-0.990*	-0.147	-1.829	0.497	0.009	0.010	0.019	0.068
	(0.589)	(0.331)	(1.181)	(1.919)	(0.006)	(0.017)	(0.025)	(0.042)
Lender's B/L Ratio	0.001	-0.005	0.007	-0.030	0.000	0.000	0.000	0.000
	(0.006)	(0.007)	(0.005)	(0.031)	(0.000)	(0.000)	(0.000)	(0.001)
Borrower's L/B Ratio	0.002	-0.001	0.011	-0.036***	0.000	-0.000	0.000	0.000
	(0.002)	(0.001)	(0.007)	(0.010)	(0.000)	(0.000)	(0.000)	(0.000)
LT Maturity	-0.185	0.003	-0.194	0.260	0.124	0.110	0.092	0.122**
	(0.199)	(0.051)	(0.141)	(0.382)	(0.084)	(0.087)	(0.077)	(0.062)
Observations	19,643	7,856	8,042	3,745	19,643	7,856	8,042	3,745
R-squared	0.079	0.038	0.081	0.164	0.061	0.170	0.098	0.380
Number of pairs	3,705	2,475	2,416	1,291	3,705	2,475	2,416	1,291

Notes: Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$
All models include bank-pair and maintenance period specific fixed-effects.

Chapter 3

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

3.1 Introduction

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

Network analysis of the degree of interconnectedness in the financial system can inform policymakers on optimal bank resolutions mechanisms and how regulation can help to reduce instability. Empirical networks have been used for (deterministic) stress test exercises (see Upper (2011) for a comprehensive review). Of critical importance in macro prudential policy is the identification of key players in the financial network, which according to the International Monetary Fund (IMF), the Bank for International Settlements (BIS) and the Financial Stability Board (FSB) should be determined in terms of their size, connectedness and substitutability. Network centrality measures, developed to assess centrality in other contexts and adapted to the context of financial networks, can guide national authorities in their assessment of the systemic importance of financial and non-financial institutions. In the financial economic literature network analysis has mostly been applied to payment systems, interbank lending markets, and more recently extended to capture the mutual exposure of financial institutions to other asset classes, including derivatives contracts, in a multilayer networks framework (Markose et al. (2012), Bargigli et al. (2015), Leon et al. (2014), Molina-Borboa et al. (2015) and Aldasoro and Alves (2015)).

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

We evaluate each measure in a quarterly panel data regression set-up of bank pairs, i.e. lender and borrower match, for the period 2006-2009 and separately for three sub-periods that encompass the latest 2007-2008 financial crisis: phase I (01 January 2006-30 June 2007, using the key date of the Two Bear Stearns' hedge fund bankruptcy was 31 July 2007), phase II (01 July 2007-30 September 2008, using the key date of Lehman Brothers collapse was 15-Sep-2008) and phase III (01 October 2008-31 December 2009).

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

The remainder of this article is organized as follows. Section 3.2 discusses previous findings in the literature and how they relate to our paper. Section 4.4 describes the data and variables. Section 3.4 provides methodology of the empirical analysis. In section 3.5, we present and discuss the results of the regression analysis. Section 3.6 discusses the results and concludes.

3.2 Network centrality and financial markets

A number of papers have investigated the interplay between financial distress and topological characteristic of interbank networks, focusing on the network resilience to different kinds of shocks (Iori et al. (2006); Nier et al. (2007), Gai et al. (2011), Battiston et al. (2012); Anand et al. (2012), Lenzu and Tedeschi (2012); Georg (2013); Roukny et al. (2013), Acemoglu et al. (2015)). While some authors have argued that a more interconnected architecture could enhance the resilience of the system to failure of an individual bank, because credit risk is shared among more creditors, others have suggested that a higher density of connections may function as a destabilizing force, facilitating financial distress to spread further through the banking system. The overall picture that emerges from this body of work is that the density of linkages has a non monotonous impact on systemic stability and its effect varies with the nature of the shock, the heterogeneity of the players and the state of the economy. Thus no optimal network structure, that is more resilient under all circumstances, can be identified (see Chinazzi and Fagiolo (2013) for a recent survey on systemic risk and financial contagion).

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

In particular for the e-MID market, while early studies (Iori et al. (2008)) have revealed a fairly random network at the daily scale, a non-random structure has been uncovered for longer aggregation periods. Monthly and quarterly aggregated data show that since the 1990s a high degree of bank concentration occurred (Iazzetta and Manna (2009)), with fewer banks acting as global hubs for the whole network. The hubs tend to cluster together and a significant core-periphery structure has been observed (Finger et al. (2013)). Hatzopoulos et al. (2015) have investigated the matching mechanism between lenders and borrowers in the e-MID market and its evolution over time. They show that, when controlling for bank heterogeneity, the matching mechanism is fairly random. Even though matches that occur more often than those consistent with a random null model (over expressed links) exist and increase in number during the crisis, neither lenders nor borrowers systematically present several over expressed links at the same time. The picture that emerges from their study is that banks are more likely to be chosen as trading partners because they trade more often and not because they are more attractive in some dimension (such as their financial healthiness or because they charge lower rates).

Fricke and Lux (2015a) and Squartini et al. (2013) have investigated if the

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

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

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

Bech and Atalay (2008) analyze the topology of the Federal Funds market by looking at overnight transactions from 1997 to 2006. They show that reciprocity and centrality measures are useful predictors of interest rates, with banks gaining from their centrality. Akram and Christophersen (2010) studies the Norwegian interbank market over the period 2006-2009. He observes large variations in interest rates across banks, with systemically more important banks, in terms of size and connectedness receiving more favorable terms. Gabrieli (2012) tests whether measures of centrality can help explaining heterogeneous patterns in the interest rates paid to borrow unsecured funds in the e-MID market, once bank size and other bank and market factors are controlled for [2].This paper shows that the effect of interconnectedness on interbank borrowing costs is very different before versus after August 2007; and that banks of different size profit from different forms of centrality before the crisis and lose from different forms after the crisis.

Similar to Gabrieli (2012), we also study the e-MID market and implement a number of centrality measures in our analysis. The main difference with Gabrieli paper is that, like Akram and Christophersen (2010), she perform the analysis on daily networks while we compute centrality measures on quarterly aggregated transaction networks. This choice is motivated by the analysis of Finger et al. (2012) who show that the e-MID networks appear to be random at the daily level, but contain significant non-random structure for longer aggregation periods. While the use of daily networks is justified by the fact that the underlying loans are O/N the daily networks are not representative for the underlying 'latent' network. Daily transactions are rather random draws from the true underlying network with the realizations depending on current liquidity need. A much higher degree of structural stability is achieved for longer aggregation periods, monthly or quarterly. At

[2] Furthermore, there is also a very high interconnectedness in other interbank markets besides the traditional interbank lending market (see for example Markose, Giansante, and Shaghaghi, 2012 for the CDS market)

the daily scale, several banks act exclusively as lenders or borrowers, and liquidity flows over short paths resulting in very small values of centrality according to most measures, which is not the case at longer aggregation scales. In addition we perform the regression analysis not per bank but per pair, assessing simultaneously the role of lender and borrower centrality in a transaction on the interest rates.

3.3 Data and variables definition

We use tick-by-tick data of the Italian e-MID from 01 January 2006 to 31 December 2009. We have detailed information about each transaction; time, volume of trade, maturity, interest rate, the side of the transaction (buy/sell) and the code of the banks acting as quoter and aggressor, country of origin and size of both parties. The interest rate is expressed as annual rate and the volume of the transaction is provided in millions of Euros. The e-MID market includes contracts with maturities varying from one day to one year. We restrict our analysis to overnight (O/N) and the overnight long (ONL[3]), which consists of more than 90% of all e-MID transactions as the interbank market is mainly a market for short-term trades. If loans with longer maturities were included in the dataset, it would be difficult to derive a representative interest rate for the market, as longer term loans tend to be infrequent.

3.3.1 Interest Rate Spread

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

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

bank pair ij as

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

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

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

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

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

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

3.3.2 Network Centrality Measures

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

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

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

Nodes with more ties to other nodes have alternative ways to satisfy their needs, in our contest they have greater opportunities to exchange liquidity. Choice makes these nodes less dependent on other nodes, and in this sense more powerful, such as in bargaining better rates. Thus a simple measure of a node centrality is its degree. When links are directed, it is common to distinguish centrality based on in-degree from centrality based on out-degree. Nodes that receive many ties are said to be prominent, or to have high prestige or trust. Nodes who have high out-degree are said to be influential. Formally indegree and outdegree centrality are defined as

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

In matrix form, this can be expressed as

$$InEigenvector = A^T InEigenvector,$$

$$OutEigenvector = AOutEigenvector,$$

where InEigenvector and OutEigenvector are vectors of centrality scores[4]. Thus the centralities are given by the elements of the eigenvector of A or A^T corresponding to

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

an eigenvalue of 1, which in general has no non-zero solution. One way to make the equations solvable is to normalize the rows (columns) so that each adds up to 1 and A and A^T become a stochastic matrix. The other way, first suggested by Bonacich (1972), is to assume that each individual's status is proportional (not necessarily equal) to the weighted sum of the individuals to whom she is connected, in which case the equation can be rewritten as

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

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

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

A practical problem with eigenvector centrality is that it works well only if the graph is (strongly) connected, i.e. if each node is reachable from every other node in the network. Real undirected networks typically have a large connected component. However, real directed networks do not. If a directed network is not strongly connected, only vertices that are in strongly connected components or in the out-component and in-component[5] of the strongly connected components can have non-zero eigenvector centrality. This happens because nodes with no incoming edges have, by definition, a null InEigenvector centrality score, and so have nodes that are pointed to only by nodes with a null InEigenvector centrality score (and the analogous for the OutEigenvector centrality). Thus, when a node is in a directed acyclic graph, centrality becomes zero, even though the node can have many edges

[5] The in-component of a node is the set of vertices from which that node can be reached; the out component is the set of vertices that can be reached from that node.

connected to it. A way to work around this problem is to give each node a small amount of centrality for free, regardless of the position of the vertex in the network,

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

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

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

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

The infinite sum converges, so for example $InKatz = (I - \alpha A^T)^{-1} \cdot \mathbf{1}$ as long as $\alpha < 1/\lambda_1$, where λ_1 is the maximum value of an eigenvalue of A^T. As a result, eigenvector centrality can be interpreted as a distance between nodes measured by unrestricted walks of any length, rather than by paths or geodesics.

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

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

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

where β the damping factor (that is the parting of PageRank that is transferred by a node). For $\beta = 1$ page rank converges to eigenvector centrality (normally $\beta = 0.85$ is used). $Pagerank$ can be reformulated in matrix format as $InPagerank(j) = (I - \beta A^T D^{-1})^{-1} \cdot \delta \mathbf{1}$ where D is a diagonal matrix of out-degrees and $\delta = (1 - \beta)/n$. As a result of Markov theory, it can be shown that PageRank is the steady state probability distribution of a random walk with a restart probability δ. Thus PageRank can be interpreted as the fraction of time that a random walk(er) will spend at a node over an infinite time horizon. The restart probability allows the random process out of dead-ends (dangling nodes). PageRank (as well as SinkRank below) can be generalized to weighted networks by replacing the adjacency matrix with the weights matrix and the nodes' degrees with their strengths.

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

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

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

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

where y_{ik} represents the value of the loans borrowed by bank k from bank i and y_i all loans given by bank i. The centrality of the node can then be measured by the increase of the sum of the harmonic distance of a node from all other nodes in the network[6]. Acemoglu et al. (2015) shows that the matrix Q, whose elements are $q_{ij} = y_{ij}/y_i$, is a stochastic matrix and hence can be interpreted as the transition probability matrix of a Markov chain. For this Markov chain, one can define the mean hitting time from i to j as the expected number of time steps it takes the chain to hit state j conditional on starting from state i. Acemoglu et al. (2015, p.588) show that the harmonic distance from bank i to j is equal to the mean hitting time of the Markov chain from state i to state j. Acemoglu et al. (2015) argues that "various off-the-shelf (and popular) measures of network centrality (such as eigenvector or Bonacich centralities) may not be the right notions for identifying systemically important financial institutions. Rather, if the interbank interactions exhibit non-linearities similar to those induced by the presence of unsecured debt contracts, then it is the bank closest to all others according to our harmonic distance measure that may be 'too-interconnected-to-fail.' " (pp. 566-567) Similar to Acemoglu et al. (2015) measure Soramaki's SinkRank is based on absorbing Markov chains. SinkRank is defined as

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

where m is the number of absorbing states and $n-m$ the number of non absorbing states and q_{ij} the element of the matrix $Q = (I - S)^{-1}$ and S is the matrix of transition probability for non-absorbing states. Q is a matrix whose elements give the number of times, starting in state i a process is expected to visit state j before

[6]Acemouglu's Harmonic distance is, in our terminology an $out-centrality$ measure, and the corresponding in version could also be defined.

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

Table 3.1 shows the summary statistics for the network centrality variables used in the regression models below.

Figure 3.2 illustrate the average and quantiles of indegree of borrower and outdegree of lender for three phases of 2007-2008 financial turmoil. Both variables show a higher inter-quantile range before Lehman's collapse than after. There is, however, a sharp decrease in the upper quantile of both measures during the second phase.

Figure 3.3 shows the average and quantiles of closeness and betweenness centrality over the time. Although there is no clear pattern in the betweenness centrality of banks, closeness decreases during the second and third phase of the 2007-2008 financial turmoil, a trend that is similar to the local degree centrality measures. Figure 3.4 shows no clear trend in the quantiles of the eigenvector-based centrality measures but some of the distributions appear to become more right skewed towards the end of the analyzed period.

Figures 3.5-3.7 show the distribution of centrality measures for the entire sample and for the three different subsamples, phases I-III. We discuss these figures in more details in the Results section.

Global centrality measures tend to correlate with local centrality measures as, by construction, high degree can lead to high centrality. To quantify the importance of this effect, we regress the nodes global InCentrality (OutCentrality) versus their Indegre (Outdegree) and plot the coefficients of the pooled OLS regressions, for each quarter separately, in Figure 3.8. The plots show interesting dynamics: while correlations decrease over time for pagerank, they increase for closeness and have a non monotonous behavior for betweenness. We do not explore in this paper what consequences such dynamic change may have in terms of the banking system stability, but we do control for these correlations when assessing the effect of global centrality on interbank spreads.

