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The role of bank relationships in the interbank market

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ABSTRACT

This paper empirically explores 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 USA, unaffected by search costs and other fictions. We show that stable relationships exist and that they played 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.

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 that 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, b).

During the crisis, increased uncertainty about counterpart 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; Brauning and Fecht, 2012). Overall these studies have shown that banks build

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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 report 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, 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, affect 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 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 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, persist 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. We also do not 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 shows 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 Lehman's bankruptcy, as the lender can exploit its position of power over the borrower.

The remainder of this paper is organized as follows. Section 2 covers key notes in the literature. Section 3 explains how the interbank market operates with specific focus on the e-MID platform. Section 4 describes the data and methodology. Section 5 presents and discusses regression analysis. Section 6 concludes.

2. Literature review

One of the first papers studying the relationship driven behaviour 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 paper 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 neighbours. 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 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 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.

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 to not 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 et al. (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 types 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.

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 account for about 70% of 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 fine-tuning and structural operations. Standing facilities aim to provide and absorb O/N liquidity. Two standing facilities, administered in a decentralized 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 7 pm 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 exercises 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.

4. Data and econometric modelling

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-June-06 to 7-August-07	Before crisis	Two Bear Stearns' hedge fund bankruptcy (31-July-07)	14
8-August-07 to 7-October-08	During crisis	Lehman Brother's collapse (15-September-08)	14
8-October-08 to 7-December-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 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 Fig. 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 to December 2009 with a sharp fall in the last quarter of 2008.

[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.

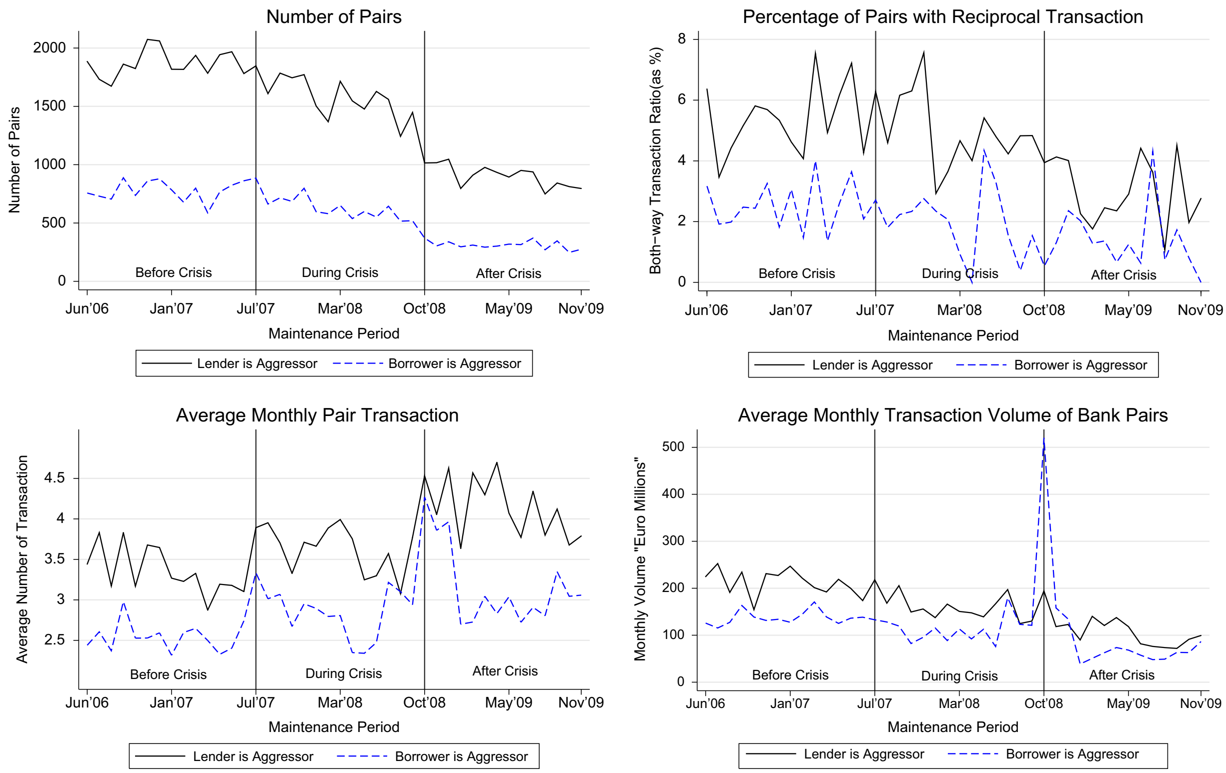

Fig. 1. Descriptive analysis for bank pairs.

