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Abstract

There is substantial heterogeneity in the structure of trading relationships in the US overnight interbank lending market: Some banks rely on spot transactions, while a majority form stable, concentrated borrowing relationships to hedge liquidity needs. Borrowers pay lower prices and borrow more from their concentrated lenders. When there are exogenous shocks to liquidity supply (days with low GSE lending), concentrated lenders insulate borrowers from the shocks without charging significantly higher interest rates.

Key Words: interbank lending, OTC markets
JEL: G21, G10, D40, E59

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I. Introduction

A large fraction of transactions in the economy are negotiated and settled in over-the-counter (OTC) markets. Mortgage-backed securities, derivatives, corporate bonds, and syndicated bank loans are only a few examples of large OTC markets. Despite their importance to the economy, surprisingly little empirical research has been done on the functioning of these markets, mainly due to the lack of available transactions data. In this paper we study a specific OTC market, the overnight interbank lending market in the US, for which we can obtain detailed information on individual transactions. We analyze how trading relationships in this market are formed and how they affect pricing and the provision of liquidity across banks.

We first show that a majority of banks in the interbank market form long-term, stable and concentrated lending relationships, which have a significant impact on how liquidity shocks are transmitted across the market. But we also document large and persistent heterogeneity in the extent to which some banks rely on concentrated relationships for lending and borrowing. Even in the set of frequent borrowers, the median borrower tends to fill 50% or more of daily borrowing from only one lender. In contrast, a smaller subset of banks does not have very concentrated relationships.

Interestingly, the majority of theories of OTC markets abstract from this important dimension and assume that participants in the market engage in spot transactions without endogenously forming relationships between counterparties. For example, Duffie, Gârleanu and Pedersen (2005) are one of the first to analyze how trading frictions affect pricing and liquidity in OTC markets. Similarly, Vayanos and Weill (2008) and Afonso and Lagos (2014) analyze the dynamics of the government-bond market and the federal funds market, respectively. This literature provides a theory of dynamic asset pricing that explicitly models prices and equilibrium allocations as a function of investors' search ability, bargaining power, and risk aversion. While we believe that these theories capture some of the fundamental economic forces in the interbank market, our results show that it is important to understand the endogenous creation of relationships through which liquidity is provided and shocks spread through the market.

Our analysis suggests that the pattern of relationship formation we observe in the interbank lending market is largely consistent with an explanation that relies on liquidity hedging between banks. Borrowers match with lenders whose liquidity needs are negatively correlated, which might also imply that their business strategies are very dissimilar. Holding constant geographic proximity, counterparties are negatively correlated in customer payment patterns and their non-performing loan rates.[1] In other words, banks with liquidity shortfalls match with those that have excess liquidity on the same days.

Alternative explanations that have been developed in finance for the formation of long term relationships between credit intermediaries often rely on the reduction of information asymmetry. These models would predict that banks that are more opaque and thus more difficult to analyze, should rely more on relationships. See for example Rajan (1992) or Boot and Thakor (1994). However, our analysis shows that most of the classical measures of bank opacity do not appear to be predictive of concentrated borrowing relationships, e.g. publicly traded equity, Tier 1 ratio, amount of non-performing loans. This runs counter to what would have been expected under an information asymmetry story. We also find that banks that borrow from a more

[1] One possible explanation for the importance of geographic proximity is the fact that historically clearing speeds were faster within Federal Reserve districts, which are regionally determined.

concentrated and stable set of lenders (we will call these lending arrangements "relationships") tend to borrow smaller amounts and access the market less frequently.

In a second step, we look at the role that borrowing relationships play in determining credit terms. While borrowers with more concentrated lenders tend to face slightly higher interest rates overall, they get the biggest loan amounts and the most favorable interest rates from their most important counterparties. This suggests that borrowers face an upward sloping supply curve and choose to get credit from lenders which charge them lower interest rates. This relationship is not mechanically driven by borrowers endogenously taking the largest loans from the lender that gives them the best interest rate at a given point in time: relationships are measured in the month before a given transaction and relationships with counterparties are highly persistent over time (the proportion of total borrowing coming from the top lender has a correlation of 0.86 after three lags).

Interestingly, we do not find that this result is driven by symmetry in lending relationships (borrowing from and lending to the same bank), since fewer than 20% of lending relationships are symmetric. This means most lending relationships are of the form where one side is always providing liquidity while the other is demanding it. While borrowers get slightly lower interest rates from lenders that they also lend to, the magnitude is economically insignificant. These findings again are consistent with a model where some banks match with lenders whose liquidity needs are negatively correlated with their own, allowing the borrowers and lenders to insure each other against liquidity shocks at favorable rates.