3.3.3 Other control variables

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

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

Another key determinant of O/N rates is the time of a transaction. While Angelini (2000) using hourly e-MID data shows no intraday pattern of interest rates, Baglioni and Monticini (2008) and Gabbi et al. (2012) find a decreasing trend in the O/N rate as the trading day progresses. The intraday slope becomes more pronounced with the financial crisis and, in particular, after the Lehman Brothers collapse. The intraday term structure of interest rate is due to the maturity of O/N deposits which are expected to be reimbursed at 9 am of the day following the trade. The increase in the slope of the yield curve after the default of Lehman apparently creates a risk-free profit opportunity. Baglioni and Monticini (2008) suggest that this opportunity is not arbitraged away for two main reasons: uncertainty about availability of liquidity late in the afternoon and an increase in the implicit cost of collaterals. Similar to Baglioni and Monticini (2008), we also examine the effect of the time interval of the transaction performed. Instead of dividing the day into hourly segments, we use only two slots: morning (8 am - 1 pm) and afternoon (1 pm - 6 pm). Morning-Afternoon (AM/PM Ratio) is the fraction of the difference between number of transactions that occur during morning and afternoon to all transaction of each pair at a given period. In the interbank market, participants must repay the loans at 9 am on the next trading day of transaction. Hence, morning interest rates have a premium to account for the longer maturity period than those transactions in the afternoon.

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

3.4 Econometric Model

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

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

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

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

Network variables are introduced one at a time in different specifications, together for both lender and borrower. The reason is that while they are intended to describe different features of the network they are very correlated with each other.

For global measures, we consider specifications both with and without controlling for the local network counterparts. Network variables are considered in logarithm form, and as such, regression coefficients should be interpreted as the effect of doubling network centrality on spreads, in basis points.

All specifications include a set of baseline covariates given by Transaction Ratio(%), AM/PM Ratio, Quot/Agg Ratio, Reciprocity Ratio, O/N Trading Amount of Lender, O/N Trading Amount of Borrower, described in section 3.3.3. The inclusion of these covariates is to isolate the effect of network characteristics on transaction spreads from bank- and pair-specific variables that contribute to spreads (see Temizsoy et al., 2015, for a description of the effect of these variables on spreads).

3.5 Results

3.5.1 Local network measures

As a first approximation to the effect of network centrality on the interbank market we evaluate the effect of local centrality measures (in logs) on spreads. Table 3.2 shows the effect of degree centrality on interbank spreads. Columns (1)-(4) presents a specification with lenders (L) and borrowers (B), indegree and outdegree. The results show that B with high indegree pay higher spreads, and this effect increases in magnitude as the financial crisis evolves. The pooled effect determines that doubling borrowing links (i.e. increasing the logarithm of the indegree centrality measure by 1 unit) increases interest rate by 1.437 basis points in all pooled periods, which corresponds to 0.653, 0.929, and 3.849 in phases I, II and III, respectively. That is, B pay a premium to be able to get more partners in the interbank network, and this increases when systemic risk increases. We might thus speculate that financial uncertainty directs banks towards looking for better connections within the established network structure and they paid a premium for the number of links.

L have no clear pattern regarding outdegree network centrality measures. L outdegree has a non-significant effect for all pooled periods (column (1)), positive for phases I and II (columns (2) and (3)), and negative (although not significant) for phase III (column (4)). This shows that L were able to obtain better rates for having more links within the network before Lehman's collapse, but the effect reverses after it. L thus pay a price for diversification when systemic risk increases. Possibly this suggests that in the presence of systemic risks, banks diversify their transactions, and incur in worse interest rates. Diversification may in turn increase uncertainty as well established information flows with a few partners are reduced (see Temizsoy et al., 2015).

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

Figure 3.5, first row, shows the bivariate kernel density estimation for lenders (L) outdegree and borrowers (B) indegree, for the all periods together, phase I, phase II and phase III. The graphs show a differentiated behavior for lenders and B. L outdegree has lower dispersion in phase I than in Phases II and III, thus indicating increasing heterogeneity in L as the financial crisis evolves. B indegree, on the other hand, has decreasing dispersion across phases. In fact the phase I plot indicates the existence of B with many lenders, which eventually disappear in the following phases.

Figure 3.5, second row, shows the bivariate kernel density estimation for outdegree and indegree of L, while the third row does it for outdegree and indegree of B, for the all periods together, phase I, phase II and phase III. The second row also shows that, from the point of view of L, banks borrow from less counterparts overtime, while outdegree becomes bimodal in phase III. The graphs in the third row indicate an overall reduction in the amount of incoming and outgoing links, in this case from the point of view of B.

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

3.5.2 Global network measures

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

Consider first the effect of betweenness in table 3.3. Recall that betweenness measures a bank's access to the interbank liquidity. When all pooled periods are considered, InBetwenness has a negative effect for both L and B, and OutBetweenness has a positive significant effect for B. For B, the effects increase in absolute value as the financial crisis evolves (i.e. the largest effect is in phase III). When local centrality is controlled for, only OutBetweenness remains significant. For L, the largest effect appear in phase III, where InBetweenness has a large negative effect while OutBetweenness is positive and significant. When both *in* and *out* measures are interacted B obtain a negative effect, which is significant for all pooled periods and for phase II. The fact that L coefficients are not significant suggests that the effect is not driven by market power, as otherwise both L and B would benefit from it, but by a 'too-interconnected-to-fail' perception of the B that benefit of lower spreads because the market participants believe highly connected borrowers will be bailout in case of default to avoid systemic effects. Then network interconnectedness were perceived as an asset for B during the crisis (i.e. phase II), and this vanishes after Lehman's collapse.

Now consider the effect of closeness in table 3.4. Closeness is the inverse of the average shortest distance of a bank from all banks that are reachable from it, and thus, a bank with higher closeness is connected to more banks. For B, InCloseness has a large positive and significant effect for all periods and subperiods, except for phase II when local centrality is controlled for. For L, OutCloseness is negative, and statistical significant. These results suggest that both B and L pay a premium for being interconnected to the network, and this increases when systemic risk is high. Note that in this case the interaction for B of *in* and *out* has a positive coefficient for all pooled periods but not significant for subperiods.

Figures 3.6-3.7 plot betweenness of L and B bivariate density estimates. The figures clearly reveal two features producing an L-shaped density in betweenness. First, the existence of a large number of L for which betweenness is either zero or close to zero, possibly L who do not borrow. Second, there is also a big proportion of B that also have zero or small betweenness. For closeness, figure 3.6 also reveals two types of borrowers, some with positive closeness and some with close to zero closeness. The latter group increases as a proportion of the total amount of borrowers in phase III.

Tables 3.5-3.7 present the coefficient estimates of different global network variables using eigenvector centrality measures. All specifications include the same control variables as described in section 3.3.3, although they are not reported.

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

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

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

3.6 Conclusion

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

In our regression analysis we find that borrowers pay a premium (i.e. higher rates) for being central. However, lenders' centrality do not necessarily leads to higher rates. However, there is also evidence pointing out to the 'too-interconnected-to-fail' hypothesis that favors brokers, in particular during the acute phase of the latest financial crisis. That is, banks that are central both as borrowers and lenders at the same time, receive a discount on their funding rates. This effect is only present for borrowers.

Favorable rates obtained by more central banks do not necessarily reflect lower credit risk owing to any implicit government guarantee against default. It could also reflect higher bargaining power and/or lower credit risk through more diversified portfolios. Disentangling these effects is difficult in the case of OTC markets where market participants actively search for counterparties. When counterparties meet, they negotiate terms privately, often ignoring prices available from other potential counterparties and with limited knowledge about trades recently negotiated elsewhere in the market. Thus better connected banks may have better access to liquidity and benefit from better rates in compensation of their intermediation role. But the e-MID is a fully transparent trading platform. There is little scope for intermediation in this market. Search frictions and lack of information on rates offered by alternative lenders cannot be responsible for the observed cross-sectional dispersion of O/N rates in this market. Nonetheless our analysis does not allow to identify why centrality affect banks terms of trade in a financial network. The theoretical literature does not help us in this respect. While several theoretical papers have analyzed how the incentives of single agents to form linkages affect the resulting network topology (Goyal and Vega-Redondo (2007), Babus (2011), Babus (2013), van der Leij and Kovarik (2012)) leading in some cases to a core-periphery structure (in 't Veld et al. (2014), Lux and Farboodi (2013)) they do not provide any insights on the benefit of centrality in terms of prices.

Acknowledgements

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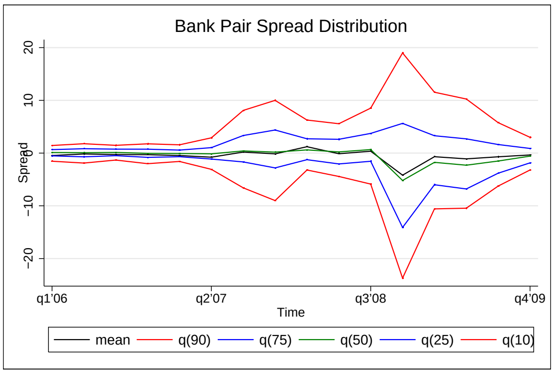
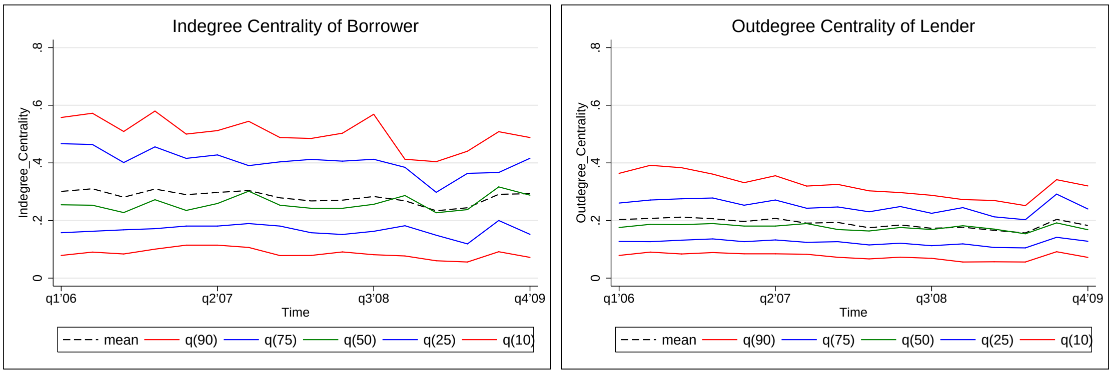
Figure 3.1: Bank Pair Spread over Time



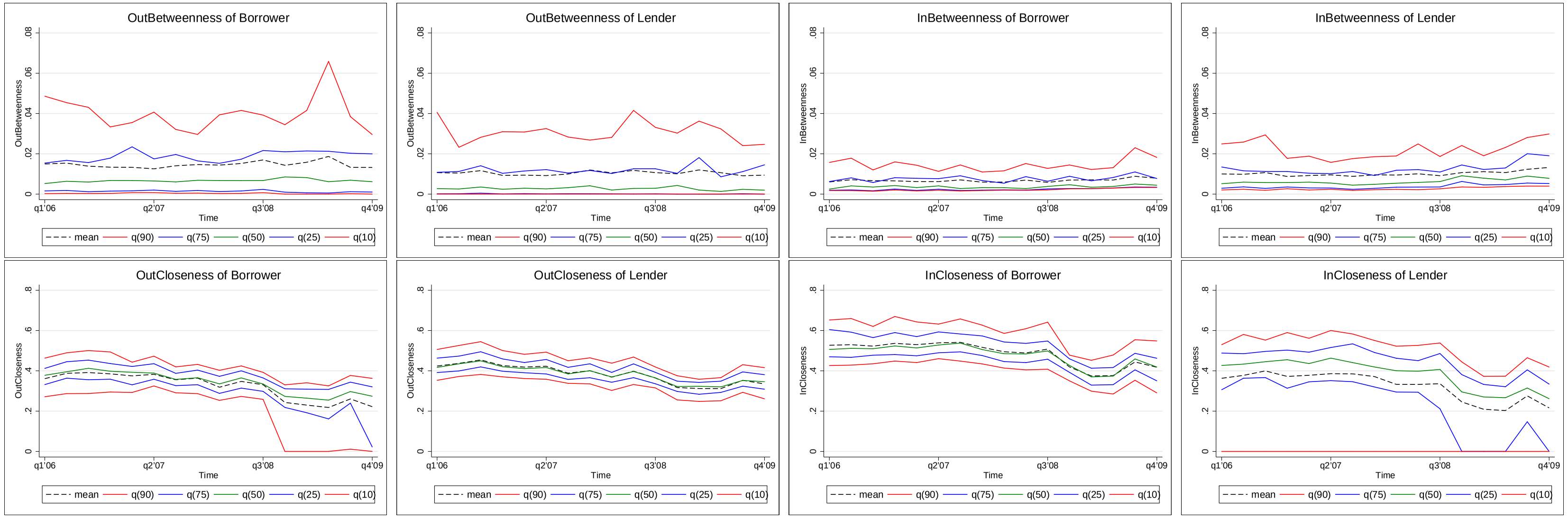
Note: All figures shown in graphs above are averaged to quarterly values.

