Relationship Lending in the Interbank Market and the Price of Liquidity

Falk Bräuning[*] Falko Fecht[†]

March 11, 2013

Abstract

This paper empirically investigates the effect of interbank relationship lending on banks' access to liquidity. We find that established lending relationships significantly helped banks to obtain liquidity particularly in the wake of the financial crisis in 2007. Our analysis is based on German interbank payment data which we use to construct a panel of unsecured overnight loans between 1079 distinct borrower-lender pairs. Matching this data with various market, bank and bank pair characteristics permits us to disentangle the role that relationship lending plays in mitigating search frictions and in overcoming informational asymmetries about counterparty credit risk. While we find some indication that lending relationships help banks containing search frictions in the interbank market, our results also show that relationships have a significant impact on interbank credit availability and pricing due to private information about counterparties' credit quality.

[*]VU University Amsterdam and Tinbergen Institute, De Boelelaan 1105, 1081 HV Amsterdam, Netherlands, Phone: +31.2059.86010, Fax: +49.2059.86020, `f.brauning@vu.nl`

[†]Frankfurt School of Finance and Management, Sonnemannstrasse 9-11, 60314 Frankfurt am Main, Germany, Phone: +49.69.154008.441, Fax: +49.69.154008.4441, `f.fecht@fs.de`

We thank Diego Cerdeiro, Valeriya Dinger, Heinz Herrmann, Achim Hauck, André Lucas, Albert Menkveld, Cyril Monnet, Ulrike Neyer, Klaus Schaeck, Viktors Stebunovs, Günseli Tümar-Alkan and Sweder van Wijnbergen. We also thank seminar and workshop participants at Central Bank of Luxembourg, Deutsche Bundesbank, European Central Bank, Norges Bank, University Düsseldorf, University Osnabrück, Tinbergen Institute, VU University Amsterdam and WHU-Beisheim School of Management for valuable comments. We are thankful to the Research Centre of the Deutsche Bundesbank for data access and hospitality while part of this paper was written in Frankfurt. Bräuning gratefully acknowledges financial support by the Dutch Science Foundation (NWO).

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 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

[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.

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 relevant 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 (if the former leaves some rent to the borrower). 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 through credit default, also the stability of interbank borrowers is seriously endangered if a financial institution that serves as interbank relationship lender fails. Therefore, 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. This 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]

Despite its utmost relevance, there is very little empirical research on the role of private information in the interbank market. In this paper we contribute to the literature by providing first empirical evidence that peer monitoring prevails in the German interbank market and that private information about counterparties' creditworthiness matters for the liquidity reallocation in the banking sector. We use an algorithm similar to 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 distinct 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 when perceived credit risk was high. 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 bilaterally negotiated interest rates in a regression based approach.

[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*) .

We find that relationships matter for the availability and pricing of interbank credit even after controlling for bank and borrower-lender pair specific characteristics. As regards to interest rates charged, our results indicate that relationship lenders already charged higher interest rates from 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, when the sub-prime crisis kicked in and led to a market-wide increase in interbank rates in July/August 2007 relationship lenders on average gave a economically and statistically significant discount to their close borrowers.

In our empirical approach we are able to disentangle whether it is asymmetric information about counterparty risk that relationship lending helps overcome or whether it is only search frictions that are mitigated by repeated interbank lending as suggested by Ashcraft and Duffie (2007), amongst others. Separating these two effects is important because only if it is indeed private information about counterparty credit risk that makes relationship lending an important factor then a decentralized interbank market can be efficiency enhancing. If relationship lending only matters because it mitigates search costs then a centralized market directly eliminates these frictions and the benefits from relationship lending become redundant. We separate these two effects, first, by controlling for negatively correlated liquidity shocks of each pair of banks. Having found a counterparty who usually has offsetting liquidity needs is a reason why repeated lending might occur in the presence of search frictions. Second, we calculate the past surplus that the borrower and the lender extracted from a relationship to also control for the incentives to stick to an established relationship rather than searching for a new counterpart. Finally, we introduce an interaction term between the relationship measures and a variable that indicates when market tightness is high and hence search frictions prevail. While our results show that search costs indeed play a role and relationships help mitigate them, lending relationships are also and particularly important in overcoming information asymmetries about borrowers credit quality. These findings 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.

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. 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 borrower'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 the empirical contributions of Furfine (1999), Cocco et al. (2009) and 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.

[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.

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) apply 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 shocks, 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.

Finally, our paper is also related to the theoretical contributions of Bhattacharya and Gale (1987), Bhattacharya and Fulghieri (1994), Freixas et al. (2000), Allen and Gale (2000) and Freixas et al. (2011), who 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. In these models interbank deposits must be rolled over (at favorable rates) in order to implement an efficiency enhancing sharing of liquidity risks in the interbank market. Our paper shows that repeated lending in the interbank market exists and indeed implements such an efficiency enhancing smoothing of liquidity risks.

The remainder of the paper is structured as follows. In section 2, we briefly provide some

[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.

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 the econometric model 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 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 operations 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 period. 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.

[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.

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.

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-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, were 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] We do not observe the reason for the individual payment and thus cannot identify interbank loans 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 considerably 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 this improved algorithm based on EONIA, but we focus on overnight loans only which 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 we found 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 especially for our sample period, compare Furfine (2001) and Heijmans et al. (2011) for an in depth assessment. 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

[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.

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 at 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. Like the balance sheet data it is confidential and not publicly available. 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 records 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]

[INSERT FIGURE 1 HERE]

Figure 1 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

[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.

the solid vertical line (in red). Figure 2 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 3). 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 2 AND FIGURE 3 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. However, the cross-sectional variation (standard deviation) of interest rates is significantly higher which might indicate differences in counterparty risk assessment. Also during the crisis we 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; compare also Afonso et al. (2011) and Heijmans et al. (2011) for similar evidence.

[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

So far we have been vague about the precise notion of relationship lending. 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 a 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 based on the frequency or concentration of borrowing and lending have been used in the interbank lending literature.

As first and rough measure of relationship lending we use the frequency of interaction between any two banks in the overnight market. 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.

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

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 captures how often a lender received a signal about the borrower and how often they successfully closed and settled a deal. 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.

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 compute the relationship variables over a period of the last 30 days with $T = \{t-1, ..t-30\}$. This rolling window length was proposed in Furfine (1999) but we have tried longer periods for robustness checks. A drawback of this relationship measure is that it relies solely on the frequency of interaction but does not take the depth, i.e. the amount lent, into account. Furthermore, it does not normalize the interaction frequency with the interbank market activity of both banks. A certain number of transaction with a particular counterparty might be low for an active trader in the overnight market, while it is indicating a strong dependency on the respective counterparty if a bank is overall only infrequently participating in this market. Therefore we construct alternative relationship measures that take this into account.

In order to get a more detailed understanding of what is driving the role of relationship lending in the interbank market we also use more subtle measures of lending relationships. We employ the concept of a relationship that considers how important a particular counterparty is for a bank relative to all other banks in the interbank market, for each borrower and lender separately. Similarly to Cocco et al. (2009), we computed the amount $y_{ijt'}$ 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 T. 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. Because relationships are persistent but not immutable over time we also compute these relationship variables over a period of the last 30 days with $T = \{t-1, ..t-30\}$.

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

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

where we again use $T = \{t-1, ..t-30\}$. Both variables are negatively correlated with the number of different counterparties and asset size. In the sequel we call a relationship lender a high LPI bank and a relationship borrower a high BPI bank when applying these measures. Note that our notion of interbank relations is thus based only on the observed overnight loan panel. 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.[13]

Most of the relationship lending literature has focused on bank's *borrowing* concentration (BPI) or the duration of borrowing relations with a particular bank to proxy for the strength

[13] As a further relationship measure we also used the amount lent from one bank to another over a rolling window of 30 days normalized by the sum of the overall lending of the lender and borrowing of the borrower. With this alternative specification we obtain qualitatively similar results, which are available from the authors upon request.

of the lending relation, because these two measures clearly match two distinct theoretical notions of relationship lending. The duration or frequency 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 BPI measures the dependency of a borrower on a particular lender, giving also an indication of the lender's market power over the borrower and the lender's ability to extract a rent from this lending relationship.

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 exposure in the unsecured lending market. Banks with such a lending structure economize of fixed costs of monitoring and should have stronger incentives to intensely monitor their small number of (relationship) borrowers. Therefore they should, everything else equal, have superior information about the creditworthiness of those banks than spot lenders. 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 about many assets, or specialize and acquire more precise signals about fewer assets depending on expectation which assets they will hold in the future. Similarly, a bank only invests a large part of its interbank portfolio with one counterparty if it has some indication that this is a relatively low credit risk.

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. This indicator, also known as Eigenvector centrality, is a global network measure for a bank's interconnectedness. A high centrality measure indicates that a bank is more connected particularly to more connected counterparts. Thus this measure captures the extent to which a bank has established other lending relationships especially to banks that themselves dispose of a wide network of relationships. 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.[14] Better capitalized banks can withstand larger losses. Thus their outstanding debt bears a lower default risk allowing them to borrow at lower rates.[15] Moreover, since banks might not be able to precisely 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 are the reserve balances. A low ratio of actual reserves being held relative to reserve requirements should increase the probability that a bank borrows in the interbank market and increase the interest rate that it is willing to pay (and vice versa). Thus we follow Fecht et al. (2011) and derive the normalized excess reserves ($excess\_reserve$) as a measure of banks' liquidity status. Excess reserves are the difference between the actual reserve holdings of a bank on the respective day and the reserves the bank still 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. As an alternative proxy for the liquidity status of a bank, we also compute its cumulative reserve holdings divided by its cumulative reserve requirements ($fulfillment$) over the respective days of the maintenance period. However, we use this measure only for robustness checks, because it does not capture to what extent the current liquidity holdings of a bank permit it to fulfill the remaining reserve requirements over the rest of the maintenance period.

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. In order to control for banks' liquidity risk that results from the maturity mismatch of banks' assets and liabilities we use as a second measure banks' liquidity creation ($liq\_creation$), which is long-term assets plus short-term liabilities over total assets (times one half), see Berger and Bouwman (2009).

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 2 and Figure 3 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

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

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

days of the MROs.

Further, we expect aggregate financial variable to influence interest rates and matching. 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.

Since we are primarily interested in the role lending relationships play in overcoming informational asymmetries about counterparty credit in the interbank market, we must control for the effect that established relationships have on mitigating search costs. Thus we construct several variables at the bank pair level that capture the efficiency gains of a bank from approaching the same lender again rather than looking for a new counterpart.

As a first measure 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 opposite 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 therefore be more likely to form a lending relationship (see Fecht et al. (2012) for a theoretical model of this argument). But more importantly, if a bank learned through past lending relationships that a particular counterpart has negatively correlated liquidity shocks, it is reasonable for this bank to approach this particular counterpart again in search for liquidity. Thus including this variable ensures that observed effects of lending relationships on availability and pricing of interbank loans are not driven by the fact some bank pairs are more likely to trade because of opposing liquidity needs.