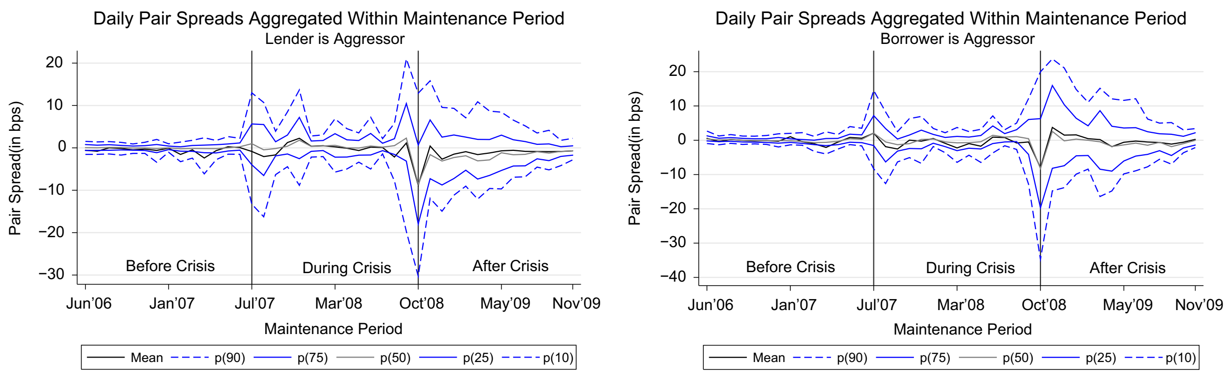

Fig. 2. Daily O/N spread aggregated within maintenance periods.

4.2. *Variable definitions*

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

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

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 $\overline{r}_m^d$ is the daily volume weighted average rate over all transactions carried out by the bank pairs in a given day the transaction n corresponds to, which is calculated as

$$\overline{r}_m^d = \frac{\sum_{j=1} \sum_{i=1} \sum_{n=1}^{N_{ij,d}} r_{ij,n} \times V_{ij,n}}{\sum_{j=1} \sum_{i=1} \sum_{n=1}^{N_{ij,d}} V_{ij,n}}, \tag{2}$$

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

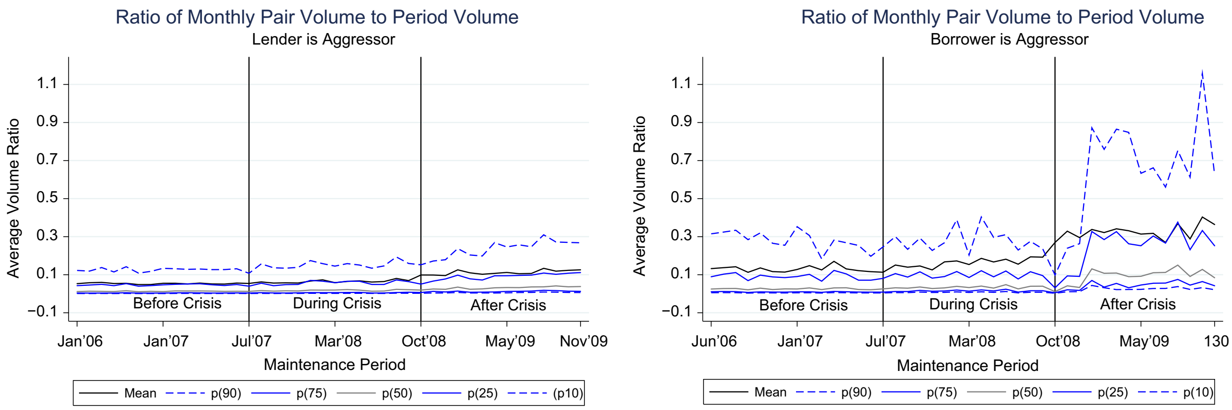

Fig. 3. Aggregated trading volume-normalized within maintenance periods.

As shown in Fig. 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 lenders 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 bank pair for flow of funds in the interbank market. This is calculated as

$$VN_{ij,t} = \frac{\sum_{n=1}^{N_{ij,t}} V_{ij,n}}{\sum_{h=1} \sum_{k=1} \sum_{n=1}^{N_{hk,t}} V_{hk,n}}. \tag{3}$$

Fig. 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.