Next, to understand the role of relationships in the pricing of liquidity and the transmission of supply shocks, we look at unpredicted shocks to the supply of liquidity. Our proxies for supply shocks in the interbank market are days when Government Sponsored Enterprise (GSE) lending is unusually low.[2] We explore two types of shocks to GSE lending: (1) what we call counterparty shocks, which are borrower-specific dates when the specific GSE counterparties that a given bank is borrowing from are lending least and (2) GSE market shocks, which are dates when the lending of GSEs aggregated across the market is low. According to market participants, incidences of low GSE lending are due to unpredicted changes in mortgage prepayments and other mortgage features. Specifically, we identify the five percent of days where GSEs unexpectedly lend the least by first controlling for known GSE-by-GSE variation in lending on certain calendar dates as well as changes in mortgage rates. The resulting residuals are unrelated to macroeconomic or banking level indicators.

We find that concentrated lending relationships are important for their counterparties in insuring against liquidity shocks. On days when a borrower's GSE counterparty lends unusually low amounts, they are able to expand borrowing from their most concentrated non-GSE lenders. In contrast, the rest of the banks in the interbank market (those without relationships) face a higher interest rate and reduced loan amounts on these dates. These results support the idea that lenders provide preferential liquidity insurance to their concentrated borrowers. Surprisingly, these lenders do not seem to demand a higher interest rate on these days, even though one could have expected that the lender's bargaining power with respect to the borrower is increased. However, we also find that the liquidity insurance provided from relationship lenders is not as large on days when there is a supply shock across a large number of GSEs in the market.

[2] In 2005 through 2009, GSEs supplied about 40% of liquidity to the interbank market but they are typically only lenders (not borrowers) in the market.

Our findings suggest that even if a liquidity shock affects only a subset of banks, it is transmitted to the rest of the banking market in ways that are affected by trading relationships. This is contrary to standard search models with random spot transactions where supply shocks have a symmetric effect on all banks in the market. These results underscore the importance of understanding relationships in this OTC market. But we cannot tell if the transmission of the liquidity shock to the periphery of banks is inefficient. Banks that face higher costs of liquidity shortfalls may endogenously build concentrated relationships to protect their access to liquidity. In contrast, banks that rely on spot transactions might be able to absorb liquidity shocks more easily and thus do not need to invest in relationships.

Finally, we examine the role of relationships in facilitating access to interbank lending in the financial crisis as an example of a major shock to liquidity.[3] We build on the analysis of Afonso, Kovner and Schoar (2011) and interact our relationship variable with indicator variables for each of the days after the failure of Lehman Brothers. Concentrated relationships did not appear to have provided banks with greater access to liquidity during the days following the Lehman collapse. While this result confirms the previous conclusion that relationships in this market only insure against idiosyncratic but not market wide shocks, we cannot rule out that banks which have more concentrated relationships might also be those that are differentially affected by the crisis, as discussed in Afonso, Kovner and Schoar (2011).

A benefit of using data from the overnight interbank market relative to other OTC markets is that we can analyze transactions using estimates on counterparties, prices, and amounts extracted from the Federal Reserve payments system. Specifically, transactions used in this study are identified as overnight loans from the universe of all Fedwire Funds Service (Fedwire)

[3] We thank an anonymous referee for this suggestion.

transactions using an algorithm similar to the one proposed by Furfine (1999). However, a drawback of the data is that since interbank transactions are not disclosed directly by counterparties, we cannot be sure that some loans are not missed, that some loan terms are not misidentified, or that some payments are not misclassified as loans. Historically, algorithms based on the work of Furfine have been used as a method of identifying overnight or term federal funds transactions. The Research Group of the Federal Reserve Bank of New York has recently concluded that the output of its algorithm based on the work of Furfine[4] may not be a reliable method of identifying federal funds transactions.[5] This paper, therefore, refers to the transactions that are identified using the Research Group's algorithm as overnight or term loans made or intermediated by banks. Use of the term "overnight or term loans made or intermediated by banks" in this paper to describe the output of the Research Group's algorithm is not intended to be and should not be understood to be a substitute for or to refer to federal funds transactions. For this reason, this paper focuses on interbank lending activity in general, rather than on the subset of interbank lending transactions generally used, under Regulation D, to refer to obligations that are exempt from reserve requirements.[6]

II. Literature Review

Our paper is related to the literatures on OTC markets and banking relationships. In OTC markets, an investor seeking to purchase or sell an asset first needs to find a trading partner and then, once they meet, bargain over the terms of the transaction. Duffie, Gârleanu and Pedersen

[4] It should be noted that for its calculation of the effective federal funds rate, the Federal Reserve Bank of New York relies on different sources of data, not on the algorithm output.