Second, we expect that banks choose to stick with a previous counterpart also based on the rates it paid to this counterparty relative to other market participants. Whether to invest in further search for new counterparts depends on how successful deals with a particular counterpart were in the past. Thus the matching probability between lending bank i and borrowing bank j should depend positively on the surplus bank i and j realized when trading with each other, compared to the other available bargaining options. For this purpose we derive the average rate obtained by a lender on loans over the past 30 days: $\bar{r}_{it}^{len} = \frac{1}{N}\frac{1}{T}\sum_j \sum_{t' \in T} r_{ijt'} = \frac{1}{N}\sum_j \bar{r}_{ijt}$, with $T = \{t-1, ..., t-30\}$ similarly to the construction of the relationship variables. Then we compute the (past realized) surplus for lender i as $sur\_len_{ijt} = \bar{r}_{ijt} - \bar{r}_{it}^{len}$. Similarly we compute $sur\_bor_{ijt} = \bar{r}_{jt}^{bor} - \bar{r}_{ijt}$ for the surplus of borrower j.[16] The surplus variables proxies for the true surplus relative to the unobserved outside options for bank i and j, respectively. Note that this variable not only captures the incentives of the borrower and lender to stick to a lending relationship rather than looking for a better

[16]We normalize the surplus for each bank with respect to the minimal surplus, and we set the realized surplus equal to zero if bank i and j did not trade during the last 30 days.

deal, it might also reflect elements of informational asymmetries about counterparty risk: That a particular lender offers a better deal to a borrower than other market participants might simply result from his better or more precise credit risk assessment of the borrower. However, including this control variable ensures that the remaining effect of established relationships on interbank lending is not driven by search cost considerations but rather reflects private information on counterparty credit risks obtained through lending relationships.

Finally, we also control directly for changes in aggregate search costs by including time varying measures of the probability with which a borrower will find a new lender. We use the fraction of number of lenders divided by number of borrowers ($market\_tight$) per day and the total number of transactions per day ($total\_trans$).

Table 11 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 Selection Model

We use a regression based approach to investigate the effect of relationships on the access to liquidity and the price paid for it. Because participation in the interbank market is endogenous and we only observe the bilateral interest rate when a matching was successful, i.e. a loan is given, we need to take into account the possibility of sample selection on unobservables that may lead to inconsistent parameter estimates. Therefore we use a bivariate sample selection model similar to Heckman (1979) that comprises the outcome equation for the interest rate

$$r_{ijt} = \begin{cases} r^*_{ijt} & \text{if } z_{ijt} = 1 \\ - & \text{if } z_{ijt} = 0 \end{cases} \tag{5}$$

and the the selection equation for z_{ijt} that indicates an interbank loan

$$z_{ijt} = \begin{cases} 1 & \text{if } y^*_{ijt} > 0 \\ 0 & \text{if } y^*_{ijt} \leq 0 \end{cases} \tag{6}$$

The observed variables r_{ijt} and z_{ijt} are linked to the latent variables y^*_{ijt} and r^*_{ijt} which are modeled by the linear relation

$$r^*_{ijt} = w_{ijt}\beta + u^{len}_i + u^{bor}_j + u_t + u_{ijt} \tag{7}$$

$$y^*_{ijt} = w^*_{ijt}\beta^* + u^{len*}_i + u^{bor*}_j + u^*_t + u^*_{ijt}. \tag{8}$$

where w_{ijt} and w^*_{ijt} are the vectors of exogenous variables, $u^{len}_i(u^{len*}_i)$ is a lender fixed effect, $u^{bor}_j(u^{bor*}_j)$ is a borrower fixed effect and $u_t(u^*_t)$ is a time fixed effect to take into account unobserved heterogeneity.[17] Further, we 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 $\rho = 0$ a separate

[17]To avoid simultaneity problems we only enter at time t predetermined covariates in the regressions.

estimation of the outcome equation is valid, otherwise the OLS parameter estimators for the outcome model are generally biased. Instead of estimating the two equations jointly by Maximum likelihood, we follow the popular approach of the Heckman two-stage procedure that gives consistent parameter estimates. Therefore we first estimate a standard Probit model for z_{ijt} given by equations (6) and (8), and then correct for possible selection bias by including the inverse Mills ratio in the interest rate equations. This two-step approach hinges on a valid exclusion restriction: the selection equation must comprise at least one variable that affects only matching but not the interest rates. We will use the surplus variables as the exclusion restriction which satisfies these requirements.

We aim at disentangling the role relationships play in mitigating search costs and in overcoming informational asymmetries. Thus we not only include the aforementioned control variables, i.e. the correlation of liquidity shocks and the surplus of the lender and the borrower. In order to further separate these two channels, we specify w_{ijt} (and analogously w_{ijt*}) in our baseline model as

$$w_{ijt} = x_{ijt}\beta_x + \beta_{rel}rel_{ijt} + \beta_{crisis}crisis_t \times rel_{ijt} + \beta_{tightness}tightness_t \times rel_{ijt} \tag{9}$$

where x_{ijt} are the control variables and the variable rel_{ijt} generically denotes the relationship variable. Then we interact rel_{ijt} with a dummy variable ($crisis$) that indicates the time period starting from 9 August 2007.[18] During the crisis period uncertainty about counterparty risk increased dramatically.[19] Thus private information about counterparty risk becomes more important for the allocation and pricing of liquidity. Consequently a positive effect of the first interaction term on the matching probability in (8) and a negative one on the interest spread in (7) would be a further indication that relationship lending indeed mitigates uncertainty about counterparty risk. The second interaction term $\beta_{tightness}tightness \times rel_{ijt}$ interacts the relationship variable with a dummy variable that indicates days with tighter markets for borrowers. In those periods it was more difficult to find a new counterparty. Hence search cost for borrowers were high and banks had to rely to a larger extent on their established relationships in the overnight market.[20] Therefore the second interaction term further controls for time varying effects that established relationships have on containing search costs (search frictions unrelated to credit risk uncertainty). A positive effect of this interaction term on the matching probability in (8) and a negative one on the interest spread in (7) would suggest that particularly when finding a new counterparty is costly borrowing from the relationship lender is likely and less costly.

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

[19] Flannery et al. (2013) provide empirical evidence that bank opacity indeed dramatically increased during the crisis.

[20] We set the dummy variable $tightness_t$ to one if the day was in the top quantile of the distribution of the market tightness variable. Note that we proxy search frictions with the degree of market tightness which is based on realized loan only. In the robustness section we also check that our results hold for the other possible proxy of aggregate search frictions $total_trans$.

5.2 Frequency of Interaction

Table 3 presents the estimation results of the binary choice model with *log_rel* as the relationship variable. In Column (1), we present the estimation results of a basic model including asset sizes and liquidity positions for both lender and borrower, the correlation of liquidity shocks, the total reserves and liquidity supply as control variables. As expected we find that banks with excess liquidity are more likely to lend and banks short in liquidity are more likely to borrow. In line with the findings of the univariate analysis larger banks tend to be borrowers in the interbank market, while we do not find a significant size effect for lenders. Also for the correlation of liquidity shocks of a bank pair we do not find a significant effect on the probability that these two banks enter a credit relationship. For the time effects we find our priors confirmed: In periods of higher credit default risk, i.e. a higher average CDS of German banks, fewer overnight interbank loans were granted. Also we find a weak and not robust reduction in the lending activity for periods with larger liquidity supply by the ECB.[21]

Regarding our key variable of interest we find that the estimated coefficient of the relationship variable is positive and highly significant indicating that banks rely on repeated interactions with specific counterparties. Also the reverse relationship measure has a positive and significant coefficient supporting the view that banks mutually provide liquidity to each other. These findings are in line with theoretical prediction that banks form relationships to mitigate frictions in the interbank market. However, even though the correlation of liquidity shocks controls for some of the benefits of repeated interaction in reducing search costs, these first results do not necessarily permit us to disentangle which type of frictions they help overcome, whether relationships help mitigate search frictions or asymmetric information about counterparty risk.

Column (2) presents the model when we include in addition the two interaction terms of the relationship variables with the crisis dummy and the market tightness. The coefficient of the first interaction terms ($crisis \times log\_rel$) is not significantly different from zero indicating that lenders were not more likely in the crisis to lend to frequent borrowers. This suggests that the elevated uncertainty about banks' credit risk in the crisis did not induce banks to further focus their lending on those counterparties with whom they anyway interact most intensely. Similarly, for the interaction with the proxy for high search friction ($market\_tight$) we do not find a significant effect. Hence our results do not provide evidence that borrowers are more likely to receive overnight liquidity from relationship lenders when markets are tight and borrowers face relatively few lenders in the market.

[INSERT TABLE 3 HERE]

In model (3) we add as further control variables the surplus that the borrower realized in the past transactions with the respective lender and the surplus that the lender realized in the past when lending to this borrower. This should further control for search costs as the

[21]Note, that model (1), like all models, includes borrower and lender fixed effects and dummy variables to take into account end of year and end of maintenance period effects, as well as different behavior on settlement days of the MROs. The estimates are omitted to save space.

incentives to look for new trading partners should be lower the more attractive the previous lending relationship was. However, we do not find evidence that banks mutual surplus from a trading relationship increases the frequency of interaction. On the contrary, we find that a lower surplus extracted by the borrower in trades with a particular lender increases the probability that this pair again agrees on a interbank loan. So far our analysis does not take into account that a borrower might be dependent on a particular relationship lender. This dependency, however, is likely to cause these results. The more sophisticated relationship measures applied in the next sections' analysis takes the mutual dependencies into account and the results we obtain indeed confirms this interpretation.

Column (4) presents the results of a specification where we include as a further control variable the Bonacich centrality measure. While we do not find a significant effect of the lender's centrality, our results suggest that banks which are more in the center of the interbank network are indeed more likely to borrow in this market.[22] In column (5) we show the results of the full model that includes in addition the liquidity risk of the lender and borrower bank as controls. This should capture the probability that a bank needs to borrow or lend in the interbank market due to a liquidity shocks. However we do not find any significant effect neither for the borrower nor for the lender.

Finally, in model (6) we include a full set of daily time dummies in the model while dropping the aggregate market condition variables. Hence in this specification we completely control for common time effects such as increases in the aggregate market tightness, changes in the transactions volume etc. A Wald statistic of the null hypothesis that all time fixed effects are zero is 2321.36 which is much larger than the asymptotic 5% critical value of the respective χ^2-distribution (p-value of 0.00). Thus unobserved heterogeneity between different days of the sample period plays a role. But taking this into account does not change our key results regarding the influence of established lending relationships.