Figure 3.2: Quantile Analysis Degree Centrality



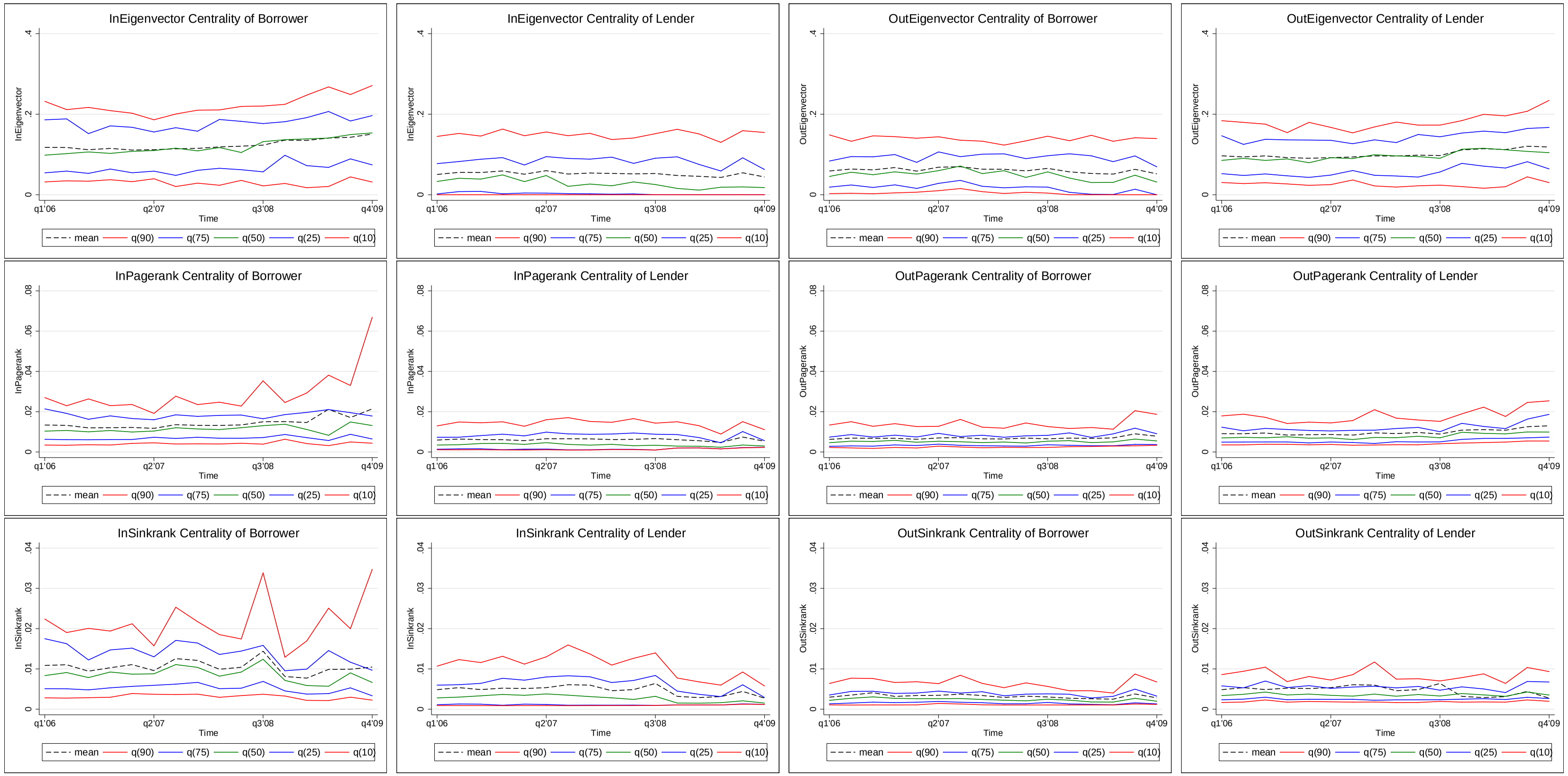
Note: All figures shown in graphs above are averaged to quarterly values.

Figure 3.3: Quantile Analysis of Betweenness & Closeness



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

Figure 3.4: Quantile Analysis of Eigenvector, Pagerank, Sinkrank



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

Figure 3.5: Bivariate Kernel Density - Local Network Measures (*Graph Type; Directed:Yes, Weight:None*)

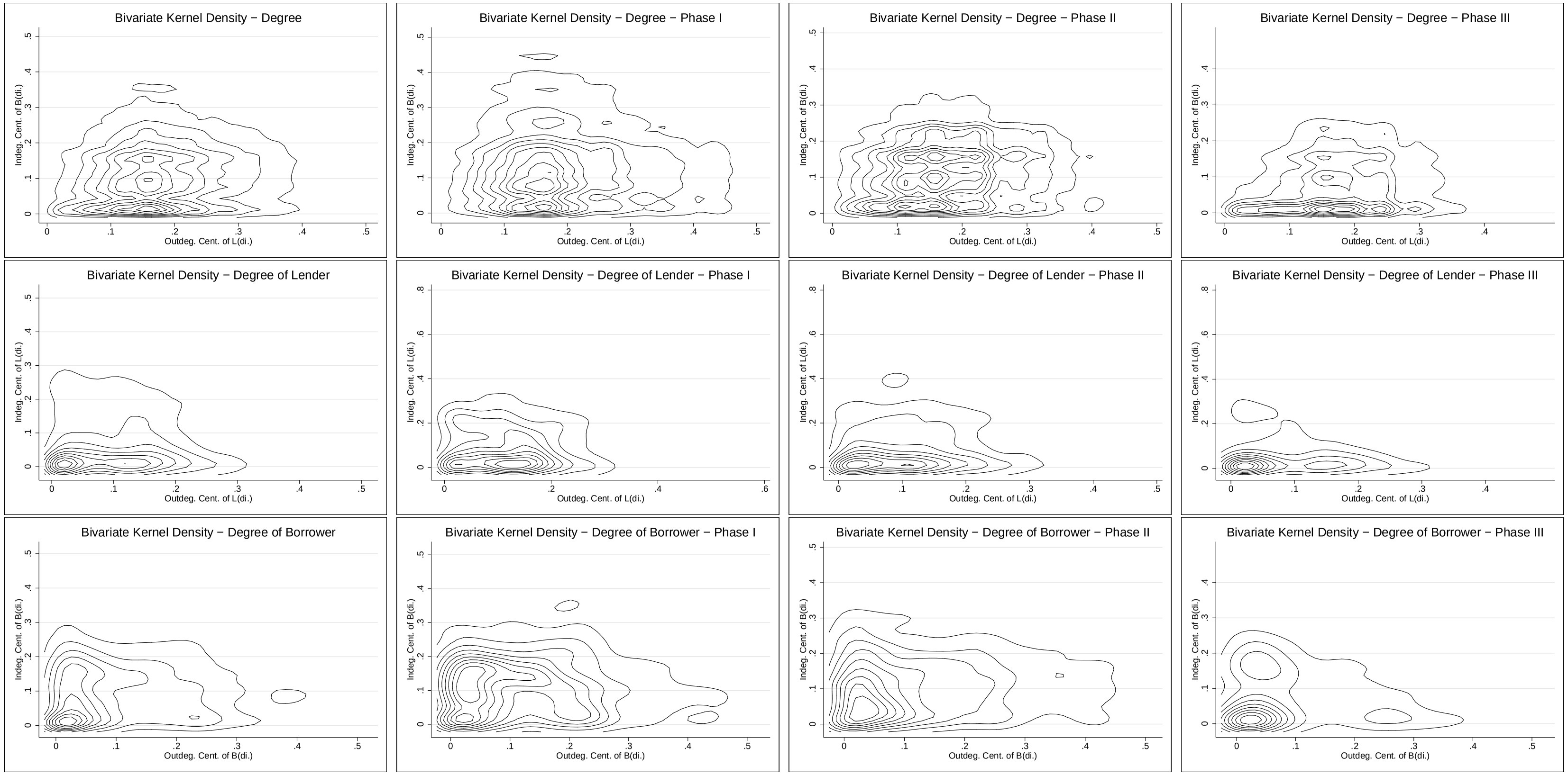


Figure 3.6: Bivariate Kernel Density - Global Network Measures(In) (*Graph Type; Directed:Yes, Weight:None*)

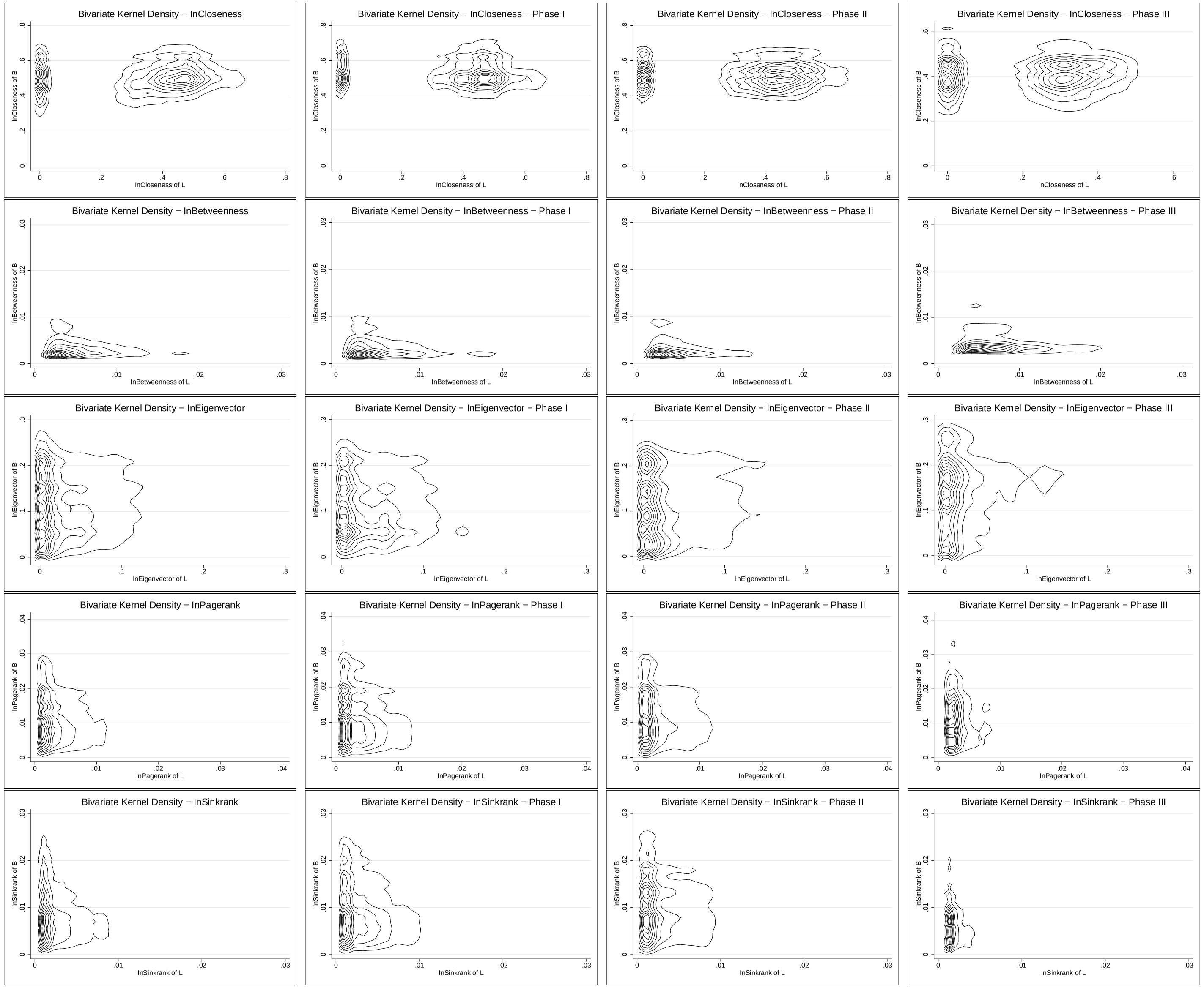


Figure 3.7: Bivariate Kernel Density - Global Network Measures(Out) (*Graph Type; Directed:Yes, Weight:None*)

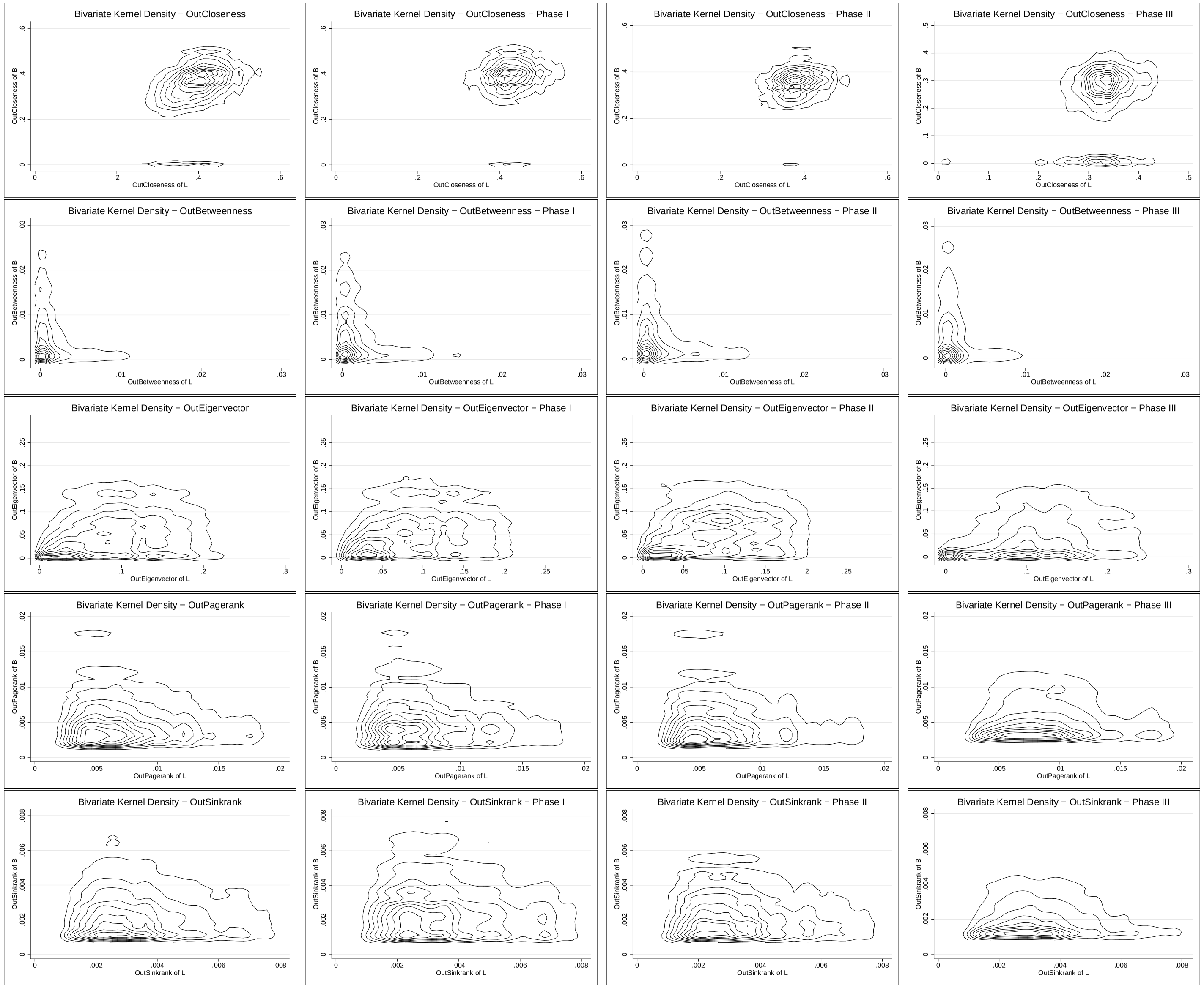
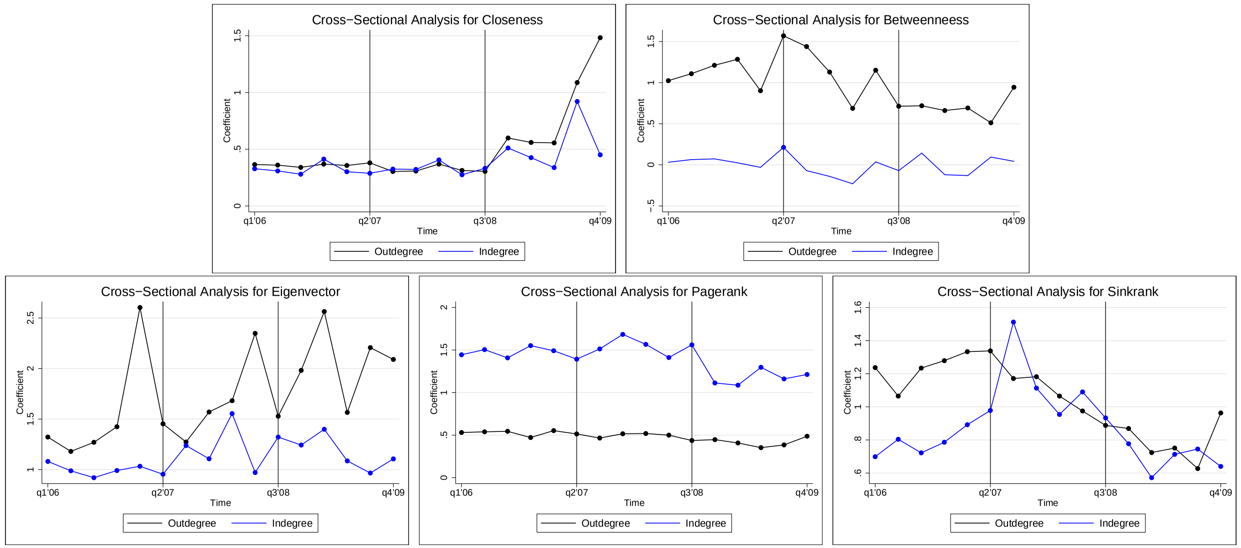