[5] The output of the algorithm may include transactions that are not fed funds trades and may discard transactions that are fed funds trades. Some evidence suggests that these types of errors in identifying fed funds trades by some banks may be large.

[6] See more on reserve requirements of depository institutions (regulation D) at http://www.ecfr.gov/cgi-bin/retrieveECFR?gp=&SID=0b6cb62ec4ab1c67db1c7b78a3f3201b&n=12y2.0.1.1.5&r=PART&ty=HTML

(2005) are the first to introduce search and bargaining characteristics in a model to study trading frictions in OTC markets.[7] Other theoretical contributions propose search-based models to study specific OTC markets. For example, Vayanos and Weill (2008) focuses on the government-bond market to explain the on-the-run phenomenon; Atkeson, Eisfeldt and Weill (2012) analyzes the trading structure in the credit default swaps market, while Afonso and Lagos (2013, 2014) study trading and reallocation of liquidity in the fed funds market.

Using network theory, Babus (2012) studies the formation of relationships between traders to understand how intermediation arises endogenously in OTC markets. In line with the prediction from that model, we find that borrowers with more concentrated lenders get more favorable terms from their most important counterparties. However, all transactions are not intermediated by a central counterparty in the US interbank market.

Several recent empirical papers on network formation document the core-periphery structure of the interbank networks. Studies of the unsecured interbank markets in the US (Bech and Atalay (2010), Gofman (2011)), Germany (Craig and von Peter (2010)), Italy (Fricke and Lux (2012), Iori et al. (2008)) and Denmark (Rørdam and Bech (2009)), among others, describe network structures where few banks have many counterparties while the majority trade with few counterparties. Using broader definitions of the interbank market, Langfield, Liu and Ota (2014) and Lelyveld and Veld (2012) also find a core-periphery structure in the UK and Dutch interbank market, respectively. Consistent with their findings of sparse interbank networks, we see that most banks in the US interbank market establish stable relationships.

[7] Their work has been generalized by Lagos and Rocheteau (2007, 2009), Vayanos and Wang (2007), Duffie, Gârleanu, and Pedersen (2007), Weill (2008) and Afonso (2011), among others. See also Duffie (2012) for an excellent overview of OTC markets.

Acharya and Bisin (2010) depart from the search and bargaining and the network approaches to OTC markets to highlight the role of opacity of OTC markets in the build-up of excessive leverage and inefficient risk-sharing during the 2007-09 financial crisis. To limit the potential for excessive risk-taking, Duffie, Li and Lubke (2010) propose increasing transparency and greater counterparty credit risk management in the market for OTC derivatives.

We find that interbank markets are OTC markets in which borrowers and lenders tend to establish lending relationships. Our findings are thus also informed by the vast theoretical and empirical literature on the effect of relationships on credit availability and loan terms.[8] Of course, most of the literature on relationship banking considers the relationship between firms and financial institutions.

To our knowledge, Furfine (1999) is the first to document the existence of relationships in the US interbank market. Furfine shows that large institutions form multiple relationships while smaller ones have few counterparties. Furfine (1999) argues that banking relationships play a role in the funds market for smaller institutions that choose to establish relationships to alleviate information asymmetries.[9] However, our analysis suggests that opacity is not predictive of concentrated borrowing. Furfine's work was followed by empirical studies in other countries.

Consistent with our findings, Cocco, Gomes and Martins (2009) show that, in the Portuguese interbank market, small banks rely more on relationships and that these relationships are established between banks with less correlated liquidity shocks. Similarly, Affinito (2012) shows

[8] For a detailed survey of the literature, see Elyasiani and Goldberg (2004), Boot (2000) and Onega and Smith (2000).

[9] Furfine (2001) also considers that borrowing institutions may build relationships to establish that they are a good credit risk. In this paper, Furfine finds that fed funds rates reflect differences in the borrower's credit risk suggesting that banks monitor the risk present in their interbank transactions.

that, in Italy, domestic banks also establish stable and strong relationships. Finally, Bräuning and Fecht (2012) find that German banks also rely on repeated interactions with counterparties.

III. Data

a. Estimates of overnight interbank trading activity

We extract information on overnight unsecured interbank trading activity from a proprietary transaction-level dataset of all transfers sent and received by institutions through Fedwire Funds Service (Fedwire) – an electronic large-value payment system owned and operated by the Federal Reserve. Interbank transactions in the US are not observed directly because the field that specifies the type of payment is coded only voluntarily in Fedwire, so to identify payments likely to be overnight loans from the universe of all payments, we use an algorithm developed by the Research Group of the Federal Reserve Bank of New York that is similar to the one proposed by Furfine (1999).[10] As discussed in the introduction, we cannot determine which of these transactions meet the reserve requirements of depository institutions definition of fed funds (Regulation D) and we will thus refer in this paper to the transactions identified by the Research Group's algorithm simply as interbank loans.

