Relationship Lending and Peer Monitoring: Evidence from Interbank Payment Data

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Abstract

This paper empirically investigates the effect of interbank relationship lending on banks' access to liquidity. Our analysis is based on German interbank payment data which we use to create a panel of unsecured overnight loans between 1079 bank pairs. The data shows that banks rely on repeated interactions with the same counterparties to trade liquidity. For the price of credit, we find that in the run-up to the recent financial crisis of 2007/08 relationship lenders charged already higher interest rates to their borrowers after controlling for other bank specific characteristics. By contrast, during the crisis borrowers paid on average lower rates to their relationship lenders compared to spot lenders. We argue that the observed interest rate differences are in line with relationship lenders having private information about the creditworthiness of their borrowers.

1 Introduction

How do the social costs and benefits of a decentralized interbank market compare with those of a centralized interbank market, i.e. an interbank market intermediated by a central counterparty? The recent financial crisis has vividly shown the costs of a decentralized interbank market. In particular, the failure of Lehman Brothers generated financial contagion though interbank exposures, brought about domino effects and destabilized ultimately many banks that did not have any direct credit exposure to Lehman. Worries that borrowers in the interbank market might be affected by this systemic risk led to a freeze of money markets in most developed countries. The failure of the interbank market in reallocating liquidity efficiently within the banking sector induced fire sales which had severe repercussions in the general financial markets bringing the financial system close to a meltdown. In addition the money market freeze also impeded a transmission of the monetary easing that was intended

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to improve financing conditions and contain the macroeconomic consequences of the financial crisis. In order to avoid these effects central banks intervened not only by injecting additional liquidity in the banking sector but also by adjusting their monetary policy instruments. This effectively made central banks the intermediary for large parts of the money markets.[1]

But given that central banks were forced during the crisis to intermediate in money markets the question emerges why they should not resume the role of a central counterparty in general. Doing so they could not only eliminate interbank contagion risk and prevent large scale money market freezes but also improve transparency and foster matching efficiency in this market. Besides the fact that not all banks might dispose of sufficient collateral to fund their entire liquidity needs through collateralized transactions with the central banks, the main argument for a decentralized interbank market usually put forward is that it ensures peer monitoring (see, for instance, Flannery (1996) and Rochet and Tirole (1996)). Banks are assumed to be in a better position to gather and process information about their peers and if this private information is reflected in interbank credit conditions it leads to a superior allocation of funds in the banking sector. The central bank as central counterparty in the money market would not only lack this information, it would also seriously dampen (if not completely eliminate) banks' incentives to provide such private information and their ability to trade on it. Consequently, in order to assess the downside of central banks intermediation in money markets during the crisis and to evaluate whether central banks should move forward in becoming the central counterparty in money markets also in tranquil periods it is of utmost importance to have a precise estimate of the role private information played in those markets before and during the financial crisis.

However, a good estimate of the importance of private information and relationship lending in money markets is also most important for another regulatory reason. If private information acquired through frequent transactions allows an interbank bank lender to better assess the credit risk of his counterpart, borrowers of good quality should receive cheaper funding from their interbank relationship lender than from other banks. But this means that a failure of an interbank relationship lender might imply a loss of valuable private information and an increase in the funding costs of its borrowers which might ultimately even lead to their failure. Consequently, if relationship lending prevails in interbank markets financial contagion is not only affecting interbank lenders though credit default, also the stability of interbank borrow-

[1]In December 2007 the FED adapted its operational framework and introduced, among others, the term auction facility (TAF) which allows all depository institutions to regularly receive direct credit from the central bank at the marginal bid rate determined in biweekly auctions. In addition the FED system reduced the penalty charged for discount window lending to 50 bp. above the fed funds rate while as of October 2008 it started paying interest on any reserves held by banks with the FED. Initially the remuneration was 75 bp. below the lowest federal funds rate of the respective maintenance period but the spread was quickly reduced to 35 bp. More obviously, the ECB also resorted to monetary policy instruments that effectively made it the intermediary for large parts of the Euro money markets. In October 2008 the ECB moved to fixed rate tenders with a full allotment in its repo operations and complemented this with a narrowing of the "channel", the difference between the rate on the marginal lending facility and the deposit facility, to 100 bp. Thus the "bid-ask-spread" when trading overnight liquidity with the ECB declined which reduced banks' incentives to enter interbank credit positions even further. The sum of funds deposited with and lent from the ECB through its standing facilities amounted to more than 115% of Euro area banks' required reserve in late 2008 while it was still less than 1% in the first half of 2008.

ers is seriously endangered if a large financial institution that serves as interbank relationship lender fails. Consequently, when defining systemically important financial institutions (SIFIS) it needs to be also considered whether or not a bank disposes of private information about its peers and whether it serves as an interbank relationship lender. The notion that private information about counterparties' credit risk is important in interbank markets and a relationship lender in these markets is hard to substitute must be the key reason why the Financial Stability Board assesses systemic importance of a bank with respect to its interbank interconnectedness not only on the liability side but also on its asset side.[2]

In this paper we provide first empirical evidence that peer monitoring prevails in the German interbank market and that private information about counterparties' creditworthiness matter for the liquidity reallocation in the banking sector. We use an algorithm as in Furfine (1999) to identify unsecured overnight loans from interbank payment data, complement it with balance sheet information, banks' reserve holdings and other data, and construct a panel of unsecured overnight loans from March 1, 2006 until November 15, 2007 between 1079 bank pairs. A key feature of our dataset is that it covers the beginning of the financial crises 2007-08. This allows us to compare the effects of interbank relationship lending before and during the crisis. Using pairwise measures of lending and borrowing frequency and concentration as proxies for relationship lending we first describe interbank relationship lending patterns in the German interbank market. We then estimate the effect of relationship lending on pairwise matching probabilities and negotiated interest rates.

We find that interbank relationship lending affects credit conditions even after controlling for bank and borrower-lender pair specific characteristics, such as asset sizes and institutional structure. Specifically, our results indicate that relationship lenders already charged higher interest rates to their close borrowers in the run-up to the crisis (starting from spring 2007) when rates from uninformed spot lenders were still low. By contrast, relationship lenders on average gave a discount of about 13 bp to their close borrowers when the sub-prime crisis kicked in and led to a market-wide increase in perceived counterparty risk in July/August 2007. These observed interest rate differences are in line with theories of peer monitoring and relationship lending (compare Boot (2000)) which argue that proximity between a lender and its borrower mitigates asymmetric information problems about the borrower's creditworthiness. Thus our findings confirm the view that interbank relationship lenders could better identify their low risk borrowers during the crisis and charge them lower interest rates than spot lenders, while particularly the observed time patters in the interest rate differences are in contrast to Ashcraft and Duffie (2007) who find evidence for search frictions playing a key role in the OTC federal funds market. Our result that lending relationships provided a larger benefit for borrowers especially during the crisis, when trading volumes in the unsecured overnight market peaked, suggests that matching problems do not account for the

[2]See IMF/BIS/FSB "Report on Guidance to assess the systemic importance of financial institutions, markets and instruments: initial considerations" (October 2009) (*www.financialstabilityboard.org/publications/r_091107c.pdf*) and Basel Committee on Banking Supervision "Global systemically important banks: Assessment methodology and the additional loss absorbency requirement", Consultative Document, July 2011, p. 7, (*www.bis.org/publ/bcbs201.pdf*) .

major benefits of interbank relationships.

Related literature

Our paper draws on the large body of theoretical contributions that points out the implications of different informational frictions prevailing in the interbank market. Bhattacharya and Gale (1987), Bhattacharya and Fulghieri (1994), Freixas et al. (2000) and Allen and Gale (2000), for instance, extend the standard banking model of Diamond and Dybvig (1983) to a multi bank setting and study how the structure, efficiency and resilience of the interbank market is affected if banks' idiosyncratic liquidity needs are private information. Rochet and Tirole (1996), Freixas and Holthausen (2005), Freixas and Jorge (2008), and Heider et al. (2009) model the implications that asymmetric information of borrowers' credit risk has on tiering in the interbank market as well as on credit risk spreads and potential freezes in the unsecured interbank market.[3] However, none of these theoretical papers studies how the repeated interaction between banks affects these informational asymmetries and their implications.[4]

Due to the lack of a formal interbank relationship lending theory, we also borrow heavily from the vast literature on relationship lending between banks and non-financial firms. In this literature it is well established that close ties between a bank and a borrowing firm influence the firm's access to finance in several possible ways (see Boot (2000) for a summary). Sharpe (1990), Rajan (1992), Petersen and Rajan (1995) and Hauswald and Marquez (2003), for instance, argued that repeated lending facilitates monitoring and screening and thereby mitigates problems of asymmetric information about a borrow's creditworthiness, because subsequent monitoring of the same borrower is more efficient as it involves lower monitoring costs and/or improves the signal about the borrower's creditworthiness. As these models point out, it strongly depends on the credit market conditions to what extend the informational advantage of a relationship lender mitigates the borrowing firms' funding constraints. The related empirical work, such as Petersen and Rajan (1994) and Berger and Udell (1995), tries to quantify these implications by using the frequency of a credit relationship between a borrower and a lender and the concentration in the borrower-lender relationship as proxies for the intensity of the lending relationship. We follow this approach to measure interbank relations.[5]

Our paper is most closely related to contributions of Furfine (1999), Cocco et al. (2009) and

[3] Empirical evidence that asymmetric information about counterparty risk is indeed prevailing in the interbank market and was particularly important during the financial crisis is reported, for instance, by Afonso et al. (2011).

[4] An exception is Babus (2010)'s model of network formation, where agents rely on costly relationships to access information about the transaction record of counterparties and decide on whether to trade risky assets over-the-counter.

[5] Petersen and Rajan (1994) and Degryse and Ongena (2005), for instance, use in addition measures of geographical proximity between a lender and borrower as a proxy for private information. But Petersen and Rajan (2002) show for the U.S. that even in the financing of small and medium size firms distance became less relevant for credit relationship as information and communication technologies improved. Thus we do not consider local proximity between banks in Germany as an important determinant of interbank relationships and informational advantages in the interbank market.

Affinito (2011) who also study relationship lending in the interbank market. While Furfine (1999) shows that relationship lending indeed prevails in the U.S. interbank market, Cocco et al. (2009) find that banks in the Portuguese market use relationships to insure against liquidity shocks, and that banks with higher lending and borrowing concentration generally trade at more favorable terms. However, Cocco et al. (2009)'s data set does not cover the recent financial crisis. Thus in contrast to our paper they cannot use this period of elevated uncertainty about counterparties' credit risk to identify the extent to which such informational asymmetries are key drivers of relationship lending. Using more recent data on the Italian interbank market Affinito (2011) reveals that interbank relationships exist also in Italy, persist over time, and worked well during the recent crisis. But lacking charged interest rate in the bilateral credit relations he cannot study pricing impacts of interbank lending relationships.

Interbank lending is commonly based on loans of very short maturity but unsecured and of large volume. Thus relationship lending in this market is transaction based but involves large credit risks. In such a market participants can extract information about their counterparties' credit risk through repeated interaction. An interbank lender can infer from a delayed or reneged repayment on an outstanding interbank loan that a particular borrower has a liquidity shortage (see Babus (2010)). From repeated interaction he might even be able to assess the probability with which a particular borrower experiences a liquidity shortage and adapt his credit conditions accordingly. In addition, banks may also monitor their counterparties outside the interbank lending market. A lender may use publicly observable information like CDS prices and credit ratings to assess a borrower's creditworthiness, or banks may run costly creditworthiness checks to acquire private information on the riskiness of each other, see Broecker (1990). But these monitoring costs are largely fixed costs. Thus banks economize on these costs through repeated lending to the same set of borrowers. Intensive monitoring of all possible counterparts in the market is too costly. Moreover, by repeatedly monitoring this small subset of all banks lenders acquire a more precise signal about the default risk of their few borrowers, compare Furfine (1999) and Craig and von Peter (2010). [6]

Another more recent theoretical contribution by Duffie et al. (2005) stresses the role of search frictions in OTC wholesale markets such as the unsecured interbank market. Ashcraft and Duffie (2007) applies those ideas to the OTC federal fund market and studies to what extent banks also repeatedly interact with the same counterparties to insure against liquidity risk in the presence of search frictions that result from asymmetric information about liquidity condition elsewhere in the market (search frictions that are unrelated to the evaluation of counterparty risk). If a particular bank can always interact with the same counterparty to smooth out liquidity shock, it avoids costly counterparty search in a decentralized market but relies on the insurance mechanism of the relationship. This argument is also given by Cocco et al. (2009) and Afonso et al. (2011) who find that borrowers with higher liquidity shocks rely more on relationships to access liquidity and trade generally at more favorable prices.

[6] This argument is also theoretically modeled by Nieuwerburgh and Veldkamp (2010) who show that an investor may choose concentrated portfolios to improve information acquisition depending on expectations about future asset holdings.

However, our paper contradicts this view. Since we find that rates charged by relationship lenders were particularly lower than market rates during the crisis, when the trading volume in the overnight market was elevated, our results suggests that matching fictions cannot be the key driver of lending relationships.

The remainder of the paper is structured as follows. In section 2, we briefly provide some institutional background of interbank lending and the most important features of the German banking system. Section 3 describes the panel dataset on which we base our empirical analysis. Section 4 defines measures of interbank relationships and other variables. In section 5, we present and discuss the results of the regression analysis and section 6 concludes. The appendix contains all graphs and tables.

2 Institutional Background

2.1 Liquidity and the Interbank Market

In the primary market for liquidity, the European Central Bank (ECB) lends central bank money to banks against collateral through open market operations, namely regular weekly main refinancing operations (MRO), monthly longer-term refinancing operations (LTRO) and fine-tuning and structural operations. During our sample period the MROs were conducted on a weekly basis as a variable tender procedure with a minimum bid rate, which is commonly called target rate. In addition to these open market operations the ECB provides two standing facility for banks to manage liquidity. At the marginal lending facility banks can borrow overnight central bank money against collateral at a penalty rate which was 100 basis points above the minimum bid rate in our sample. The deposit facility allows banks to invest overnight excess liquidity at a rate which was 100 basis points below the minimum bid rate. During the day banks can borrow at a zero interest rate from the ECB but also only against eligible collateral.

Banks' holdings for central bank money are driven by liquidity shocks that result from their day to day business, such as the need to pay for an asset or to pay out customers withdrawing their deposits. These business related factors are embedded in a regulatory framework that also affects banks' liquidity demand. In particular, the ECB requires a bank to hold a fraction of its short term liabilities on its central bank account. These reserve requirements must be fulfilled on average during the maintenance period that usually lasts four weeks. Moreover, negative reserve balances at the end of any day force banks to borrow through the marginal lending facility at a penalty rate. Thus, a bank tries to avoid negative end of day balances and targets compliance with the reserve requirements on the last day of the maintenance period.

But when managing its liquidity a banks does not solely depend on reserves that it can borrow directly from the ECB. In the secondary market banks reallocate liquidity amongst themselves through either secured or unsecured lending. In normal times unsecured lending is relatively more attractive since there is no need to use costly collateral and interest rates for unsecured overnight loans (by far the most commonly traded maturity[7]) are typically in between the corridor set my the rates of the standing facilities.

2.2 The German Banking System

The German banking system is traditionally a system of universal banking and has a three-pillar structure. The first pillar, the private domestic commercial banks, accounted for about 36 percent of the entire banking sector in terms of balance sheet total by end of June 2011. The second pillar are the public banks. This group comprises the savings banks and the savings banks' regional head institutions, the Landesbanks, which are jointly owned by the respective state and the regional association of savings banks. While the Landesbanks account for about 18 percent of the German banking sector in terms of balance sheet total, the savings banks had around 13 percent of the German banking sector's asset under management by the end of June 2011. The cooperative banking sector with the credit cooperatives and the cooperative central banks, which are primarily owned by the regional credit cooperatives, constitute the third pillar. They presented 11 percent of the German banking sector of which the credit cooperatives accounted for 8 percentage points. Besides those major banking groups special purpose banks and buildings societies (Bausparkassen) account for about 10 percent and 2 percent of the banking sector, respectively. Branches of foreign banks operating in Germany made up 11 percent of the German banking sector. All figures are taken from Bundesbank (2011).

This three pillar structure affects the way liquidity is reallocated in the banking sector. The public banks as well as the cooperative banking sector form a relatively closed giro system. On balance, the second-tier institutions – the savings banks and the credit cooperatives – typically achieve a significant liquidity surplus due to their retail business structure. Within the giro systems, they pass this excess liquidity on to the respective head institution which redistributes it to other second-tier institutions. Thus savings (i.e. public) and cooperative banks may have less of a need to participate directly in the market for reserves than private banks because they rely on formal relationship networks within their respective sector. Figure 1 summarizes the institutional background on liquidity provision by the ECB and reallocation in the German banking system.