Figure 3.8: Global InCentrality (OutCentrality) vs their Indegre (Outdegree)



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

Table 3.1: Summary Statistics

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

Table 3.2: All O/N Loans - Local Network Measures as Determinants of Interest Rate Spread

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

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

Table 3.3: All O/N Loans - Global Network Measures as Determinants of Interest Rate Spread (Betweenness)

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

All network measures are in logarithmic form. In all models, we control for same variables used in the analysis of local network measures in table 3.2; transaction ratio, AM/PM ratio, quoter/aggressor ratio and ON trading volume. ON Trading Volume is used as proxy for bank size. In the second set of results, we also control for indegree and outdegree of both lender and borrower. *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses.

Table 3.4: All O/N Loans - Global Network Measures as Determinants of Interest Rate Spread (Closeness)

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

All network measures are in logarithmic form. In all models, we control for same variables used in the analysis of local network measures in table 3.2; transaction ratio, AM/PM ratio, quoter/aggressor ratio and ON trading volume. ON Trading Volume is used as proxy for bank size. In the second set of results, we also control for indegree and outdegree of both lender and borrower. *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses.

Table 3.5: All O/N Loans - Global Network Measures as Determinants of Interest Rate Spread (Bonacich eigenvector)

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

All network measures are in logarithmic form. In all models, we control for same variables used in the analysis of local network measures in table 3.2; transaction ratio, AM/PM ratio, quoter/aggressor ratio and ON trading volume. ON Trading Volume is used as proxy for bank size. In the second set of results, we also control for indegree and outdegree of both lender and borrower. *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses.

Table 3.6: All O/N Loans - Global Network Measures as Determinants of Interest Rate Spread (Pagerank)

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

All network measures are in logarithmic form. In all models, we control for same variables used in the analysis of local network measures in table 3.2; transaction ratio, AM/PM ratio, quoter/aggressor ratio and ON trading volume. ON Trading Volume is used as proxy for bank size. In the second set of results, we also control for indegree and outdegree of both lender and borrower. *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses.

Table 3.7: All O/N Loans - Global Network Measures as Determinants of Interest Rate Spread (Sinkrank)

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

All network measures are in logarithmic form. In all models, we control for same variables used in the analysis of local network measures in table 3.2; transaction ratio, AM/PM ratio, quoter/aggressor ratio and ON trading volume. ON Trading Volume is used as proxy for bank size. In the second set of results, we also control for indegree and outdegree of both lender and borrower. *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses.

Chapter 4

Effect of Economical and Monetary Shocks on Country Risk: Application of GVAR model

4.1 Introduction

The 2007-2008 financial turmoil urged governments of advanced economies to step in to the center of financial systems and assume the risk of privately held debt across capital markets. Consecutive bail-outs and governments' intervention to protect *"too big to fail"* institutions led to a stream of risk transmission from private financial sector to public sector, eventually leading to a lack of investor confidence in sovereign debt. As a result, spillover and contagion among countries attracted great attention after the global financial crisis. With multiple European countries being in the center of debt troubles, rapidly weakening situation in the Eurozone attracted a number of empirical papers covering the issues of sovereign risk in the euro area. Most importantly, the debt crisis in Greece, Ireland and Portugal focused the attention of the sovereign bond spreads literature on the interdependence of countries' risks.

This paper contributes to the understanding of (i) how monetary policies affect sovereign risk, (ii) international linkages among sovereign risks and, (iii) heterogeneity among Eurozone countries, using an econometric specification of Credit Default

Swaps (CDS) as a proxy of country-specific sovereign risk.

The literature on sovereign risks and contagion is very extensive, and it has recently focused on Europe. Most papers analyze contagion mechanism and study its determinants. Dungey and Martin (2007) analyze the linkage between countries and financial markets and find significant evidence of spillover and contagion during East Asian financial crisis of 1997-98. Fratzscher (2009) studies the transmission channels of US shocks to foreign exchange markets and finds that macroeconomic variables and financial exposure are important elements of transmission for both advanced and emerging markets. Diebold and Yilmaz (2009) examine the spread of shocks in global equity markets using variance decomposition methods. Bekaert et al. (2010) provide evidence on the importance of monetary shocks. Niehof (2014) finds that foreign shocks have a higher effect on countries with higher debts, and European bond markets are primarily driven by European shocks. There is also evidence of global interdependency and determinants of volatility of bond spread changes across countries.

There is strong evidence of co-movement of government bond spreads in the Euro area. The government spreads are generally decomposed into three main factors of the government bond spreads: risk aversion, fiscal factors and liquidity factors (Codogno et al., 2003; Geyer et al., 2004; Manganelli and Wolswijk, 2009; Haugh et al., 2009).

Apetite for risk is an important driver of sovereign bond spreads in the Euro area. US corporate bond spreads, as a proxy of global risk measure, is found statistically significant factor of European bond spreads (Codogno et al., 2003; Geyer et al., 2004; Manganelli and Wolswijk, 2009; Sgherri and Zoli, 2009). With the start of Economic and Monetary Union of the European Union (EMU) and until the middle of 2008, sovereign bond yields for EMU member countries remained relatively close to each other. However, after late 2008 with financial markets realizing the impact of the crisis, sovereign bond yield spread between Germany and other Euro area countries started to widen significantly. Recent studies also confirm that the start of EMU and 2008-09 financial crisis change the effect of government debt and deficit on sovereign bond yields within the Euro area and find that Germany was perceived as a “safe-haven” in international financial market after 2008-09 financial crisis (Bernoth et al., (2012)).

The second common determinants are fiscal fundamentals and growth. Bernoth and Wolff (2008); Bernoth et al. (2012); Favero (2013) examine the effect of both debt and deficit on bond spreads. Assmann and Boysen-Hogrefe (2012) use time-varying approach and find debt to GDP ratio is the most important factor which can explain fluctuation in government bond spreads. Sovereign bond spreads become an interesting area to analyze after 2008-09 sovereign debt crisis and studies on government bond spread started to investigate whether yields co-movements differ over time. Fiscal fundamentals are time-varying factors and European co-movement differs over time (Sgherri and Zoli, 2009; Barrios et al., 2009; Attinasi et al., 2010; Borgy et al., 2011; Assmann and Boysen-Hogrefe, 2012; Bernoth et al., 2012).

The third commonly used determinant of spread yields is liquidity risk. This is a very important factor as countries within the Euro area have not perfect control over monetary decisions which are taken by the central institutions, i.e. European Central Bank (ECB). We consider the effect monetary shocks by studying M3 growth and ECB refinancing rate in our model as the main determinants of the Eurozone liquidity. We thus study how liquidity shocks and monetary policy in general affects Euro countries’ CDS. There are different results on the importance of liquidity on government bonds. Favero et al. (2010) do not find liquidity as a significant factor in sovereign bond spreads, and show that liquidity is not independent from default risk and risk aversion.

Niehof (2014) also defines a fourth element which is financial market risk of spillover due to evidence in the literature of co-movement of bond market and stock market. This is specially relevant for countries in the EMU that have the same currency, and as such, they are connected with strong links that go to European central institutions.

We apply the global vector autoregressive (GVAR) model of Pesaran et al. (2004); Chudik and Fratzscher (2011); Chudik and Pesaran (2011). This is a framework for capturing interdependence and spillovers allowing for common factors and time-varying components. Since GVAR allows for interdependencies across individual variables within and across units, we model government bond CDS relative to Germany by domestic, global, monetary and weighted foreign variables where weights are calculated using their fiscal position. We include two factors that determine the fluctuation in government bond CDS similar to Favero (2013); a local factor (fiscal fundamentals and growth), and a global factor (market's appetite for risk).

We find evidence of positive correlation between sovereign bond CDS and risk aversion for almost all countries in the Eurozone. When ECB increases its refinancing rate, we observe an increase in risk of sovereign bond of all countries due to the negative environment in Euro area. A decline in money aggregates (i.e. M3) leads to all countries becoming more fragile, hence increasing sovereign risk. In contrast, monetary policies have the opposite impact on Greece, possibly due to a differentiation effect.

The remainder of this paper is organized as follows. Section 4.2 reviews the literature on measuring monetary shocks. Section 4.3 presents the eocnometric model. In section 4.4, we describe data and perform some pre-analysis of sovereign bond CDS with 5-years maturity. In section 4.5, we provide the results, and section 4.6 concludes.

4.2 Monetary shocks in the Eurozone

Financial and non-financial markets are unlikely to respond to policy actions that were already anticipated. That is, central banks actions are systematically related to economic variables (i.e. inflation, output gap) which are both observed by the national governments, international institutions and economic agents, then then anticipatory responses occur before the actual change happens (i.e. a tightening of the monetary policy, increment of the interest rate). In that case, it is difficult to identify the causal effect of monetary policy on financial markets. Distinguishing thus between expected and unexpected policy actions is a key fundamental challenge of the literature, and for this the definition of what is a shock and how it is constructed varies.

This has been a topic of continuous interest in the US, where the Federal Reserve Bank (Fed) actions were systematically analyzed. Since Bernanke and Blinder (1992) and Sims (1992), a considerable literature employed vector autoregressive (VAR) methods to identify and measure these shocks. The canonical methodology of Christiano et al. (1996) propose to measure exogenous monetary shocks using orthogonalized shocks to the Fed funds rate (FFR) in a structural VAR model. The system is identified by assuming that Fed behavior has no contemporary effect on other "real" economic variables, but it takes these into account for policy actions.

Many other alternative methodologies have been proposed in the literature. Bernanke and Kuttner (2005) follows Kuttner (2001) in using FFR futures data to construct a measure of "surprise" rate changes. They use the event study analysis of comparing the future 1-month futures contract with the actual target rate set by the Fed. The economic rationale is that *future* interest rates reflect expectations about monetary policies, and thus, deviations of the *actual* rate from the predicted one by the futures market represent a shock. Their approach overcomes some of the problems encountered by Christiano et al. (1996)'s VAR such as the time invariant parameter issue and omitted-variable bias. These "surprise" measures of monetary policy are based only on the actual/observed policy rate. These might not fully capture monetary policy shocks for two reasons. First, agents might be able to anticipate changes in the policy rate but might be surprised about the path of monetary policy. Second, recent changes in monetary policy, such as reaching the zero lower bound and the use of unconventional monetary policy, might make FFR-based measures superfluous.

The literature emphasizes that monetary policy is multi-dimensional. Gurkaynak et al. (2005) and Buraschi et al. (2014), among others makes an important distinction between measures of surprises on the target rate (*target shocks*) and surprises on the path of monetary policy (*path shocks*). While Bernanke and Kuttner (2005) and Christiano et al. (1996) shocks fall within the category of target shocks, because they capture the unanticipated variation in monetary policy that is reflected in the current reaction of the policy instrument, *path shocks* intend to capture shocks to the path of monetary policy. More specific, Buraschi et al. (2014) define a path shock as reflecting the surprises about future policy that can be inferred from forward guidance and/or other communications by the Board members. Intuitively, Buraschi et al. (2014) path shock allows assessing agents' expectations about the evolution of monetary policy. BCW uses survey data to learn directly about agents' expectations/forecasts about different measures of economic activity and financial aggregates without imposing assumptions about the underlying data generating process. These shocks are based on expectations about the path of the

FFR controlling for forecasts about the evolution of the inflation and output gap.