Despite its general appeal, the algorithm may generate error by keeping transactions that are not overnight interbank loans, by discarding actual loans and by misidentifying the terms of some loans. Examples of transactions that may be included in the dataset but are not overnight unsecured loans are correspondent banking, term interbank loans and tri-party repurchase agreements (repos). In order to not mistakenly include tri-party repo transactions we exclude

[10] See the appendix in Afonso, Kovner and Schoar (2011) for a detailed description of the algorithm.

from our analysis transactions involving the two tri-party clearing banks, JPMorgan Chase and the Bank of New York Mellon. Other types of repo transactions, such as bilateral repos, are settled on a delivery-versus-payment basis using a different payment system, Fedwire Securities Service, or are settled by the Depository Trust Company (DTC) in the case of non-Fed eligible securities and as such are not included in our sample. We also discard transactions labeled with the text "CTR," since those loans may be more likely to be executed on behalf of customers.[11]

The algorithm will not include loans settled outside of Fedwire, for example those settled through CHIPS, a privately owned and operated electronic payment system, and those settled on the books of an institution. Loans with unusually high or low rates compared to the daily effective fed funds rate will also be discarded.[12] The algorithm may also misidentify the counterparties of a loan. For instance, loans made on behalf of client nonfinancial firms and client banks may be misattributed to the correspondent bank. Finally, the algorithm may misidentify the rate of the loan if there are several payments that meet the criteria of the algorithm in terms of timing. Kovner and Skeie (2013) evaluate the relationship between the algorithm estimates and measures of fed funds activity as filed in the Consolidated Financial Statements for Bank Holding Companies (FR Y-9C) and find the two are highly correlated.

b. Description of the sample

The sample of transactions includes information on the date, amount of the loan, implicit interest rate, time of delivery, and time of return as well as the identity of the lender and the borrower of

[11] Using data provided by BGC Brokers (a large interbank dollar broker), McAndrews (2009) finds that the use of the customer code "CTR" as a proxy for a Eurodollar loan results in a 92 percent chance of correctly identifying Eurodollar loans, with an 8 percent chance of Type 1 error of counting fed funds loans as Eurodollars, and a 21 percent level of Type 2 error of falsely excluding Eurodollar loans counted as fed funds.

[12] On a given day, the algorithm will miss loans with rates lower than 50 basis points below the minimum brokered fed funds rate (known as *low*) and higher than 50 basis points above the maximum brokered fed funds rate (*high*) published by the Markets Group of the Federal Reserve Bank of New York from a daily survey of the four largest fed funds brokers. The algorithm will also miss negative rates.

every transaction sent over Fedwire. Borrowers and lenders are identified at the lead American Banking Association (ABA) level, which corresponds to a unique identifier assigned to institutions by the Federal Reserve (RSSD). For this analysis, we aggregate transactions to the bank holding company (BHC) level, dropping intra-BHC transactions, and aggregate loans between each borrower-lender pair on a daily basis, calculating the rate for each borrower-lender pair as a weighted average. We examine the time period beginning January 1, 2003 and ending December 31, 2007 to avoid unusual activity associated with the government intervention associated with the 2008 financial crisis.[13]

Although most of the US dollar unsecured interbank lending market is an overnight market, many borrowers do not borrow every day. We thus estimate measures of concentration over the previous month, rather than daily, and compare those measures to weighted average borrowings and prices in that month. We also limit the analysis to institutions that borrowed more than 50 days in a given calendar year (frequent borrowers). These frequent borrowers make up more than two thirds of the banks we observe ever borrowing in this time period and account for close to 90% of total interbank borrowing. In addition to borrowing more often, frequent borrowers borrow larger amounts, with the mean monthly amount for a frequent borrower of $327 million compared to $30 million for less frequent borrowers. Finally, we focus our analysis on frequent borrowers as we are less likely to measure the relationships of frequent borrowers with error. For example, an infrequent borrower with two lending counterparties who borrows only once a year will be measured as having 100% concentration in the first and second year. A borrower who borrows every day from its two lenders will correctly be measured as having two equal

[13] The results are unaffected by ending the sample in 2007, prior to the ABCP crisis, or in April 2008, prior to the collapse of Lehman Brothers.

relationships. Summary statistics on frequent borrowers are presented in Table 1 and discussed in subsection C below.