[INSERT FIGURE 1 HERE]

3 Data Description

3.1 Extracting Overnight Loans from Payment Data

We use a computer algorithm similar to Furfine (1999, 2001) to identify and extract overnight loans from interbank payment data. This data comprises all transaction records from RTGSplus (Real Time Gross Settlement Plus) the German part of the TARGET system (Trans-

[7]For instance, Heijmans et al. (2011) find that 50 percent of the number of transactions and 82 percent of the value in the Dutch unsecured money market are overnight loans.

European Automated Real-time Gross settlement Express Transfer system), the large value payment system of the Eurosystem. TARGET has been operated from 2001 until 2007 and consisted of connected, national payment systems including RTGSplus which was run by the Deutsche Bundesbank. The main part of large value payments such as interbank loans, payments for assets and also liquidity provision by central banks are settled in these systems. But very importantly, interbank repo transactions, i.e. the key form of secured interbank lending, was settled during our sample period in an alternative net settlement system called Euro1.

Amongst others, each payment record contains information about the amount sent, date and time of the transaction, and the Bank Identifier Code (BIC) of the ordering and receiving bank that uniquely identifies each institution.[8] The reason for the individual payment is not stated and thus interbank loans cannot be identified directly from the transactions. However, given the information for each payment it is possible to identify unsecured overnight loans by an algorithm that searches for payments from bank i to bank j on day t, and the reverse payment (from bank j to bank i) plus a small amount corresponding to a plausible interest payment on the next day $t+1$. This also means that we can not only infer the amount of the loans but also the respective interest rate as $i_{ijt} = (repayment_{t+1}/payment_t - 1) \cdot 360$.[9]

Furfine (1999) was the first to use interbank payment data from the Fedwire system in order to extract interbank loans. He considered only payments of minimum \$1 million dollars and increments of \$100,000, and used a 'plausibility corridor' for the interest rate based on the fed funds rate. Recently, Heijmans et al. (2011) have adapted and refined the Furfine algorithm for the European interbank market by defining a 'plausibility corridor' based on EONIA and EURIBOR for short and longer term loans, respectively.[10] Their improved algorithm allows to search for loans with maturities up to one year. In this paper we also use an algorithm based on EONIA, but focus on overnight loans that are the most common maturity. Specifically, we consider amounts of at least €1 million and increments of €100,000 and adopt the plausibility corridor for overnight loans proposed by Heijmans et al. (2011) with 50 basis points below and above EONIA during our sample period.

Of course, we cannot be completely sure that this method really identifies all interbank overnight loans and only those. The trade off between incorrectly identifying a transaction as an overnight loan and missing an overnight loan is affected by the parameters of the algorithm, especially the width of the plausibility corridor. A particular problem occurs if one particular payment has more than one refund match (1:N match) or if there are several payments but only one refund is found (M:1 match). In our data there was a small number of such multiple matches (486) and we decided to take the first (return) transaction to identify a loan. Theoretically, also M:N matches are possible but we did not observe them in our data.

Despite these intrinsic problems the method seems to work reasonably well in identifying interbank loans, compare Furfine (2001) and Heijmans et al. (2011) for an in depth assessment.

[8] For a more detailed description of RTGSplus see the respective information guide, Bundesbank (2005).

[9] We compute interest rates p.a. based on 360 days, analogously to EONIA.

[10] EONIA (Euro OverNight Index Average) is an effective overnight interbank market rate based on a sample large European banks. EURIBOR (Euro Interbank Offered Rate) is a offer rate for maturities from one week up to one year.

In particular, the plausibility corridor of EONIA +/- 50 basis points does not seem to be a binding constraint in our data since only about 180 out of 20999 candidate loans (with a larger corridor of 1 - 10%) fall outside this corridor. A visual inspection of the loans outside the corridor suggests that we do not introduce a sample selection bias. By contrast to most other publicly available data, a big advantage of the filtered data is that we have transaction level data on unsecured interbank loans including the interest rate the loan was agreed upon. Moreover, this method does not focus only on loans from very large banks as, for instance, the EONIA panel does, but gives a much more comprehensive dataset with respect to the cross-sectional dimension of the population.[11]

The TARGET payment data covers the period from March 1, 2006 to November 15, 2007. On November 19, 2007 TARGET2 a fully integrated pan-European real time gross settlement system replaced TARGET that only linked the national real time gross settlement systems of the EMU member states. This payment dataset was matched with data from other sources. First, individual bank's balance sheet information of monthly frequency is used. The monthly balance sheet statistics were obtained from the Deutsche Bundesbank and report domestic banks' assets and liabilities on a monthly basis. This statistics contains an analytically important breakdown of the balance sheet items by type, term and debtor and borrower sector for each German bank. Second, we make use of individual bank's daily reserve information, also obtained from the Deutsche Bundesbank. This data lists end of business day reserve holdings of each institution as well as the institution's reserve requirement over the maintenance period. Other data, for example, data on monetary policy actions such as changes in target rates and open market operations were collected from the ECB homepage. Moreover, we use CDS prices of German banks which we collected from The Depository Trust and Clearing Corporation.

3.2 Descriptive Analysis of the Panel Dataset

We model the matching probability for a lending bank i and a borrowing bank j at time t as well as the interest rate spread, defined as the difference between the interest rate for an observed overnight loan and the ECB target rate, formally $r_{ijt} = i_{ijt} - target_t$. For this purpose we use the discussed data to construct a panel dataset with days as the time unit and bank pairs as the cross sectional unit. Because we have identified transaction level data from the payment data we aggregate multiple loans on the same day for the same bank pair to one observation and compute a volume weighted average interest rate.[12]

[11] In May 2007, RTGSplus had 194 direct participants, including all major German banks by asset size. Besides RTGSplus, corporate banks and saving banks run their own payment systems and participate with other banking sectors often through their central institutes only. Therefore our sample contains relatively few bank from these sectors.

[12] In our final panel dataset, 844 observations contain more than one loan; the largest number of loans per day between the same banks is 17. Moreover, we drop banks for which we do not have balance sheet or reserve data. This implies that we are focusing on loans between German banks since only those banks must report their balance sheet data to the Bundesbank. We also dropped banks that participated less than 50 times and pairs that transacted less than once which reduces the number of different banks in the panel to 77 and the number of pairs to 1079.

[INSERT FIGURE 2 HERE]

Figure 2 depicts the ECB target rate, the EONIA rate and the daily volume weighted average interest rate computed from our data. On most days EONIA is some basis points above the central bank's target and the average rate from our data is close to but above EONIA. The latter observation provides further evidence that our algorithm has successfully identified overnight loans. It is also striking that the volatility of the two average rates apparently increased after the start of the financial crisis on August 9, 2007, indicated by the solid vertical line (in red). Figure 3 shows the number of lending banks (lenders) and borrowing banks (borrowers) active in the market on each day of the sample. Most of the times more institutions lent than borrowed in the market, implying that, at least in our sample, lending banks lent on average smaller amounts whereas borrowing banks borrowed larger amounts. A visual inspection also reveals that the peaks of both series coincide with the last day of the maintenance period indicated by vertical dashed lines (in gray). The same holds for the total amount lent per day and the total number of loans per day (Figure 4). Thus market activity is typically higher at the end of the maintenance period. The plots also suggest different behavior of the series before and during the financial crisis.

[INSERT FIGURE 3 AND FIGURE 4 HERE]

We use a t-test to formally check if the aggregate time series exhibit a mean shift after the start of the crisis. For most series we find significantly different means before and during the crisis (see Table 1). Interestingly, the mean spread to the target rate is smaller during the crisis (though the cross-sectional standard deviation of interest rates is significantly higher) which presumably reflects that also relatively good borrowers had to resort to overnight credit during the crisis. Thus during the crisis we also have significantly more loans per day (40.9 vs. 54.8) and a higher total volume per day (5042.4 vs. 8595.9), corresponding to a 70 percent increase. On average, we observe also significantly more borrowers per day (17.1 vs. 19.1) and more lenders (25.9 vs. 27.2) during the crisis, though the latter difference is not significantly different from zero. Furthermore total reserve holdings by the banking system increased slightly after August 9, but the difference is not statistically significant. These figures show that during the first stage of the financial crisis banks continued to lend out funds overnight and interbank market activity even increased in this very short-term segment of the money market. This finding also suggest that search frictions (that were unrelated to the evaluation of counterparty risk) did not increase after the start of the crisis.

[INSERT TABLE 1 HERE]

Previous studies have argued and shown that small banks are typically net lenders in the US interbank market, either because such banks are deposit collectors or because there is few public information about the creditworthiness of small banks limiting the number of lenders. As a consequence, they manage their reserve in a way that they are net lenders, compare Ho and Saunders (1985). Table 2 depicts the number of borrowers and lenders, how often each bank borrowed or lent as well as the respective amounts for banks of different asset sizes. We find that small banks (with less than 1 billion Euro asset size) are on average net lenders and have on average only 1.5 lenders (vs. 6.5 borrowers), confirming the results of Furfine (1999) and Cocco et al. (2009) for the German market.

[INSERT TABLE 2 HERE]

Analogously, large banks might be able to borrow from multiple lenders because monitoring of these banks is easier due to publicly available information. Likewise, large banks might need to borrow from more lenders to satisfy their liquidity demand. We expect large banks to borrow and lend larger amounts of money for two reasons. The first is just a scale argument since larger banks need larger funds for their day-to-day business. Second, large banks may act as intermediaries that act both as lender and borrower in the interbank market (compare Craig and von Peter (2010) for a network analysis of the German interbank market). The last row of Table 2 shows that large banks (with more than €100 billion asset size) have on average 34 different lenders and borrow and lend larger amounts than banks from other asset size classes. Moreover, about 13 percent of the 1079 bank pairs in our sample have a borrower and a lender with asset size larger than €100 billion, and in almost 70 percent both banks have asset size larger than €10 billion. Thus we also find evidence in our data that size of the a bank correlates strongly with its lending and borrowing relationships.

4 Variables

4.1 Interbank Relationships

According to Boot (2000), the definition of relationship banking in the bank-firm context centers around two issues, namely proprietary information and multiple interactions, emphasizing that close ties between the bank and its borrower might facilitate monitoring and screening and can mitigate problems of asymmetric information about the borrower's creditworthiness. Petersen and Rajan (1994) note that the strength of a relationship between a firm and a bank can be measured by its duration, through interaction over multiple products or by the concentration of a firm's borrowing with one creditor. Similar variables have been used in the interbank lending literature, see Furfine (1999).

As a first relationship variable we consider therefore a measure based on the number of interbank loans between two specific banks. More precisely, we compute the logarithm of one plus the number of days a bank i has lent to bank j over a certain time period T.

$$log\_rel_{ijt} = \log(1 + \sum_{t' \in T} I(y_{ijt'} > 0)) \quad (1)$$

where $I(\cdot)$ is the indicator function and y_{ijt} denotes the amount lent from bank i to bank j at time t. This variable measures repeated interaction and corresponds to the strength of a relationship. In the lines of Petersen and Rajan (1994) it is a proxy for private information due to the lender's past experience with the borrower. (We also considered the number of (directed) transactions between two banks, but both measures are highly correlated.) Because in the case of interbank lending both borrower and lender are financial institution and can, for instance, cooperate by mutually providing liquidity to each other. We therefore also consider the possibly two-side nature of interbank relationships by computing the variable *log_rel_rev* as the number of days the current borrower *lent* to the lender,

$$log\_rel\_rev_{ijt} = \log(1 + \sum_{t' \in T} I(y_{jit'} > 0)) \tag{2}$$

We decided to compute the relationship variables over a period of the last 30 days, but also tried longer periods for robustness checks.

Further, we refine the concept of a relationship by looking at how important the counterparty is relative to the bank's overall engagement, for each borrower and lender separately. Similarly to Cocco et al. (2009), we computed the amount lent from lender i to borrower j at time t summed over a certain time period T relative to the overall amount lent by bank i over the same period. Formally, the lender preference index (LPI) is defined as

$$LPI_{ijt} = \frac{\sum_{t' \in T} y_{ijt'}}{\sum_j \sum_{t' \in T} y_{ijt'}}. \tag{3}$$

We set the variable to zero if the denominator is zero, i.e. if the lender did not lend at all. Similarly, we compute the borrower preference index (BPI) as the amount borrowed by bank j from bank i at time t, y_{ijt}, summed over a certain time period T relative to the overall amount borrowed by bank j

$$BPI_{ijt} = \frac{\sum_{t' \in T} y_{ijt'}}{\sum_i \sum_{t' \in T} y_{ijt'}}. \tag{4}$$

Both variables are negatively correlated with the number of different counterparties and asset size. Similarly to the duration of a relationship, Petersen and Rajan (1994) suggest to use the firm's borrowing concentration as a proxy for private information. However, they point out that concentration measures are also related to the creditor's bargaining power.[13]

Most of the interbank literature has focused on bank's *borrowing* concentration (BPI) or the duration of borrowing relations with a particular bank to proxy for the strength of the lending relation, because these two measures clearly match two distinct theoretical notions of relationship lending. While the BPI measures the dependency of a borrower on a particular lender giving also an indication of the lenders market power over the borrower and the lenders ability to extract a rent from this lending relationship, the duration of a lending relation allows to assess the potential informational advantage that a particular lender has over other market participants due to information that he received through the repeated interaction.

The *lending* concentration of a bank (LPI) captures a more subtle aspect of relationship lending. A larger LPI indicates that the lending bank has a relatively concentrated credit risk

[13]Note that we measure interbank relations only from observed overnight loans. Of course, the overnight money market is only one market in which two particular banks can have close ties and interact repeatedly with each other. Thus our relationship measures capture only one dimension of two banks' relationship.

exposure. Banks with such an undiversified lending structure should have stronger incentives to intensely monitor their small number of (relationship) borrowers and therefore should have superior information about the creditworthiness of those banks than spot lenders.[14]

4.2 Control Variables

In our empirical analysis we control for other factors that affect interbank market participation and the associated interest rate if a loan is observed.

For the lending and borrowing decision, a bank's size (*size*) measured by the natural logarithm of total assets is an important factor. Also for the negotiated interest rate the lender and borrower size has been shown to matter in the sense that larger banks generally trade at better rates, compare Furfine (2001) and Cocco et al. (2009). For the borrower side, larger banks seem to be more credit worthy due to better available information or because they might be subject to too-big-to-fail policies. Also, large banks may be able to make profitable investments in overnight loans because they can better refinance themselves, compare Ashcraft and Duffie (2007). Similarly, banks that are more active or more important in the interbank market might obtain better rates. For this purpose we compute the Benacich centrality (*centrality*), a network measure that captures the importance of a certain node in the network, possibly depending on the positions of other nodes; see Bech and Atalay (2009) for an application to interbank markets.

As a further proxy for credit risk we use the equity ratio (*equity_ratio*) as equity over total assets.[15] Better capitalized banks can withstand larger losses. Thus their outstanding debt bears a lower default risk allowing them to borrow at lower rates.[16] Moreover, since banks might not be able fully the assess the credit risk of their counterparties, banks with higher equity ratio may be more likely to obtain credit at all.

Since banks have to pay a penalty if they fail to meet the reserve requirements, a key driver of banks' market participation. A low ratio of actual reserves being held relative to reserve requirements should increase the probability that a bank participates in the interbank market making and increase the interest rate that it is willing to pay. Thus as a first proxy for the liquidity status of a bank, we compute its cumulative reserve holdings divided by its cumulative reserve requirements ($fulfillment$) over the respective days of the maintenance period. However, this measure does not capture to what extent the current liquidity holdings of a bank permit is to fulfill the remaining reserve requirements over the rest of the maintenance period. Thus we follow Fecht et al. (2011) and derive the normalized excess reserves (*excess_reserve*) as a second measure of banks' liquidity status. Excess reserves are the difference between the reserve holdings of a bank on the respective day and the reserves the bank

[14] Compare also the more general treatment of information acquisition under concentrated portfolios in Nieuwerburgh and Veldkamp (2010). In this model investors can acquire noisy signals of many assets, or specialize and acquire more precise signals about fewer assets depending on expectation which assets they will hold in the future.

[15] Note that our equity ratio is computed from balance sheet data and thus differs from the classical risk-weighted equity ratio.