Econometric models for the US have particular features that cannot be found in Euro area countries. While the ECB is the central bank of Euro area countries its policies may not be directly linked to individual countries' performance but to more aggregate performance at the Eurozone. The primary objective of the ECB, as laid down in Article 127(1) of the Treaty on the Functioning of the European Union, is to maintain price stability within the Eurozone. The Governing Council in October 1998 defined price stability as inflation of under 2%, "a year-on-year increase in the Harmonised Index of Consumer Prices (HICP) for the Euro area of below 2%" and added that price stability "was to be maintained over the medium term". The basic tasks, as defined in Article 3 of the Statute, are to define and implement the monetary policy for the Eurozone, to conduct foreign exchange operations, to take care of the foreign reserves of the European System of Central Banks and operation of the financial market infrastructure under the TARGET2 payments system and the technical platform (currently being developed) for settlement of securities in Europe (TARGET2 Securities). The ECB has, under Article 16 of its Statute, the exclusive right to authorise the issuance of Euro banknotes. Member states can issue Euro coins, but the amount must be authorised by the ECB beforehand (upon the introduction of the Euro, the ECB also had exclusive right to issue coins). The principal monetary policy tool of the European central bank is collateralised borrowing or repo agreements. These tools are also used by the US Fed, but the Fed does more direct purchasing of financial assets than its European counterpart. The collateral used by the ECB is typically high quality public and private sector debt.

Unlike the US Fed, the ECB has only one primary objective but this objective has never been defined in statutory law, and the HICP target can be termed adhoc. In fact, the ECB has been at the center of the recent European crisis with interventions that exceeded its original mandate. On 9 May 2010, the 27 member states of the European Union agreed to incorporate the European Financial Stability Facility (EFSF). The EFSF's mandate is to safeguard financial stability in Europe by providing financial assistance to Eurozone Member States. The EFSF is authorised to use the following instruments linked to appropriate conditionality:

(i) To provide loans to countries in financial difficulties (e.g. Greek bailout);

(ii) To intervene in the primary and secondary debt markets. Intervention in the secondary debt market will be only on the basis of an ECB analysis recognising the existence of exceptional financial market circumstances and risks to financial stability.

(iii) Act on the basis of a precautionary programme.

(iv) Finance recapitalisations of financial institutions through loans to governments.

Both for US and Europe, the classical tools of monetary policy (i.e. FFR for the US, managing the ECB refinancing rate for the ECB) lost its flexibility and effectiveness as it reached the zero lower bound. US monetary authorities gradually changed its policy instruments by considering forward guidance and QE (Quantitative Easing).[1] In contrast to the Fed, the ECB normally does not buy bonds outright. The normal procedure used by the ECB for manipulating the money supply has been via the so-called refinancing facilities. In these facilities, bonds are not purchased but

[1]Forward guidance is a change in the strategy of underpinning policy communication. The structure of FOMC statements has been modified to include: (i) an economic outlook, in January 2000; (ii) qualitative statements about future policy inclinations, in August 2003; (iii) calendar based-guidance, in August 2011; (iv) outcome-based guidance, in December 2012. Quantitative Easing policies consist of purchases, by the central bank of specified quantities of long-term financial assets. This could be separated into QE1, (late 2008-2009) and QE2 (2010 q2-2011 q2). While QE1 consisted of purchases of MBS, Treasuries and Agency securities, QE2 focused only on the purchase of long-term Treasury securities. The Fed intervened in both Treasury and mortgage securities in QE1 and QE2.

used in reverse transactions: repurchase agreements, or collateralised loans. These two transactions are similar, i.e. bonds are used as collaterals for loans, the difference being of legal nature. In the repos the ownership of the collateral changes to the ECB until the loan is repaid.

This changed with the recent sovereign-debt crisis. The ECB always could, and through the late summer of 2011 did, purchase bonds issued by the weaker states even though it assumes, in doing so, the risk of a deteriorating balance sheet. As of 18 June 2012, the ECB in total had spent €212.1bn (equal to 2.2% of the Eurozone GDP) for bond purchases covering outright debt, as part of its Securities Markets Programme (SMP) running since May 2010. On 6 September 2012, the ECB announced a new plan for buying bonds from Eurozone countries. The duration of the previous SMP was temporary, while the Outright Monetary Transactions (OMT) programme has no ex-ante time or size limit. On 4 September 2014, the bank went further by announcing it would buy bonds and other debt instruments primarily from banks in a bid to boost the availability of credit for businesses. The Emergency Lending Assistance (ELA) programme was designed for financial institutions in a liquidity crisis, such as the Greek banks in the course of the 2015 Greek financial snafu, when the banks experienced massive deposit flight. On 9 March 2015 the ECB started its own Quantitative Easing programme, which was designed to ease sovereign stress in its member states. Purchases are €60bn per month. The program is expected to last until at least September 2016. Though the ECB's main refinancing operations (MRO) are from repo auctions with a (bi)weekly maturity and monthly maturation, the ECB now conducts long-term refinancing operations (LTROs), maturing after three months, six months, 12 months and 36 months. In 2003, refinancing via LTROs amounted to €45bn which is about 20% of overall liquidity provided by the ECB.

There is also an extensive literature exploring monetary shocks in Europe, although the changing institutional environment makes it less conclusive. Barran et al. (1996), Ramaswamy and Slok (1998), Dornbusch et al. (1998) analyze the monetary transmission across countries in Europe before Euro was introduced and finds that European countries respond similarly to the monetary shocks but with different magnitude. Since the data used by these study are before EMU was established, they only consider monetary policy effect and/or interest rate changes for each country separately. After euro-zone was established, there has been further studies considering effect of common Euro area monetary policy shocks and in the Euro area. Georgiadis (2015) included ECB intervention in addition to macroeconomic variables (output growth, inflation etc.) to analyze determinant of transmission of Euro area monetary policy and concludes that economies of Euro area countries are affected by the ECB's monetary policy and transmission of monetary policy in Euro area countries differs. The results of his research confirms to results of similar studies related to effect of monetary policy shock in Eurozone (also see Ciccarelli et al., 2012; Georgiadis, 2014).

We analyze the effect of monetary shocks on sovereign risk using two monetary measures. The first one is the ECB refinancing rate and the second one is broad money aggregate (M3). M3 is the broadest measure of money supply, and Euro area M3 money supply includes following items; (i) liabilities of the money-issuing sector and central government liabilities with a monetary character held by the money-holding sector, (ii) currency in circulation, (iii) overnight deposits, (iv) deposits (v) repurchase agreements (vi) money market fund shares (vii) debt securities up to 2 years. Changes in both monetary variables are assumed to be exogeneous to individual Eurozone countries' sovereign risk, once interdependence is taken into account.

4.3 GVAR model

We use global vector autoregressive (GVAR) models to capture time-varying interdependence of variables (see also Diebold and Yilmaz, 2009; Dees et al., 2007; Diebold and Yilmaz, 2009; di Mauro and Pesaran, 2013; Favero, 2013). Our baseline specification is

$$\begin{aligned}\Delta S_{it} = \quad & \beta_{i0} + \beta_{i1}S_{it-1} + \beta_{i2}\Delta RiskAv_{it} + \beta_{i3}(D_{it} - D^{g}_{it}) + \beta_{i4}(B_{it} - D^{g}_{it}) \\ & +\beta_{i5}ln(ECB)_{it} + \beta_{i6}ln(M3)_{it} + \beta_{i7}ln(oil)_{it} + \beta_{i8}W^{d}_{it-1} + \beta_{i9}W^{b}_{it-1} + \mathbf{u}_{it},\end{aligned} \tag{4.1}$$

$$S_{it} = CDS_{it} - CDS^{g}_{t}, \quad \text{and} \quad \mathbf{u}_t \sim i.i.d.\,(0, \Sigma)\,,$$

$$i = 1, 2, ..., N, \; t = 1, 2, ..., T,$$

where $\mathbf{u}_t$ is the collection of shocks for the N countries and Σ is a $N \times N$ variance-covariance matrix of contemporaneous shocks interdependence.

In this model, the initial determinants of CDS of 5-years sovereign bond over CDS of 5-years German (g) bund of a country i for a given period t, S_{it}, are fiscal fundamentals. We use two proxies for country's macroeconomic and fiscal conditions: debt to GDP ratio (B_{it}) and deficit to GDP ratio (D_{it}). Second and third determinants are global risk aversion ($\Delta RiskAV_{it}$) and monetary policies (which are proxied by $ln(ECB)$ refinancing rate and $ln(M3)$). Finally we also consider oil prices (in logs) as a proxy for global shocks that might affect the sovereign risk in Euro area. These common variables are treated as exogenous.

The GVAR specification allows for time-varying interdependencies among countries. A time-varying weighting matrix captures the importance and influence of country j on country i's economy. Following Favero (2013) we employ fiscal fundamentals as distance between countries to construct the interrelation matrix of the GVAR specification. We rescale debt to GDP and deficit to GDP ratios as in Favero (2013) based on Maastricht Treaty framework for time t as

$\mathrm{dist}^B_{ji,t} = |B_{j,t} - B_{i,t}|/0.6$, and $dist^D_{ji,t} = |D_{j,t} - D_{i,t}|/3\omega^B_{ji} = \dfrac{1/dist^B_{ij}}{\sum \frac{1}{dist^B_{ij}}}$ and $\omega^D_{ji} = \dfrac{1/dist^D_{ij}}{\sum \frac{1}{dist^D_{ij}}} W^b_{it} = \sum \omega^B_{ji} S_{it}$ and $W^d_{it} = \sum \omega^D_{ji} S_{it}$

The contemporaneous global CDS spreads (W^b_{it} and W^d_{it}) are not included in the model like a standard GVAR model, because these variables are unlikely to be exogenous due to low number of cross-section units. Therefore, we use lags of global spread in our specification.

4.4 Data

4.4.1 CDS and other data

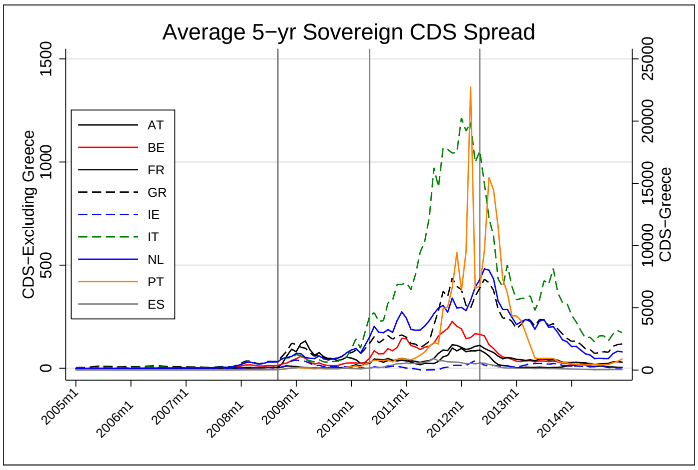
A credit default swap (CDS) is a swap contract in which the protection buyer of the CDS makes a series of premium payments to the protection seller and, in exchange, receives a payoff if the bond goes into default. CDS is direct measure of the default risk but not of the probability of default, as the price of a CDS depends both on the probability of default and on the expected recovery value of the defaulted bond. Moreover, such measure is not perfect; CDS differentials might also reflect the different liquidity of different sovereign CDSs, as well as counterparty risk (i.e. the risk that the protection seller of the CDS is not able to honour her obligation when the bond goes into default).

The data on daily CDS with maturities between 1 and 10 years are provided by Bloomberg and S&P Capital-IQ starting from 2006. In particular, we consider the monthly mean of 5-years CDS bonds.

The primary goal of this paper is to analyze the effect of monetary policy on Euro area countries' sovereign risks, as measured by 5 years CDS bonds. We focus on ten countries: Austria, Belgium, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal, and Spain. The sample has monthly frequency and runs from January 2006 to December 2014.

Considering the findings of Bernoth et al. (2012) on Germany's "safe-haven" status in Euro area, the CDS relative to German bund reveals the risk that an investor takes by buying a specific sovereign bond. Therefore, CDS data used in our study is the spread to CDS of German bund.

Figure 4.1: Monthly Average 5-yr Sovereign CDS Spread (in basis points)



Note: CDS relative to CDS of German Bunds have seen two stress periods in last 10 years. First, CDS spreads in Eurozone increased sharply in 2008/09 global financial crisis. Between mid 2009 and mid 2011, CDS spread in the zone decreases, however with the start of Euro area crisis in may 2010, CDS spreads move up sharply.

If the country's fiscal position degrades in comparison to the benchmark country (Germany in our case), the CDS of government bond spread increases due to demand of higher default risk premium. Debt to GDP and fiscal deficit to GDP ratios are the most common fiscal variables used as a proxy of country-specific credit risk.[2] We

[2]Some of the studies which use debt to GDP ratio as credit risk indicator are Favero and Missale

use both variables constructed from Eurostat. Since these variables have quarterly frequency, we interpolate data from quarterly to monthly using cubic splines.

We also include US corporate long-term Baa-Aaa spread (as per Moody's rating scale) in our analysis in order to control for time-varying global risk aversion which is a conventional measure in the related literature (Codogno et al., 2003; Geyer et al., 2004; Bernoth and Erdogan, 2012; Bernoth et al., 2012; Favero, 2013). When there is high uncertainty in the market, the investors prefer safer bonds to riskier corporate bonds. Therefore difference between low-grade bond (Baa) and high-grade bond (Aaa) increases.

4.4.2 Unit root and structural break tests

The possibility of unit root is one of the key issues facing econometric modeling. Therefore, we present the results of unit root tests (without a possible structural break) in table 4.1. The t-statistics reported in the table for Augmented Dickey-Fuller (ADF) and Philips-Perron unit root tests corresponds to the statistics with the longest significant lag and 4 lags, respectively. The lag length used in ADF unit root test is selected by the Akaike Information Criterion (AIC) based on the standard ADF regressions. In addition to the result of unit root test for individual country, we also include results for panel. We run the unit root tests using time trend and a constant.

Our results point out that CDS of 5-years government bond has unit root for all countries apart from Netherlands according to ADF. However, the version of CDS that we use in our model, CDS of sovereign bond relative to CDS of German bund,

(2012); Favero (2013); Manganelli and Wolswijk (2009); Beirne and Fratzscher (2013); Bernoth and Erdogan (2012); Bernoth et al. (2012); Aizenman et al. (2013). Credit risk is proxied then by deficit to GDP in the study of Bernoth and Erdogan (2012); Bernoth et al. (2012). Beirne and Fratzscher (2013); Lane (2012); de Grauwe and Ji (2012) use current account deficit or fiscal balance in their studies.

are stationary for all countries and also for panel. Unit root test of all explanatory variables, that we include in our baseline mode, are also reported in the table 4.1[3].