We augment the interbank lending data with quarterly information on bank characteristics as filed in the Consolidated Financial Statements for Bank Holding Companies (FR Y-9C) or Call Report for banks that are not bank holding companies, which provide information on credit risk variables, total assets and financial ratios. Therefore, we also limit the sample to include only borrowers for which this information is available. We include all 394 lenders in calculating trading relationships, regardless of whether they have Y-9C or Call Report data available. Summary statistics for the subset of lenders that have regulatory data available are shown in Table 1.

c. Summary statistics and variables of interest

Table 1, Panel A presents summary statistics with one observation per (frequent) borrower in a month, including only months in which the borrower participated in this market.[14] We first look at *Monthly Weighted Average Spread*, which is defined as the monthly average of the difference between the weighted average daily interest rate for a given bank and the target fed funds interest rate on that day. Alternatively, the spread could be defined with respect to the effective fed funds rate. The effective rate typically moves closely to the target rate and the correlation of the two rates during the sample period is 0.9985. We select the target rate rather than the effective rate because the posted effective rate represents the trades arranged by major brokers and this brokered rate could be different from the rates negotiated directly by banks. In a given month, the average spread paid by borrowers is 6.1 basis points, but there is a remarkable amount of

[14] Summary statistics for less frequent borrowers are available upon request.

variation in the spreads paid by borrowers within a month. The standard deviation of the average spreads in a month for the same borrower is 11 basis points. This variation may be driven by time effects or by differences in spreads charged by different lenders. There is also significant variation in the *Monthly Average Amount* – the average amount borrowed in a month – with a mean and median average amount borrowed of $327 million and $202 million, respectively.

Our primary measure of bank relationship concentration is *Volume Share*, the monthly amount borrowed from a lender divided by the borrower's total borrowing (from all lenders) in that month. Rather than borrowing the same amount from several lenders, borrowers appear to concentrate their borrowing in a single top lender – the average *Volume Share* for banks' largest lender (*Top Lender*) is 53% while the average *Volume Share* for a particular lender is 2%. For robustness, we also calculate *Number Share*, the number of days a bank borrows from a lender in a month divided by the total number of days that the borrower borrowed in that month, and consider alternative measures of the link between counterparties, such as the length of the relationship and the number of times the borrower borrowed from a lender divided by the borrower's total number of transactions in that month. These other measures were highly correlated with *Volume Share* and generated similar results. As shown in Table 1 Panel C, *Volume Share* and *Number Share* are highly correlated (0.95) and highly persistent (correlation between a measure and its lagged value is greater than 0.80). While the analysis in the paper focuses on *Volume Share*, results are similar if calculated using *Number Share*.

In addition, we examine the overall concentration of borrowers' relationships. We calculate *3-Firm HHI* as the sum of the squared value of the percentage of total monthly borrowing from borrowers' three largest relationships. On average, frequent borrowers have concentrated trading patterns with their lenders, with an average *3-Firm HHI* of 0.43.[15] As shown in Table A2 in the Appendix, *3-Firm HHI* and the *Volume Share* of the top lender are highly correlated (0.990).

We also look to see how much symmetry there is in lending relationships across borrowers and lenders. In other words, if bank A is the most important lender to bank B, does this relationship also hold in the other direction? That is, is bank B also the most important lender to bank A? This symmetry does not have to hold automatically, since borrowing and lending banks might have very different credit needs. But it is important to understand if there is symmetry (or one might also think of it as reciprocity) in lending relationships, since it could have implications for the pricing of credit between banks. If pairs of banks provide mutual insurance against liquidity shocks via long term (two-sided) lending relationships, the value of these relationships might not be fully reflected in the interest rates but in lending volumes.

In Panel B of Table 1, we start by calculating how likely it is that there is symmetry in borrowing relationships across two banks. Observations here are at the borrower-month level, for a total of 11,805 observations. We define reciprocity in lending relationships based on activities within one year. The first row shows that, on average, 14% of the lenders of a given bank only lend (never borrow) in the current month. Of course, by definition, 86% of lenders then have to be borrowers as well, which is reported in the next row. To establish symmetry, we now look at the percentage of lenders to a given borrower that both lend and borrow in the current year from this borrower. We condition here on the full sample of transaction years and find that only 34% of borrowing transactions are with lenders who will also within the same month borrow themselves from this original borrower. Even if we only condition on the transactions that are with lenders

[15] Less frequent borrowers have even more concentrated relationships with an average *3-Firm HHI* of 0.909.

who borrow at all in a given year, i.e. the 86% of the sample, the fraction only goes up to 38%. This means the occurrence of symmetry is very low in the sample, which provides an upper bound for the instances where banks could provide mutual liquidity insurance to each other. When we repeat the same calculation but value-weight each transaction, our results are virtually unchanged. When we shorten the reciprocity window to one month, results are halved, meaning that immediate reciprocity is even less common.