[16] Furfine (2001) has documented a significant effect of bank's equity ratio on the interest rates it pays in the federal funds market.

needs to hold on a daily basis to fulfill its reserve requirement until the end of the maintenance period. In order to take into account that a bank can better smooth negative excess reserves the more days are still to go in the maintenance period, excess reserves are normalized by the number of days left in the maintenance period in order to derive the normalized excess reserve.

Previous studies have found that liquidity risk affects the pricing of interbank loans (Cocco et al. (2009)). If a bank is exposed to relatively large liquidity shocks it might need to trade funds at unfavorable prices. Our first proxy for liquidity risk (liq_risk) is based on the standard deviation of daily change in reserve holdings over the last month, normalized by the reserve requirements. Moreover, we compute the correlation of liquidity shocks ($corr\_shocks$), that is the daily change in reserve holdings, between two banks over the last month. A high negative correlation implies that two banks are likely to be on the opposing sides of the market. Thus banks with a high negative correlation can benefit more from the risk sharing in a mutual lending relationship and should therefor be more likely to form a lending relationship (see Fecht et al. (2012) for an theoretical model of this argument). In order to control for banks' liquidity risk that results from the maturity mismatch of banks' assets and liabilities we use a as a second measure related to Berger and Bouwman (2009) banks' liquidity creation ($liq\_creation$), which is long-term assets plus short-term liabilities over total assets (times one half).

Moreover, Fecht et al. (2008) have documented calendar effects in markets for liquidity; banks are more likely to participate at the end of the maintenance period to comply with reserve requirements and at the end of the calendar year for accounting reason. We have already seen from Figure 3 and Figure 4 that the number of banks, number of loans and the total amount lent is apparently higher at the last day of the maintenance period when reserve requirements become binding. Similarly, we might expect increased redistribution of liquidity on settlement days of the MROs. However, it is also possible that on these days trading decreases because banks have already satisfied their liquidity needs. In any case we expect significant calendar effects in our data and take this into account by the inclusion of dummy variables for the last days of the maintenance period, last days of the year and settlement days of the MROs.

Further, total reserve holdings at the beginning of a day ($total\_reserve$) as well as total liquidity supply of the Eurosystem (liq_supply) might increase market activity and put downward pressure on interest rates. We thus include both variables as covariates in the regression analysis. By contrast, aggregate credit risk conditions might make banks reluctant to lend funds out, or only at the cost of a higher risk premium. We proxy for changes in aggregate credit risk by the daily change in the average of credit default swap (CDS) prices for 15 large German banks (ΔCDS). Thereby we try to disentangle bank specific credit risk from a common risk factors that affects all institutions in the same way.

Table 16 in the appendix summarizes the definitions and depicts the mean, standard deviation and number of observations of all variables used in the empirical analysis.

5 Regression Analysis

5.1 Matching Probabilities

We use a regression based approach to investigate the effect of relationships on the access to liquidity. Let $z_{ijt} = 1$ if bank i (lender) and bank j (borrower) agree on an overnight loan at day t. We then model the conditional matching probability $P(z_{ijt} = 1|\Omega_{t-1}) = E(z_{ijt}|\Omega_{t-1})$, conditional on the information set Ω_{t-1}. For this purpose introduce the latent variable y^*_{ijt} such that

$$z_{ijt} = \begin{cases} 1 & \text{if } y^*_{ijt} > 0 \\ 0 & \text{if } y^*_{ijt} \leq 0 \end{cases} \tag{5}$$

and assume the general linear index function model

$$y^*_{ijt} = x^*_{ijt}\beta^* + \beta^*_{rel} rel_{ijt} + \beta_{crisis} \cdot crisis \cdot rel_{ijt} + u^{len*}_i + u^{bor*}_j + u^*_{ijt}, \tag{6}$$

where $u^*_{ijt} \sim \mathcal{N}(0, 1)$ are i.i.d. error terms that satisfy the predeterminedness condition , $E[u^*_{ijt}|\Omega_{t-1}] = 0$, x^*_{ijt} is a vector of controls, and u^{len*}_i and u^{bor*}_j are lender and borrower specific fixed effects that account for unobserved bank heterogeneity. The variabel rel_{ijt} is generically for the relationship measure which we expect to have a positive coefficient. We also interact rel_{ijt} with a dummy variable ($crisis$) that indicates the time period starting from 9 August 2007 since we want to allow for a different effect of relationship lending during the financial crisis, in particular we expect that information about counterparty risk becomes more important.[17] Together, equations (5) and (6) give a standard panel Probit model which we estimate using maximum likelihood that gives consistent estimates under weak regularity conditions.

Table 3 presents the estimation results of the binary regression model with the frequency measure (log_rel) as the relationship variable. In Column (1), the model includes asset sizes and liquidity position for both lender and borrower, the total reserves and liquidity supply, and the correlation of liquidity shocks as control variables. The estimated coefficient of the relationship variable is positive and highly significant indicating that banks rely on repeated interactions with the same counterparties. This is in line with theoretical prediction that banks form relationships to mitigate search frictions and asymmetric information about counterparty risk. Everything else equal, larger lenders are less likely and large borrowers more likely to participate, both effects are significantly different from zero at the 5% level. This resembles the descriptive findings that small banks are typically net lenders and big banks are typically net borrowers in the market. Also bank's reserve balance has the expected effect: banks that have a relatively larger surplus on their reserve account are more likely to provide funds to other banks and those with a larger deficit are more likely to borrow. Interestingly, we find that the coefficient of the correlation of liquidity shocks is positive (though not significant at

[17] August 9, 2007 is widely recognized at the start of the financial crisis. On this day BNP Paribas suspended withdrawals form some of its hedge funds invested in sub-prime mortgage-backed securities due to the inability to mark these assets in the market.

the 5% level) and thus a higher correlation increases the matching probability. Note, that model (1), like all models, includes dummy variables to take into account end of year and end of maintenance period effects. The estimates are omitted to save space, but the effects are positive and significant at the 5% level. By contrast, there is no significant effect of settlement days of the MROs.

[INSERT TABLE 3 HERE]

Column (2) presents the model when we allow the effects of relationships to change with the start of the financial crisis on August 9, 2007. The coefficient of the interaction term ($crisis \times log\_rel$) is not significantly different from zero indicating that lenders were not more likely to lend to borrowers with whom they have a relationship during the crisis than before. This means that relationship lenders did not primarily channel their credit provision to banks they interacted most frequently with in the past - in this view non-relationship borrowers were not credit rationed but had similar access to funds than before the crisis. We also find that the coefficient of ΔCDS, the proxy for aggregate credit risk, is negative and significant at the 5% level. Thus an increase in credit risk on average decreases the probability of an overnight loan everything else equal.

To investigate if banks that maintain a relationship cooperate and mutually provide liquidity to each other, we also include the relationship variable log_rel_rev that measures how often the current borrower has lent to the lender in the previous time. The positive and significant parameter estimate in column (3) indicates that, ceteris paribus, banks are more likely to lend to banks that are their relationship lender in turn. However, the effect does not change during the financial crisis as the insignificant coefficient of the interaction term shows. Model (3) also contains the centrality measure for the borrower and lender. Both coefficients are positive and significant and thus banks that are more central in the interbank market are more likely to participate. Note, that the borrower size coefficient turns insignificant, indicating the positive correlation with the previously omitted centrality measure. Column (4) shows the model that contains also liquidity risk as a control variable. The parameter estimate is positive for the borrower and negative for the lender, but not significantly different from zero at the 5% level.

Column (5) presents the full model with borrower and lender specific intercept. A Wald statistic of the null hypothesis that all bank specific intercepts are zero is 2862.27 which is much larger than the asymptotic 5% critical value of the respective χ^2-distribution (p-value of 0.00). Unobserved bank specific characteristics thus lead to a substantially better fit of the model, and we reject the null hypothesis of model (4) in favor of the FE model (5). The estimates for asset size revert signs on both the lender and borrower side, indicating that these variables were correlated with the unobserved fixed effect. The results show that, ceteris paribus, larger and more central banks are more likely to lend and more central banks are more likely to borrow. The relationship measure still has a significant effect though its magnitude decreases slightly. Also the parameter estimate of the reversed measure remains positive and even increases in value by about 50 percent. As a consequence, we find that the number of previous interactions has a strong positive effect on the matching probability of two banks.

[INSERT TABLE 4 HERE]

Table 4 shows the results for the the concentration measures LPI and BPI as more refined relationship variables. In the basic specification (1), we find that both lending and borrowing concentration have a significantly positive effect on the matching probability. Thus, on both market sides, banks tend to interact with counterparties with whom they traded a large share of their total volume in the past. When we allow the effect to change during the crisis, we find that banks with higher borrowing concentration in the past are significantly more likely to borrow from their relationship lenders after August 9, 2007. We cannot reject the null hypothesis of no change during the crisis for the coefficient of LPI, though. One possible explanation for these findings is that banks with a high borrowing concentration find it during the crisis more difficult to borrow from lenders who never provided credit to them in the past (because switching from a relationship lender to a spot lender might be interpreted as the relationship lender's reluctance to provide credit to the borrower due to its bad creditworthiness).

Column (5) presents the full model including fixed effects for borrower and lender. A Wald test rejects the null of model (4) against the alternative of model (5) at any conventional significance level (Wald statistic of 25391.96, asymptotic p-value of 0.00). Again, we find that the effect of asset size reverts sign if we include fixed effects. Large and central banks are more likely to participate on both sides of the market, though the effect of size is not significant at the 5% level for the borrower. Also the coefficients of the liquidity status variable increase in absolute values and have the expected signs, but the null of no effect can be only rejected for the lender's liquidity status. Contrary to the models with the frequency relationship measure, we find that in model (5) with LPI and BPI, aggregate liquidity supply has a significantly positive effect on the matching probability. This difference are likely due to the collinearity between log_rel and liquidity supply. The effect of relationships is again not qualitatively different if we allow for fixed effects.[18]

In all model specifications we find that banks repeatedly lend and borrow from the same counterparties, even after controlling for other influences like bank size. Relationships are thus an important institution that help banks to manage liquidity. We find that borrowers that obtained major part of credit from few banks before the crisis were more likely to borrow from these relationship lenders when perceived counterparty risk increased market wide in August 2007.

[18]Also the quantitative effects are quite large. For instance, computing the upper bound of the marginal effect of LPI, $\phi(x^{*'}\beta^*)\beta^*_{LPI}$, gives approximately $0.4 * 1.487 = 0.5948$, since $\phi(x^{*'}\beta^*) \leq 1/\sqrt{2\pi} \simeq 0.4$ with maximum at $x^{*'}\beta^* = 0$.

5.2 Interest Rates

After having established a positive effect of relationship lending on the probability of a loan, we examine the effect of relationship lending on the interest rate. We therefore assume a linear regression model for the bilaterally negotiated interest rate spread (relative to ECB target rate) of the loan

$$r_{ijt} = x_{ijt}\beta + \beta_{rel} rel_{ijt} + \beta_{crisis} \cdot crisis \cdot rel_{ijt} + u_i^{len} + u_j^{bor} + u_{ijt}, \tag{7}$$

where u_i^{len} and u_j^{bor} are lender and borrower specific fixed effects, u_{ijt} is an i.i.d. error term that satisfies $E[u_{ijt}|\Omega_{t-1}] = 0$, x_{ijt} is a vector of controls and rel_{ijt} is the relationship variable. Again we allow a different effect of relationship lending after 9 August 2007 as we expect that differences in counterparty risk assessment might particular prevail when level and dispersion of credit risk are high. The model parameters are estimated using ordinary least squares (OLS) which is a consistent estimator under standard assumptions. In all regressions we computed cluster robust standard errors.

Table 5 presents the parameter estimates using the number of past transactions as the relationship variable. Model (1) includes asset size and equity ratio as well as liquidity status as bank specific control variables. At the 5% level, the size coefficients are significantly different from zero for both sides of the market; larger lending banks receive on average higher rates, while larger borrowing banks pay less interest rates everything else equal. Also borrowers with a higher equity ratio pay less interest rate, but this effect is only significant at the 10% level. Further, an increase in liquidity supply leads to a significant decrease in interest rates and a higher correlation in liquidity shocks between two banks make them negotiate significantly lower rates. This supplements the findings of the previous section that a larger correlation also increases the matching probability.[19] The estimated coefficient of the relationship variable is close to zero and statistically not significant indicating that there is no effect of relationship lending on interest rates.

[INSERT TABLE 5 HERE]

However, if we allow the effect of relationship lending to change with the start of the financial crisis as in model (2), we find that during the crisis relationship lenders charges significantly lower rates to their counterparties compared to what a spot pair would negotiate. On the other hand the data also shows that before August 2009 borrowers paid higher rates to their relationship lenders. From column (2), we also see that change in average credit risk is priced as the coefficient for ΔCDS is significant and positive. Note, that with the inclusion of ΔCDS also the coefficient of total reserves turns negative and significant. A higher total volume on the reserve accounts at the beginning of the day brings down interest rates just as a higher liquidity supply by the Eurosystem. Column (3) and (4) present a model that includes

[19] One possible explanation for these findings is that banks with positively correlated liquidity shocks are similar (for instance, with respect to their balance sheet structure). If this similarity between a lender and a borrower leads to a better assessment of counterparty risk and to lower monitoring costs, the lender might be more inclined to lend to similar borrowers and might provide cheaper credit.

bank's interbank centrality and liquidity risk, respectively. The coefficient of the centrality variables are positive, those for liquidity risk are negative, but all are not significantly different from zero at the 5% level. The results of the binary choice regressions indicate that banks cooperate and mutually provide liquidity to each other. In model (4) we examine if this cooperation extends to the negotiated interest rates. However, we do not find a significant effect of the reversed relationship measure - when it comes to prices cooperation seems to be limited as lenders do not give a discount to banks that are their relationship lenders in turn.

The full model (5) includes all control variables and borrower and lender specific fixed effects. An F-test rejects model (4) against model (5) at any convenient significance level (F-statistic of 38.45; asymptotic p-value of 0.00). We find that relationship lenders charged significantly lower rates during the crisis even after controlling for unobserved heterogeneity by bank specific intercepts. Also economically the estimated effect is important: everything else equal, a bank that lent funds to its borrower on everyday during the last month charges on average 12.7 basis points less than to a borrower with no interaction during the last month. Moreover, relationship lenders charge higher rates before the crisis, but this effect is only significant at the 10% level and about ten times smaller in absolute values than during the crisis. Similarly to the other models, we find that a borrowing bank's asset size and equity ratio influence the interest rate it is charged. This result is in line with Furfine (2001)'s findings for the federal funds market, that banks are able to identify counterparty's credit risk and actually price this risk in overnight interest rates. Further, we find that more central lenders receive significantly better rates, possibly because more active banks are in a better position to offer (high rate) loans when in need for funds themselves, because they can "lay off" their positions later, compare Ashcraft and Duffie (2007).

[INSERT TABLE 6 HERE]

To get further insight about the economic reasons for the observed interest rate differentials, Table 6 presents the parameter estimates using the two-sided concentration measures LPI and BPI. In the simplest model (1) with asset size, equity ratio and liquidity status as bank specific controls, both estimated coefficients of LPI and BPI are slightly positive but not significant at any convenient level. Allowing the effect to change during the crisis in specification (2), we find again that pairs with a higher lending concentration (a higher LPI) lent at relatively higher rates before the crisis and at lower rates during the crisis. Both effects are significant at the 5% level, but the coefficient of the interaction term is in absolute values about 6.5 larger and economically significant. Everything else equal, a bank pair with $LPI = 1$ negotiate a 13 basis points discount compared to a pair with $LPI = 0$. The coefficient of BPI increases slightly but is not significant at the 5% level, such as the interaction term. These results are robust to the introduction of other control variates and lender and borrower fixed effects in model (5). Noteworthy, the coefficient of BPI turns negative (though not significant) and thus before the crisis, we find qualitatively similar values as Cocco et al. (2009) for the Portuguese market. We again find that, ceteris paribus, larger bank and banks with higher equity ratio pay less on the borrowing side. Interestingly, we estimate the same effects on the lending side, though smaller in magnitude. The asset size coefficient is compared to the model with the frequency relationship variable significant (Table 5, model (5)). One possible explanation might be that better capitalized and larger banks have lower refinancing cost and can thus provide liquidity at lower rates in turn.

In sum, these findings do not support the conventional relationship lending view along the lines of Petersen and Rajan (1995). Neither can we confirm the view that during a crisis a lender that gained market power over a debtor due to concentrated borrowing will try to preserve future rents from this credit relationship and provide liquidity support at more favorable rates during the crisis, nor do we find that in normal times a more concentrated borrowing leads to a lock-in effect of the borrower that permits the lender to charge a margin.