4.2.2. Lending relationship variables

With the 2007-2008 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 an 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 behaviour 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 new versions of preference indexes and use the number of transactions, rather than the volume, as a measure of strength of a relationship. Our choice is motivated by the fact that banks are heterogeneous. We do not want to bias the results toward the large banks that trade more volumes with each other simply because they are big. Moreover, our main interest is testing 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 ($LPI_{ij,t}$) 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

[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).

preference index is computed as

$$LPI_{ij,t} = \frac{\sum_{n=1}^{N_t} y_n^{i \to j}}{\sum_{n=1}^{N_t} y_n^{i \to any} / outdegree_{i,t}}, \tag{4}$$

where $n = 1, 2, \ldots, N_t$ 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, defined as the number of banks to which a lender lends.

Similarly we define the borrower preference index ($\mathrm{BPI}_{ij,t}$) 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:

$$BPI_{ij,t} = \frac{\sum_{n=1}^{N_t} y_n^{i \to j}}{\sum_{n=1}^{N_t} y_n^{any \to j} / indegree_{j,t}}, \tag{5}$$

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 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), $t = 1, 2, \ldots, T$. 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 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.

Fig. 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. 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.

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 contradicts with each other in terms of the way it affects the rates (Furfine, 2001; Angelini et al., 2011; Gabrieli, 2011,2012). Therefore we believe that 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 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

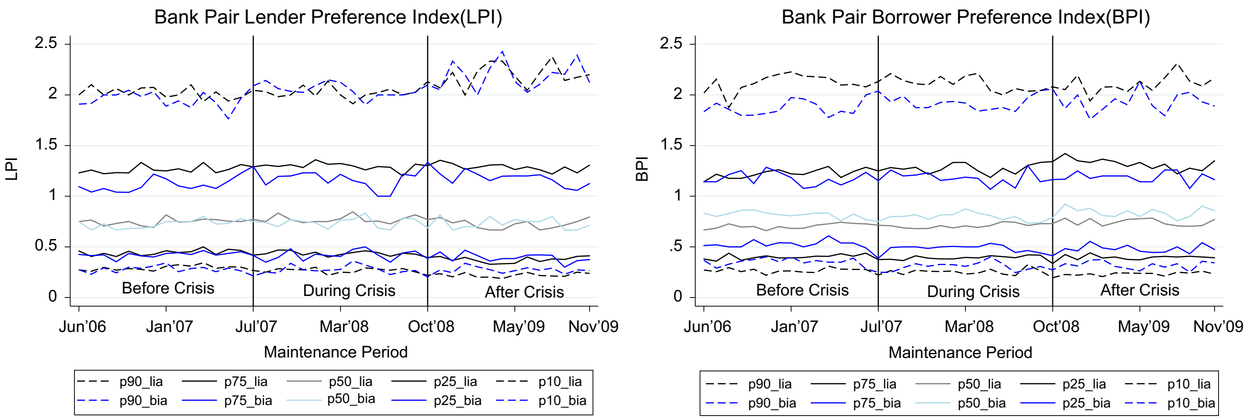

Fig. 4. Bank pairs preference indexes.

percentages of the observations with deals for longer term maturities are 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 the borrower (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. Tables 1 and 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 appears in the Appendix.

4.3. Econometric modelling

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 traded. 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 $i \rightarrow j$ (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 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 a stronger relationship with a counterparty, as measured by *LPI* and *BPI*, increases the probability of having transactions with the same counterparty in the next month. The dependent variable 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 intended 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:

$$LPI_{ij,t}(\text{or } BPI_{ij,t}) = \beta_0 + \beta_1 A_{ij,t} + \beta_2 B_{i,t} + \beta_3 C_{j,t} + u^{(1)}_{ij,t}, \quad u^{(1)}_{ij,t} = \mu^{(1)}_{ij} + \delta^{(1)}_t + e^{(1)}_{ij,t}, \tag{6}$$

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 capture

[4] For lender, assuming that 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 that 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.

Table 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	10,011
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 61,085 and 24,161, respectively.

banks' unobserved characteristics such as ownership and long-term pair relationships. The time fixed-effects capture the evolution of the market across time and common shocks that affect all banks.