In the next part of this table, we limit the sample to frequent borrowers. Instances of reciprocity in this sample are even lower, with only 19% of lenders to frequent borrowers representing symmetric relationships. Finally, we look more closely only at a bank's largest and most important lender (we use the variable *Top Lender* as explained above). This asks whether the lender from which a given bank received the biggest fraction of funding borrows from this bank. We again see that even among the most important relationships, only 45% of the monthly observations are symmetric. In fact, this estimate is even an upper bound: if a borrower has multiple banks of the same maximum share, for example two lenders with 40% share and one with 20% share, we classify the bank as having symmetric relationships if even one of the two largest lenders (one of the two 40% share banks) also borrows from the bank. The amount of symmetry is roughly halved if we require the borrowing and lending to take place within the same month. Overall, these results confirm that the instances of symmetric borrower-lender relationships are limited, and that mutual liquidity insurance motives cannot be the main explanation driving our observed pricing dynamics. We will explore this dimension further in Section V when we look at loan terms.

IV. Determinants of Counterparty Concentration

The two predominant theories of why banks might form concentrated trading relationships are on the one hand based on the traditional relationship banking literature, relationships may evolve to reduce the costs of information asymmetry when some borrowers are more opaque than others. On the other, based on the idea that if transaction costs of finding counterparties in the interbank market are high, banks may match with counterparties that have inversely correlated liquidity needs to reduce these costs. Lenders and borrowers would only defect and trade with other counterparties (or increase prices) if the benefits from trading with others outweighs the continuation value of the relationship.

a. Determinants of concentration

We begin by analyzing which types of banks form concentrated lending relationships. For that purpose we study the concentration of borrowers' three largest relationships in a month as measured by *3-Firm HHI* – the sum of the squared value of the percentage of total monthly borrowing from borrowers' three largest relationships. We estimate the following equation:

$$3 - Firm\ HHI_{b,t_m} = \beta\left(IB_{b,t_{cp}-1}\right) + \delta\left(X_{b,t-1}\right) + \gamma(District\ Ratio) + \varepsilon_{b,t_m} \qquad [1]$$

where b indexes borrowing banks and t_m indexes time in months. $IB_{b,t_{cp}}$ is a vector of characteristics of the borrower's interbank activity in the previous year including: *Log Average Amount,* the logarithm of the monthly average of the daily amount borrowed by the bank; *Log Avg StDev Amount,* the logarithm of the monthly average of the standard deviation of the daily amount borrowed by the bank, normalized by the monthly average of daily amount borrowed in the previous year; *Frequency*, the fraction of days we observe a bank borrowing in the interbank market per month, averaged over the number of months the bank is in the sample; and *Lent Last Year*, a binary variable equal to one if the borrower lent in this market in the previous year. We also include *Log Assets*, defined as the logarithm of assets, as a measure of bank size.

$X_{b,t-1}$ is a vector of bank characteristics of interest, measured as of the previous quarter. We first look at measures that should be associated with the bank's opacity (based on Morgan (2002)) such as: *Publicly Traded*, an indicator variable equal to one if the bank has publicly traded stock; the logarithm of the amount of several types of assets: *Loans, Trading Assets*, *Cash and Deposits,* and *Fixed Assets and Premises,* and the *Tier 1 Ratio*, the ratio of tier 1 risk based capital to risk weighted assets. We also include financial characteristics associated with bank profitability such as *%NPL*, the proportion of non-performing loans to total loans and *Rolling 8Q SD ROA*, the rolling 8 quarters standard deviation of return on assets. We also add a measure of funding stability, the *%Deposits,* total deposits divided by assets.

Finally, we include a measure of the relative number of borrowers and lenders in a district, *District Ratio,* defined as the monthly average number of borrowers that borrowed in a bank's Federal Reserve district divided by the monthly average number of lenders active in the same district.[16] Variable definitions are summarized in the Appendix.

The results of these specifications are shown in Table 2. As might be expected, more active borrowers have less concentrated relationships, although the economic magnitudes are relatively small. For each additional 10% increase in average borrowing, HHI decreases by 0.011, or 2.5%. This is primarily driven by higher borrowing needs – banks that borrow a lot have less concentrated relationships. While the sign on assets is positive and statistically significant, in

[16] Results are similar if estimated using simply the logarithm of (the inverse of) the number of lenders active in the sample time period in a bank's Federal Reserve district.

regressions without controls for bank borrowing amount, the sign on bank assets changes from positive to negative. The more frequently banks borrow, the less concentrated are their trading patterns. This may reflect the fact that frequent borrowers borrow even on days when their main lenders do not lend. Banks with highly variable borrowing needs (high standard deviation of amount borrowed) also have less concentrated trading. We do not estimate a consistently statistically significant relationship between lending in the previous year and concentration. Of course, from the cross sectional analysis we cannot rule out a story where better banks borrow more and have access to more lenders because they are more creditworthy.