Our findings are also in contrast to those of Ashcraft and Duffie (2007) who argue that banks form relationships to avoid costly counterparty search under asymmetric information about the liquidity shocks of other banks. After August 9, 2007 total interbank market activity increased in the unsecured overnight segment of the money market that we consider in our analysis. This suggests that the probability of finding a counterpart with the opposing liquidity shock increased implying a decline in overall search costs during this period. Thus the probability of contracting with a relationship lender should decline and the difference between rates charged by spot lenders and relationship lenders in the money market should decline. However, we find that the positive effect of having a lending relationship on the matching probability is, if anything, higher during the crisis. At the same time the effect of a stronger lending relationship on the rate at which a borrower receives funding was larger during the crisis. Moreover, anecdotal evidence suggests that interbank loans are mostly borrower initiated; however using the refined relationship measures LPI and BPI we do not find evidence that borrowing but lending concentration of a bank matters for the interest differences. Therefore, search frictions cannot be the key drivers of the observed impact of relationship lending.

Our observed pattern rather results from differences in counterparty risk assessment between relationship lenders and spot lenders, as argued by among others Furfine (1999). The repeated interaction permits relationship (log_rel) lenders to better assess the true credit quality of their borrowers. After receiving a more precise indication of the credit quality of their borrower lenders will only continue to lend to borrowers for which they continue to have a positive risk assessment. Thus the longer a relationship lasts the more precise is the information about a relationship borrower and the better is his perceived credit risk by the relationship lender. Thus the willingness to lend again increases. Similarly, a higher concentration in his interbank credit portfolio on a particular borrower (LPI) might reflect that a lender received some private information after screening indicating a high quality of the borrower. Moreover, the high concentration risk might also induces the lender to better screen and monitor his relationship borrowers giving him a more precise indication of the credit risk of those few borrowers on which he focusses his portfolio, compare Nieuwerburgh and Veldkamp (2010). Thus a lender is less likely to ration a borrower to whom he lent large parts of his interbank credit portfolio explaining the the positive effect of a high LIP on the matching probably.

The implications of a more precise counterparty risk assessment of relationship lenders on the difference between the interest rate charged by a spot lender and the relationship lenders are less clear cut. On the one hand the more precise information that the relationship lender has about a counterpart along with the better quality of borrowers to whom the relationship lender lends suggest that he can offer better rates than spot lenders. On the other hand the more precise information might permit the relationship lender to lend to poor quality borrowers charging an adequate risk premium rather than rationing those borrowers as spot lenders would do. However, the effect of a higher level and dispersion of credit risk in the interbank market is straightforward. As modeled in Heider et al. (2009) a higher counterpart credit risk and particularly a higher uncertainty about counterparty credit risk will induce spot market lenders to charge a higher risk premium, if they decide to lend.[20] This will lead to adverse selection and a further deterioration of the credit risk faced by spot lenders. Consequently, during periods of elevated uncertainty about credit risk the informational advantage of relationship lenders should be larger permitting them to offer credit to their relationship borrowers at a lower rate compared to spot lenders. During the financial crisis the perceived counterparty risk was undoubtedly relatively high. Thus our findings that repeated lending to a certain borrower as well as a high concentration of the lenders' interbank credit portfolio on a particular borrower had especially during the crisis a dampening effect on the charged interest rate, confirms this view.

5.2.1 The Precrisis Period

If relationship lenders can better assess their borrowers one could also expect that they charged relatively higher rates to their riskier borrowers (or denied credit) compared to spot lenders, well before the crisis kicked in and led to a market wide reassessment of risk in August 2007. To investigate this hypothesis we allow for an other interaction between the relationship variable and a dummy (*precrisis*) being one in the run-up to the crisis (in what follows we refer to this period as the *precrisis*). Our model then becomes

$$r_{ijt} = x_{ijt}\beta + \beta_{rel} \cdot rel_{ijt} + \beta_{crisis} \cdot crisis \cdot rel_{ijt} + \beta_{precrisis} \cdot precrisis \cdot rel_{ijt} + u_{ijt},$$

where we have omitted fixed effects for notational brevity. Since it is not clear when the precrisis started, we consider different periods. Table 7 shows the parameter estimates of the relationship variables for starting days from 1 October 2006, 1 November 2006, ..., 1 July 2007, each until 8 August 2007, all based on the full model including precrisis and crisis interactions. Table 7 also depicts the F-statistic and asymptotic p-value for the hypothesis $H_0 : \beta_{rel} = \beta_{precrisis\_rel}$. The upper panel with *log_rel* as the relationship measure shows that for all starting days of the precrisis relationship lenders charged on average significantly higher

[20]Note that lenders might rather ration borrowers when uncertainty about credit risk becomes too large. Inducing a selection bias in our estimates of the interest rates: In times of elevated uncertainty about credit risk spot lenders will only lend to borrowers whose credit risk is undoubtedly good but charge a low rate. In section 5.3.3 we estimate our model with a Heckman correction to show that our results are robust to this selection bias.

rates during the precrisis, everything else equal. By contrast, we do not find a significant effect of log_rel before the precrisis (which one could interpreted as tranquil times).

[INSERT TABLE 7 HERE]

The lower panel displays the results if we use LPI as the relationship variable. Similarly, we find significant precrisis mark-ups from relationship lenders during the precrisis period; however, only if the starting day is larger than November 2006. Moreover, we find that before the precrisis lenders with higher LPI charge higher rates, though the effects are economically not strong. Still, the hypothesis $\beta_{rel} = \beta_{precrisis\_rel}$ can be rejected if we choose the precrisis small enough as in column (9) and (10) of Table 7. Thus, also relationship lenders defined by lending concentration charged higher rates relative to spot lenders in the run up to the crisis (compare the findings of Cocco et al. (2009)). However, the effects are more pronounced if we use the relationship measure based on the frequency of interaction.

All coefficients of the precrisis interaction terms increase in magnitude as the precrisis period gets shorter, indicating that the mark up a relationship lender charges on average is higher the closer we move to the crisis. To get further insights about the timing of the mark-up Figure 5 depicts the F-statistic of $H_0 : \beta_{rel} = \beta_{precrisis\_rel}$ for different starting days of the precrisis (we consider each day from 1 October 2006 until 31 July 2007). For log_rel (as well as $norm\_rel$ – an alternative relationship measure that we introduce for robustness checks) the statistic is highest if the precrisis starts on the June 7. For LPI the F-statistic is higher if the breakpoint is on 1 July.[21]

[INSERT FIGURE 5 HERE]

Thus the data shows that in the run-up to the crisis relationship lenders charged on average higher rates than spot lenders, but during the crisis they charged on average lower rates. This finding holds for all definitions of an interbank relationship as long as we incorporate the lender's exposure into the relationship measure. We argued that the evidence is in line with theory of peer monitoring and relationship lending: relationship lenders, or more precisely banks with a concentrated lending structure, already discovered and priced increased counterparty risk when spot lender rates were still low. On the other hand after subrime related problems became public and market wide assessment of coutnerparty risk shot up relationship lenders could still identify their low risks and charge on average lower rates.[22] Moreover, we

[21] However, we cannot use ordinary p-values to estimate the breakpoint based on a *supF* test. The test statistic is asymptotically not χ^2-distributed because the individual test statistics are not independent. In a second version of this paper we will also include results of bootstrap p-values for a formal break point estimation. In what follows we assume that the precrisis started on June 7, 2007 being aware that this date does not come from a formal test procedure. Note also that if we run the F-test on the overall sample it peaks during beginning of August 2007, which coincides with the beginning of the crisis.

[22] We allowed the effect of relationships on the matching probability to change during the precrisis, too. However, the coefficient of the interaction term is not significantly different from zero at the 5% level in any specification. We also considered banks that used to borrow from relationship lenders in normal times (e.g., in the upper 25%-percentile of BPI) but switched to spot lenders during the precrisis (in the lower 25%-percentile of BPI). Interestingly, in unreported regressions we find that these *switchers* had to pay significantly more compared to banks that always used to shop around for funds (always in the lower 25%-percentile of BPI). Thus spot lenders might perceive switching as an adverse signal about the institution's creditworthiness.

find that also in normal times banks with a more concentrated lending charge slightly higher interest rates as also reported in Cocco et al. (2009). Finally, there is no significant effect of a bank's borrowing concentration on interest rates.

5.3 Robustness and Extensions

5.3.1 Different Relationship Variables

As a further relationship measure, we used the amount lent from lender i to borrower j over a certain time period T (last 30 days) and normalize it by the total amount lent by lender i plus the total amount borrowed by borrower j. To account for the skewness of the amounts lent we enter them in logarithms. Formally, our third relationship variable is thus computed as

$$norm\_rel_{ijt} = \frac{\log(\sum_{t\in T} 1 + y_{ijt})}{\log(\sum_i \sum_{t\in T} 1 + y_{ijt}) + \log(\sum_j \sum_{t\in T} 1 + y_{ijt})}. \quad (8)$$

Contrary to the (log) number of days on which two banks transacted, this variable captures the pairwise lending intensity based on the amount lent, accounting for the overall market activity of the lender and borrower. Thus, it takes into account how much a lender exposes itself to the credit risk of the borrowing institution as well as the borrower's importance to the lender. Unlike the other two relationship variables, this variable is not strongly correlated with asset size or market activity and is more comparable across banks of different sizes. Analogously, we compute the variable *norm_rel_rev* with the numerator being the amount lent from the borrower j to the lender i over a certain time period T.

Table 8 presents the estimation results of the basic binary choice model with *norm_rel* as the relationship variable. As before we find that relationship lenders are more likely to lend funds to each other after controlling for other factors. Contrary to the pure frequency measure (*log_rel*), the effect of relationships increases during the crisis similar to the model that includes BPI. This reflects the correlation between BPI and *norm_rel*. The estimation results of the interest rate model (Table 9) confirm that relationship lenders charged lower interest rates during the crisis than spot lenders, but higher rates in the run-up to the crisis, compare the analysis of the precrisis period above. The results are thus robust with respect to different measures of bank relationships.

[INSERT TABLES 8 AND 9 HERE]

Table 10 also shows that our results regarding the impact of relationship lending on interbank rates in the pre crisis period are robust to using this alternative measure of relationship lending. Note that in column (8) and (10) the estimated parameters are significantly positive at the 5% level also before the crisis. This is due to the fact that *norm_rel* is correlated with LPI.

[INSERT TABLE 10 HERE]

In the main analysis we have computed the relationship variables based on market activity of the last 30 days, analogously to Ashcraft and Duffie (2007). However, the choice of this reference period is to some extend arbitrary and we check the sensitivity of the results to other time periods. Since we expect relationships to be persistent but not immutable over time, we considered a period of three month and the overall sample. Table 11 presents the results for the interest rate model when we compute the relationship variable based on information from the overall sample. Clearly, the findings that relationship lenders charged a mark-up in the run up to the crisis, but gave a discount during the crisis also hold when we measure relationships based on a longer horizon. In unreported regressions we have confirmed that the results also hold if we use a reference period of three months.

[INSERT TABLE 11 HERE]

5.3.2 Different Control Variables

We have tried to avoid an omitted variable bias by the choice of our covariates and the inclusion of borrower and lender specific fixed effects. In unreported results we have also verified that the results continue to hold for a model with bank pair fixed effects and a full set of daily time dummies, as well as the combination of both. Thereby, we control for bank (pair) specific time-invariant characteristics and a common time trend that might be correlated with our relationship variable and the interest rate. We also investigate if our results are sensitive to the definition of our covariates and Table 12 presents the regression results with alternative control variables. In particular, we proxy a bank's liquidity status with $fulfillment$ and measure liquidity risk by *liq_creation*. The coefficient of $fulfillment$ are not statistically significant at the 5% level, but *liq_creation* has a significant, negative effect. Moreover, we include fungible assets over total assets (*fungible*) since banks with the possibility to sell assets quickly might rely less on unsecured interbank borrowing. However, we cannot reject the hypothesis that the share of fungible assets has no effect as the estimated parameter is not significant. Importantly, for all relationship variables the estimate parameters stay qualitatively similar, especially the precrisis mark-up and the discount after the start of the crisis given by relationship lenders.

Because we are concerned that the i.i.d. assumptions for the error term is violated and standard errors are underestimated, we computed standard errors in different ways by clustering at the borrower level, bank pair level or by clustering at days, see Petersen (2009). Thereby, we allow for different variances across clusters and possible correlation of error terms within each cluster. The results are robust with respect to the different computation methods but are not presented here to save space.

[INSERT TABLE 12 HERE]

5.3.3 Selection Model

In the main analysis we have estimated the binary choice model and the interest rate model separately, thereby assuming that conditional on the information set the two equations are independent. However, participation in the interbank market is endogenous and we need to take into account the possibility of sample selection on unobservables that may lead to inconsistent parameter estimates. According to Heckman (1979) we use a bivariate sample selection model that comprises the selection equation and the outcome equation

$$r_{ijt} = \begin{cases} r^*_{ijt} & \text{if } z_{ijt} = 1 \\ - & \text{if } z_{ijt} = 0 \end{cases} \tag{9}$$

The two latent variables y^*_{ijt} and r^*_{ijt} are modeled by the linear relation

$$r^*_{ijt} = x_{ijt}\beta + \beta_{rel} rel_{ijt} + u^{len}_i + u^{bor}_j + u_{ijt} \tag{10}$$

$$y^*_{ijt} = x^*_{ijt}\beta^* + \beta^*_{rel} rel_{ijt} + u^{len*}_i + u^{bor*}_j + u^*_{ijt}. \tag{11}$$

Further, assume the error terms (u^*_{ijt}, u_{ijt}) follow a bivariate normal distribution with variances $\sigma^2_{u^*} = 1 = \sigma^2_u$ and correlation ρ. If this correlation is zero a separate analysis of the two models is valid, otherwise the OLS parameter estimates of the outcome model are generally biased. We therefore use Maximum Likelihood estimators which are consistent and efficient under standard assumptions, see Cameron and Trivedi (2005).

[INSERT TABLE 13 HERE]

Table 13 presents the results for the full model for all three relationship variables including precrisis and crisis interaction terms. The results are qualitatively the same and also quantitatively very similar to the findings from the main analysis indicating that they are not driven by a selection bias. Formally, the estimate of *athrho* ($= 1/2 \log[(1+\rho)]/(1-\rho))$ is not significantly different from zero at the 5% level. Thus, we cannot reject the null hypothesis that the error terms of the two equations are uncorrelated, i.e. that there is no selection on unobserved factors. Therefore, we conclude that it is valid to analyze the interest rate model and the binary choice model separately as we have done in the main analysis.

5.3.4 Small Borrowers

The traditional bank-firm relationship literature has argued that relationship lending might be particularly relevant for small borrowers, see Petersen and Rajan (1994). The idea is that for small businesses the asymmetric information problem might be more pronounced than for big borrowers, as for the latter more and better publicly available information exists (for instance, large firms are monitored by the financial press or are subject to credit ratings). By contrast, public information about small borrowers is relatively scarce and lenders need to rely more on own monitoring efforts to generate information about the state of its counterparty. As a consequence, the informational advantage of a relationship lender versus a spot lender might be larger if the borrower is small. Similar arguments can be made for the interbank market and we therefore allow for an other interaction with the relationship variables and an indicator variable being one if a borrower's total asset size is less than €1 billion (13 banks), and interact this variable with the precrisis and crisis dummy.

[INSERT TABLE 14 HERE]

Table 14 presents the results for the interest rates model. In column (1) we include *log_rel*, in column (2) *norm_rel*, and in column (3) we use LPI and BPI as the relationship variable. During the precrisis period relationship lenders charged on average an additional mark-up to small borrowers, if we use *log_rel* or *norm_rel*. The coefficient for the latter variable is also significant. If we use LPI the coefficient is negative, though not significant. The interaction with BPI is positive but only significant at the 10% level. For all specifications, small borrowers pay during the crisis higher rates to their relationship lenders than medium-sized or large banks. The effect is significant for *rel* and *rel_norm* and about the same size (in absolute values) as the estimate for the crisis interaction variable, offsetting part of the crisis discount. To formally check whether during the crisis relationship lenders did not charge different rates to small borrowers than spot lenders, we test the null hypothesis $\beta_{crisis\_rel} + \beta_{crisis\_rel\_small} = 0$. The test results are depict in Table 14. In all three cases we cannot reject the null hypothesis. Thus, we do not find evidence that monitoring is particularly effective for small borrowers, by contrast, the results suggest that monitoring of small banks does not differ between relationship and spot lenders.[23] However, remember that our sample does not include a large share of small banks (especially the very small ones) as many of these belong to the cooperative or saving banks sector running their own relatively closed payment system.