In sum, we find that both the frequency of past lending relationship and reversed lending relationships plays an important role in determining whether a new loan is granted between a pair of banks. Thus established lending relationships and reciprocal relationships are an important factor in improving bank's access to liquidity. The inclusion of various control variables that capture different facets of search costs does not change the significant impact of lending relationships on the matching probability.[23] Hence these results provide first evidence that established lending relationships in the interbank market not only mitigate search costs but also have a further effect. They supposedly also help to overcome informational asymmetries about counterparty credit risk and thereby contain credit rationing in the interbank market.

After having established a positive effect of relationship lending on the probability of a loan, we examine the effect of relationship lending on the bilateral interest rate conditional

[22] See also Bech and Atalay (2009) for a similar result.

[23] Also the quantitative effects are quite large. For instance, computing the upper bound of the marginal effect of log_rel, $\phi(w^*\beta)\beta_{log\_rel}$, gives appximately $0.4 \cdot 0.786 = 0.314$, since $\phi(x^{*'}\beta^*) \leq 1/\sqrt{2\pi} \simeq 0.4$ with maximum at $x^{*'}\beta^* = 0$.

on a loan being observed. Table 4 presents the second stage parameter estimates of the interest rate regression using the correction for sample selection with the inverse Mill's ratio. The selection equation for all models consist of the full model for the matching probability including daily fixed effects (Table 3, Column 6). The basic interest rate model (1) includes asset size and equity ratio as well as liquidity status as bank specific control variables. The results indicate not only that larger banks pay less in the interbank market as one would expect, surprisingly they also receive a lower interest rate. As expected borrowers with a higher equity ratio pay significantly lower interest rate. This result is in line with Furfine (2001)'s findings for the federal funds market, that banks are able to identify counterparty credit risk and actually price this risk in overnight interest rates.[24] Interestingly, a higher equity ratio also reduces the interest rate a bank receives on an overnight loan, everything else equal. In contrast to the matching model, the normalized excess reserves of both lender and borrower do not have a strong and robust significant effect on the negotiated rates. As regards to the aggregate time varying controls, an increase in liquidity supply by the Eurosystem leads to a significant decrease in interest rates and a higher correlation in liquidity shocks between two banks make them negotiate significantly lower rates.[25] We also see that change on average credit risk is priced as the coefficient for ΔCDS is significant and positive. Most importantly, though, the estimated coefficient of the relationship variables log_rel is negative and statistically significant at the 1% level. Similarly, the reciprocal relationship variables log_rel_rev also has a significantly negative effect on the interest rate spread, although, the economic significance of this effects is substantially lower. Thus banks that trade liquidity more frequently with each other trade at lower interest rates. This suggests that established lending relationships provide banks with cheaper access to liquidity and improve their ability to share liquidity risks.

[INSERT TABLE 4 HERE]

In model (2) we include the interaction terms in the specification to get further insights into the channels through which relationship lending affects the price of liquidity. If we allow the effect of relationship lending to change with the start of the financial crisis, we find that during the crisis lender gave an even larger discount to their frequent borrowers (high log_rel). This suggest that banks that acquired more precise information about their counterparties through frequent interaction were in a better position to assess their counterparties' credit risk in the period of elevated uncertainty about banks' default risks. Thus they could offer liquidity at a lower risk premium than spot lenders. The interaction term with the market tightness, i.e. our proxy for aggregate variations in search frictions, has no significant effect on the interest rates. Thus banks trading with their most frequent counterparties do not pay

[24]Note that the bank balance sheet statistic used in our analysis is confidential supervisory data of the Bundesbank not available to market participants.

[25]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.

significantly different rates when the market is tight.[26]

The model (3) includes the Bonacich centrality measure as a further control variable. We expect that more central lenders are able to negotiate higher rates and more central borrowers are able to get cheaper credit. However, we find only that the coefficient for the lender has the expected sign and is significant. Thus more central lenders receive significantly better rates. This might reflect they have a more precise knowledge of the aggregate market value of liquidity or it might be due to the fact that they can offer loans also in periods of tight markets, because they can easier balance their positions later, compare Ashcraft and Duffie (2007).

Column (4) reports the estimates including also the liquidity risk of the lending and borrowing bank as control variable. The coefficient is negative but only marginally significant for the lender. For the borrowers' liquidity risk we do not find any effect at all. Most importantly, though, also for these alternative specifications we still find that banks pay significantly lower rates to their more frequent lenders in general and in particular during the crisis. Remember that all model specifications not only include time varying control variables at the bank level but also borrower and lender fixed effects. Thus we fully take into account any bank specific time-invariant heterogeneity.

In column (5) we include in addition a full set of daily time fixed effects. In this specification we thus control also for general market effects, for instance, effects that are specific to days during the crisis or to days at which market tightness was particularly elevated.[27] Although the inclusion of daily time fixed effects renders the influence of some of our control variables only marginally significant or even insignificant, our key finding remains robust: conditional on a positive lending decision, borrowers pay a significantly lower interest rate when borrowing from their most frequent lender. During the crisis period with elevated uncertainty about counterparty credit risk this effect was significantly more pronounced (although both effects are quantitatively smaller after including time dummies).

For robustness checks, we also consider in specification (6) a model with both time fixed effects and pair fixed effects instead of lender and borrower fixed effects. We hence control in this specification for unobserved characteristics at the pair level, like borrower and lender belonging to the same banking group. Our estimates show that even then our key finding holds and relationship lenders charge significantly lower rates from their frequent borrowers during the crisis.

In sum, also for the interest rate spread we find that even after controlling for the different ways in which established relationships can mitigate search costs, we find that more frequent interaction with a particular lender reduces significantly the spread that a borrower pays. Thus in addition to reducing search costs, established lending relationships have an effect on the price interbank borrowers pay for liquidity suggesting that they help overcome informational asymmetries about counterparty credit risk. This interpretation is further confirmed by our

[26]Note again that all models include borrower and lender fixed effects and dummy variables to take into account end of year and end of maintenance period effects, as well as different behavior on settlement days of the MROs. The results are omitted to save space.

[27]An F-test rejects model (4) against model (5) at any convenient significance level.

finding that established relationships have a particularly strong effect on the spread in the crisis period when uncertainty about bank default risks was most severe.[28] Given the large volumes estimated effects are also economically important: everything else equal, a bank relationship lenders charged about 4 bp less from their borrowers than spot lender.

5.3 Concentration of lending relations

The relationship lending variable that we used in the previous analysis only capture one dimension of relationships. The frequency of interaction only measures how often a pair of banks closed and settled an overnight loan contract. It thus proxies only how often information was exchanged. Our LPI and BPI variables go beyond that and also capture how important a particular lending relationship is for the lender and the borrower. They therefore also measure the depth of the relationship which also proxy for the quality of the information. Moreover, they also capture how relevant any private information is that can be extracted from established relationships. Thus we replicate our previous analysis using these more sophisticated relationship measures.

Table 5 presents the estimation results of the binary regression model using LPI and BPI as the relationship variable. Column (1) presents the results using the basic set of control variables. The estimated effects confirm our previous findings regarding the influence of bank characteristics on the matching probability. Interestingly, using this specification we find that contrary to our expectations banks with more correlated liquidity shocks are more likely to lend to each other. 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. Most importantly, though, the estimated coefficients of both relationship measures are positive and highly significant. This indicates that borrowers which are particularly dependent on the liquidity provision of one lender are more likely to receive funding from this lender. Conversely, the more concentrated the overnight lending portfolio of a lender on one particular borrower the stronger is his tendency to provide again funds to this counterpart.

Column (2) presents the model when we also include the two interaction terms of the relationship variables with the crisis dummy and the market tightness. The coefficient of the first interaction terms ($crisis \times LPI$) is not significantly different from zero indicating that lenders were not more likely to lend to borrowers to whom they lent a larger fraction in the past. For the the borrower concentration index (BPI) we find, however, a positive and significant interaction term with the crisis dummy showing that particularly during the crisis a banks has a higher chance of receiving an overnight loan from a counterparty the more concentrated its past borrowing was on this lender. Thus after August 9 banks relied more on their relationship lenders to cover their liquidity needs. For the interaction with the proxy for high search

[28] See Flannery et al. (2013) for empirical evidence that indeed uncertainty about banks' asset value increased during the crisis.

friction (*market_tight*) we find significant and economically intuitive coefficients. First we see that when the interbank market is tight and hence there are few lenders available, banks with a high borrowing concentration rely even more on their relationship lender. Conversely when there are relatively many borrowers, lending banks with a high lending concentration have a larger choice and thus a weaker tendency to lend to their usual borrower. Thus the extent to which banks rely on their interbank relationships seems to depend on the available alternatives in the market and thus on the search costs involved finding a new lender.

[INSERT TABLE 5 HERE]

In the model shown in column (3) we add again the lender's and borrower's surplus extracted in past trades with the respective counterpart as further explanatory variable. Interestingly, contrary to our previous results when using these relationship measures that take the mutual dependency of borrowers and lenders into account, we find that indeed a high surplus realized in past trades by both borrowers and lenders increases the probability of a new overnight loan between the two banks. This is an important finding because it shows that relationship building and thus network formation is not arbitrary. It is determined by the mutual surplus that can be extracted. Thus efficiency gains seem to be a key driven of the structure of the interbank lending network.

Column (4) presents the results of a specification where we include the Bonacich centrality measure as a global network measure in addition to the local relationship variables. Based on our more sophisticated relationship measures we find that indeed both the lenders and the borrowers connectedness has a positive effect on the probability that a new loan is granted between two banks. In column (5) we add the liquidity risk of the lender and borrower bank as a control, but again find that both have no significant impact on the matching probability. In model (6) we check the robustness of the results by including again a full set of daily time dummies in the model while dropping the aggregate market condition variables.[29] This allows us again to control for common time effects such aggregate variations in the market tightness.

In all those specifications the effect of our key variables of interest, i.e. our relationship measures, remain qualitatively and quantitatively unchanged.[30] Even after controlling for various aspects of search costs we find that the concentration of a lender's and a borrower's relationship with a particular counterpart are important determinants for whether they agree on an overnight loan. While we also find evidence that relationships are important in mitigating search costs particularly in times of tight money markets, this suggests, however, that intense lending relationships also help to acquire private information about couterparty's credit quality. A lender with a high LPI seems to have more capacity and incentives to closely monitor the respective borrowers. A borrower with a high BPI allows the lender to receive a more precise signal from more focused interactions and to economize on monitoring costs.

[29]A Wald statistic of the null hypothesis that all time fixed effects 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).

[30]Again 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 $0.4 * 1.468 = 0.5752$, since $\phi(x^{*'}\beta^*) \leq 1/\sqrt{2\pi} \simeq 0.4$ with maximum at $x^{*'}\beta^* = 0$. The actual size of the marginal effect, however, depends on the value of the covariates.