The most important analysis in this paper corresponds 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:

$$S_{ij,t} = \gamma_0 + \gamma_1 LPI_{ij,t} + \gamma_2 BPI_{ij,t} + \gamma_3 A_{ij,t} + \gamma_4 B_{i,t} + \gamma_5 C_{j,t} + u^{(2)}_{ij,t}, \quad u^{(2)}_{ij,t} = \mu^{(2)}_{ij} + \delta^{(2)}_t + e^{(2)}_{ij,t}. \tag{7}$$

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

$$VN_{ij,t} = \eta_0 + \eta_1 LPI_{ij,t} + \eta_2 BPI_{ij,t} + \eta_3 A_{ij,t} + \eta_4 B_{i,t} + \eta_5 C_{j,t} + u^{(3)}_{ij,t}, \quad u^{(3)}_{ij,t} = \mu^{(3)}_{ij} + \delta^{(3)}_t + e^{(3)}_{ij,t}. \tag{8}$$

Table 2
Participation of banks by bank size.

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

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).

5. Results

5.1. Stability of relationship

We first study the suitability of the preference indexes described above to predict a bank pair survival. Tables 3 and 4 present the survival analysis for the subsamples of lender is aggressor (LiA) and borrower is aggressor (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 4 for the BiA subsample.

5.2. Lending relationship

After studying the stability of relationships, we next study banks' characteristics that are correlated with the preference indexes. Tables 5 and 6 estimate the determinants of lending relationships LPI and BPI for LiA and BiA subsamples, respectively, using least-squares pairwise fixed-effects 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 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.

Table 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	3866	2330	2459	1563
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	2780	1553	1709	1058
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	9512	11,419	6711
Number of pairs	2100	1113	1257	721

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

Controlling for 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 banks' 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 suggests that lenders have no incentive to 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 coexistence 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).

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 7 and 8 show least-squares pairwise fixed-effects 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.

Table 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	16293	5436	5909	2674
Number of pairs	1810	1057	1045	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	4036	4471	1868
Number of pairs	1067	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	2985	3566	1545
Number of pairs	733	397	426	180

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

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 counterpart 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 counter parties. 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 to 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

Table 5
LiA – determinants of LPI and BPI.

Variables	Dep.var.: LPI				Dep.var.: BPI			
	(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	6066	4449	4441	2728	6066	4449	4441	2728

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

Table 6
BiA – determinants of LPI and BPI.

Variables	Dep.var.: LPI				Dep.var.: BPI			
	(1) All	(2) Before crisis	(3) During crisis	(4) After crisis	(5) All	(6) Before crisis	(7) During crisis	(8) 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	7856	8042	3745	19,643	7856	8042	3745
R-squared	0.179	0.186	0.421	0.244	0.174	0.328	0.384	0.210
Number of pairs	3705	2475	2416	1291	3705	2475	2416	1291

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

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 aggressors they pay higher rates because of the bid-ask spread. Possibly any advantage from trading with preferential counter parties is diluted by this.

Table 7
LiA – 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	0.587***	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	6066	4449	4441	2728	6066	4449	4441	2728

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

Table 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	7856	8042	3745	19,643	7856	8042	3745
R-squared	0.078	0.037	0.079	0.163	0.078	0.038	0.079	0.162
Number of pairs	3705	2475	2416	1291	3705	2475	2416	1291