Another important problem in the econometric modeling that we might face is the possibility of structural breaks. The issue is likely to be observed in economies that are subject to significant political, social and economical events. The fact that country-specific models within GVAR are specified conditional on foreign and global variables should somewhat eliminate the structural break issue. Since the GVAR framework is vulnerable to this problem (Dees et al. (2007)), we run three tests; (i) the possible breaks in our dependent variable, (ii) possible breaks in the regression (iii) confirmation of on whether break dates apply to all countries.

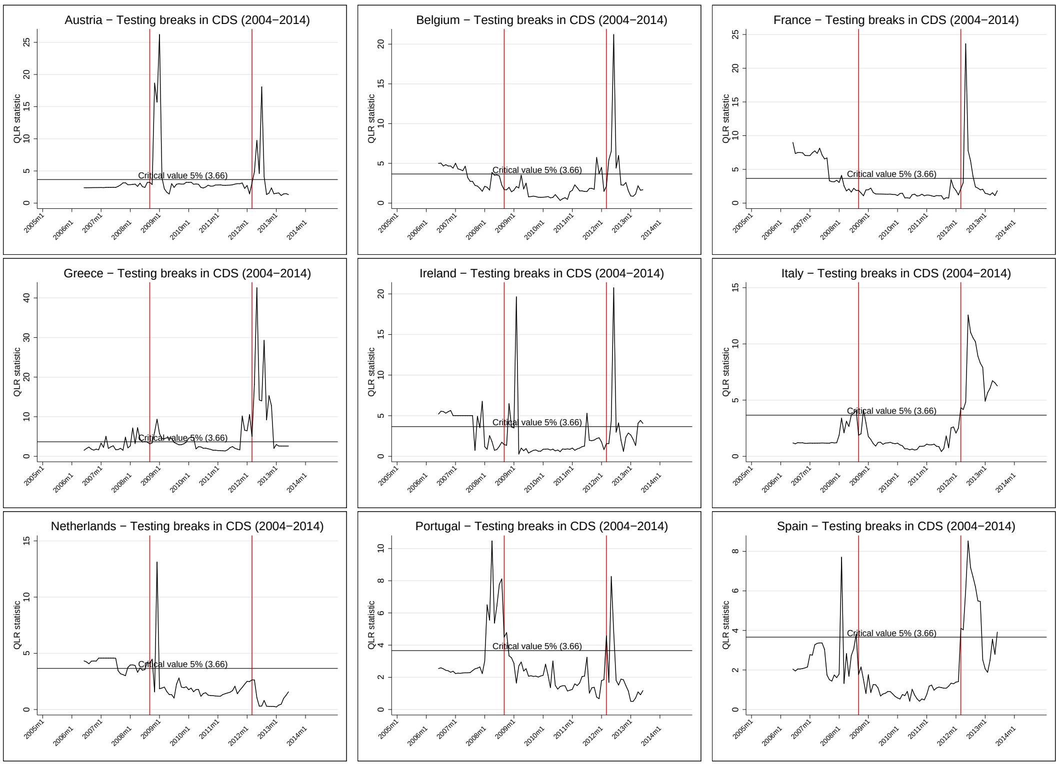
We apply Quandt Likelihood Ratio(QLR) structural break test in CDS of sovereign bond over CDS of German Bund for nine countries in Eurozone in order to determine the periods where trend of CDS is statistically changed at 5% significance level. Graph 4.2 shows QLR statistic of the structural breaks in CDS from the beginning of 2006 to the end of 2014 for each country. Apart from Belgium and France, trend of sovereign risk of all other countries is affected by 2007-2008 financial crisis. Almost all countries' risk show structural change for the Greece debt crisis in 2012, but only trend of sovereign risk for Netherlands is not affected by 2012 debt crisis.

We also run the QLR test for unknown dates to determine the structural breaks in country-specific models and report our result in graph 4.3. There is statistically significant variation in the structure of the model for almost all countries. In line with the QLR results in variable level, only Netherlands has no structural change in model.

Finally, we apply Chow test for each possible break point in model that we

[3]Favero (2013) states that non-stationary exogenous variable can be used in GVAR model, therefore we employ Debt/GDP ratio relative to Germany. Debt/GDP ratio relative to debt/GDP ratio of Germany is the only variable in our model that has unit root.

Figure 4.2: Quandt Likelihood Ratio (QLR) Structural Break in CDS relative to German Bund

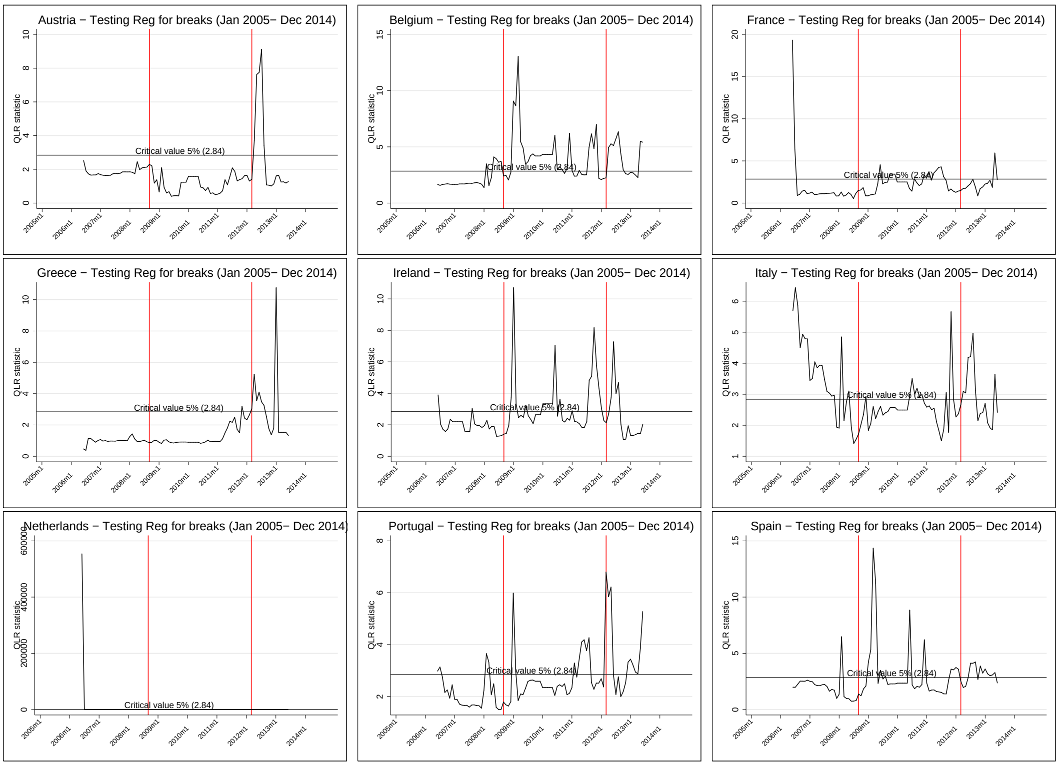


Note: We check structural break in CDS for 4 lags. Vertical red lines represent Aug'09 for 2007-2008 financial crisis and Mar'12 for 2012 Greece debt crisis respectively. Horizontal black line is for critical value of F-test at 5% significance level.

determine using QLR test; Sep'08, Apr'10 and Apr'12 and present results in table 4.2. We run regression for each country separately and the only possible break affects all countries is Apr'12 which is the period closer to Greece debt crisis.

Overall, not surprisingly, there is strong evidence of structural instability and almost all countries are affected by recent financial and debt crisis. Therefore, we also run our baseline GVAR model before and after 2012 Greece debt crisis in order to detect the changes in the effect of domestic and foreign variable on sovereign risk.

Figure 4.3: Quandt Likelihood Ratio (QLR) Structural Break in Regression



4.5 GVAR results

In this section we present and interpret the result of seemingly unrelated regression (SUR) using GVAR model and impulse response function for country-specific shocks and monetary shocks.

4.5.1 Seemingly unrelated regression model

We present the results of SUR for nine countries using GVAR model in order to analyze interdependence of countries in Euro area and other the factors that affect country risk.

In table 4.3, our sample data covers the period from the beginning 2006 to the end of 2014. In order to compare the changes before and after 2012 Greece debt crisis, we also run the same regression for a sub-sample between Jan-2006 and Dec-2012. The results for before and after 2012 Greece debt crisis are provided in tables 4.4 and 4.5.

CDS spread is negatively affected by its lag for all countries which is in line with the findings of Favero (2013). However, only Portugal presents positive effect when we include all periods in our analysis. However, when taking into account the subsample before the 2012 Greece debt crisis, Portugal is also negatively affected by its CDS lag.

When M3 increases in the Eurozone, the government risk of almost all countries decreases, except for Greece that is affected in the opposite direction. Similar results are obtained for the effect of ECB refinancing rate. An increase in ECB refinancing rate increases sovereign risk of all countries except Greece. A tightening of the monetary policy (i.e. M3 decreases or ECB increases) is thus associated with a negative signal on the Euro zone countries' CDS. The case of Greece deserves special attention.

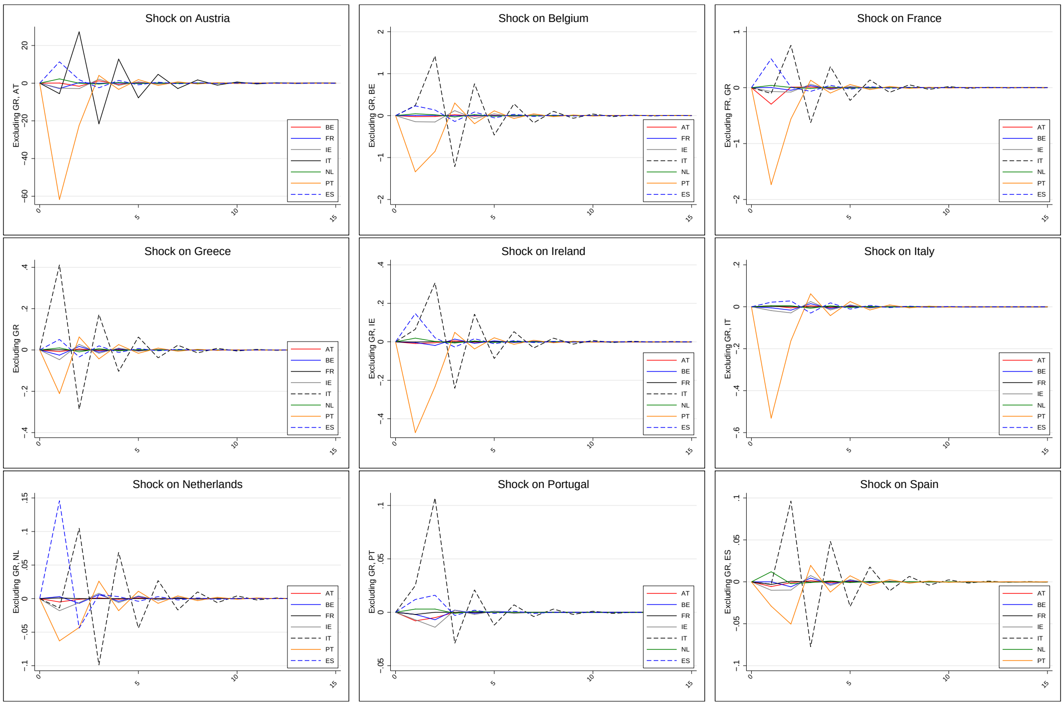
As anticipated, there is a positive relationship between risk aversion and sovereign bond CDS for almost all countries, but statistically significant for only Austria and Italy (an increase in uncertainty for the corporate bond market leads to a rise in sovereign risk).

4.5.2 IRF

Graph 4.4 and 4.5 show impulse response functions. First set of graphs present how other countries (excluding Greece) are affected by a shock in a given country, where the second set of graphs shows the effect of a shock in a given country on Greece and country itself.

Shocks in all countries including Portugal has positive effect on sovereign risk

Figure 4.4: Impulse Response Functions - Excluding Effect on Greece and Country Itself



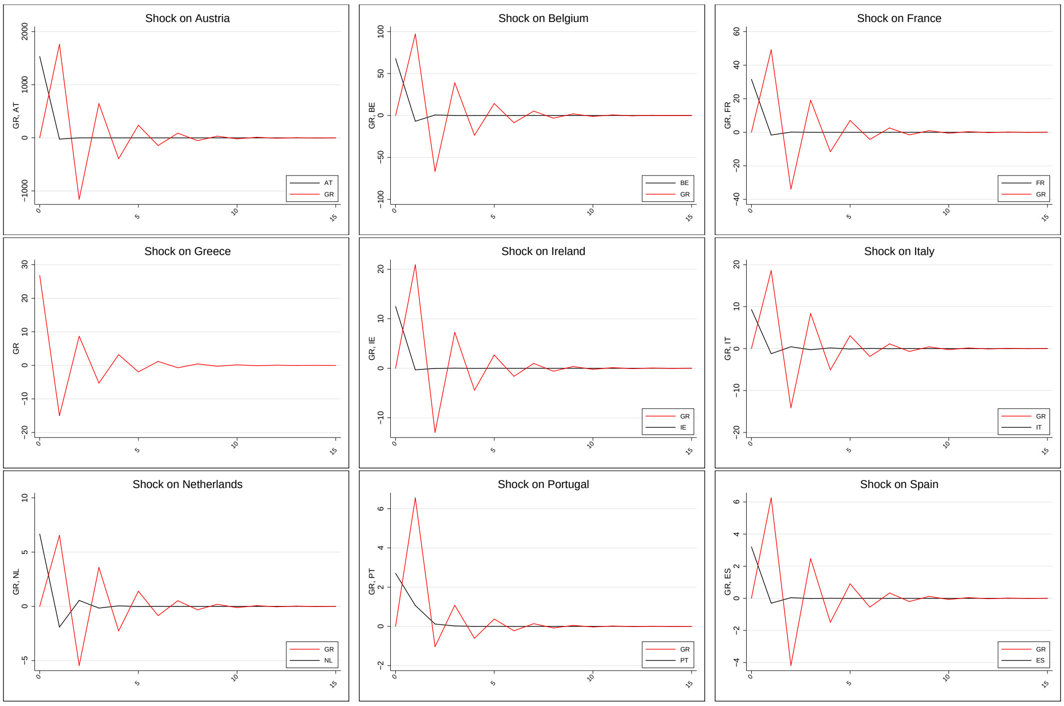
of Greece. If any country's sovereign risk deteriorates relative to the benchmark country (Germany), this shock also impacts Greece as well and Greece's position also weakens.