Both effects ensure that more concentrated lending relationships contain adverse selection problems and credit rationing in the interbank market and thus ensure a better access to liquidity.

After conditioning on time effects, during the crisis banks with a high lending concentration had a lower tendency to lend to their regular borrowers. In light of the theory relationship lending facilitates screening and hence relationship lenders should be better able to identify bad credit risks in their portfolio and stop lending to them if the credit risk assessment is not sufficient. The negative coefficient of the interaction term does indeed suggest that on average relationship lenders did credit ration some of the borrowers with whom they had prior trading relations, possibly because they were better able to identify bad risks, because they cut back lending to high risk borrowers in the interbank market or because they simply tried to diversify their interbank credit risk exposures.

Next we examine the effect of the concentration of relationship lending on the bilateral interest rate conditional on a loan being observed. Table 6 presents the second stage parameter estimates of the interest rate regression using the the LPI and BPI and a correction for sample selection with the inverse Mill's ratio. The selection model is given in table 5, column 6. The basic interest rate model (1) includes again only our bank specific control variables and the aggregate time varying factors. The estimated effects of both aggregate market conditions and bank characteristics are qualitatively and quantitatively the same as in the specification using the interaction frequency (log_rel) as relationship indicator. However, the estimated coefficient of the relationship variables LPI is positive and statistically significant at the 1% level indicating that relationship lenders receive higher interest rates from their close borrowers. Also banks with a higher borrowing concentration pay higher rates to their relationship lenders but this effect is only significant at the 10% level.

[INSERT TABLE 6 HERE]

In model (2) we again include the interaction of the relationship lending variables with the crisis dummy and the market tightness to further disentangle the role of relationships in mitigating search costs and in overcoming uncertainty about counterparties' credit risk. If we allow the effect of relationship lending to change with the start of the financial crisis, we find that during the crisis relationship lenders (high LPI) charge significantly lower rates from their counterparties compared to what a spot pair would negotiate. We do not find this effect for relationship measured by BPI. Note that this result is conditional on a loan being given. Hence, when relationship lender decided to give credit they did it at significantly lower rates than before the crisis. Also in this specification we find that before August 2007 pairs with high LPI trade at higher rates, while the coefficient of BPI becomes insignificant. As regards to the interaction with the market tightness measure we do not find any significant effect. Thus the effect of both more concentrated lender and borrower relationships on the price of liquidity does not vary with market tightness and thus search costs.

The model (3) includes the Bonacich centrality measure as a further control variable. Column (4) reports the estimates including also the liquidity risk of the lending and borrowing bank as additional time varying bank characteristics. Again we find for both additional explanatory variables effects that are quantitatively and qualitatively consistent with our estimates using the frequency of interaction as relationship measure. Most importantly, though, also for these alternative specifications we still find that relationship lenders charged lower rates during the crisis.

In column (5) we again include in addition a full set of daily time fixed effects to account for unobserved time varying aggregate effects.[31] Finally, we also consider in specification (6) a model with both time fixed effects and pair fixed effects instead of lender and borrower fixed effects. In this specification we obtain significantly lower rates for banks who borrow from their main relationship lender compared to spot lenders (high BPI) before the crisis, but this effect reverses after August 2007 possibly due to increased market power over borrowers with concentrated borrowing.[32] The finding that higher BPI borrowers obtain better rates before the crisis is in line with evidence for the Portuguese market, see Cocco et al. (2009). Regarding the LPI, we find that rates charged from relationship lenders (high LPI) compared to spot lenders were not different before the crisis. However, our result still holds that conditional on a positive lending decision, relationship lenders charged lower rates during the crisis from their close borrowers (though the effect is quantitatively smaller after including time dummies). Thus even after controlling for any unobserved characteristics at the pair level, like borrower and lender belonging to the same banking group, our finding that relationship lenders charge lower rates from their close borrowers in the crisis continues to hold. Also economically the estimated effect is important: everything else equal, a bank charges from its key borrower in the crisis on average 12.7 basis points less (2.6 bp with time fixed effects) than from a borrower with whom he had no interaction during the last month.

In sum, using our more sophisticated relationship measures our findings do not support the conventional relationship lending view from corporate finance 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 (higher BPI) 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. If anything, our results suggest the opposite, that the benefit of concentrated borrowing decreases during the crisis possibly because the bargaining power of lenders relative to their high BPI borrowers increased.

Our findings rather support the view that differences in counterparty risk assessment prevail between relationship lenders and spot lenders, as argued by among others Furfine (1999). This might result from several effects. First, the repeated and more focused interaction permits relationship lenders to better assess the true credit quality of their borrowers. After receiving a more precise indication of the credit quality of their borrowers, lenders will only

[31] 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).

[32] A t-test with $H_0: \ \beta_{BPI} + \beta_{crisis\_BPI} = 0$ gives a Chi-square statistic of 4.78 and p-value of 0.028. We thus conclude that during the crisis high BPI borrowers had to pay a mark-up to their lenders.

continue to lend to peers for which they have a sufficiently positive and sufficiently precise risk assessment. Particularly the more precise risk assessment permits a relationship lender to charge an adequate risk premium rather than ration opaque borrowers as spot lenders tend to do. Thus relationship lenders tend to charge higher interest rates.[33] Second, a higher concentration in his interbank credit portfolio on a particular borrower (LPI) might result from economizing on monitoring costs. After a positive risk assessment the lender will charge a risk premium as a compensation for the concentration risk in his interbank credit portfolio. Relatedly, 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 focuses his portfolio, compare Nieuwerburgh and Veldkamp (2010). Finally, a high LPI might also emerge endogenously. A lender who received some private information after screening indicating a high quality of the borrower might decide to focus his lending on this borrower. Given that credit quality is relatively persistent and given that due to the concentration in lending the relationship lender will gain more precise information he will also be more willing to lend again. All those effects that result from informational advantages of relationship lenders over spot lenders explain the positive effect of a high LPI on the matching probably and on the interest charged by a relationship lender.

The negative coefficient of $crisis \times LPI$ for the matching probability and particularly for the interest rate spread suggest that relationship lenders cut their lending to particularly risky borrowers in the period of elevated uncertainty about counterparty credit risk while at the same time provide liquidity to their main borrowers at a much lower risk premium than less informed spot lender. This finding is very much in line with the theory. As modeled, for instance, 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. 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 and more important 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.

5.4 Robustness and Extensions

While our market tightness measure is clearly related to search frictions, we have also checked that our results do not hinge on this specific proxy. We therefore computed a dummy that takes value one on days which fall in the lowest quantile of the distribution of number of

[33]Note that from a theoretical perspective one could of course also expect that due to higher uncertainty about counterparty credit risks spot lenders charge a higher lemons premium and this at higher average interest rate. Our findings, though, rather support the view that spot lenders tend to ration opaque borrowers.

transactions per day. For a high total interbank market activity we expect that the probability of finding a counterpart with the opposing liquidity shock increased, implying a decline in overall search costs. On the other hand low transaction days should correspond to high search frictions. The estimation results for the matching model are depict in Table 7, those for the interest rate model in Table 8. We find that on days with many transactions banks with a highly concentrated lending portfolio were more likely to lend to other borrowers. We do not find an effect of the interaction term with BPI. For the price of liquidity we see interest rates were not significantly different from zero after controlling for the full model with time fixed effects. All results of the interaction term between relationship variable and the crisis dummy are not affected.

[INSERT TABLE 7 AND 8 HERE]

In the main specifications we used a carefully selected set of control variables in the model to avoid an omitted variable bias due to unobserved heterogeneity in the data. We also showed robustness with respect to the inclusion of borrower and lender specific fixed effects as well as time fixed effects, and time and pair fixed effects. 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 9 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*, see the discussion of the covariates. 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, the estimated parameter is not significant. Most importantly, though, for all relationship variables the estimate parameters stay qualitatively similar and hence the finding that relationship lenders charged lower interest rates during the crisis continues to hold throughout all model specifications.

[INSERT TABLE 9 HERE]

5.4.1 The Precrisis Period

Given the results which suggest that relationship lenders can better assess the creditworthiness of their close borrowers, we examine in this subsection to what extent relationship lender 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. The idea is that differences in counterparty risk assessment in the cross-section (relation vs. spot lenders) might not have changed in August 2007 but might well have changed even before. 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

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

where x_{ijt} includes all fixed effects as well as the interaction term with market tightness for notational brevity. Since it is not clear when the precrisis started, we consider different periods. Table 10 shows the parameter estimates of the relationship variables but omitts the results for other variables for clarity. The upper panel with LPI as the relationship measure shows that for all starting days of the precrisis relationship lenders charged on average higher rates during the precrisis (except July), everything else equal. The effect is about one basis point and is largest in magnitute and significant when the precrisis starts at 1 March 2007. By contrast, we find a slightly negative but insignificant effect of LPI before the precrisis (which one could interpreted as tranquil times).

[INSERT TABLE 10 HERE]

The lower panel displays the results if we use *log_rel* as the relationship variable. Similarly as before, we find positive mark-ups from relationship lenders compared to the normal time during the precrisis period; however, the effects are signigicantly different from zero only if the starting day is between November 2006 and March 2007. Thus, also relationship lenders defined by the frequency of interaction started charging higher rates from their close borrowers in the run up to the crisis. This effect holds after conditioning on interbank market participation and on a daily set of time dummies. In all specifications we find again that before the precrisis lenders with higher *log_rel* charge lower rates.

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 sub-prime related problems became public and market wide assessment of counterparty risk shot up relationship lenders could still identify their low risks and charge on average lower rates compared to spot lenders.[34]

[34]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.

6 Conclusion

Our results show that established lending relationships matter both for the availability and the pricing of interbank liquidity. Thus lending relationships improve the reallocation of liquidity in the interbank market and the failure of an important relationship lender in the interbank market impairs the liquidity management of its relationship borrowers. This might trigger a liquidity shortage and ultimately a failure of those financial institutions as well. Thus our results complement the existing work on contagion risk in the interbank market. According to our findings the failure of a large bank not only generates negative externalities for its creditors. If this bank also serves as an important relationship lender in the interbank market, its failure will also significantly endanger the stability of its borrowers which might also generate further domino effects. Thus our findings support the view that also a bank's connectedness on its asset side is an important component when assessing whether it is too-big- or too-connected-to-fail.

A further important implication of these results is that interbank relations are fairly persistent: Established credit relationships are a good predictor of future relationships between two banks. This also means that the network structure of the overnight markets is relatively persistent and that the matrix of bilateral exposures does not change drastically from one day to the next. If this was not the case any contagion analysis based on the network structure of bilateral exposures in the overnight market and the identification of systemically important financial institutions based on this analysis would be useless. Thus our results provide an important argument justifying this approach.