In addition to bank size, we find only little evidence that bank opacity is associated with concentrated relationships. The signs on the amount of loans (+), cash and deposits (+) and fixed assets and premises (-) are positively associated with measures of bank opacity as documented by Morgan (2002), but are not statistically significant. In addition, variables like tier 1 capital ratio or whether the bank is publicly traded are not significantly related to borrowing concentration (column (3)), suggesting that information asymmetry is not of primary importance in explaining lending relationships in the market. Similarly, measures of risk such as % NPLs and the standard deviation of ROA are actually negatively associated with concentration once all controls are included, although statistical significance varies. Finally, in districts with more lender power (higher ratios of borrowers to lenders or fewer lenders), banks have more concentrated borrowing, perhaps because relationship lenders can extract more rents in the face of less competition in those districts (column (6)), although again the relationship is not statistically significant. The final specification includes all of the possible explanatory variables in a single column.

b. Determinants of existing relationships

We next look at the pairing choice of borrowers and lenders. We begin by creating a balanced panel of all possible borrower/lender duples between 140 frequent borrowers and 420 lenders with available data on bank characteristics. We first examine the variable *Relationship*, an indicator variable equal to one if the borrower borrows from the lender in any calendar year in which both the borrower and the lender are active between January 1, 2003 and December 31, 2007. The mean of *Relationship* is 0.057 indicating that most borrowers pair with very few of the possible lenders (Table A1 in the Appendix). For all borrower/lender pairs with relevant data in our sample we estimate a probit model of the following specification:

$$
\begin{aligned}
&Relationship_{b,l} = \\
&\qquad = \beta\left(Geography_{b,l}\right) + \lambda\left(Difference\ in\ Assets_{b,l}\right) + \pi\left(Symmetry_{b,l}\right) \\
&\qquad + \theta\left(Similarity\ of\ Cash\ Flows_{b,l}\right) + \varphi_b + \gamma_l + \varepsilon_{b,l}
\end{aligned}
\qquad [2]
$$

where b indexes borrowers and l indexes lenders, and $Geography_{b,l}$ is a vector of location characteristics including *Same District, Same State* and *Geographic Distance*, the haversine distance between the headquarters of the bank measured in (logarithm of) miles. $Difference\ in\ Assets_{b,l}$ measures the difference between the borrower's and lender's assets, normalized by the borrower's assets, all in logarithms. $Symmetry_{b,l}$ measures if the borrower bank has ever lent to the lender bank, measured as broadly as possible with an indicator variable equal to one if this symmetry exists at any point in the sample period. $Similarity\ of\ Cash\ Flows_{b,l}$ is a vector of correlations of the borrower's and lender's businesses as measured by *Correlation of %NPL* or *Correlation of Net Customer Funds*. In order to control for fixed differences among borrowers and lenders (for example in their relative size or propensity to participate in the market), we include fixed effects for borrowers (φ_b), lenders (γ_l) in several of the specifications. Detailed variable definitions are available in the Appendix.

We use these different measures of the similarity of banks (geography, size, risk, and cash flow patterns) to understand whether banks choose to trade with similar or different counterparties. We include borrower fixed effects in all specifications and then in columns (1)-(4) of Table 3 we add each control consecutively. We include in each equation a very broad measure of symmetry and see that banks are more likely to borrow from lenders to whom they have previous lent money, although the explanatory power of this variable, as measured by adjusted r-squared, is relatively small. Specification (4) of Table 3 includes all the measures of banks' businesses, and we find that banks are more than 4.2 times more likely to pair with banks in the same district and on top of that 20 times more likely to contract with banks in the same state. While banks pair with other banks in the same geography, as well as banks that are geographically closer, they are matching with otherwise dissimilar banks. Borrowers are less likely to pair with lenders that have correlated NPLs. As a proxy for cash flow needs that may be hard for banks to anticipate, we look at the correlation of net customer transfers and the probability of trading. Rather than trading with banks whose net customer transfers are similar, banks borrow from banks that may have more excess cash precisely when their own liquidity needs are higher. One exception is size. As the difference in size between two banks increases, those banks are less likely to trade.