All countries are negatively affected by their own shocks in the following period, however shocks in Portugal has positive effect on the country. The reason might be that Portugal has different economical structure than other countries. Regression results also confirm that lag of CDS has different effect for all periods and before 2012.

Portugal, Spain and Italy are also highly affected by the shock of other countries in terms of magnitude. The difference is that Spain and Italy are positively affected by the shocks in other countries, however the shocks have negative effect on Portugal.

Regardless of the source of shocks, the largest effect is always on Greece in terms of magnitude. The other countries that follow Greece are Portugal, Spain and Italy. Although the magnitude of reflection of shock on these three countries are relatively small in comparison to Greece, figure 4.4 shows that they are affected by shocks more than other Euro area countries.

Figure 4.5: Impulse Response Functions - Effect on Greece and Country Itself

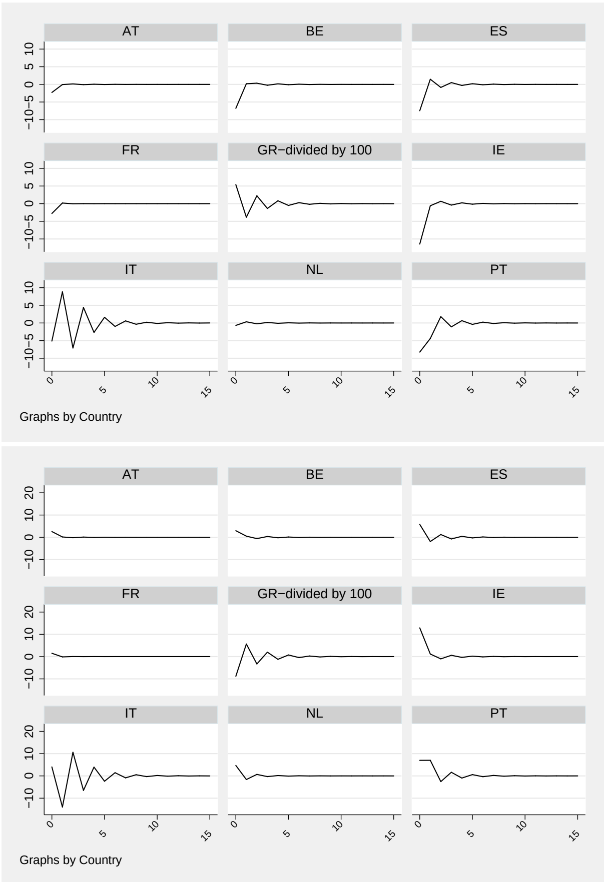


Graph 4.6 presents impulse response function for monetary shock on country risk for each country. The set of graphs on the left and right hand side show the monetary shocks in terms of money aggregate (M3) and ECB refinancing rate respectively.

An increase in money aggregate (M3) makes all countries more fragile and increase sovereign risk. However, Greece is affected by change in M3 in a different way than all other Eurozone countries in our sample. When ECB increases the M3, the shock creates a positive effect on Greece and CDS of 5-yrs government bond relative to CDS of Germany decreases.

As expected, shocks caused by changes in ECB rates have opposite effect on shocks generated by M3. Similar to the result of M3 above, Greece is affected by the shock in opposite direction. In cases where ECB increases refinancing rate, it can be interpreted as sensitivity to crisis and uncertainty in Euro area rises. Therefore, the shock increases sovereign risk.

Figure 4.6: Impulse Response Functions - Monetary Shocks



Note: The set of graphs shows the monetary shocks on countries. Money aggregate (M3) and ECB refinancing rate are used as proxy for monetary policy and reported on the left and right hand side of the graph respectively.

4.6 Conclusion

With increase in risk transmission to public sector, this paper draws attention to Eurozone debt crisis which affected sovereign bond spread and the CDS. It is crucial to understand how monetary policies affect the country risk, international linkages between country risks and whether drivers of risk change across countries. Since Global VAR allows for interdependencies across individual variables within and across units, we model government bond CDS relative to Germany by domestic, global, monetary and weighted foreign variables where weight is calculated using their fiscal position. As expected there is positive relationship between risk aversion and sovereign bond CDS for almost all countries. When distance between countries are measured based on distance of deficit/GDP ratio of a country, sovereign risk of Portugal and Ireland benefit from any common shock in the Eurozone. An increase in ECB refinancing rate is a signal of negative environment in Euro area, therefore it increases risk of government bond of all countries. A decrease in money aggregate (M3) makes all countries more fragile and increase sovereign risk. In cases where ECB increases refinancing rate, it can be perceived as sensitivity to crisis and uncertainty in Euro area surges. Therefore, the shock increases sovereign risk. However, Greece is affected by monetary policies in a different way than all other Eurozone countries in our sample. When ECB increases the M3 or decreases refinancing rate, Greece benefits from the shock and CDS of 5-yrs government bond relative to CDS of Germany decreases.

Table 4.1: Unit Root Tests

CDS of 5-yrs bond relative to CDS of German Bund with same maturity					
Variable		ADF at level	ADF at first difference	PP at level	PP at first difference
Austria	AT	-2.280	-6.432***	-2.341	-8.924***
Belgium	BE	-1.723	-6.475***	-1.529	-7.677***
France	FR	-1.639	-6.158***	-1.618	-7.974***
Greece	GR	-2.820	-11.853***	-3.335*	-16.550***
Ireland	IE	-0.868	-4.906***	-1.047	-9.252***
Italy	IT	-1.936	-5.473***	-1.812	-8.108***
Netherlands	NL	-3.576 **	-6.710***	-2.968	-7.224***
Portugal	PT	-0.889	-5.378***	-1.285	-10.530***
Spain	ES	-1.360	-6.492***	-1.187	-8.142***
CDS	Panel	1.136	-18.254***	2.247	-24.017***
Debt/GDP Ratio					
Variable		ADF at level	ADF relative to GR	PP at level	PP relative to GR
Austria	AT	-3.326*	-2.221	-2.405	-3.555**
Belgium	BE	-1.735	-1.807	-2.117	-2.316
France	FR	-1.970	-1.203	-2.058	-2.009
Greece	GR	-1.730	-1.976	-2.325	-2.666
Ireland	IE	-0.282	-0.921	-0.928	-1.352
Italy	IT	-1.213	-0.336	-1.799	-1.120
Netherlands	NL	-1.717	-1.497	-2.132	-2.311
Portugal	PT	-1.538	-1.708	-1.649	-1.860
Spain	ES	-4.250***	-2.518	-2.683	-1.950
Debt/GDP	Panel	-5.311***	-7.222***	1.770	1.043
Deficit/GDP Ratio					
Variable		ADF at level	ADF relative to GR	PP at level	PP relative to GR
Austria	AT	-3.719*	-3.427*	-4.012**	-4.452***
Belgium	BE	-4.968***	-4.810***	-4.199***	-4.200***
France	FR	-3.735**	-3.195*	-3.426*	-3.942**
Greece	GR	-2.523	-2.985	-3.388*	-3.757**
Ireland	IE	-1.943	-2.090	-2.621	-2.839
Italy	IT	-3.302*	-2.829	-4.157***	-4.197***
Netherlands	NL	-1.995	-2.779	-3.446*	-4.191**
Portugal	PT	-2.608	-3.990**	-3.101	-4.101**
Spain	ES	-3.260*	-4.228***	-2.871	-3.755**
Debt/GDP	Panel	-21.035***	-23.140***	-6.789***	-7.844***
Other Variables					
Variable		ADF at level	ADF at first difference	PP at level	PP at first difference
Ln(Oil)		-1.606	-7.624***	-2.682	-7.760 ***
Ln(Ecb)		-1.784	-9.274***	-1.953	-9.403***
Ln(M3)		-3.572**	-8.502***	-3.674**	-9.025***
Baa-Aaa(Risk)		-1.732	-6.025***	-2.348	-5.882***

Notes: Philips-Perron test results are based on lag(4).

Table 4.2: Structural break test for baseline regression for known dates: sep'08, apr'10 apr'12

Country	Code	F$(9, n)$	Prob	F$(9, n)$	Prob	F$(9, n)$	Prob
		sep-08		apr-10		apr-12	
Austria	AT	3.40	0.002	0.69	0.717	3.72	0.001
Belgium	BE	2.90	0.006	3.50	0.001	4.98	0.000
France	FR	1.51	0.167	3.04	0.005	1.72	0.096
Greece	GR	0.64	0.761	1.10	0.380	5.25	0.000
Ireland	IE	1.37	0.224	1.71	0.1089	2.72	0.008
Italy	IT	1.36	0.226	2.80	0.008	3.12	0.002
Netherlands	NL	1.30	0.262	3.82	0.001	11.57	0.000
Portugal	PT	2.18	0.035	2.01	0.052	5.86	0.000
Spain	ES	1.09	0.385	1.96	1.38	0.218	0.053

Notes: We apply the Chow test for each break separately. After confirming that 2012-apr is break point for all countries, we drop observations which date is greater than 2012-apr in order to test break for 2009-sep and 2010-apr. Therefore, we were able to test if there is a second common break in the dataset.

Table 4.3: CDS Spreads on Bunds, SUR - Sample: Jan'06-Dec'14

Variable	AT	BE	FR	GR	IE	IT	NL	PT	ES
L.Spread	-0.016	-0.101***	-0.052*	-0.56***	-0.025	-0.131***	-0.286***	0.16***	-0.095***
	(0.033)	(0.029)	(0.03)	(0.075)	(0.03)	(0.029)	(0.044)	(0.048)	(0.028)
Weight(1)	0.008	0.007***	0.002***	12.439***	-0.015**	-0.037**	0	-0.012**	0
	(0.008)	(0.003)	(0.001)	(1.65)	(0.007)	(0.016)	(0.002)	(0.006)	(0.004)
Weight(2)	-0.03	-0.009	-0.007	1.649	-0.005	0.058***	0.012***	-0.267***	0.079***
	(0.019)	(0.007)	(0.007)	(4.01)	(0.028)	(0.015)	(0.003)	(0.062)	(0.027)
Debt/GDP	0.18	-0.805**	0.025	-37.457*	0.073	0.175	1.142***	-0.178	-0.017
	(0.367)	(0.38)	(0.188)	(22.394)	(0.395)	(0.697)	(0.163)	(0.918)	(0.345)
Deficit/GDP	0.242	-0.077	0.129	16.01	-0.596	0.716	0.433***	0.046	-0.451
	(0.354)	(0.248)	(0.21)	(30.869)	(0.514)	(0.76)	(0.12)	(1.608)	(0.353)
ln(M3)	-2.226	-6.573***	-2.693***	522.742**	-11.079*	-4.961	-0.666	-7.988	-7.229**
	(1.435)	(1.655)	(0.831)	(222.277)	(6.395)	(3.202)	(0.464)	(9.477)	(3.522)
ln(ECB)	2.923*	3.361	1.701	-999.307*	14.607	4.576	5.331***	7.915	6.579
	(1.646)	(2.051)	(1.651)	(563.47)	(14.15)	(7.071)	(0.881)	(22.655)	(8.169)
ln(Oil)	-22.182*	-9.804	-2.519	898.454	-82.292	-50.132*	-3.856	-40.841	-21.973
	(13.05)	(14.907)	(7.623)	(1930.516)	(53.088)	(26.661)	(4.262)	(72.9)	(28.832)
L.Risk Aversion	13.951*	12.724	6.894	552.459	-7.192	27.155*	-0.039	2.405	18.764
	(7.492)	(8.415)	(4.433)	(1150.172)	(30.921)	(15.482)	(2.408)	(43.767)	(17.072)
Constant	3.25	33.951***	4.878**	1435.151	16.712	6.649	18.942***	15.946	10.589
	(2.891)	(11.189)	(1.884)	(1405.506)	(10.484)	(30.389)	(2.712)	(23.222)	(7.268)
No of Obervation	93	93	93	93	93	93	93	93	93
R^2	0.203	0.213	0.190	0.607	0.170	0.344	0.478	0.211	0.187

Notes: Weight(1) and Weight(2) are weighted average government bonds relative to German government bunds of all countries where weights are based on deficit/GDP and debt/GDP respectively.

Table 4.4: CDS Spreads on Bunds, SUR - Sample: Jan'06-Mar'12

Variable	AT	BE	FR	GR	IE	IT	NL	PT	ES
L.Spread	0.018	-0.182***	-0.108**	-0.356**	-0.214***	-0.217***	-0.431***	-0.317***	-0.242***
	(0.057)	(0.044)	(0.046)	(0.167)	(0.062)	(0.059)	(0.063)	(0.092)	(0.05)
Weight(1)	0.009	0.023***	-0.001	9.85***	-0.024***	-0.138***	-0.014***	-0.006	0.011
	(0.015)	(0.004)	(0.005)	(1.706)	(0.009)	(0.031)	(0.004)	(0.005)	(0.008)
Weight(2)	0.001	0.008	0.052***	14.622***	-0.078	0.128***	0.038***	0.296**	-0.045
	(0.036)	(0.012)	(0.016)	(4.988)	(0.05)	(0.029)	(0.006)	(0.124)	(0.055)
Debt/GDP	-0.047	-0.996**	-0.647*	-143.708***	3.555***	0.503	1.518***	8.224***	3.374***
	(0.47)	(0.43)	(0.351)	(26.731)	(1.104)	(1.207)	(0.19)	(2.113)	(1.066)
Deficit/GDP	-0.394	-0.006	-0.056	40.278	0.702	0.05	0.51***	1.575	-0.721*
	(0.626)	(0.257)	(0.291)	(31.219)	(0.594)	(0.731)	(0.129)	(1.259)	(0.383)
ln(M3)	-3.656	-5.182**	-4.432***	-243.248	13.225	-5.056	0.138	5.882	-3.382
	(2.694)	(2.443)	(1.413)	(245.316)	(10.401)	(4.245)	(0.637)	(9.241)	(4.219)
ln(ECB)	9.759	0.587	5.379*	-322.869	2.873	0.839	6.161***	11.508	4.696
	(7.154)	(6.137)	(3.1)	(590.806)	(23.909)	(10.314)	(1.718)	(22.65)	(9.906)
ln(Oil)	-27.946	-10.71	-2.943	-251.481	-38.428	-59.897**	-9.895**	-52.074	-15.206
	(17.482)	(17.755)	(8.637)	(1710.933)	(67.068)	(29.966)	(4.33)	(63.887)	(27.672)
L.Risk Aversion	9.457	9.207	3.933	-516.536	1.422	16.916	-2.625	10.113	13.447
	(10.32)	(10.492)	(5.138)	(1017.74)	(38.588)	(17.932)	(2.551)	(36.941)	(16.583)
Constant	-2.195	39.023***	3.774	6643.809***	108.144***	-1.301	24.009***	-44.477*	101.653***
	(5.031)	(13.226)	(2.299)	(1340.961)	(28.659)	(47.731)	(3.486)	(24.486)	(26.991)
No of Obervation	63	63	63	63	63	63	63	63	63
R^2	0.178	0.261	0.220	0.583	0.180	0.356	0.621	0.307	0.139

Notes: Weight(1) and Weight(2) are weighted average government bonds relative to German government bunds of all countries where weights are based on deficit/GDP and debt/GDP respectively.