Being able to control for the role of relationship lending in mitigating search costs we are able to show that relationships also matter in overcoming informational asymmetries regarding counterparty credit risk. Thus our 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.

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.[35]

References

Affinito, M. (2011). Do interbank customer relationships exist? and how did they function over the crisis? learning from italy. Systemic risk, basel iii, financial stability and regulation 2011, Bank of Italy.

Afonso, G., Kovner, A., and Schoar, A. (2011). Stressed, not frozen: The federal funds market in the financial crisis. *Journal of Finance*, 66(4):1109–1139.

Allen, F. and Gale, D. (2000). Financial contagion. *Journal of Political Economy*, 108(1):1–33.

Ashcraft, A. B. and Duffie, D. (2007). Systemic illiquidity in the federal funds market. *The American Economic Review*, 97(2):pp. 221–225.

Babus, A. (2010). Strategic relationships in over-the-counter markets. Mimeo.

Bech, M. L. and Atalay, E. (2009). The topology of the federal funds market. Working Paper Series 986, European Central Bank.

Berger, A. N. and Bouwman, C. H. S. (2009). Bank liquidity creation. *Review of Financial Studies*, 22(9):3779–3837.

Berger, A. N. and Udell, G. F. (1995). Relationship lending and lines of credit in small firm finance. *The Journal of Business*, 68(3):351–81.

Bhattacharya, S. and Fulghieri, P. (1994). Uncertain liquidity and interbank contracting. *Economics Letters*, 44:287–294.

Bhattacharya, S. and Gale, D. (1987). Preference shocks, liquidity, and central bank policy. In Barnett, W. and Singleton, K., editors, *New Approaches to Monetary Economics*. Cambridge University Press.

Boot, A. W. A. (2000). Relationship banking: What do we know? *Journal of Financial Intermediation*, 9(1):7–25.

Broecker, T. (1990). Credit-worthiness tests and interbank competition. *Econometrica*, 58(2):429–52.

Bundesbank (2005). *TARGET-Leitfaden für Kreditinstitute.*

Bundesbank (2011). Banking statistics - statistical supplement to the monthly report june 2011.

[35]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.

Cocco, J. F., Gomes, F. J., and Martins, N. C. (2009). Lending relationships in the interbank market. *Journal of Financial Intermediation*, 18:24–48.

Craig, B. R. and von Peter, G. (2010). Interbank tiering and money center banks. Working Paper 322, Bank for International Settlements.

Degryse, H. and Ongena, S. (2005). Distance, lending relationships, and competition. *Journal of Finance*, 60(1):231–266.

Diamond, D. W. and Dybvig, P. H. (1983). Bank runs, deposit insurance, and liquidity. *Journal of Political Economy*, 91(3):401–19.

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

Fecht, F., Grüner, H. P., and Hartmann, P. (2012). Financial integration, specialization, and systemic risk. *Journal of International Economics*, forthcoming.

Fecht, F., Nyborg, K. G., and Rocholl, J. (2008). Liquidity management and overnight rate calendar effects: Evidence from german banks. *The North American Journal of Economics and Finance*, 19(1):7–21.

Fecht, F., Nyborg, K. G., and Rocholl, J. (2011). The price of liquidity: The effects of market conditions and bank characteristics. *Journal of Financial Economics*, 102(2):344 – 362.

Flannery, M. J. (1996). Financial crises, payment system problems, and discount window lending. *Journal of Money, Credit and Banking*, 28(4):804–24.

Flannery, M. J., Kwan, S. H., and Nimalendran, M. (2013). The 2007â€“2009 financial crisis and bank opaqueness. *Journal of Financial Intermediation*, 22(1):55 – 84. ¡ce:title¿Research on the Financial Crisis¡/ce:title¿.

Freixas, X. and Holthausen, C. (2005). Interbank market integration under asymmetric information. *The Review of Financial Studies*, 18(2):pp. 459–490.

Freixas, X. and Jorge, J. (2008). The role of interbank markets in monetary policy: A model with rationing. *Journal of Money, Credit and Banking*, 40(6):1151–1176.

Freixas, X., Martin, A., and Skeie, D. (2011). Bank liquidity, interbank markets, and monetary policy. *Review of Financial Studies*, 24(8):2656–2692.

Freixas, X., Parigi, B., and Rochet, J.-C. (2000). Systemic risk, interbank relations, and liquidity provision by the central bank. *Journal of Money, Credit, and Banking*, 32(3):611–638.

Furfine, C. H. (1999). The microstructure of the federal funds market. *Financial Markets, Institutions & Instruments*, 8:24–44.

Furfine, C. H. (2001). Banks as monitors of other banks: Evidence from the overnight federal funds market. *Journal of Business*, 74:33–57.

Hauswald, R. and Marquez, R. (2003). Information technology and financial services competition. *Review of Financial Studies*, 16(3):921–948.

Heckman, J. J. (1979). Sample selection bias as a specification error. *Econometrica*, 47(1):153–61.

Heider, F., Hoerova, M., and Holthausen, C. (2009). Liquidity hoarding and interbank market spreads: The role of counterparty risk. Working Paper Series 1126, European Central Bank.

Heijmans, R., Heuver, R., and Walraven, D. (2011). Monitoring the unsecured interbank money market using target2 data. DNB Working Papers 276, Netherlands Central Bank, Research Department.

Ho, T. S. Y. and Saunders, A. (1985). A micro model of the federal funds market. *Journal of Finance*, 40(3):977–88.

Nieuwerburgh, S. V. and Veldkamp, L. (2010). Information acquisition and under-diversification. *Review of Economic Studies*, 77(2):779–805.

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

Petersen, M. A. and Rajan, R. G. (1995). The effect of credit market competition on lending relationships. *The Quarterly Journal of Economics*, 110(2):407–43.

Petersen, M. A. and Rajan, R. G. (2002). Does distance still matter? the information revolution in small business lending. *Journal of Finance*, 57(6):2533–2570.

Rajan, R. G. (1992). Insiders and outsiders: The choice between informed and arm's-length debt. *Journal of Finance*, 47(4):1367–400.

Rochet, J.-C. and Tirole, J. (1996). Interbank lending and systemic risk. *Journal of Money, Credit and Banking*, 28(4):pp. 733–762.

Sharpe, S. A. (1990). Asymmetric information, bank lending, and implicit contracts: A stylized model of customer relationships. *Journal of Finance*, 45(4):1069–87.

A Figures

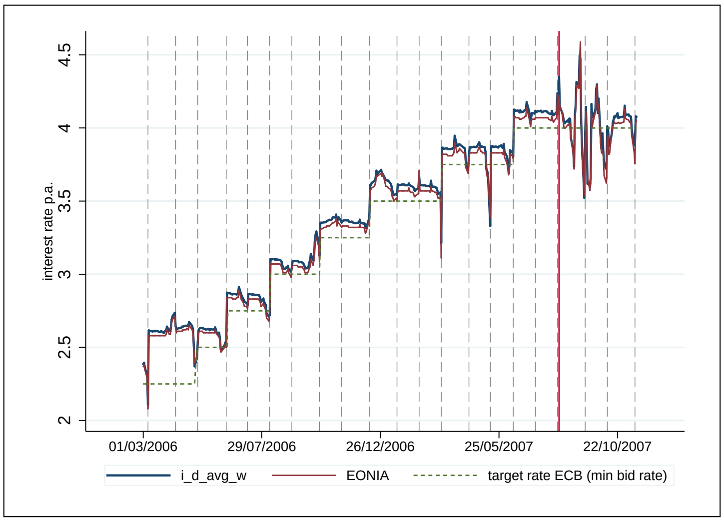

Figure 1: Average daily interest rate, EONIA and ECB target rate: e *i_d_avg_w* is the volume weighted average overnight interest rate from our panel dataset. *EONIA* is Euro OverNight Index Average. *target rate ECB* is minimum bid rate at main refinancing operations. Vertical dashed lines (in gray) indicate end of maintenance period, vertical solid line (in red) indicates start of the financial crisis on August 9,2007.

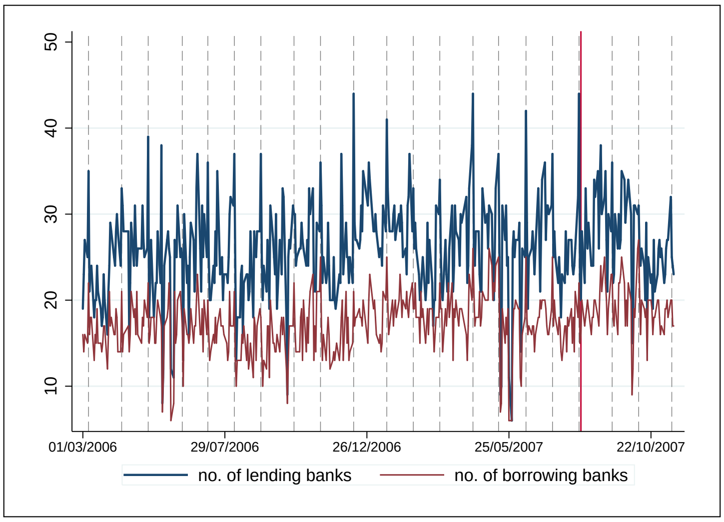

Figure 2: Number of lending and borrowing banks per day: Number of different lending and borrowing banks per day. Vertical dashed lines (in gray) indicate end of maintenance period, vertical solid line (in red) indicates start of the financial crisis on August 9, 2007.

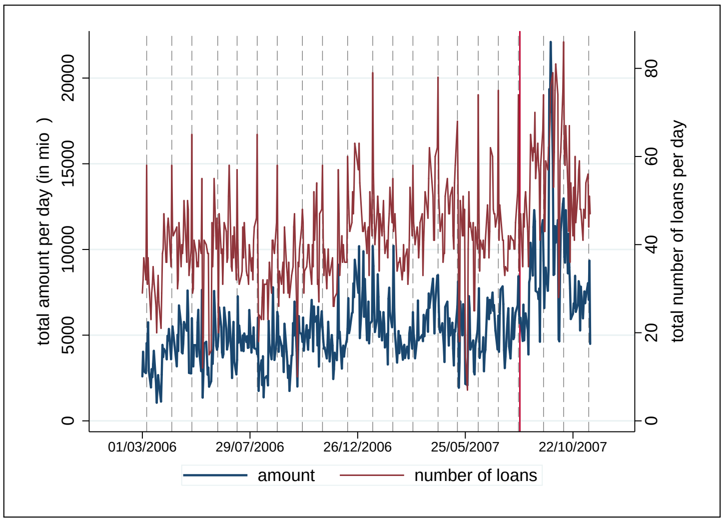

Figure 3: Total amount of all loans (in €million) on a given day and total number of loans. Vertical dashed lines (in gray) indicate end of maintenance period, vertical solid line (in red) indicates start of the financial crisis on August 9, 2007.