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

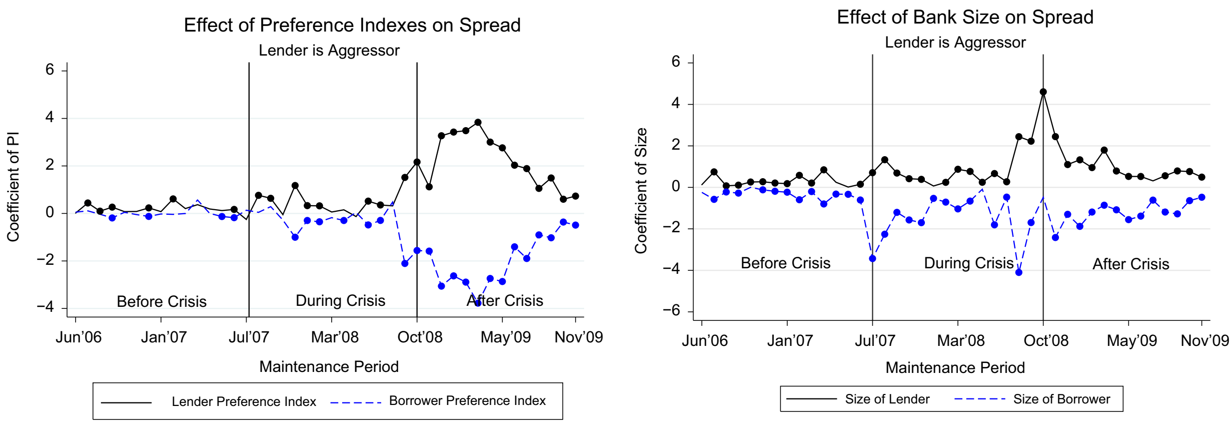

Fig. 5. LiA – effect of preference indexes and banks size on O/N spread. *Note*: Bold data points coefficients significant at 10%.

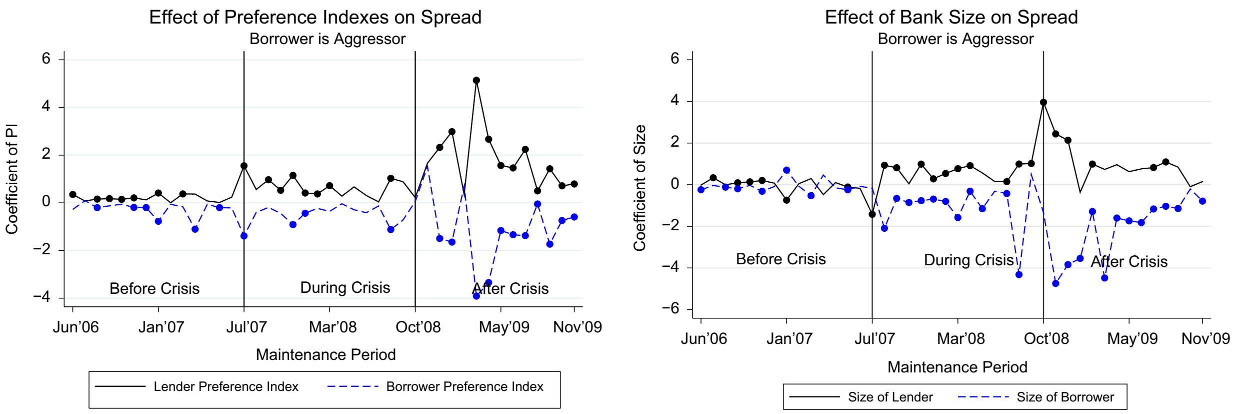

Fig. 6. BiA – effect of preference indexes and banks size on O/N spread. *Note*: Bold data points coefficients significant at 10%.

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 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.

Fig. 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 Lehman's bankruptcy. The trend changes in the Spring 2009 suggesting that the ECB injection of liquidity starts easing the liquidity crisis. The effect of these variables 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.

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 Fig. 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

Table 9
LiA – analysis by bank size.

Size of borrower	Size of lender					
	Foreign	Major	Big	Medium	Small	Minor
Coefficient of LPI on O/N spreads						
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						
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.
All models include bank-pair and maintenance period specific fixed effects.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

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 9 and 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, the 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.

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 11 and 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 analyses are conditional on the pairs' characteristics (i.e. fixed-effects), this reflects that

Table 10
BiA – analysis by bank size.

Size of lender	Size of borrower					
	Foreign	Major	Big	Medium	Small	Minor
Coefficient of LPI on O/N spreads						
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						
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.
All models include bank-pair and maintenance period specific fixed effects.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

for a given pair, volume increases the more preferential relationship that 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 (Figs. 7 and 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 only after crisis for the second dataset. When lender is aggressor, lender's higher borrowing/lending ratio leads to 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 has negative, positive, and positive relations with the volume of ON transaction before, during and after crisis, respectively. The change in sign of this variable suggests 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.

5.5. *Robustness analysis*

5.5.1. *Attrition bias*

As noted by an anonymous referee, one potential concern is that of attrition bias. Fig. 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 affect 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.