5.3.5 Relationship Lending and Banking Sector

Finally, we investigate if relationship lenders from different sectors charge different interest rates from their counterparties; for instance, it might be that public banks are less effective than private institutes in monitoring counterparty risk, see Hau and Thum (2009) for a comparison of private vs. public German bank performance during the crisis. Therefore, we split the dataset into four subsamples by sorting the lenders into four different bank groups, namely cooperative sector, saving banks, special purpose banks and private banks (including branches of foreign banks), and run the full model with *log_rel* on these subsamples. Table 15 depicts the results. Lenders from each sector charged similar rates to their relationship borrowers than to market borrowers and in the run-up to the crisis they charged significantly higher rates to their relationship borrowers. Thus we do not find evidence that ownership matters for a bank's ability to monitor counterparty risk. Also during the crisis they charged on average lower rates than spot lenders, but the parameters are only significantly different from zero at the 5% level for lenders from the private and saving banks (i.e. public) sector, possibly because relatively few observations for cooperative banks and special purpose banks. Note that we need variation in two dimensions (across banks and across time) to estimate the effect of our relationship variables during the precrisis and crisis period. Moreover, we impose the same starting day of the precrisis (June 7, 2007) for all different sectors. This is

[23] We have also estimated the matching probabilities including small borrower interaction terms. However, the results are not significant and are not presented to save space, but can be requested from the authors.

restrictive since some sectors might have charged higher interest rates earlier than others.

[INSERT TABLE 15 HERE]

Interestingly, the parameter estimates of the bank specific control variables differ qualitatively across the four subsamples. In particular, we find that lenders from the cooperative and savings bank sector charge significantly higher rates to more central borrowers. By contrast, if the lender belongs to the private sector or is a special purpose bank, more central borrowers pay significantly lower interest rates. Thus there seems to be sector specific unobserved heterogeneity that we do not account for in our main analysis where we impose the same coefficients for banks from all sectors. However, We do not find qualitatively different results for market wide variables, and also the correlation of liquidity shocks has again a negative price impact (though not significant in all subsamples).

6 Conclusion

In this paper we use German interbank payment data to construct a panel of unsecured overnight loans between 1079 different bank pairs. From this data we computed pairwise measures of relationships between banks and examine how these variables affect interbank lending. Specifically, the relationship variables are based on repeated interaction and lending or borrowing concentration.

Our empirical investigation shows that even after controlling for bank specific and pair specific factors banks are more likely to receive a loan from a particular lender the more often they borrowed from this lender in the past, the more concentrated their borrowing is on that particular lender and the more concentrated the interbank credit portfolio of the lending bank is on the respective borrower. Thus our findings support the view that established lending relationships matter for the availability of interbank credit and affect the reallocation of liquidity through the interbank market. Consequently, it is likely that the failure of an important relationship lender in the interbank market impairs the liquidity management of its borrowers and might trigger a liquidity shortage at those financial institutions as well. During the crisis we find that it was particularly the concentration in outstanding debt on a particular borrower that fostered the availability of credit from that counterparty. Our results also indicate that past reciprocal lending relationships affect the probability that a borrower receives an overnight loan from a particular borrower suggesting that interbank relationship lending indeed serves as a mutual risk sharing arrangement.

When examining the role of relationships on the pricing of overnight loans we find that relationship lending significantly affected the interest rate charged by lenders during the crisis. After August 2007 banks charged higher rates to borrowers they did not know, i.e. whose risk they could hardly assess and to whom they lend only a small fraction of their interbank credit portfolio. By contrast, relationship lenders could supposedly better identify credit risk of their counterparties and supply lower rates to low risk borrowers. Interestingly, we also find that relationship lenders have to some extent anticipated the financial crisis by charging higher interest rates in the run-up to the crisis.

In sum, these findings provide strong empirical evidence of the existence of private information in the interbank market. Thus there seems to be some significant benefit from having a decentralized unsecured interbank market as a means to reallocate liquidity in the banking sector. These benefits need to be balanced against the larger systemic risk that unsecured decentralized markets bring about compared to a secured money market cleared by a central counterparty. To that end our evidence also suggests that there are benefits from a relatively wide corridor between the marginal lending rate and deposit rate set be the ECB for its standing facilities.

Our results also complement the existing work on contagion risk in the interbank market. According to our findings the failure of large bank not only generates negative externalities for its creditors. If that this bank also serves as an important relationship lender in the interbank market, its failure will also significantly impair the liquidity management of its borrowers which might also generate domino effects. Thus our findings support the view that also a bank connectedness on its asset side is an important component when assessing whether it is too-large or too-connected-to-fail.

However, our study does only provide qualitative evidence of peer monitoring and in the further debate it is of course necessary to quantify both costs and benefits in order to find a balanced solution for the organization of liquidity markets. In particular, it would be important to examine the effects of relationship lending during the second phase of the financial crisis when lending volumes declined significantly and banks preferred hoarding liquidity rather than lending it out.[24]

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[24] Also, we have used an aggregate shock in August 2007 to compare interest rates between relationship and spot lenders. For a more detailed understanding of relationship lending and peer monitoring it would however be important to identify adverse, bank specific stress and investigate if we find evidence that relationship lenders have anticipated these problems. Similarly, we did not consider in this paper possible shifts in maturities during the crisis which might be different for relationship lenders and spot lenders.

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A Figures

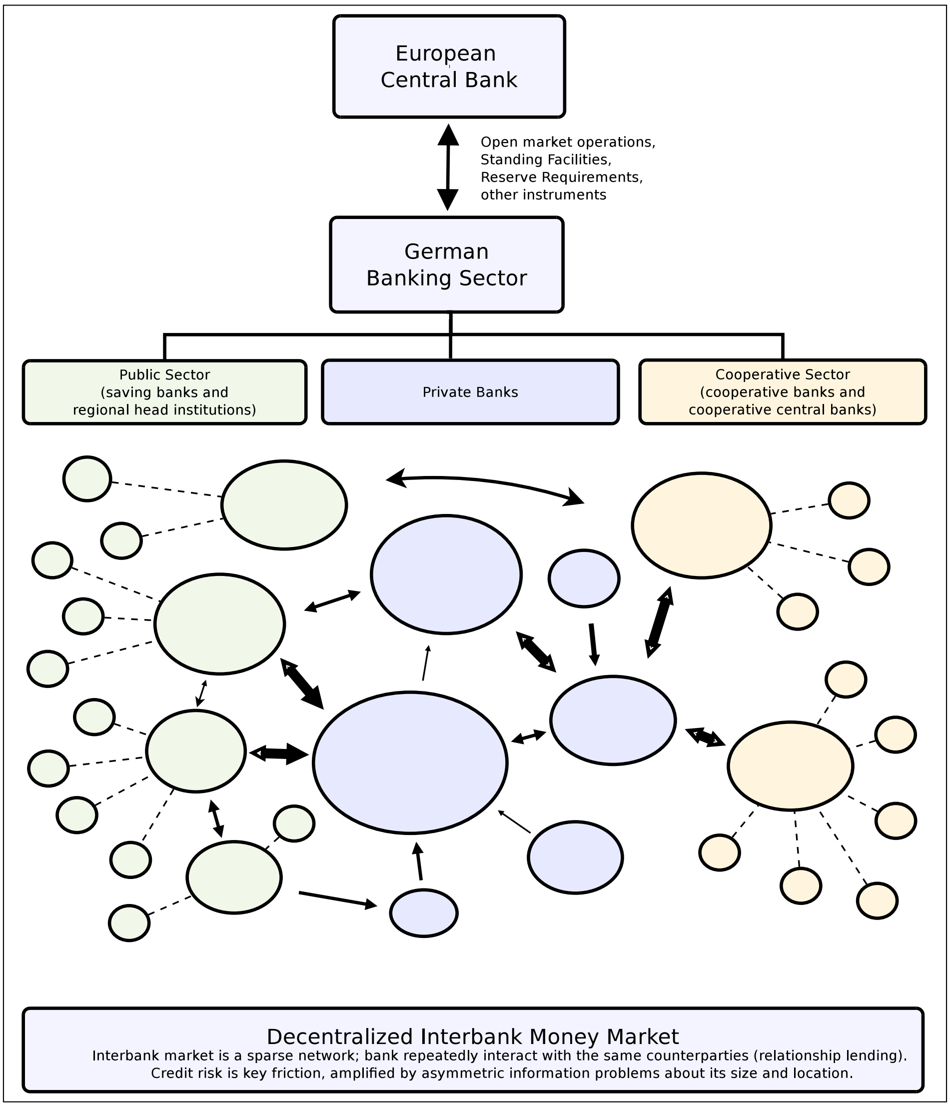

Figure 1: Liquidity in the Banking System: The figure depicts the liquidity provision by the central bank (primary market) and reallocation in the decentralized unsecured interbank market (secondary market). Larger ellipses (arrays) correspond to larger banks (money flows). The three pillar structure of the German banking system is indicated by ellipses of different colours. Saving banks (cooperative banks) are connected with their regional head insitutions (central cooperative banks) by dashed lines. They often do not interact with other sectors directly but only via the regional head insitutions or central cooperative banks.

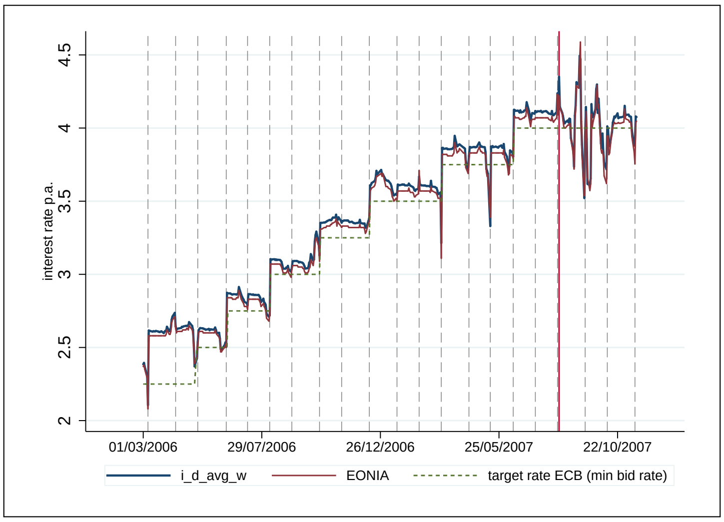

Figure 2: Average Daily Interest Rate, EONIA and ECB Target Rate: e *i_d_avg_w* is the volume weighted average overnight interest rate from our panel dataset. *EONIA* is Euro OverNight Index Average. *target rate ECB* is minimum bid rate at main refinancing operations. Vertical dashed lines (in gray) indicate end of maintenance period, vertical solid line (in red) indicates start of the financial crisis on August 9,2007.

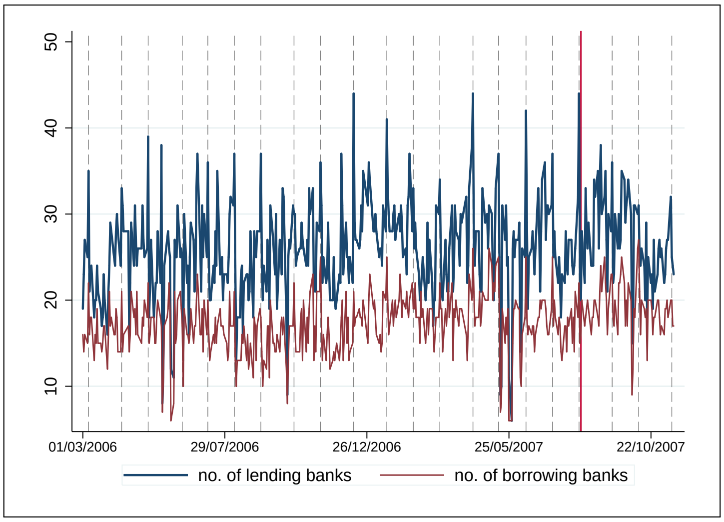

Figure 3: Number of Lending and Borrowing Banks per day: Number of different lending and borrowing banks per day. Vertical dashed lines (in gray) indicate end of maintenance period, vertical solid line (in red) indicates start of the financial crisis on August 9, 2007.

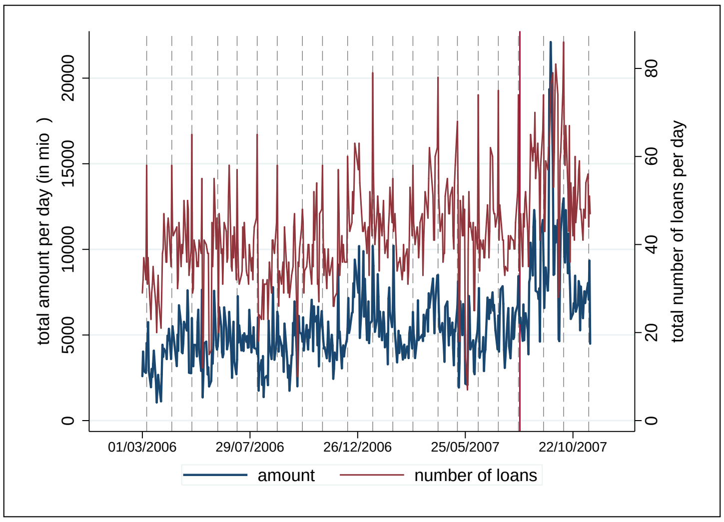

Figure 4: Total amount of all loans (in €million) on a given day and total number of loans. Vertical dashed lines (in gray) indicate end of maintenance period, vertical solid line (in red) indicates start of the financial crisis on August 9, 2007.

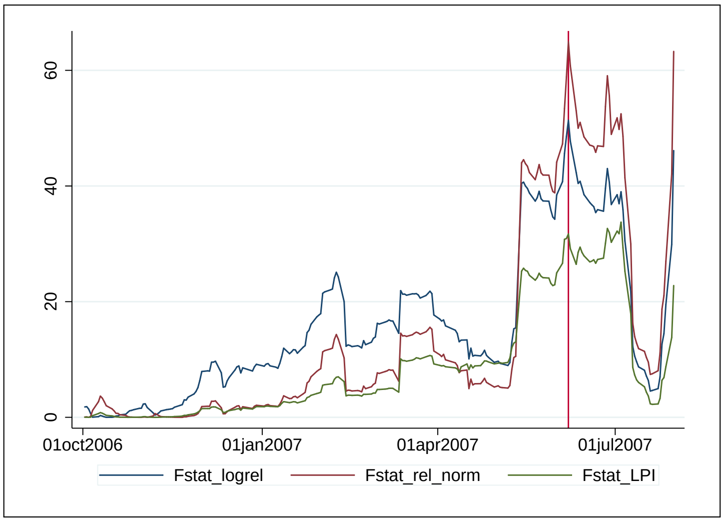

Figure 5: F-statistic of $H_0 : \beta_{rel} = \beta_{precrisis\_rel}$; F-statistic of the hypothesis $H_0 : \beta_{rel} = \beta_{precrisis\_rel}$ for different starting days of the precrisis (October 1, 2006 until July 31, 2007). Test statistics for *log_rel* and *norm_rel* peak at starting day June 7, 2007 (vertical red line).