Table 4.5: CDS Spreads on Bunds, SUR - Sample: Apr'12-Dec'14

Variable	AT	BE	FR	GR	IE	IT	NL	PT	ES
L.Spread	-0.062	-0.283***	-0.327***	-0.846***	-0.439***	-0.318***	-0.12*	-0.123	-0.311***
	(0.054)	(0.061)	(0.074)	(0.125)	(0.044)	(0.049)	(0.061)	(0.103)	(0.061)
Weight(1)	0.014***	0.007***	0.004***	8.412***	-0.005	-0.044***	0.004***	-0.042***	0
	(0.004)	(0.002)	(0.001)	(2.863)	(0.003)	(0.011)	(0.001)	(0.009)	(0.002)
Weight(2)	-0.05***	0.006	-0.014	14.314*	0.013	0.06***	0.019***	-0.135	0.065**
	(0.016)	(0.009)	(0.011)	(8.56)	(0.025)	(0.011)	(0.003)	(0.092)	(0.031)
Debt/GDP	-0.171	1.505**	-0.444	-115.453	-0.297	-0.812	3.41***	-5.318	-2.283**
	(0.513)	(0.636)	(0.591)	(104.204)	(0.989)	(1.051)	(0.376)	(4.598)	(1.148)
Deficit/GDP	0.19	0.414	-0.068	52.881	-29.253***	0.229	0.851***	-3.184	-0.325
	(0.205)	(0.352)	(0.439)	(40.862)	(3.572)	(1.487)	(0.147)	(3.22)	(0.503)
ln(M3)	-5.161*	-9.87***	-1.67	3719.907***	11.482	-6.754	-2.701*	-0.496	-9.871
	(2.887)	(3.763)	(2.753)	(1173.31)	(11.828)	(9.289)	(1.571)	(38.012)	(11.704)
ln(ECB)	4.98	17.301***	8.472*	-4087.824*	10.122	39.174***	12.038***	57.433	34.556**
	(3.216)	(4.945)	(4.678)	(2144.684)	(13.456)	(13.27)	(2.276)	(45.341)	(15.598)
ln(Oil)	-25.04**	-40.182**	-13.841	10223.61**	-93.229**	-21.196	14.013**	-9.284	-12.775
	(12.693)	(16.894)	(10.735)	(4973.402)	(39.049)	(36.669)	(6.188)	(148.865)	(52)
L.Risk Aversion	8.433	56.291***	35.235***	-4882.74	85.032**	190.14***	-2.44	397.01**	260.56***
	(12.624)	(19.137)	(12.063)	(5162.694)	(39.539)	(38.378)	(5.812)	(161.461)	(50.13)
Constant	10.407**	-15.296	28.335***	3536.907	-112.792*	126.732**	47.284***	386.817	110.325***
	(4.933)	(18.135)	(7.862)	(8978.168)	(67.074)	(57.273)	(5.899)	(263.16)	(31.272)
No of Obervation	30	30	30	30	30	30	30	30	30
R^2	0.563	0.659	0.667	0.709	0.851	0.765	0.719	0.529	0.648

Notes: Weight(1) and Weight(2) are weighted average government bonds relative to German government bunds of all countries where weights are based on deficit/GDP and debt/GDP respectively.

Chapter 5

Conclusion

This chapter synopsizes the methodological and empirical findings generated by this dissertation. As this dissertation is composed of three different empirical studies, a summary of their findings and their limitations are discussed separately, and agendas for future researches are explored.

5.1 Chapter 2

In Chapter 2, we investigate how the effect of bank relationships on interbank interest rate spread and financial stability evolved during 2007-08 financial turmoil. Unlike other studies that argue about the determinants of e-MID borrowing cost, this study also includes the bank's relationship and study the stability of relationships.

One issue with working with the e-MID data is that entry or exit of banks from the e-MID platform is driven by endogenous decisions, and thus, this may lead to a self selection bias (see Gabbi et al. (2014) for a recent analysis of this issue). For this reason we limit the analysis to the banks that traded actively on the electronic platform during the period of study. Trimming away the entering and exiting banks reduces the sample size significantly. Since banks that are dropped from the sample are less likely to have relationships, this is likely to overstate the importance of relationships among banks. Nevertheless, we would like to emphasize that there is no standard model that accounts for entry and exit in the interbank market. We do not have an exclusion restriction for building a structural model using our data. One particular problem is that we do not observe the identity of the bank (only up to a code) and we cannot know the financial situation (balance sheet) of each bank. For this reason we cannot observe the reason for an exit from the e-MID.

Banks can engage in other over-the-counter (OTC) trades, which are not observed in the e-MID (the reason discussed above). Since the e-MID is a transparent platform, banks may decide not to post any bid on the e-MID market to avoid a reputation effect (i.e. a borrower posting an urgent need for funds). More specifically, it might be the case that after the occurrence of the financial crisis only banks with sound financial conditions would remain trading in the e-MID market whereas troubled banks would search for alternative ways of obtaining financing in more opaque markets. Some papers have analyzed bank survival using the bank financial situation as regressors to model participation. For example Angelini et al. (2011) show that banks characteristic such as credit ratings, capital ratios, or profitability remained roughly unchanged during the precrisis and crisis periods or improved slightly. Neither borrower and lender liquidity nor their shortage of capital correlated with spreads in their study. They address the potential self-selection problem on longer maturity loans in the e-MID market but conclude that these type of distortions did not influence their empirical findings. More recently, Iori et al. (2015b) reject an overwhelming presence of survivorship bias in their analysis of the overnight segment of the e-MID market. While they find some effect during the early periods of the financial crisis (where banks that dropped had obtained, in the preceding periods, higher borrowing rates than those banks that remained in the market) they do not find statistically significant differences in funding rates between dropping and surviving banks after the collapse of Lehman Brothers.

Our LPI and BPI are local measures, in the sense that they capture lending and borrowing relationships within the banks with existing relationships, and not a global measure, as it does not takes into account the number of banks or other transactions happening simultaneously at the same time. As a matter of fact, by construction, LPI and BPI have an aggregated value of 1 for all aggregated banks and for each individual bank. As such, we cannot use it for explaining entry and exit of banks.

The chapter implements an estimation strategy to account for potential attrition bias. However the analysis is done at the level of bank pairs and not individual banks due to following reasons; First, our measure of analysis are bank-pairs and not individual banks. We claim that "As a result of this data trimming for entering and exiting banks, the number of banks during the period analyzed decreases from 200 to 140." We then focus on selection bias for bank-pairs for our restricted sample of 140 banks that participate in all periods. Our results are then valid for the subsample of banks that actively participate in the e-MID market for the entire sample. Second, pairs however do fluctuate considerably over the period of analysis. We use a bank-pair-level fixed-effects strategy in all models. Therefore, unobserved characteristics of pairs, as long as they remain "fixed" for all periods is controlled for. Our results should thus be interpreted as whether conditional on the pair unobservable fixed characteristics building a relationship with a certain counterpart has an effect on price and/or volume. Third, attrition or survivorship bias is however a potential concern if time-varying pair-specific shocks are correlated with our relationship variables, LPI and BPI. We then implement a Heckman-type selection model to account for potential attrition bias. The results appear in the new robustness section of chapter 2. The results show that controlling for potential attrition bias at the bank-pairs level does not change the main results of the paper, that is, the effect of LPI and BPI on interbank spreads and trading volumes.

The other point to be discussed might be that there are no controls for the financial health of the banks in the sample and this information is unobserved. So, the question might be raised as whether banks are pairing repeatedly with healthy banks because they are healthy, or because the relationship is valuable on other dimensions such as lowering information costs.

As we remark in the chapter, we do not observe the identity of the bank. That is, we only have a code that we can identify throughout the sample period but cannot really observe the real name of the bank. As a result we do not observe the healthiness situation of a particular bank. Angelini, et al. (2011) and Gabrieli (2011a, 2011b) note that the bank credit ratings did not change much over the financial crisis period. Of course, since credit ratings loose credibility we are not sure if banks were actually looking at credit ratings and we do not know what private or public information was available to each bank. Note that in all cases we use a panel data model with fixed-effects at the pair-level. That is, we control for unobserved characteristics of the pair, a model which also contains information about each bank, i.e. lender and borrower. Then, unobserved characteristics regarding healthiness are captured by pair-level dummy variables. This strategy is valid as long as unobserved characteristics are fixed across time. This may not happen if lending/borrowing decisions are affected by a time-varying healthiness factor structure, that is, if the variables are affected by particular situations of a bank at a given time (i.e. current balance sheet situation). We refer to this factor as the residual component in the error component structure, eg. e_{ijt}.

As discussed above, we do not have a structural model and then, the coefficients cannot be interpreted as causal effects. To be clear, we cannot completely rule out that relationships (as measured by LPI and BPI) are themselves "only" caused by the banks' matching process based on their specific financial situation. This does not seem to be the case in the overnight e-Mid market, as explained below in the reply to your next comment. However, even if this was true, for a bias to occur, in the sense that this makes LPI or BPI to be correlated with e_{ijt}, then a particular relationship measure should have an effect on the banks' financial healhiness. That is, banks match with each other based on their healthiness (controlled for fixed-effects), and then further interaction has an effect on spreads/volume (i.e. through the residual e) which feedbacks into more relationship lending.

Nevertheless, we believe the data provide weak evidence pointing out that this feedback effect is small. When we study survival of a bank-pair into the next months we find that spreads are not statistically significant, while LPI and BPI are (see tables 3 and 4). However, LPI and BPI are significant determinants of spreads, even when controlling for potential survivorship bias.

The other question might be why we do not analyze why links are created in Chapter 2 although links between banks i and j are almost surely not random and a structural model would reveal much more. In fact, when controlling for bank heterogeneity, the matching between lenders and borrowers in the e-MID market is fairly random. Hatzopoulos et al. (2015) have shown that, given a lender who makes l transactions over a given period of time and a borrower who makes b transaction over the same period, and such that they trade m times with each other over that period, m is consistent with a random matching hypothesis for almost all lender/borrower pairs. Even though matches that occur more often than consistent with a random hypothesis (over expressed links) exist and increase during the crisis it is never the case that all incoming links to a given bank are over expressed. The picture that emerges from Hazopoulos et al. (2015) study is that banks are more likely to be chosen as trading partners because they trade more often and not because they are more attractive in some dimension (such as their financial healthiness). As discussed above in our paper we do not have a structural model that explains the banks location in the network. We study if relationships within a network structure, once formed, possibly initially at random, are important for explaining spreads and volumes. While feedback effects between relationships and prices are possible (that is relationship leads to better prices and this in turn leads to stronger relationships in a self-reinforcing loop), and this makes it difficult to establish to causality of the effects, our claim that lending relationships play an important for the interbank market is still valid.

5.2 Chapter 3

In Chapter 3, we study that local and global measures of centrality identify different features of how the network characteristics affect the interbank market funding rates. Local measures show that having more links increases borrowing costs for B and reduces premia for L. We interpret this effect as a premium paid by lenders to diversify counterparty risk, and by borrowers to reduce funding risk.

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

To disentangle the role of local factors (degree) on global centrality measures in the analysis, we control for local degree in our regressions. The fact that global effects remain statistically significant after controlling for the local network effects, suggests that overall global and local network effects operate on a different level in the e-MID market. Our constructed global eigenvector-based measures of centrality are in general in line with the local measures of centrality when looked at in isolation. For banks being central is a cost. Note that, in general, the highest effect in absolute value corresponds to either phases II or III. In fact, the coefficient sign for all pooled periods is either dominated by that of phase II or phase III. The higher spreads paid by both L and B with high in-centrality measures suggests the market associates InEigenvalue centrality with higher credit risk.

Betweenness, on the other hand, is high, and different from zero, for banks that both lend and borrow, and it increases as the intermediation role of banks increase. This measure is thus probably large for the banks in the core and small for those in the periphery. The negative coefficient for InBetweenness for both lenders and borrowers suggest the market participants perceive borrowers who are central according to this measure as too connected to fail, likely to be bailout in case of default to avoid systemic effects, and as such offer them a discount. This interpretation is confirmed by the negative coefficient observed for B when the *in* and *out* centrality measures are interacted, indicating again that large B that are central in both directions obtain lower funding rates. However, L do not benefit from high betweenness or the joint *in* and *out* network centrality. The fact that only B, and not L, benefit from joint centrality point to a 'too-interconnected-to-fail' hypothesis rather to a broker or intermediation effect. As such, these B get better deals for funding in the interbank markets, and this is probably due to the market perception of their network positioning. This effect is the largest in phase II, when banks became affected and/or aware of systemic risk. For L, the market perception about their network positioning (i.e. fragility) dominates their strategic location for intermediation (as in Gabrieli and Georg, 2014).

5.3 Chapter 4

In chapter 4, we study how European monetary policies affect the countries sovereign risk, international linkages between country risks, and whether risk determinants differ across countries using the global vector autoregressive (GVAR) model. The empirical findings indicate that the shocks that originated from monetary policy shocks lead to an increase in country risks because of sensitivity to crisis and uncertainty in Euro zone. However, Greece is affected by monetary shocks on the opposite way due to the particular fragile situation of the Greece economy.

This chapter investigation can be inproved in several directions. First, our analysis in this study covers data from ten countries from the Euro area where one (Germany) is used as a benchmark. The research analysis can be improved if all remaining countries in the Euro area (or possibly in the European Union) are incorporated into the analysis. Second, robustness analysis could be implemented to evaluate the GVAR methodology.

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