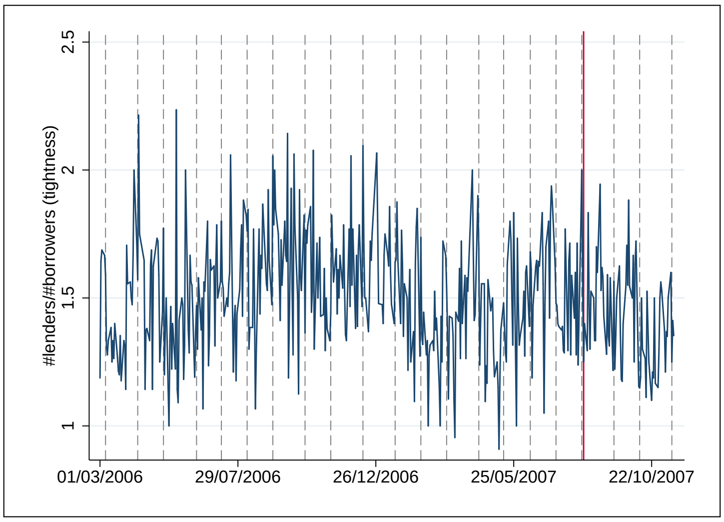

Figure 4: Market tightness per day (number of lenders divided by number of borrowers). Vertical dashed lines (in gray) indicate end of maintenance period, vertical solid line (in red) indicates start of the financial crisis on August 9, 2007.

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; *tightness* is *num_len* devided by *num_bor*; *total_reserves* 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***
tightness	1.52	1.43	0.09	3.22***
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 amount 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 bio							
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 bio							
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 bio							
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 bio							
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* and search frictions proxy *tightness*. 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 (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
asset_size^{len}	0.117**	0.120**	0.124***	0.117**	0.119**	0.104**
	(2.41)	(2.48)	(2.58)	(2.44)	(2.50)	(2.05)
excess_reserves^{len}	0.013***	0.013***	0.013***	0.013***	0.013***	0.013***
	(4.57)	(4.54)	(4.59)	(4.57)	(4.26)	(3.88)
centrality^{len}				0.014	0.014	0.018
				(1.22)	(1.25)	(1.57)
liq_risk^{len}					−0.149	−0.124
					(−0.61)	(−0.52)
asset_size^{bor}	−0.063	−0.061	−0.047	−0.050	−0.050	−0.084
	(−0.86)	(−0.83)	(−0.63)	(−0.67)	(−0.68)	(−1.03)
excess_reserves^{bor}	−0.013*	−0.013*	−0.013*	−0.013*	−0.013*	−0.019**
	(−1.80)	(−1.86)	(−1.84)	(−1.81)	(−1.88)	(−2.41)
centrality^{bor}				0.021***	0.021***	0.021***
				(3.86)	(3.91)	(3.84)
liq_risk^{bor}					0.212	0.084
					(0.83)	(0.32)
log_rel	0.776***	0.773***	0.778***	0.769***	0.769***	0.786***
	(38.40)	(35.54)	(33.56)	(29.68)	(29.67)	(29.36)
log_rel_rev	0.155***	0.156***	0.155***	0.160***	0.160***	0.163***
	(9.30)	(9.26)	(9.21)	(9.23)	(9.20)	(9.48)
crisis×log_rel		0.008	0.017	0.020	0.020	−0.018
		(0.53)	(1.18)	(1.36)	(1.35)	(−0.99)
market_tight×log_rel		0.007	0.008	0.008	0.008	0.022
		(0.63)	(0.73)	(0.73)	(0.73)	(1.36)
sur_len			−0.041	−0.050	−0.049	−0.065
			(−0.91)	(−1.10)	(−1.07)	(−1.26)
sur_bor			−0.112**	−0.117**	−0.117**	−0.157***
			(−1.97)	(−2.05)	(−2.06)	(−2.59)
corr_shocks	0.029	0.028	0.029	0.030	0.030	0.023
	(1.59)	(1.51)	(1.56)	(1.61)	(1.60)	(1.24)
ΔCDS	−0.039***	−0.029***	−0.033***	−0.033***	−0.033***	
	(−3.13)	(−3.11)	(−3.48)	(−3.49)	(−3.47)	
total_reserves	0.023	0.034	0.031	0.028	0.028	
	(0.80)	(1.16)	(1.05)	(0.96)	(0.96)	
liq_supply	−0.106*	−0.092	−0.081	−0.077	−0.076	
	(−1.73)	(−1.43)	(−1.25)	(−1.19)	(−1.17)	
_cons	−2.323**	−2.659***	−2.953***	−2.873***	−2.910***	−3.145***
	(−2.46)	(−2.69)	(−2.93)	(−2.88)	(−2.92)	(−3.03)
Bor/Len FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	No	No	No	No	Yes
Loglikelihood	-45903.6	-45895.8	-45892.2	-45878.9	-45878.1	-45356.5
Observations	447785	447785	447785	447785	447785	447785

t statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Estimation Results for Interest Rate Model (*log_rel*). Parameter estimates of the second stage Heckman selection model for bilateral interest rates (dependent variable: interest rate spread in percent, selection model Table 3, model 6) using the relationship variable *log_rel* and search frictions proxy *market_tightness*. t-statistics in parentheses correspond to the null hypothesis that the parameter is zero, and are computed based on standard errors estimates corrected for two-stage estimation. 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 (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
asset_size^{len}	-0.025^{***}	-0.016	-0.023^{**}	-0.021^{**}	-0.010^{**}	-0.006
	(-2.59)	(-1.63)	(-2.31)	(-2.17)	(-2.17)	(-1.25)
equity_ratio^{len}	-0.452^{***}	-0.536^{***}	-0.595^{***}	-0.576^{***}	-0.091^{*}	-0.077
	(-3.92)	(-4.72)	(-5.22)	(-5.02)	(-1.71)	(-1.52)
excess_reserves^{len}	-0.001^{*}	-0.001	-0.001	-0.001	-0.000	0.000
	(-1.69)	(-1.36)	(-1.27)	(-1.05)	(-0.82)	(0.54)
centrality^{len}			0.007^{***}	0.007^{***}	0.002^{***}	0.001
			(4.58)	(4.68)	(3.03)	(1.16)
liq_risk^{len}				-0.063^{*}	0.020	0.017
				(-1.67)	(1.09)	(1.03)
asset_size^{bor}	-0.239^{***}	-0.131^{***}	-0.122^{***}	-0.123^{***}	-0.013	-0.013
	(-8.88)	(-4.87)	(-4.56)	(-4.59)	(-0.95)	(-0.93)
equity_ratio^{bor}	-2.798^{***}	-2.240^{***}	-2.106^{***}	-2.205^{***}	-0.326	-0.166
	(-5.27)	(-4.34)	(-4.07)	(-4.25)	(-1.35)	(-0.64)
excess_reserves^{bor}	-0.000	0.001	0.001	0.001	0.000	-0.000
	(-0.44)	(1.07)	(1.05)	(1.24)	(0.78)	(-0.52)
centrality^{bor}			0.000	0.000	0.002^{***}	0.002^{***}
			(0.14)	(0.09)	(4.38)	(4.17)
liq_risk^{bor}				-0.111	0.066^{**}	0.047
				(-1.61)	(1.99)	(1.43)
log_rel	-0.033^{***}	-0.040^{***}	-0.039^{***}	-0.039^{***}	-0.025^{***}	0.004
	(-5.25)	(-6.35)	(-6.29)	(-6.28)	(-3.71)	(0.45)
log_rel_rev	-0.005^{*}	-0.006^{**}	-0.006^{*}	-0.006^{*}	-0.001	-0.000
	(-1.72)	(-2.01)	(-1.85)	(-1.82)	(-0.62)	(-0.04)
crisis_×log_rel		-0.039^{***}	-0.038^{***}	-0.038^{***}	-0.010^{***}	-0.009^{***}
		(-23.19)	(-22.95)	(-22.93)	(-7.41)	(-7.36)
market_tight×log_rel		0.003	0.003	0.003	0.000	0.000
		(1.42)	(1.32)	(1.36)	(0.19)	(0.03)
corr_shocks	-0.024^{***}	-0.020^{***}	-0.020^{***}	-0.020^{***}	-0.001	-0.000
	(-5.87)	(-4.94)	(-5.01)	(-4.99)	(-0.66)	(-0.01)
ΔCDS	0.023^{***}	0.024^{***}	0.025^{***}	0.024^{***}		
	(11.94)	(13.05)	(13.16)	(12.86)		
total_reserves	-0.007	-0.043^{***}	-0.043^{***}	-0.044^{***}		
	(-1.17)	(-6.72)	(-6.82)	(-6.88)		
liq_supply	-0.546^{***}	-0.477^{***}	-0.476^{***}	-0.477^{***}		
	(-36.40)	(-31.23)	(-31.28)	(-31.30)		
inverse Mill's	-0.050^{***}	-0.073^{***}	-0.070^{***}	-0.070^{***}	-0.041^{***}	0.001
	(-5.10)	(-7.54)	(-7.16)	(-7.15)	(-3.83)	(0.08)
_cons	9.797^{***}	8.158^{***}	8.132^{***}	8.146^{***}	0.482^{***}	0.286^{*}
	(33.02)	(26.56)	(26.48)	(26.46)	(3.00)	(1.78)
Bor/Len FE	Yes	Yes	Yes	Yes	Yes	No
Time FE	No	No	No	No	Yes	Yes
Pair FE	No	No	No	No	No	Yes
Observations	15857	15857	15857	15857	15857	15857

t statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Estimation Results for Matching Probabilities (LPI & BPI). ML parameter estimates of the binary choice model using the relationship variables LPI and BPI, and search frictions proxy *tightness*. 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 (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
asset_size^{len}	0.352***	0.351***	0.273***	0.222***	0.221***	0.173**
	(4.58)	(4.55)	(3.53)	(3.00)	(2.99)	(2.28)
excess_reserves^{len}	0.014***	0.013***	0.013***	0.013***	0.013***	0.012***
	(4.09)	(4.06)	(3.76)	(3.81)	(3.47)	(3.18)
centrality^{len}				0.124***	0.124***	0.132***
				(9.91)	(9.83)	(9.80)
liq_risk^{len}					0.133	0.101
					(0.71)	(0.53)
asset_size^{bor}	0.150	0.137	−0.047	−0.009	−0.012	−0.085
	(1.20)	(1.09)	(−0.41)	(−0.08)	(−0.11)	(−0.68)
excess_reserves^{bor}	−0.013*	−0.014*	−0.015**	−0.014*	−0.014*	−0.019**
	(−1.82)	(−1.93)	(−2.00)	(−1.87)	(−1.93)	(−2.37)
centrality^{bor}				0.056***	0.056***	0.056***
				(8.13)	(8.18)	(8.20)
liq_risk^{bor}					0.307	0.062
					(0.96)	(0.19)
LPI	1.513***	1.518***	1.449***	1.438***	1.438***	1.468***
	(25.71)	(24.52)	(22.33)	(21.48)	(21.47)	(21.87)
BPI	0.964***	0.910***	0.872***	0.823***	0.823***	0.842***
	(10.85)	(9.88)	(9.32)	(8.31)	(8.30)	(8.39)
crisis×LPI		0.045	−0.114	−0.062	−0.062	−0.231***
		(0.51)	(−1.40)	(−0.80)	(−0.79)	(−2.87)
crisis×BPI		0.200**	0.093	0.099	0.098	0.002
		(2.02)	(0.98)	(1.01)	(1.00)	(0.02)
market_tight×LPI		−0.082*	−0.108**	−0.097**	−0.097**	−0.097*
		(−1.92)	(−2.48)	(−2.23)	(−2.22)	(−1.94)
market_tight×BPI		0.138**	0.123**	0.115**	0.114**	0.113*
		(2.45)	(2.23)	(2.09)	(2.06)	(1.94)
sur_len			0.514***	0.458***	0.458***	0.567***
			(9.81)	(8.87)	(8.86)	(10.12)
sur_bor			0.650***	0.612***	0.611***	0.643***
			(9.60)	(9.41)	(9.42)	(9.67)
corr_shocks	0.061**	0.058**	0.051**	0.052**	0.051**	0.046**
	(2.54)	(2.42)	(2.16)	(2.26)	(2.23)	(1.98)
ΔCDS	−0.044***	−0.045***	−0.014	−0.013	−0.012	
	(−4.61)	(−4.76)	(−1.49)	(−1.43)	(−1.33)	
total_reserves	−0.058*	−0.032	0.009	−0.014	−0.012	
	(−1.94)	(−1.08)	(0.31)	(−0.47)	(−0.43)	
liq_supply	0.101	0.093	−0.043	0.024	0.024	
	(1.31)	(1.23)	(−0.58)	(0.34)	(0.33)	
_cons	−9.112***	−9.116***	−5.080***	−5.537***	−5.522***	−4.079***
	(−6.04)	(−6.13)	(−3.58)	(−4.04)	(−4.04)	(−2.73)
Bor/Len FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	No	No	No	No	Yes
Loglikelihood	-49088.6	49054.6	-48755.4	-48445.7	-48444.5	-47883.9
Observations	447785	447785	447785	447785	447785	447785

t statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Estimation Results for Interest Rate Model (LPI & BPI). Parameter estimates of the second-stage Heckman selection model for bilateral interest rates (dependent variable: interest rate spread in percent, selection model Table 5, model 6) using the relationship variables LPI and BPI, and search frictions proxy *tightness*. t-statistics in parentheses correspond to the null hypothesis that the parameter is zero, and are computed based on standard errors estimates corrected for two-stage estimation. 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 (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
asset_size^{len}	−0.015	−0.027***	−0.032***	−0.031***	−0.015***	−0.011***
	(−1.56)	(−2.83)	(−3.32)	(−3.18)	(−3.20)	(−2.46)
equity_ratio^{len}	−0.427***	−0.496***	−0.590***	−0.571***	−0.085	−0.077
	(−3.71)	(−4.38)	(−5.17)	(−4.98)	(−1.64)	(−1.51)
excess_reserves^{len}	−0.000	−0.000	0.000	0.000	0.000	0.000
	(−0.53)	(−0.23)	(0.36)	(0.56)	(0.18)	(0.13)
centrality^{len}			0.014***	0.014***	0.001	−0.001
			(7.62)	(7.66)	(0.85)	(−0.93)
liq_risk^{len}				−0.064*	0.018	0.021
				(−1.72)	(1.03)	(1.23)
asset_size^{bor}	−0.232***	−0.176***	−0.153***	−0.154***	−0.007	−0.001
	(−8.62)	(−6.55)	(−5.65)	(−5.68)	(−0.53)	(−0.93)
equity_ratio^{bor}	−2.645***	−2.569***	−2.228***	−2.320***	−0.283	−0.053
	(−4.96)	(−4.88)	(−4.23)	(−4.39)	(−1.15)	(−0.20)
excess_reserves^{bor}	−0.001	−0.000	−0.000	−0.000	0.000	−0.000
	(−1.18)	(−0.04)	(−0.32)	(−0.13)	(0.00)	(−0.02)
centrality^{bor}			0.002	0.002	0.002***	0.001**
			(1.37)	(1.31)	(2.95)	(2.36)
liq_risk^{bor}				−0.094	0.066**	0.041
				(−1.37)	(2.02)	(1.25)
LPI	0.043***	0.034***	0.073***	0.072***	−0.009	−0.008
	(4.78)	(3.73)	(6.95)	(6.85)	(−1.22)	(−1.05)
BPI	0.017*	0.005	0.014	0.013	−0.020***	−0.015**
	(1.96)	(0.53)	(1.44)	(1.38)	(−3.82)	(−2.40)
crisis×LPI		−0.131***	−0.127***	−0.127***	−0.026***	−0.020***
		(−15.91)	(−15.34)	(−15.35)	(−5.85)	(−4.52)
crisis×BPI		−0.011	−0.010	−0.010	0.034***	0.037***
		(−1.07)	(−1.02)	(−0.98)	(7.26)	(8.00)
market_tight×LPI		0.016	0.016	0.016	0.003	0.001
		(1.63)	(1.55)	(1.59)	(0.54)	(0.24)
market_tight×BPI		−0.014	−0.014	−0.014	−0.009	−0.010
		(−1.07)	(−1.05)	(−1.05)	(−1.51)	(−1.67)
corr_shocks	−0.022***	−0.019***	−0.018***	−0.018***	−0.000	−0.010
	(−5.34)	(−4.70)	(−4.42)	(−4.41)	(−0.24)	(−1.67)
ΔCDS	0.020***	0.023***	0.022***	0.021***		
	(10.79)	(12.21)	(11.66)	(11.41)		
total_reserves	−0.009	−0.033***	−0.036***	−0.036***		
	(−1.44)	(−5.24)	(−5.66)	(−5.71)		
liq_supply	−0.546***	−0.507***	−0.502***	−0.502***		
	(−36.69)	(−33.90)	(−33.41)	(−33.45)		
inverse Mill's	0.024***	0.004	0.034***	0.033***	−0.014**	−0.014**
	(3.78)	(0.65)	(4.34)	(4.25)	(−2.53)	(−2.43)
_cons	9.407***	8.824***	8.479***	8.496***	0.482***	0.257
	(30.52)	(28.07)	(26.71)	(26.68)	(2.93)	(1.61)
Bor/Len FE	Yes	Yes	Yes	Yes	Yes	No
Time FE	No	No	No	No	Yes	Yes
Pair FE	No	No	No	No	No	Yes
Observations	15857	15857	15857	15857	15857	15857

t statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Estimation Results for Matching Probabilities (LPI & BPI). ML parameter estimates of the binary choice model using the relationship variables LPI and BPI and search frictions proxy *total_trans*. 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 (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
asset_size^{len}	0.352***	0.349***	0.271***	0.219***	0.219***	0.174**
	(4.58)	(4.55)	(3.50)	(2.98)	(2.97)	(2.30)
excess_reserves^{len}	0.014***	0.013***	0.013***	0.013***	0.013***	0.012***
	(4.09)	(4.08)	(3.77)	(3.82)	(3.50)	(3.18)
centrality^{len}				0.124***	0.124***	0.132***
				(9.85)	(9.77)	(9.80)
liq_risk^{len}					0.120	0.098
					(0.64)	(0.51)
asset_size^{bor}	0.150	0.132	−0.055	−0.016	−0.020	−0.088
	(1.20)	(1.05)	(−0.48)	(−0.14)	(−0.17)	(−0.71)
excess_reserves^{bor}	−0.013*	−0.014*	−0.015**	−0.014*	−0.014*	−0.019**
	(−1.82)	(−1.94)	(−2.01)	(−1.88)	(−1.94)	(−2.38)
centrality^{bor}				0.056***	0.056***	0.057***
				(8.12)	(8.17)	(8.21)
liq_risk^{bor}					0.284	0.072
					(0.89)	(0.22)
LPI	1.513***	1.529***	1.461***	1.450***	1.450***	1.470***
	(25.71)	(24.42)	(22.33)	(21.50)	(21.49)	(21.74)
BPI	0.964***	0.934***	0.895***	0.845***	0.845***	0.854***
	(10.85)	(10.16)	(9.59)	(8.59)	(8.58)	(8.59)
crisis×LPI		0.027	−0.137*	−0.085	−0.084	−0.245***
		(0.30)	(−1.69)	(−1.09)	(−1.08)	(−3.02)
crisis×BPI		0.200**	0.091	0.096	0.095	0.007
		(2.02)	(0.96)	(1.00)	(0.98)	(0.07)
total_trans×LPI		−0.209***	−0.249***	−0.244***	−0.242***	−0.111*
			(−3.71)	(−4.46)	(−4.43)	(−1.83)
total_trans×BPI		−0.132	−0.140	−0.136	−0.135	−0.029
		(−1.29)	(−1.38)	(−1.34)	(−1.34)	(−0.29)
sur_len			0.520***	0.463***	0.463***	0.566***
			(9.94)	(9.01)	(8.99)	(10.12)
sur_bor			0.654***	0.616***	0.615***	0.643***
			(9.68)	(9.50)	(9.51)	(9.68)
corr_shocks	0.061**	0.059**	0.052**	0.053**	0.053**	0.047**
	(2.54)	(2.47)	(2.22)	(2.32)	(2.29)	(1.99)
ΔCDS	−0.044***	−0.046***	−0.014	−0.014	−0.013	
	(−4.61)	(−4.84)	(−1.53)	(−1.47)	(−1.38)	
total_reserves	−0.058*	−0.024	0.018	−0.005	−0.004	
	(−1.94)	(−0.80)	(0.61)	(−0.17)	(−0.13)	
liq_supply	0.101	0.074	−0.065	0.003	0.002	
	(1.31)	(0.98)	(−0.88)	(0.03)	(0.03)	
_cons	−9.112***	−8.898***	−4.793***	−5.254***	−5.243***	−4.057***
	(−6.04)	(−6.00)	(−3.40)	(−3.86)	(−3.86)	(−2.72)
Bor/Len FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	No	No	No	No	Yes
Loglikelihood	-49088.6	-49042.0	-48737.9	-48428.6	-48427.6	-47884.4
Observations	447785	447785	447785	447785	447785	447785

t statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Estimation Results for Interest Rate Model (LPI/BPI). Parameter estimates of the second stage Heckman selection model for bilateral interest rates (dependent variable: interest rate spread in percent, matching equation in Table 7, model 6) using the relationship variable LPI and BPI and search frictions proxy $total\_trans$. t-statistics in parentheses correspond to the null hypothesis that the parameter is zero, and are computed based on standard errors estimates corrected for two-stage estimation. 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 (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
asset_size^{len}	−0.015	−0.027***	−0.032***	−0.031***	−0.015***	−0.011**
	(−0.91)	(−2.82)	(−3.31)	(−3.17)	(−3.22)	(−2.46)
equity_ratio^{len}	−0.425**	−0.491***	−0.586***	−0.566***	−0.086*	−0.078
	(−2.45)	(−4.34)	(−5.14)	(−4.94)	(−1.65)	(−1.53)
excess_reserves^{len}	−0.000	0.000	0.000	0.000	0.000	0.000
	(−0.28)	(0.01)	(0.61)	(0.81)	(0.17)	(0.15)
centrality^{len}			0.014***	0.014***	0.001	−0.001
			(7.64)	(7.68)	(0.81)	(−0.89)
liq_risk^{len}				−0.065*	0.018	0.021
				(−1.76)	(1.05)	(1.26)
asset_size^{bor}	−0.233***	−0.175***	−0.151***	−0.152***	−0.007	−0.001
	(−6.02)	(−6.51)	(−5.59)	(−5.63)	(−0.51)	(−0.10)
equity_ratio^{bor}	−2.641***	−2.481***	−2.136***	−2.236***	−0.280	−0.044
	(−4.37)	(−4.72)	(−4.06)	(−4.24)	(−1.14)	(−0.17)
excess_reserves^{bor}	−0.001	−0.000	−0.000	−0.000	0.000	−0.000
	(−0.68)	(−0.09)	(−0.37)	(−0.16)	(0.01)	(−0.03)
centrality^{bor}			0.002	0.002	0.002***	0.001**
			(1.54)	(1.47)	(2.93)	(2.43)
liq_risk^{bor}				−0.105	0.066**	0.041
				(−1.52)	(2.00)	(1.24)
LPI	0.042***	0.043***	0.082***	0.081***	−0.009	−0.007
	(2.75)	(4.70)	(7.84)	(7.73)	(−1.24)	(−0.94)
BPI	0.016	0.010	0.019**	0.018*	−0.020***	−0.015**
	(1.16)	(1.07)	(2.00)	(1.94)	(−3.84)	(−2.38)
crisis×LPI		−0.133***	−0.129***	−0.129***	−0.026***	−0.020***
		(−16.12)	(−15.54)	(−15.55)	(−5.74)	(−4.52)
crisis×BPI		−0.013	−0.012	−0.012	0.033***	0.036***
		(−1.31)	(−1.25)	(−1.21)	(7.03)	(7.82)
total_trans×LPI		−0.052***	−0.054***	−0.054***	0.003	0.001
		(−4.48)	(−4.63)	(−4.66)	(0.50)	(0.15)
total_trans×BPI		−0.045**	−0.044**	−0.045**	−0.006	−0.004
		(−2.56)	(−2.51)	(−2.52)	(−0.75)	(−0.50)
corr_shocks	−0.022***	−0.018***	−0.017***	−0.017***	−0.000	−0.000
	(−3.08)	(−4.42)	(−4.12)	(−4.11)	(−0.24)	(−0.50)
ΔCDS	0.020***	0.022***	0.021***	0.021***		
	(10.83)	(11.96)	(11.38)	(11.12)		
total_reserves	−0.008	−0.028***	−0.031***	−0.031***		
	(−0.80)	(−4.49)	(−4.91)	(−4.95)		
liq_supply	−0.548***	−0.517***	−0.512***	−0.513***		
	(−21.73)	(−34.58)	(−34.06)	(−34.10)		
inverse Mill's	−0.365**	0.008	0.038***	0.037***	−0.014**	−0.013**
	(−2.17)	(1.22)	(4.88)	(4.78)	(−2.54)	(−2.22)
_cons	9.303***	8.863***	8.516***	8.535***	0.488***	0.251
	(21.27)	(28.24)	(26.85)	(26.83)	(2.99)	(1.57)
Bor/Len FE	Yes	Yes	Yes	Yes	Yes	No
Time FE	No	No	No	No	Yes	Yes
Pair FE	No	No	No	No	No	Yes
Observations	15857	15857	15857	15857	15857	15857

t statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Estimation Results Using Different Covariates. Parameter estimates of the second stage Heckman selection model for bilateral interest rates (dependent variable: interest rate spread in percent) for three different relationship variables based on alternative covariates. t statistics in parentheses correspond to the null hypothesis that the parameter is zero, and are computed based on standard errors estimates corrected for two-step estimation. 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.

	Model (1)	Model (2)	Model (3)	Model (4)
asset_size^{len}	−0.004	−0.003	−0.004	−0.003
	(−0.59)	(−0.38)	(−0.59)	(−0.41)
equity_ratio^{len}	−0.023	−0.000	−0.022	−0.001
	(−0.38)	(−0.00)	(−0.37)	(−0.02)
fungible^{len}	−0.047***	−0.041**	−0.047***	−0.041**
	(−2.81)	(−2.46)	(−2.80)	(−2.47)
liq_creat^{len}	−0.000	−0.000	−0.000	−0.000
	(−0.72)	(−0.57)	(−0.71)	(−0.57)
fulfillment^{len}	0.004**	0.004***	0.004**	0.004***
	(2.51)	(2.71)	(2.51)	(2.70)
centrality^{len}	0.002***	0.001	0.002***	0.001
	(3.15)	(1.11)	(3.13)	(1.19)
asset_size^{bor}	−0.007	−0.003	−0.006	−0.003
	(−0.45)	(−0.22)	(−0.44)	(−0.21)
equity_ratio^{bor}	−0.327	−0.332	−0.326	−0.324
	(−1.29)	(−1.31)	(−1.29)	(−1.28)
fungible^{bor}	−0.028	−0.017	−0.028	−0.017
	(−1.06)	(−0.63)	(−1.06)	(−0.62)
liq_creat^{bor}	0.001	0.001	0.001	0.001
	(1.60)	(0.89)	(1.61)	(0.83)
fulfillment^{bor}	−0.001	−0.001	−0.001	−0.001
	(−0.52)	(−0.38)	(−0.52)	(−0.40)
centrality^{bor}	0.002***	0.002***	0.002***	0.002***
	(4.40)	(3.24)	(4.39)	(3.33)
LPI		0.003		0.004
		(0.40)		(0.61)
BPI		−0.014**		−0.014**
		(−2.54)		(−2.48)
crisis×LPI		−0.032***		−0.032***
		(−7.08)		(−7.02)
crisis×BPI		0.053***		0.052***
		(10.29)		(10.04)
market_tight×LPI		0.005		
		(0.85)		
market_tight×BPI		−0.013**		
		(−1.98)		
total_trans×LPI				0.002
				(0.29)
total_trans×BPI				−0.006
				(−0.71)
log_rel	−0.008		−0.009	
	(−1.23)		(−1.25)	
log_rel_rev	−0.001		−0.001	
	(−0.54)		(−0.53)	
crisis×log_rel	−0.006***		−0.006***	
	(−4.38)		(−4.45)	
market_tight×log_rel	−0.001			
	(−0.34)			
total_trans×log_rel			−0.001	
			(−0.58)	
corr_shocks	−0.002	−0.001	−0.002	−0.001
	(−0.90)	(−0.70)	(−0.90)	(−0.70)
inverse Mill's	−0.015	−0.005	−0.015	−0.004
	(−1.37)	(−0.91)	(−1.39)	(−0.72)
_cons	0.334*	0.251	0.329*	0.238
	(1.78)	(1.36)	(1.74)	(1.28)
Len/Bor FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
N	15857	15857	15857	15857

t statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Parameter estimates of the second stage Heckman selection model for bilateral interest rates for different starting dates of *precrisis*. Dependent 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 LPI and interaction terms in the full model (all control variates and borrower/lender and time FE omitted from output). The bottom panel shows the results for log_rel. t statistics in parentheses correspond to the null hypothesis that the parameter is zero, and are based on standard errors estimates corrected for two-step estimation.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
starting day *pecrisis*:	1 Oct 2006	1 Nov 2006	1 Dec 2006	1 Jan 2007	1 Feb 2007	1 Mar 2007	1 Apr 2007	1 May 2007	1 Jun 2007	1 Jul 2007
LPI	−0.012	−0.013*	−0.012	−0.011	−0.010	−0.011	−0.010	−0.010	−0.009	−0.009
	(−1.58)	(−1.70)	(−1.58)	(−1.53)	(−1.41)	(−1.46)	(−1.32)	(−1.37)	(−1.25)	(−1.24)
crisis×LPI	−0.023***	−0.022***	−0.022***	−0.023***	−0.023***	−0.022***	−0.024***	−0.024***	−0.026***	−0.026***
	(−4.43)	(−4.33)	(−4.52)	(−4.66)	(−4.87)	(−4.76)	(−5.24)	(−5.22)	(−5.72)	(−5.81)
precrisis×LPI	0.004	0.006*	0.006	0.007*	0.007*	0.010***	0.006	0.009**	0.000	−0.001
	(1.15)	(1.75)	(1.64)	(1.86)	(1.86)	(2.71)	(1.47)	(2.14)	(0.04)	(−0.19)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bor/Len FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
log_relAB	−0.027***	−0.028***	−0.028***	−0.029***	−0.028***	−0.029***	−0.026***	−0.026***	−0.024***	−0.025***
	(−3.94)	(−4.05)	(−4.04)	(−4.16)	(−4.13)	(−4.20)	(−3.81)	(−3.83)	(−3.60)	(−3.66)
crisis×log_relAB	−0.008***	−0.008***	−0.008***	−0.008***	−0.008***	−0.008***	−0.009***	−0.009***	−0.010***	−0.010***
	(−5.48)	(−5.45)	(−5.65)	(−5.48)	(−5.75)	(−5.87)	(−6.81)	(−6.79)	(−7.49)	(−7.39)
precrisis×log_relAB	0.001	0.002*	0.002*	0.003**	0.003**	0.003***	0.001	0.002	−0.002	−0.001
	(1.19)	(1.68)	(1.66)	(2.53)	(2.51)	(2.68)	(0.69)	(1.26)	(−1.14)	(−0.42)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bor/Len FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: 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
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
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
sur_len	Realized (normalized) surplus compared with other loans of lender i when lending to borrower j based on 30 day rolling window	0.021	0.078	447785
sur_bor	Realized (normalized) surplus compared with other loans of borrower j when borrowing from lender i based on 30 day rolling window	0.034	0.112	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			
market_tight	Number of lenders divided by number of borrowers at day t	1.501	0.232	447785
total_trans	Total number of transactions/overnight loans at day t	42.753	11.964	447785
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 beginning 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			