Table 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	6066	4449	4441	2728

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

Table 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	7856	8042	3745
R-squared	0.055	0.119	0.099	0.268
Number of pairs	3705	2475	2416	1291

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

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 Eqs. (7) and (9). 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,

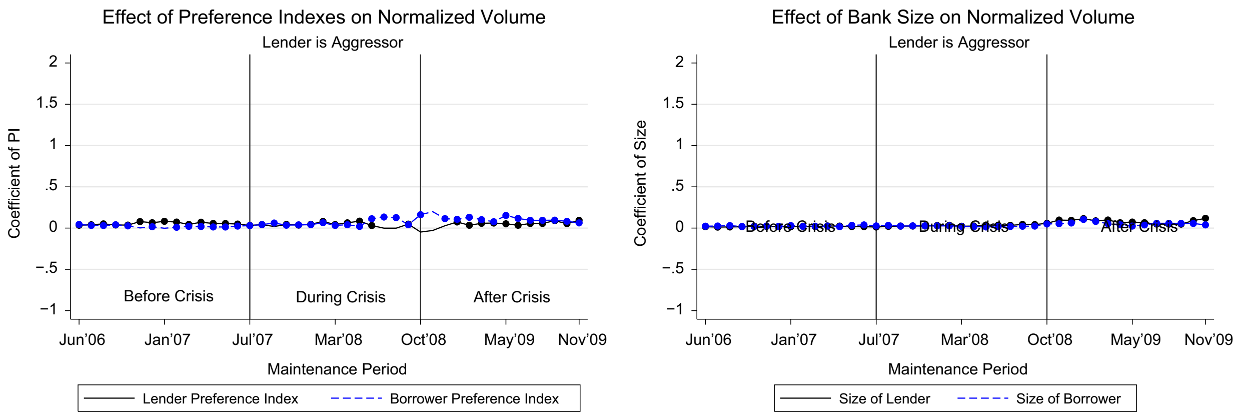

Fig. 7. LiA – effect of preference indexes and banks size on trading volume. *Note*: Bold data points coefficients significant at 10%.

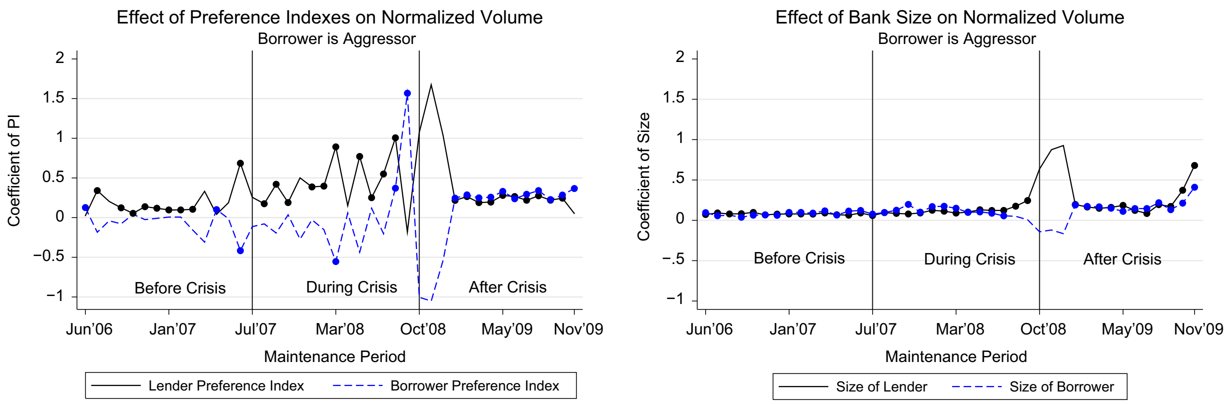

Fig. 8. BiA – effect of preference indexes and banks size on trading volume. *Note*: Bold data points coefficients significant at 10%.

we then construct the inverse Mills ratio to control for attrition bias as $invMills_{ij,t} \equiv \phi(z_{ij,t})/(1-\Phi(z_{ij,t}))$. Finally, we include *invMills* as an additional covariate in regression models (7) and (8). This last model corresponds to the second-step (i.e. outcome equation) in a Heckman selection model.

Regression results in Tables 13 and 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 7 and 8 for O/N spreads,[5] and Tables 11 and 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.

5.5.2. *Trading volume weighting*

Our two key relationship variables, LPI and BPI, were constructed using a 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 (e.g. 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 (7) and (8) with the newly defined variables.

We compte the volume-weighted lender preference index ($LPI\_vol_{ij,t}$) as the ratio of total *volume* of loans from 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

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

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

Table 13
LiA – determinants of spread and trading volume controlling for attrition bias.