B Tables

Table 1: Mean Comparison Test for Aggregate Variables, $H_0 : diff = 0$. Mean of variables before and during the crisis and mean difference (crisis = 1 after August 9, 2007). t-statistic corresponds to $H_0 : diff = 0$ and is based on unequal variances. *total_trans* is the total number of loans per day; *total_amount* is the total amount lent per day; *avg_loan_size* is the average loan size per day; *spread_avg* is the average interest rate per day minus ECB target rate; *spreadEONIA* is EONIA minus traget rate; *i_d_sd* is the daily cross-sectional standard deviation of interest rate; *num_len* (*num_bor*) is the number of lenders (borrowers) per day; *total_reserve* is the sum of banks' reserve holdings per day. Amounts in €millions.

	crisis = 0	crisis = 1	diff.	t_stat
total_trans	40.87	54.81	−13.93	−8.87***
total_amount	5042.38	8595.93	−3553.55	−8.92***
avg_loan_size	124.70	155.41	−30.72	−6.35***
spread_avg	0.11	−0.00	0.11	4.43***
spreadEONIA	0.08	0.00	0.08	3.76***
i_d_sd	0.03	0.09	−0.06	−7.37***
num_len	25.91	27.18	−1.27	−1.84*
num_bor	17.11	19.08	−1.97	−4.98***
total_reserve	20781.60	22380.36	−1598.76	−1.45

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Summary Statistics of Relationship Variables by Asset Size. Out of the 77 banks in the sample, there are 13 banks with assets size smaller than €1 billion, 20 banks with €1-10 billion, 29 banks wih €10-100 billion, and 15 banks with more than €100 billion. The *no_bor* is the number of different borrowers a bank lent to, *no_len* is the number of banks a bank borrowed. *lender* (*borrower*) shows how often a bank acted as a lender (borrower) in the market. *amount_lent* (*amount_bor*) are the total ammount lent (borrowed) in €million, net position is amount lent minus amount borrowed. All figures are based on market activity in the overall sample.

asset size	no_bor	no_len	lender	borrower	amount_lent	amount_bor	net_pos
€0-1 bil.							
mean	6.53	1.46	349.84	27.15	14410.70	190.31	14220.38
min	1	0	16	0	82	0	-1210.20
max	12	4	1579	181	90217.10	1292.20	90217.10
€1-10 bil.							
mean	9.25	3.55	190.75	29.15	13935.81	2179.45	11756.37
min	0	0	0	0	0	0	-2164
max	24	12	830	105	106897	26643.5	106897
€10-100 bil.							
mean	16.79	16.48	171.21	177.90	26317.70	20495.97	5821.734
min	4	0	19	0	825	0	-196693.40
max	28	46	618	1233	116486	204326	109926
> €100 bil.							
mean	21.47	34.10	214.40	696.60	79570.91	118825.80	-39254.85
min	11	0	21	0	4190	0	-293197
max	36	57	641	1807	377236.50	306008.50	368261.50

Table 3: Estimation Results for Matching Probabilities (*log_rel*).ML parameter estimates of the binary choice model using the relationship variable *log_rel*. t-statistics in parentheses correspond to the null hypothesis that the parameter is zero. They are computed based on robust standard errors estimates clustered at the bank pair level. Superscript *len* (*bor*) refers to lender (borrower) specific variables. All models include end of maintenance and end of year dummy variables, as well as a dummy for settlement days of the MROs. Model (5) includes lender and borrower specific fixed effects. Pseudo R^2 is one minus the log likelihood ratio of the model and a model with interecpt only.

	(1)	(2)	(3)	(4)	(5) FE
size^{len}	-0.027^{***}	-0.027^{***}	-0.049^{***}	-0.050^{***}	0.115^{**}
	(-4.18)	(-4.19)	(-9.12)	(-9.20)	(2.40)
excess_reserves^{len}	0.010^{***}	0.010^{***}	0.010^{***}	0.012^{***}	0.013^{***}
	(3.90)	(3.85)	(3.71)	(3.89)	(4.22)
centrality^{len}			0.067^{***}	0.066^{***}	0.014
			(7.16)	(7.09)	(1.26)
liq_risk^{len}				-0.438^{*}	-0.157
				(-1.84)	(-0.65)
size^{bor}	0.023^{***}	0.023^{***}	0.014	0.015	-0.064
	(2.84)	(2.84)	(1.59)	(1.63)	(-0.86)
excess_reserves^{bor}	-0.011	-0.012^{*}	-0.012^{*}	-0.012^{*}	-0.013^{*}
	(-1.63)	(-1.67)	(-1.70)	(-1.80)	(-1.89)
centrality^{bor}			0.023^{***}	0.023^{***}	0.021^{***}
			(4.60)	(4.63)	(3.72)
liq_risk^{bor}				0.299	0.210
				(1.30)	(0.83)
log_rel	0.912^{***}	0.910^{***}	0.859^{***}	0.859^{***}	0.764^{***}
	(41.08)	(38.88)	(39.38)	(39.41)	(31.01)
log_rel_rev			0.113^{***}	0.114^{***}	0.163^{***}
			(7.05)	(7.12)	(9.29)
crisis x log_rel		0.010	0.020	0.020	0.011
		(0.81)	(1.53)	(1.52)	(0.74)
crisis x log_rel_rev			0.003	0.003	-0.010
			(0.13)	(0.11)	(-0.35)
corr_shocks	0.035^{*}	0.033^{*}	0.030^{*}	0.030^{*}	0.029
	(1.91)	(1.83)	(1.65)	(1.65)	(1.55)
ΔCDS		-0.025^{***}	-0.025^{***}	-0.025^{***}	-0.029^{***}
		(-2.79)	(-2.71)	(-2.74)	(-3.11)
total_reserves	0.019	0.031	0.024	0.023	0.033
	(0.67)	(1.08)	(0.84)	(0.80)	(1.12)
liq_supply	-0.053	-0.047	-0.023	-0.020	-0.088
	(-0.97)	(-0.79)	(-0.39)	(-0.34)	(-1.37)
Intercept	-1.987^{***}	-2.169^{***}	-2.143^{***}	-2.168^{***}	-2.664^{***}
	(-3.78)	(-3.70)	(-3.65)	(-3.68)	(-2.72)
Log-likelihood	-46715.3	-46709.2	-46523.6	-46517.4	-45882.4
Pseudo R^2	0.318	0.319	0.321	0.321	0.331
Observations	447785	447785	447785	447785	447785

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Estimation Results for Matching Probabilities (LPI & BPI).ML parameter estimates of the binary choice model using the relationship variables LPI and BPI. t-statistics in parentheses correspond to the null hypothesis that the parameter is zero. They are computed based on robust standard errors estimates clustered at the bank pair level. Superscript len (bor) refers to lender (borrower) specific variables. All models include end of maintenance and end of year dummy variables, as well as a dummy for settlement days of the MROs. Model (5) includes lender and borrower specific fixed effects. Pseudo R^2 is one minus the log likelihood ratio of the model and a model with interecpt only.

	(1)	(2)	(3)	(4)	(5) FE
size^{len}	-0.108^{***}	-0.108^{***}	-0.149^{***}	-0.150^{***}	0.287^{***}
	(-6.78)	(-6.80)	(-9.48)	(-9.55)	(3.91)
excess_reserves^{len}	0.002	0.001	0.002	0.006	0.013^{***}
	(0.43)	(0.36)	(0.53)	(1.21)	(3.70)
centrality^{len}			0.234^{***}	0.233^{***}	0.129^{***}
			(12.89)	(12.93)	(10.22)
liq_risk^{len}				-0.786^{*}	0.204
				(-1.87)	(1.11)
size^{bor}	0.131^{***}	0.132^{***}	0.061^{***}	0.061^{***}	0.148
	(5.92)	(5.99)	(2.99)	(3.02)	(1.20)
excess_reserves^{bor}	-0.008	-0.009	-0.011	-0.011^{*}	-0.013^{*}
	(-1.25)	(-1.37)	(-1.57)	(-1.69)	(-1.85)
centrality^{bor}			0.078^{***}	0.078^{***}	0.066^{***}
			(7.36)	(7.41)	(8.97)
liq_risk^{bor}				0.349	0.329
				(0.71)	(0.98)
LPI	1.380^{***}	1.388^{***}	1.388^{***}	1.392^{***}	1.487^{***}
	(16.53)	(15.73)	(16.08)	(16.16)	(23.09)
BPI	1.278^{***}	1.210^{***}	0.970^{***}	0.967^{***}	0.869^{***}
	(9.29)	(8.74)	(8.35)	(8.37)	(8.94)
crisis x LPI		-0.021	0.096	0.094	0.081
		(-0.22)	(1.02)	(1.00)	(0.95)
crisis x BPI		0.344^{***}	0.266^{**}	0.268^{**}	0.204^{**}
		(3.07)	(2.38)	(2.40)	(2.04)
corr_shocks	0.085^{***}	0.082^{***}	0.075^{**}	0.076^{**}	0.058^{**}
	(2.71)	(2.59)	(2.46)	(2.48)	(2.49)
ΔCDS		-0.036^{***}	-0.033^{***}	-0.034^{***}	-0.041^{***}
		(-4.00)	(-3.54)	(-3.59)	(-4.34)
total_reserves	-0.089^{***}	-0.063^{**}	-0.084^{***}	-0.087^{***}	-0.050^{*}
	(-3.18)	(-2.33)	(-3.04)	(-3.11)	(-1.70)
liq_supply	0.338^{***}	0.308^{***}	0.381^{***}	0.387^{***}	0.149^{**}
	(3.99)	(3.96)	(4.96)	(5.01)	(2.02)
Intercept	-5.761^{***}	-5.665^{***}	-5.398^{***}	-5.429^{***}	-9.060^{***}
	(-6.72)	(-7.10)	(-7.02)	(-7.04)	(-6.39)
Log-likelihood	-55642.0	-55592.7	-53207.8	-53185.4	-48689.1
Pseudo R^2	0.188	0.189	0.224	0.224	0.290
Observations	447785	447785	447785	447785	447785

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Estimation Results for Interest Rate Model (*log_rel*). OLS parameter estimates of the interest rate model (dependent variable: interest rate spread in percent) using the relationship variable *log_rel*. t-statistics in parentheses correspond to the null hypothesis that the parameter is zero. They are computed based on robust standard errors estimates clustered at the bank pair level. Superscript *len* (*bor*) refers to lender (borrower) specific variables. All models include end of maintenance and end of year dummy variables, as well as a dummy for settlement days of the MROs. Model (5) includes lender and borrower specific fixed effects.

	(1)	(2)	(3)	(4)	(5) FE
size^{len}	0.005^{***}	0.006^{***}	0.004^{***}	0.004^{***}	-0.018
	(5.55)	(5.77)	(3.22)	(3.19)	(−1.24)
$\text{equity\_ratio}^{len}$	-0.011	-0.038	-0.052	-0.034	-0.571^{**}
	(−0.13)	(−0.44)	(−0.60)	(−0.45)	(−2.05)
liq_risk^{len}				-0.098^{*}	-0.070^{*}
				(−1.68)	(−1.74)
$\text{excess\_reserves}^{len}$	-0.001	-0.001	-0.001	-0.000	0.000
	(−0.89)	(−0.55)	(−0.54)	(−0.30)	(0.01)
centrality^{len}			0.004^{*}	0.003^{*}	0.008^{***}
			(1.67)	(1.65)	(3.45)
size^{bor}	-0.012^{**}	-0.012^{**}	-0.013^{***}	-0.014^{***}	-0.118^{***}
	(−2.55)	(−2.53)	(−2.68)	(−2.77)	(−2.97)
$\text{equity\_ratio}^{bor}$	-0.223^{*}	-0.229^{*}	-0.240^{*}	-0.266^{*}	-2.034^{**}
	(−1.80)	(−1.84)	(−1.88)	(−1.90)	(−2.05)
liq_risk^{bor}				-0.161	-0.089
				(−1.31)	(−0.80)
$\text{excess\_reserves}^{bor}$	-0.000	0.000	0.000	0.001	0.000
	(−0.41)	(0.33)	(0.26)	(0.60)	(0.40)
centrality^{bor}			0.002	0.002	0.001
			(1.40)	(1.42)	(0.64)
log_rel	0.001	0.009^{***}	0.006^{*}	0.005	0.004^{*}
	(0.43)	(3.31)	(1.73)	(1.64)	(1.66)
log_rel_rev				0.000	-0.002
				(0.05)	(−0.55)
crisis x log_rel		-0.039^{***}	-0.038^{***}	-0.037^{***}	-0.037^{***}
		(−12.88)	(−13.57)	(−12.72)	(−12.08)
crisis x log_rel_rev				-0.012	-0.014
				(−1.14)	(−1.20)
corr_shocks	-0.022^{***}	-0.018^{***}	-0.018^{***}	-0.018^{***}	-0.019^{***}
	(−3.25)	(−3.11)	(−3.24)	(−3.22)	(−3.44)
ΔCDS		0.023^{***}	0.023^{***}	0.022^{***}	0.022^{***}
		(11.25)	(11.23)	(10.78)	(10.82)
total_reserves	0.005	-0.037^{***}	-0.037^{***}	-0.038^{***}	-0.042^{***}
	(0.98)	(−6.73)	(−6.86)	(−7.12)	(−8.11)
liq_supply	-0.603^{***}	-0.499^{***}	-0.499^{***}	-0.498^{***}	-0.484^{***}
	(−28.77)	(−27.98)	(−28.15)	(−27.83)	(−26.43)
Intercept	7.440^{***}	6.591^{***}	6.622^{***}	6.628^{***}	7.881^{***}
	(32.23)	(31.13)	(31.51)	(30.96)	(16.59)
Adjusted R^2	0.235	0.272	0.273	0.274	0.302
Observations	15857	15857	15857	15857	15857

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Estimation Results for Interest Rate Model (LPI & BPI). OLS parameter estimates of the interest rate model (dependent variable: interest rate spread in percent) using the relationship variables LPI and BPI. t-statistics in parentheses correspond to the null hypothesis that the parameter is zero. They are computed based on robust standard errors estimates clustered at the bank pair level. Superscript len (bor) refers to lender (borrower) specific variables. All models include end of maintenance and end of year dummy variables, as well as a dummy for settlement days of the MROs. Model (5) includes lender and borrower specific fixed effects.

	(1)	(2)	(3)	(4)	(5) FE
size^{len}	0.004***	0.005***	0.004***	0.004***	−0.037***
	(5.25)	(5.34)	(4.60)	(4.69)	(−2.71)
$\text{equity\_ratio}^{len}$	−0.016	−0.025	−0.036	−0.019	−0.564**
	(−0.20)	(−0.29)	(−0.44)	(−0.26)	(−2.32)
liq_risk^{len}				−0.110*	−0.066
				(−1.96)	(−1.64)
$\text{excess\_reserves}^{len}$	−0.001	−0.001	−0.001	−0.000	0.000
	(−0.87)	(−0.64)	(−0.60)	(−0.34)	(0.03)
centrality^{len}			0.002	0.002	0.010***
			(0.95)	(1.03)	(3.87)
size^{bor}	−0.011***	−0.010**	−0.012***	−0.013***	−0.166***
	(−2.67)	(−2.44)	(−2.86)	(−2.94)	(−3.85)
$\text{equity\_ratio}^{bor}$	−0.228*	−0.230*	−0.234*	−0.268*	−2.516**
	(−1.84)	(−1.74)	(−1.74)	(−1.87)	(−2.51)
liq_risk^{bor}				−0.185	−0.105
				(−1.46)	(−0.86)
$\text{excess\_reserves}^{bor}$	−0.000	0.000	0.000	0.001	0.000
	(−0.43)	(0.29)	(0.23)	(0.61)	(0.21)
centrality^{bor}			0.002	0.002	−0.000
			(1.20)	(1.21)	(−0.10)
LPI	0.003	0.019**	0.018**	0.018**	0.036***
	(0.43)	(2.52)	(2.16)	(2.31)	(4.86)
BPI	0.015	0.020*	0.017	0.013	−0.010
	(1.41)	(1.86)	(1.24)	(1.03)	(−0.93)
crisis x LPI		−0.131***	−0.128***	−0.126***	−0.128***
		(−8.24)	(−8.16)	(−8.04)	(−8.18)
crisis x BPI		−0.023	−0.025	−0.024	−0.015
		(−1.03)	(−1.16)	(−1.11)	(−0.71)
corr_shocks	−0.021***	−0.018***	−0.018***	−0.018***	−0.019***
	(−3.25)	(−2.98)	(−3.11)	(−3.11)	(−3.38)
ΔCDS		0.023***	0.023***	0.022***	0.023***
		(11.35)	(11.26)	(10.59)	(11.12)
total_reserves	0.005	−0.024***	−0.024***	−0.025***	−0.034***
	(0.90)	(−4.44)	(−4.46)	(−4.63)	(−6.57)
liq_supply	−0.602***	−0.543***	−0.544***	−0.544***	−0.506***
	(−28.53)	(−28.82)	(−28.80)	(−28.75)	(−26.50)
Intercept	7.421***	6.987***	7.022***	7.039***	8.788***
	(32.90)	(32.31)	(32.22)	(32.06)	(17.26)
Adjusted R^2	0.236	0.259	0.260	0.261	0.293
Observations	15857	15857	15857	15857	15857

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: OLS Estimation Results for Relationship Variables and Interactions for Different Starting Dates of Precrisis. Dependend variable is the interest rates spread in percent. The column labels indicate the different starting date of the precrisis period. The top panel presents the parameter estimates for the relationship variable *rel* and interaction terms in the full model (including all control variates and FE). The middle panel depicts the results for *rel_norm*, the bottom panel for *LPI*. F-statistic is computed for the null hypothesis $\beta_{rel} = \beta_{precrisis\_rel}$. t statistics in parentheses correspond to the null hypothesis that the parameter is zero. They are based on robust standard errors estimates allowing for clustering at the bank pair level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	1 Oct 06	1 Nov 06	1 Dec 06	1 Jan 07	1 Feb 07	1 Mar 07	1 Apr 07	1 May 07	1 Jun 07	1 Jul 07
log_rel	0.001	0.001	0.000	0.000	−0.001	0.001	0.001	0.001	0.000	0.001
	(0.27)	(0.42)	(0.01)	(0.11)	(−0.25)	(0.30)	(0.27)	(0.61)	(0.22)	(0.52)
crisis x log_rel	−0.034***	−0.034***	−0.033***	−0.033***	−0.031***	−0.033***	−0.032***	−0.033***	−0.032***	−0.033***
	(−9.36)	(−9.93)	(−9.46)	(−9.66)	(−9.47)	(−9.93)	(−10.18)	(−10.70)	(−10.64)	(−11.43)
precrisis x log_rel	0.004**	0.004**	0.006***	0.006***	0.009***	0.008***	0.010***	0.010***	0.019***	0.022***
	(2.11)	(2.38)	(3.85)	(4.27)	(6.52)	(5.62)	(6.93)	(6.47)	(9.87)	(9.14)
F statistic	0.641	0.647	3.474	4.038	13.004	7.844	14.219	11.680	46.272	43.995
P-value	0.423	0.421	0.063	0.045	0.000	0.005	0.000	0.001	0.000	0.000
LPI	0.030***	0.030***	0.026***	0.027***	0.025***	0.028***	0.029***	0.030***	0.031***	0.032***
	(2.78)	(3.10)	(2.92)	(3.17)	(3.16)	(3.68)	(3.93)	(4.04)	(4.25)	(4.53)
crisis x LPI	−0.120***	−0.119***	−0.113***	−0.113***	−0.109***	−0.112***	−0.112***	−0.114***	−0.113***	−0.118***
	(−6.66)	(−6.89)	(−6.74)	(−6.96)	(−6.87)	(−7.06)	(−7.25)	(−7.51)	(−7.57)	(−7.83)
precrisis x LPI	0.009	0.011	0.021***	0.023***	0.034***	0.034***	0.042***	0.046***	0.065***	0.074***
	(0.88)	(1.38)	(2.78)	(3.17)	(4.76)	(4.45)	(5.63)	(6.06)	(7.46)	(6.85)
F statistic	1.191	1.281	0.109	0.079	0.520	0.211	1.118	2.073	9.041	10.546
P-value	0.275	0.258	0.741	0.778	0.471	0.646	0.291	0.150	0.003	0.001

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Estimation Results for Matching Probabilities (*norm_rel*. ML parameter estimates of the binary choice model using the relationship variable *norm_rel*. *t*-statistics in parentheses correspond to the null hypothesis that the parameter is zero. They are computed based on robust standard errors estimates clustered at the bank pair level. Superscript *len* (*bor*) refers to lender (borrower) specific variables. All models include end of maintenance and end of year dummy variables, as well as a dummy for settlement days of the MROs. Model (5) includes lender and borrower specific fixed effects. Pseudo R^2 is one minus the log likelihood ratio of the model and a model with interecpt only.

	(1)	(2)	(3)	(4)	(5) FE
size^{len}	-0.111^{***}	-0.113^{***}	-0.150^{***}	-0.151^{***}	0.168^{**}
	(-7.65)	(-7.72)	(-11.37)	(-11.44)	(2.53)
$\text{excess\_reserves}^{len}$	0.005^{*}	0.005	0.005	0.008^{**}	0.011^{***}
	(1.73)	(1.51)	(1.64)	(2.14)	(3.38)
centrality^{len}			0.172^{***}	0.171^{***}	0.073^{***}
			(8.42)	(8.41)	(4.46)
liq_risk^{len}				-0.598	-0.018
				(-1.42)	(-0.10)
size^{bor}	0.056^{***}	0.055^{***}	0.011	0.012	0.021
	(2.68)	(2.69)	(0.51)	(0.53)	(0.19)
$\text{excess\_reserves}^{bor}$	-0.008	-0.010	-0.011	-0.011	-0.015^{**}
	(-1.17)	(-1.34)	(-1.53)	(-1.50)	(-2.11)
centrality^{bor}			0.073^{***}	0.073^{***}	0.065^{***}
			(6.80)	(6.86)	(9.03)
liq_risk^{bor}				-0.273	0.186
				(-0.54)	(0.64)
norm_rel	3.476^{***}	3.403^{***}	3.074^{***}	3.073^{***}	2.661^{***}
	(22.30)	(20.80)	(22.82)	(22.89)	(20.00)
norm_rel_rev			0.372^{***}	0.375^{***}	0.437^{***}
			(4.01)	(4.05)	(5.01)
crisis x norm_rel		0.400^{***}	0.483^{***}	0.487^{***}	0.362^{***}
		(4.24)	(5.36)	(5.39)	(3.58)
crisis x norm_rel_rev			0.050	0.049	0.030
			(0.45)	(0.44)	(0.28)
corr_shocks	0.056^{**}	0.049^{*}	0.045	0.046^{*}	0.047^{**}
	(2.00)	(1.71)	(1.63)	(1.68)	(2.07)
ΔCDS		-0.027^{***}	-0.026^{***}	-0.028^{***}	-0.036^{***}
		(-3.02)	(-2.92)	(-3.11)	(-3.81)
total_reserves	-0.041	0.016	0.004	0.001	0.031
	(-1.50)	(0.61)	(0.15)	(0.03)	(1.06)
liq_supply	0.194^{**}	0.031	0.061	0.065	-0.102
	(2.41)	(0.43)	(0.87)	(0.92)	(-1.45)
Intercept	-3.902^{***}	-2.496^{***}	-2.066^{***}	-2.054^{***}	-4.115^{***}
	(-4.98)	(-3.50)	(-3.02)	(-3.00)	(-3.10)
Log-likelihood	-52595.7	-52536.4	-51204.4	-51192.0	-48605.8
Pseudo R^2	0.233	0.234	0.253	0.253	0.291
Observations	447781	447781	447781	447781	447781

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Estimation Results for Interest Rate Model (*norm_rel*). OLS parameter estimates of the interest rate model (dependent variable: interest rate spread in percent) using the relationship variable *norm_rel*. t-statistics in parentheses correspond to the null hypothesis that the parameter is zero. They are computed based on robust standard errors estimates clustered at the bank pair level. Superscript *len* (*bor*) refers to lender (borrower) specific variables. All models include end of maintenance and end of year dummy variables, as well as a dummy for settlement days of the MROs. Model (5) includes lender and borrower specific fixed effects.

	(1)	(2)	(3)	(4)	(5) FE
size^{len}	0.005***	0.006***	0.005***	0.005***	−0.018
	(6.07)	(6.62)	(5.25)	(5.13)	(−1.24)
$\text{equity\_ratio}^{len}$	−0.012	−0.028	−0.042	−0.027	−0.518*
	(−0.14)	(−0.34)	(−0.50)	(−0.36)	(−1.91)
liq_risk^{len}				−0.092	−0.066
				(−1.56)	(−1.61)
$\text{excess\_reserves}^{len}$	−0.001	−0.000	−0.000	−0.000	0.000
	(−0.88)	(−0.47)	(−0.44)	(−0.20)	(0.13)
centrality^{len}			0.003	0.003	0.007***
			(1.59)	(1.47)	(3.12)
size^{bor}	−0.012***	−0.012**	−0.013***	−0.013***	−0.092**
	(−2.60)	(−2.56)	(−2.66)	(−2.72)	(−2.35)
$\text{equity\_ratio}^{bor}$	−0.221*	−0.231*	−0.239*	−0.260*	−1.765*
	(−1.78)	(−1.85)	(−1.88)	(−1.87)	(−1.84)
liq_risk^{bor}				−0.126	−0.061
				(−1.03)	(−0.57)
$\text{excess\_reserves}^{bor}$	−0.000	0.001	0.001	0.001	0.001
	(−0.42)	(0.55)	(0.49)	(0.76)	(0.62)
centrality^{bor}			0.002	0.002	0.001
			(1.13)	(1.13)	(0.63)
norm_rel	0.013	0.056***	0.044***	0.043***	0.035***
	(1.03)	(4.24)	(3.20)	(3.20)	(3.48)
norm_rel_rev				−0.005	0.001
				(−0.44)	(0.06)
crisis x norm_rel		−0.234***	−0.231***	−0.226***	−0.225***
		(−13.88)	(−14.34)	(−13.45)	(−12.53)
crisis x norm_rel_rev				−0.024	−0.031
				(−0.61)	(−0.74)
corr_shocks	−0.022***	−0.016***	−0.016***	−0.016***	−0.017***
	(−3.27)	(−2.80)	(−2.92)	(−2.89)	(−3.14)
ΔCDS		0.023***	0.023***	0.022***	0.022***
		(11.15)	(11.13)	(10.71)	(10.62)
total_reserves	0.006	−0.043***	−0.043***	−0.043***	−0.046***
	(0.99)	(−7.89)	(−7.95)	(−8.12)	(−8.91)
liq_supply	−0.603***	−0.481***	−0.481***	−0.482***	−0.473***
	(−28.61)	(−27.44)	(−27.53)	(−27.48)	(−26.05)
Intercept	7.438***	6.426***	6.460***	6.473***	7.491***
	(32.40)	(30.91)	(31.05)	(30.60)	(15.96)
Adjusted R^2	0.235	0.276	0.276	0.277	0.305
Observations	15857	15857	15857	15857	15857

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: OLS Estimation Results for Relationship Variables and Interactions for Different Starting Dates of Precrisis. Dependend variable is the interest rates spread in percent. The column labels indicate the different starting date of the precrisis period. The top panel presents the parameter estimates for the relationship variable *rel* and interaction terms in the full model (including all control variates and FE). The middle panel depicts the results for *rel_norm*, the bottom panel for *LPI*. F-statistic is computed for the null hypothesis $\beta_{rel} = \beta_{precrisis\_rel}$. t statistics in parentheses correspond to the null hypothesis that the parameter is zero. They are based on robust standard errors estimates allowing for clustering at the bank pair level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	1 Oct 06	1 Nov 06	1 Dec 06	1 Jan 07	1 Feb 07	1 Mar 07	1 Apr 07	1 May 07	1 Jun 07	1 Jul 07
norm_rel	0.021^{*}	0.023^{*}	0.017	0.019^{*}	0.014	0.019^{*}	0.018^{*}	0.023^{**}	0.017^{*}	0.022^{**}
	(1.69)	(1.92)	(1.50)	(1.73)	(1.30)	(1.88)	(1.83)	(2.28)	(1.68)	(2.22)
crisis x norm_rel	-0.210^{***}	-0.211^{***}	-0.201^{***}	-0.203^{***}	-0.191^{***}	-0.199^{***}	-0.196^{***}	-0.204^{***}	-0.192^{***}	-0.203^{***}
	(−10.28)	(−10.65)	(−10.24)	(−10.39)	(−10.10)	(−10.59)	(−10.84)	(−11.41)	(−11.18)	(−11.92)
precrisis x norm_rel	0.021^{**}	0.022^{**}	0.034^{***}	0.034^{***}	0.054^{***}	0.048^{***}	0.062^{***}	0.060^{***}	0.123^{***}	0.149^{***}
	(2.24)	(2.49)	(3.97)	(4.17)	(6.65)	(5.85)	(7.19)	(6.49)	(11.08)	(10.36)
F statistic	0.000	0.003	0.976	0.916	7.568	3.940	9.794	7.270	50.709	54.915
P-value	0.998	0.954	0.324	0.339	0.006	0.047	0.002	0.007	0.000	0.000

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Estimation Results Using Relationship Based on Overall Sample. OLS parameter estimates of the interest rate model (dependent variable: interest rate spread in percent) for three different relationship variables (1)-(3) computed based on overall sample. t statistics in parentheses correspond to the null hypothesis that the parameter is zero. They are computed based on robust standard errors estimates clustered at the bank pair level. Superscript len (bor) refers to lender (borrower) specific variables. All models include end of maintenance period dummies, end of year dummies, dummies for settlement days of the MROs, and borrower and lender specific fixed effects.

	(1)	(2)	(3)
relation =	log_rel	norm_rel	LPI
size^{len}	−0.021	−0.022	−0.038***
	(−1.50)	(−1.57)	(−2.61)
equity_ratio^{len}	−0.492*	−0.450*	−0.561**
	(−1.86)	(−1.73)	(−2.27)
liq_risk^{len}	−0.093***	−0.091**	−0.071**
	(−2.61)	(−2.55)	(−1.98)
excess_reserves^{len}	0.000	0.000	0.000
	(0.56)	(0.71)	(0.26)
centrality^{len}	0.007***	0.007***	0.009***
	(2.75)	(2.79)	(3.32)
size^{bor}	−0.135***	−0.118***	−0.201***
	(−3.28)	(−2.89)	(−4.45)
equity_ratio^{bor}	−2.222**	−2.001**	−2.806***
	(−2.20)	(−2.02)	(−2.67)
liq_risk^{bor}	−0.124	−0.099	−0.150
	(−1.09)	(−0.88)	(−1.21)
excess_reserves^{bor}	0.001	0.002	0.001
	(1.08)	(1.25)	(0.54)
centrality^{bor}	−0.000	0.000	−0.000
	(−0.15)	(0.27)	(−0.06)
relation_oa	0.001	0.037	0.034***
	(0.58)	(1.14)	(2.80)
precrisis x **relation**_oa	0.012***	0.149***	0.086***
	(11.93)	(13.58)	(7.10)
crisis x **relation**_oa	−0.018***	−0.194***	−0.127***
	(−12.09)	(−13.30)	(−6.77)
BPI_oa			−0.021
			(−1.35)
precrisis x BPI_oa			0.043***
			(2.62)
crisis x BPI_oa			−0.019
			(−0.76)
corr_shocks	−0.017***	−0.016***	−0.021***
	(−3.09)	(−2.86)	(−3.58)
ΔCDS	0.017***	0.016***	0.019***
	(8.00)	(7.34)	(9.00)
total_reserves	−0.041***	−0.044***	−0.029***
	(−8.03)	(−8.66)	(−5.49)
liq_supply	−0.502***	−0.499***	−0.532***
	(−27.29)	(−26.90)	(−27.41)
Intercept	8.316***	8.111***	9.440***
	(17.00)	(16.38)	(18.10)
Adjusted R^2	0.319	0.323	0.299
Observations	15857	15857	15857

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Estimation Results Using Different Covariates. OLS parameter estimates of the interest rate model (dependent variable: interest rate spread in percent) for three different relationship variables (1)-(3) based on alternative covariates. t statistics in parentheses correspond to the null hypothesis that the parameter is zero. They are computed based on robust standard errors estimates clustered at the bank pair level. Superscript len (bor) refers to lender (borrower) specific variables. All models include end of maintenance period dummies, end of year dummies, dummies for settlement days of the MROs, and borrower and lender specific fixed effects.

relation =	(1) log_rel	(2) norm_rel	(3) LPI
size^{len}	-0.062^{**}	-0.057^{**}	-0.062^{**}
	(-2.15)	(-1.99)	(-2.32)
equity_ratio^{len}	-0.714^{**}	-0.631^{**}	-0.655^{**}
	(-2.18)	(-1.99)	(-2.26)
fungible^{len}	-0.044	-0.055	-0.028
	(-0.83)	(-1.03)	(-0.55)
liq_creat^{len}	-0.006^{***}	-0.006^{***}	-0.006^{***}
	(-3.89)	(-3.78)	(-3.85)
fulfillment^{len}	-0.003	-0.001	-0.005
	(-0.81)	(-0.26)	(-1.15)
centrality^{len}	0.007^{***}	0.006^{**}	0.007^{**}
	(2.85)	(2.51)	(2.32)
size^{bor}	-0.178^{***}	-0.158^{***}	-0.210^{***}
	(-4.00)	(-3.58)	(-4.48)
equity_ratio^{bor}	-2.059^{**}	-1.901^{*}	-2.357^{**}
	(-2.07)	(-1.96)	(-2.31)
fungible^{bor}	0.093	0.071	0.110
	(1.15)	(0.90)	(1.30)
liq_creat^{bor}	-0.005^{**}	-0.004^{*}	-0.006^{**}
	(-2.05)	(-1.75)	(-2.53)
fulfillment^{bor}	0.003	0.007	0.002
	(0.65)	(1.27)	(0.39)
centrality^{bor}	0.000	0.000	-0.001
	(0.17)	(0.25)	(-0.60)
relation	0.000	0.013	0.030^{***}
	(0.11)	(1.35)	(4.22)
precrisis x **relation**	0.025^{***}	0.154^{***}	0.071^{***}
	(9.48)	(11.52)	(7.58)
crisis x **relation**	-0.030^{***}	-0.176^{***}	-0.113^{***}
	(-7.61)	(-8.79)	(-7.92)
BPI			-0.026^{**}
			(-2.24)
precrisis x BPI			0.051^{**}
			(2.36)
crisis x BPI			0.024
			(1.11)
corr_shocks	-0.019^{***}	-0.018^{***}	-0.020^{***}
	(-3.14)	(-2.95)	(-3.19)
ΔCDS	0.017^{***}	0.016^{***}	0.018^{***}
	(7.51)	(7.10)	(7.83)
total_reserves	-0.035^{***}	-0.038^{***}	-0.029^{***}
	(-6.31)	(-6.86)	(-5.47)
liq_supply	-0.512^{***}	-0.509^{***}	-0.527^{***}
	(-25.87)	(-25.56)	(-25.94)
Intercept	9.380^{***}	9.088^{***}	9.854^{***}
	(16.85)	(16.07)	(16.96)
Adjusted R^2	0.307	0.311	0.301
Observations	14339	14339	14339