Variables	Dep.var.: Spread				Dep.var.: Volume			
	(1) All	(2) Before crisis	(3) During crisis	(4) After crisis	(5) All	(6) Before crisis	(7) During crisis	(8) 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	6066	4449	4441	2728	6066	4449	4441	2728

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

Table 14
BiA – determinants of spread and trading volume controlling for attrition bias.

Variables	Dep.var.: Spread				Dep.var.: Volume			
	(1) All	(2) Before crisis	(3) During crisis	(4) After crisis	(5) All	(6) Before crisis	(7) During crisis	(8) 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	7856	8042	3745	19,643	7856	8042	3745
R-squared	0.078	0.037	0.079	0.163	0.055	0.121	0.107	0.274
Number of pair_id	3705	2475	2416	1291	3705	2475	2416	1291

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

Table 15
LiA – determinants of spread and trading volume, volume weighted LPI and BPI.

Variables	Dep.var.: Spread				Dep.var.: Volume			
	(1) All	(2) Before crisis	(3) During crisis	(4) After crisis	(5) All	(6) Before crisis	(7) During crisis	(8) 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)	(0.01)	(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	6066	4449	4441	2728	6066	4449	4441	2728

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

Table 16
BiA – determinants of spread and trading volume, volume weighted LPI and BPI.

Variables	Dep.var.: Spread				Dep.var.: Volume			
	(1) All	(2) Before crisis	(3) During crisis	(4) After crisis	(5) All	(6) Before crisis	(7) During crisis	(8) 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	7856	8042	3745	19,643	7856	8042	3745
R-squared	0.079	0.038	0.081	0.164	0.061	0.170	0.098	0.380
Number of pairs	3705	2475	2416	1291	3705	2475	2416	1291

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

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

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

These variables have the same interpretation as the number-of-transactions-weighted defined above. That is, a value of 1 corresponds 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 15 and 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 11.

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 the 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 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 stops 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.

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Appendix A. Definition of variables

Formula	Description
$S_{ij,t} = \frac{\sum_{n=1}^{N_{ij,t}} (r_{ij,n} - \overline{r}_m^d) * V_{ij,n}}{\sum_{n=1}^{N_{ij,t}} V_{ij,n}}$	Monthly volume weighted spread of bank pair ij.
$VN_{ij,t} = \frac{\sum_{n=1}^{N_{ij,t}} V_{ij,n}}{\sum_{h=1} \sum_{k=1} \sum_{n=1}^{N_{hk,t}} V_{hk,n}}$	The ratio of monthly total volume of pair ij to monthly total transaction volume in the market.

[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 substitutability is one of the factor, together with bank's size, interconnectedness, complexity and global (cross-jurisdictional) activity, identified by the Basel Committee (BCBS, 2011) to assess whether a financial institution is systemically important.

$LPI_{ij,t} = \frac{\sum_{n=1}^{N_t} y_n^{i \to j}}{\sum_{n=1}^{N_t} y_n^{i \to any} / outdegree_{i,t}}$	*Lender Preference Index:* The ratio of number of loans from bank *i* to bank *j* to average number of lending transactions of *i*.
$BPI_{ij,t} = \frac{\sum_{n=1}^{N_t} y_n^{i \to j}}{\sum_{n=1}^{N_t} y_n^{any \to j} / indegree_{j,t}}$	*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.
$\text{LendersB/L ratio}_{ij,t} = \frac{\sum_{n=1}^{N_t} V_n^{any \to i}}{\sum_{n=1}^{N_t} V_n^{i \to any}}$	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 $y_n^{i \to j}$ and $L_n^{i \to j}$ are indicators of loans n borrowed by bank i from bank j with over-night and longer term maturities respectively. $V_{ij,n}$ is the 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. $\overline{r}_m^d$ is the daily volume weighted average rate over all transactions carried out by the bank pairs.

References

Affinito, M., 2012. Do interbank customer relationships exist? And how did they function in the crisis? Learning from Italy. J. Bank. Finance 36 (12), 3163–3184.

Allen, L., Saunders, A., 1986. The large-small bank dichotomy in the federal funds market. J. Bank. Finance 10, 219–230.

Angelini, P., 2000. Are banks risk averse? Intraday timing of operations in the interbank market. J. Money Credit Bank. 32, 54–73.

Angelini, P., Nobili, A., Picillo, C., 2011. The interbank market after August 2007: what has changed and why?. J. Money Credit Bank. 43, 923–958.