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13: Maximum Likelihood Estimation Results of Selection Model. Maximum likelihood parameter estimates of the selection model for three different relationship variables (1)-(3). t statistics in parentheses correspond to the null hypothesis that the parameter is zero. They are computed based on robust standard errors estimates clustered at the bank pair level. Superscript *len* (*bor*) refers to lender (borrower) specific variables. All models include end of maintenance period dummies, end of year dummies, dummies for settlement days of the MROs, and borrower and lender specific fixed effects.

relation =	(1) log_rel		(2) LPI		(3) norm_rel	
	spread	dummy	spread	dummy	spread	dummy
size^{len}	-0.027^{*}	0.111^{**}	-0.038^{***}	0.284^{***}	-0.026^{*}	0.169^{**}
	(-1.87)	(2.32)	(-2.75)	(3.88)	(-1.82)	(2.53)
$\text{equity\_ratio}^{len}$	-0.547^{**}		-0.546^{**}		-0.490^{*}	
	(-2.06)		(-2.31)		(-1.89)	
liq_risk^{len}	-0.088^{**}	-0.159	-0.073^{**}	0.198	-0.086^{**}	-0.022
	(-2.49)	(-0.65)	(-2.07)	(1.08)	(-2.42)	(-0.12)
$\text{excess\_reserves}^{len}$	0.000	0.013^{***}	0.000	0.013^{***}	0.000	0.011^{***}
	(0.30)	(4.26)	(0.36)	(3.73)	(0.50)	(3.39)
centrality^{len}	0.008^{***}	0.009	0.010^{***}	0.129^{***}	0.008^{***}	0.067^{***}
	(3.43)	(0.85)	(3.48)	(10.18)	(3.14)	(4.20)
size^{bor}	-0.167^{***}	-0.061	-0.203^{***}	0.138	-0.151^{***}	0.025
	(-3.99)	(-0.81)	(-4.50)	(1.12)	(-3.60)	(0.22)
$\text{equity\_ratio}^{bor}$	-2.505^{**}		-2.826^{***}		-2.338^{**}	
	(-2.44)		(-2.72)		(-2.32)	
liq_risk^{bor}	-0.138	0.247	-0.146	0.324	-0.112	0.222
	(-1.18)	(0.98)	(-1.14)	(0.97)	(-0.98)	(0.77)
$\text{excess\_reserves}^{bor}$	0.001	-0.013^{*}	0.001	-0.013^{*}	0.001	-0.015^{**}
	(0.63)	(-1.88)	(0.44)	(-1.84)	(0.85)	(-2.11)
centrality^{bor}	0.001	0.017^{***}	-0.000	0.066^{***}	0.001	0.062^{***}
	(0.42)	(3.06)	(-0.17)	(8.95)	(0.56)	(8.57)
relation	0.001	0.777^{***}	0.035^{***}	1.484^{***}	0.022	2.681^{***}
	(0.44)	(31.74)	(4.02)	(22.83)	(1.58)	(19.50)
precrisis x **relation**	0.023^{***}	0.017	0.074^{***}	0.034	0.147^{***}	0.029
	(11.10)	(1.09)	(7.78)	(0.41)	(12.65)	(0.34)
crisis x **relation**	-0.031^{***}	0.012	-0.112^{***}	0.088	-0.186^{***}	0.365^{***}
	(-10.54)	(0.78)	(-7.60)	(1.01)	(-11.11)	(3.42)
BPI			-0.018	0.859^{***}		
			(-1.50)	(8.97)		
precrisis x BPI			0.052^{***}	0.072		
			(3.07)	(0.80)		
crisis x BPI			-0.001	0.217^{**}		
			(-0.04)	(2.09)		
corr_shocks	-0.019^{***}	0.033^{*}	-0.020^{***}	0.058^{**}	-0.017^{***}	0.049^{**}
	(-3.42)	(1.77)	(-3.44)	(2.49)	(-3.13)	(2.16)
ΔCDS	0.017^{***}	-0.031^{***}	0.018^{***}	-0.043^{***}	0.017^{***}	-0.036^{***}
	(8.26)	(-3.29)	(8.68)	(-4.52)	(7.67)	(-3.87)
total_reserves	-0.035^{***}	0.034	-0.029^{***}	-0.048	-0.038^{***}	0.031
	(-6.79)	(1.16)	(-5.62)	(-1.63)	(-7.42)	(1.09)
liq_supply	-0.516^{***}	-0.102	-0.532^{***}	0.138^{*}	-0.511^{***}	-0.108
	(-28.15)	(-1.56)	(-28.27)	(1.87)	(-27.76)	(-1.58)
Intercept	8.822^{***}	-2.466^{**}	9.450^{***}	-8.814^{***}	8.597^{***}	-4.054^{***}
	(17.87)	(-2.50)	(18.22)	(-6.21)	(17.27)	(-3.03)
athrho	0.016		0.032		0.027	
	(0.74)		(1.07)		(0.89)	
lnsigma	-2.026^{***}		-2.019^{***}		-2.028^{***}	
	(-111.97)		(-110.79)		(-112.50)	
Log-likelihood	-36345.3		-39169.7		-39035.9	
Observations	447785		447785		447781	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 14: Estimation Results Allowing for Small Borrower Effects. OLS parameter estimates of the interest rate model (dependent variable: interest rate spread in percent) for three different relationship variables (1)-(3). t statistics in parentheses correspond to the null hypothesis that the parameter is zero. They are computed based on robust standard errors estimates clustered at the bank pair level. *small_bor* is an indicator variable being one if the asset size of the borrower is less than €1 billion. Superscript *len* (*bor*) refers to lender (borrower) specific variables. All models include end of maintenance period dummies, end of year dummies, dummies for settlement days of the MROs, and borrower and lender specific fixed effects. F-statistic and p-value correspond to $H_0 : \beta_{crisis\_rel} + \beta_{crisis\_rel\_small} = 0$.

	(1)	(2)	(3)
relation =	log_rel	norm_rel	LPI
$size^{len}$	-0.027^{*}	-0.026^{*}	-0.038^{***}
	(-1.83)	(-1.80)	(-2.73)
$equity\_ratio^{len}$	-0.558^{**}	-0.496^{*}	-0.548^{**}
	(-2.09)	(-1.90)	(-2.30)
liq_risk^{len}	-0.084^{**}	-0.083^{**}	-0.071^{**}
	(-2.35)	(-2.29)	(-1.99)
$excess\_reserves^{len}$	0.000	0.000	0.000
	(0.24)	(0.43)	(0.29)
$centrality^{len}$	0.008^{***}	0.007^{***}	0.010^{***}
	(3.39)	(3.08)	(3.59)
$size^{bor}$	-0.161^{***}	-0.144^{***}	-0.200^{***}
	(-3.85)	(-3.45)	(-4.34)
$equity\_ratio^{bor}$	-2.565^{**}	-2.388^{**}	-2.792^{***}
	(-2.49)	(-2.34)	(-2.62)
liq_risk^{bor}	-0.138	-0.112	-0.143
	(-1.17)	(-0.97)	(-1.11)
$excess\_reserves^{bor}$	0.001	0.001	0.001
	(0.68)	(0.92)	(0.50)
$centrality^{bor}$	0.001	0.001	-0.001
	(0.41)	(0.45)	(-0.30)
relation	0.000	0.015	0.030^{***}
	(0.07)	(1.53)	(4.14)
precrisis x **relation**	0.023^{***}	0.145^{***}	0.075^{***}
	(10.66)	(12.27)	(8.20)
precrisis x **relation** x small_bor	0.010	0.067^{**}	-0.044
	(1.36)	(2.23)	(-1.28)
crisis x **relation**	-0.032^{***}	-0.195^{***}	-0.112^{***}
	(-10.96)	(-11.48)	(-7.46)
crisis x **relation** x small_bor	0.030^{***}	0.175^{***}	0.086
	(4.04)	(4.50)	(1.44)
BPI			-0.019
			(-1.64)
precrisis x BPI			0.044^{**}
			(2.05)
precrisis x BPI x small_bor			0.041^{*}
			(1.67)
crisis x BPI			-0.010
			(-0.39)
crisis x BPI x small_bor			0.014
			(0.32)
corr_shocks	-0.019^{***}	-0.018^{***}	-0.020^{***}
	(-3.49)	(-3.21)	(-3.53)
ΔCDS	0.017^{***}	0.017^{***}	0.019^{***}
	(8.23)	(7.70)	(8.73)
total_reserves	-0.036^{***}	-0.039^{***}	-0.029^{***}
	(-6.84)	(-7.48)	(-5.65)
liq_supply	-0.514^{***}	-0.509^{***}	-0.532^{***}
	(-28.09)	(-27.74)	(-28.03)
Intercept	8.746^{***}	8.521^{***}	9.428^{***}
	(17.83)	(17.18)	(17.78)
F-statistic	0.85	1.95	0.14
P-value	0.357	0.163	0.708
Adjusted R^2	0.309	0.313	0.299
Observations	15857	15857	15857

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 15: Estimation Results for Lenders from Different Sectors. OLS parameter estimates of the interest rate model (dependent variable: interest rate spread in percent) for lenders from different banking sectors. t statistics in parentheses correspond to the null hypothesis that the parameter is zero. They are computed based on robust standard errors estimates clustered at the bank pair level. Superscript len (bor) refers to lender (borrower) specific variables. All models include end of maintenance period dummies, end of year dummies, dummies for settlement days of the MROs, and borrower and lender specific fixed effects.

	Cooperative Sector	Public Sector	Private Sector	Special Purpose
size^{len}	0.001	-0.042^{**}	-0.009	-0.066
	(0.07)	(-2.12)	(-0.37)	(-1.45)
$\text{equity\_ratio}^{len}$	-0.564^{***}	-0.987^{***}	0.029	-1.745
	(-3.81)	(-4.42)	(0.06)	(-1.35)
liq_risk^{len}	-0.432^{***}	-0.042	-0.063^{**}	0.054
	(-3.49)	(-0.50)	(-1.97)	(0.25)
$\text{excess\_reserves}^{len}$	0.003	0.001	-0.001	-0.003^{*}
	(1.51)	(1.00)	(-0.61)	(-1.73)
centrality^{len}	0.001	0.008^{**}	0.005	0.003
	(0.17)	(2.32)	(1.46)	(0.43)
size^{bor}	-1.153^{***}	-0.580^{***}	-0.040	-0.263^{***}
	(-5.06)	(-5.23)	(-0.87)	(-2.83)
$\text{equity\_ratio}^{bor}$	-19.497^{***}	-18.707^{***}	0.226	0.713
	(-5.76)	(-6.26)	(0.24)	(0.39)
liq_risk^{bor}	-1.100^{*}	-0.130	-0.564^{***}	-0.135
	(-1.92)	(-0.91)	(-2.75)	(-0.61)
$\text{excess\_reserves}^{bor}$	-0.008	0.001	0.002	0.001
	(-1.33)	(0.37)	(1.64)	(0.44)
centrality^{bor}	0.037^{***}	0.005^{***}	-0.009^{**}	-0.018^{***}
	(7.87)	(2.92)	(-2.02)	(-4.64)
log_rel	-0.000	-0.001	-0.000	0.002
	(-0.03)	(-0.31)	(-0.07)	(0.25)
precrisis x log_rel	0.021^{***}	0.026^{***}	0.022^{***}	0.033^{**}
	(3.89)	(7.03)	(6.61)	(2.04)
crisis x log_rel	-0.003	-0.028^{***}	-0.034^{***}	-0.009
	(-0.48)	(-7.12)	(-4.81)	(-1.06)
corr_shocks	-0.027	-0.021^{**}	-0.015^{*}	-0.010
	(-1.66)	(-2.33)	(-1.73)	(-0.63)
ΔCDS	0.032^{***}	0.011^{***}	0.026^{***}	0.019^{***}
	(4.31)	(3.56)	(6.60)	(2.84)
total_reserves	-0.061^{***}	-0.040^{***}	-0.032^{***}	-0.065^{***}
	(-4.70)	(-5.01)	(-3.51)	(-3.12)
liq_supply	-0.406^{***}	-0.510^{***}	-0.513^{***}	-0.445^{***}
	(-7.52)	(-18.40)	(-14.37)	(-7.81)
Intercept	15.891^{***}	13.438^{***}	7.196^{***}	10.229^{***}
	(8.89)	(12.49)	(10.81)	(7.05)
Adjusted R^2	0.341	0.305	0.343	0.375
Observations	1836	7746	5223	1052

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 16: Definition and Summary Statistics of Variables. Mean and Standard deviation of bank specific variables are lender specific above borrower specific. All volume in millions of €. Interest rate based on 360 day as EONIA. All logarithms are natural logarithms.

Label	Definition	Mean	Std	Obs
	bank specific variables			
size	Logarithm of total assets according to last balance sheet record	10.260 11.103	1.950 1.424	447785
equity_ratio	Equity over total assets according to last balance sheet record.	0.043 0.038	0.038 0.029	447785
fungible	Debt instruments, shares and other variable-yield securities over total assets according to last balance sheet record	0.244 0.244	0.126 0.100	447785
liq_risk	Standard deviation of daily change in reserve holdings during the last 30 days divided by reserve requirements	0.032 0.032	0.032 0.025	447785
liq_creat	0.5*(long term assets + short term liabilities)/total assets	17.160 15.103	14.129 11.981	443635
exess_reserve	reserve holding - the amount a bank needs to hold on a daily basis for the balance of the reserve maintenance period in order to exactly fulfill reserve requirements, divided by the average daily required reserves	0.161 0.117	1.444 1.056	447785
fulfillment	Bank's cumulative reserve holdings as a percentage of its cumulative required reserves in the current reserve requirement period	0.966 0.955	0.355 0.361	447785
centrality	Bonacich centrality measure. Total interbank lending/borrowing during last 30 days scaled s.t. $\sum_k centrality$ equal total number of lenders/borrowers at t	0.607 1.091	0.955 1.400	447785
	pair specific variables			
spread	Difference between overnight interest rate negotiated by lender i and borrower j and ECB target rate	0.086	0.159	15857
log_rel	Logarithm of (no. of loans from lender to borrower in the last 30 days + 1)	0.284	0.581	447785
log_rel_rev	Logarithm of (no. of loans from borrower to lender in the last 30 days + 1)	0.126	0.385	447785
norm_rel	(Logarithm of (amount lent from lender i to borrower j during the last 30 days)) / (Logarithm of (total amount lent by lender i) + Logarithm of (total amount borrowed by borrower j))	0.084	0.149	447785
norm_rel_rev	(Logarithm of (amount lent from borrower j to lender i during the last 30 days)) / (Logarithm of (total amount lent by lender i) + Logarithm of (total amount borrowed by borrower j))	0.0541	0.169	447785
LPI	Amount lent by lender i to borrower j during past 30 days, divided by overall amount lent by bank i during past 30 days	0.064	0.175	447785
BPI	Amount borrowed by borrower j from lender i during past 30 days, divided by total borrowing of bank j during past 30 days	0.043	0.149	447785
corr_shocks	Correlation of daily reserves changes of lender i and borrower j during last 30 days	0.024	0.266	447785
	market wide variables			
CDS	Three day moving average of average CDS prices for 15 German banks for which data is available	17.563	13.83	447785
total_reserve	Logarithm of total reserve holdings at begining of day t	9.926	0.239	447785
liq_supply	Logarithm of total liquidity supply of the Eurosystem at time t, including non-standard monetary policy measures that have been used since August 2007	12.084	0.100	447785
crisis	Dummy equal one from 9 August 2007 onwards			