Baglioni, A., Monticini, A., 2008. The intraday price of money: evidence from the e-MID interbank market. J. Money Credit Bank. 40 (7), 1533–1540.

BCBS (Basel Committee on Banking Supervision), 2011. Global Systemically Important Banks: Assessment Methodology and the Additional Loss Absorbency Requirement?, November. http://www.bis.org/publ/bcbs207.htm.

Boccaletti, S., Bianconi, G., Criado, R., del Genio, C., Gomez-Gardenes, J., Romance, M., Sendina-Nadal, I., Wang, Z., Zanin, M., 2014. The structure and dynamics of multilayer networks. Phys. Rep. 544 (1), 1–122.

Brauning, F., Fecht, F., 2012. Relationship Lending in the Interbank Market and the Price of Liquidity. Deutsche Bundesbank, Research Centre.

Cassola, N., Holthausen, C., Duca, M.L., 2010. The 2007/2009 Turmoil: A Challenge for the Integration of the Euro Area Money Market? Unpublished. http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.366.4915&rep=rep1&type=pdf.

Cocco, J.F., Gomes, F.J., Martins, N.C., 2009. Lending relationships in the interbank market. J. Finance 18, 24–48.

Duffie, D., Garleanu, N., Pedersen, L.H., 2005. Over-the-counter markets. Econometrica 73 (6), 1815–1847.

Fricke, D., Lux, T., 2015a. CorePeriphery structure in the overnight money market: evidence from the e-MID trading platform. Comput. Econ. 45 (3), 359–395.

Fricke, D., Lux, T., 2015b. On the distribution of links in the interbank network: evidence from the e-Mid overnight money market. Empir. Econ., http://dx.doi.org/10.1007/s00181-015-0919-x (forthcoming).

Furfine, C., 1999. Microstructure of the federal funds market. Financ. Mark. Inst. Instrum. 8 (5), 24–44.

Furfine, C., 2001. Banks as monitors of other banks: evidence from the overnight federal funds market. J. Bus. 74, 33–58.

Gabbi, G., Iori, G., Germano, G., Hatzopoulos, V., Kapar, B., Politi, M., 2012. Market Microstructure, Banks' Behaviour and Interbank Spreads. City University London, School of Social Sciences, Department of Economics Discussion Paper series Nr. 12/06.

Gabrieli, S., 2011. The Functioning of the European Interbank Market during the 2007–08 Financial Crisis. CEIS Tor Vergata Working Paper series, Nr. 158.

Gabrieli, S., 2012. Too-Interconnected versus too-big-to-fail: Banks' Network Centrality and Overnight Interest Rates. Banque de France Working Paper No. 398.

Gaspar, V., Perez-Quiros, G., Mendizabal, H.R., 2008. Interest rate dispersion and volatility in the market for daily funds. Eur. Econ. Rev. 52 (3), 413–440.

Hatzopoulos, V., Iori, G., Mantegna, R.N., Micciche, S., Tumminello, M., 2015. Quantifying preferential trading in the e-MID interbank market. Quant. Finance 15 (4), 693–710.

Heider, F., Hoerova, M., Holthausen, C., 2015. Liquidity hoarding and interbank market rates: the role of counterparty risk. J. Financ. Econ., http://dx.doi.org/10.1016/j.jfineco.2015.07.002 (forthcoming).

Iori, G., Masi, G.D., Precup, O.V., Gabbi, G., Caldarelli, G., 2008. A network analysis of the Italian overnight money market. J. Econ. Dyn. Control 32, 259–278.

Iori, G., Mantegna, R.N., Marotta, L., Micciche, S., Porter, J., Tumminello, M., 2015a. Networked relationships in the e-MID interbank market: a trading model with memory. J. Econ. Dyn. Control 50, 98–116.

Iori, G., Kapar, B., Olmo, J., 2015b. Bank characteristics and the interbank money market: a distributional approach. Stud. Nonlinear Dyn. Econom. 19 (3), 249–283.

Liedorp, F.R., Medema, L., Koetter, M., Koning, R.H., van Lelyveld, I., 2010. Peer Monitoring or Contagion? Interbank Market Exposure and Bank Risk. DNB Working Papers 248, Netherland Central Bank, Research Department.

Petersen, M.A., Rajan, R.G., 1994. The benefits of lending relationships: evidence from small business data. J. Finance 49 (1), 3–37.