Next we look at a borrower's top lender to understand if this relationship differs from the borrower's other relationships. We estimate a probit model where the variable of interest is now *Max Relationship,* which is an indicator variable equal to one for the lender who lent the most funds to the borrower. In addition to borrower fixed effects, we directly include a control for the fact that banks have different numbers of counterparties. Results are summarized in columns (5)-(7) in Table 3. We see a similar pattern in banks' top counterparties (column (7)). Among banks with which they trade, borrowing tends to concentrate with their lender with higher difference in assets, less correlated NPLs, and less correlated net customer transfers (although these last two results are now not significant), although the coefficients are no longer statistically significant. The estimated coefficient on symmetry is much smaller.

In summary, it seems that banks borrow from banks that have liquidity when they lack liquidity. Instead of lending to similar banks (which they might be better able to monitor), they lend to banks that have dissimilar businesses. This is consistent with the findings in Cocco, Gomes and Martins (2009), and in contrast with those in Furfine (2001).

Geographic considerations appear to be important too. Lending to close banks could reflect monitoring (it is easier to monitor close institutions). Alternately, in light of the persistence of relationships, lending to geographically close banks may be an historical artifact of a time when liquidity could be transferred more quickly among geographically close institutions and within Federal Reserve districts. It is worth noting that to the extent that the algorithm that identifies interbank transactions is not recording the correct ultimate counterparty, error in counterparty characteristics will be introduced and we would be less likely to estimate relationships between bank characteristics such as geography.

V. The Effects of Concentration on Interbank Loan Terms

We next test if the strength of bank relationships is associated with the pricing and amounts borrowed in the interbank market, estimating for each of the loan terms *Loan Term*$_{t,b,l}$ (spread to target and logarithm of amount borrowed) the following specification:

$$Loan\ Term_{b,l,t} = \beta\left(Volume\ Share_{b,l,tm-1}\right) + \theta\left(Symmetry_{b,l,tm-1}\right) + \varphi_b + \gamma_l + \tau_{t_m} + \varepsilon_{b,l,t_m} \qquad [3]$$

where b indexes bank borrowers, l indexes bank lenders and t_m indexes time in months. *Volume Share*$_{b,l,t_{m-1}}$ is the monthly amount borrowed from a lender divided by the borrower's total borrowing (from all lenders) in that month estimated over the previous month. *Symmetry*$_{b,l,t_{m-1}}$ is an indicator variable equal to one if the borrower ever lent to the lender in the previous twelve months. Rather than controlling for bank characteristics associated with both loan terms and relationships, we include fixed effects for borrowers (φ_b), lenders (γ_l), and months (τ_{t_m}). Specifically, we estimate how counterparty concentration is correlated with spread (or amount), controlling for: (i) The average spread (or amount) that this borrower pays on average, (ii) the average spread (or amount) this lender lends to its counterparties, (iii) the average spread (or amount) of lending in the overall market on that date, (iv) and our measure of symmetry.

This means that we look at the within borrower-lender concentration and ask whether the price of liquidity (or access to liquidity) for a given borrowing bank is related to the relationship that the borrower has with the lender.

Table 4 shows the results from these regressions, where in columns (1)-(4) the term of the loan is the spread between the loan rate and the target rate, while in columns (5)-(8) the term is the amount borrowed. In column (1) we report the results of regressing the interest rate spread on

Volume Share only controlling for calendar month fixed effects.[17] This specification de facto picks up cross sectional variation between borrowers in their lender concentration, differences within borrowers in their exposure to lenders and also daily pricing variation. The coefficient on previous month *Volume Share* is positive, but not significant, which suggests that on average borrowing banks that have more concentrated lenders may pay higher interest rates in the interbank market. This is consistent with results by Ashcraft and Duffie, reported in Chapter 2 of Duffie (2012), in which they find a positive (and statistically significant) relationship between relationship strength and spreads.

In columns (2) and (3) we successively add borrower fixed effects, lender fixed effects and time fixed effects. Interestingly, in column (2) we see that once we add a borrower fixed effect to the specification, the sign on previous month *Volume Share* flips and becomes negative and statistically significant. This means that holding the average spreads of a borrower constant (i.e. including the borrower fixed effect), banks get lower interest rates from their most important lenders. All else equal, after controlling for borrower and lender fixed effects (specification 3), when trading with a lender with a one standard deviation higher *Volume Share*, borrowers pay 0.68 bp less (an economically high 88.9% of mean spreads). These findings are in line with results in Cocco, Gomes and Martins (2009) for the Portuguese interbank market. And also consistent with those presented in Furfine (2001) that uses as measure of relationship the number of days that two banks transact in the first quarter of 2008; and with those in Bräuning and Fecht (2012) from August to November 2007, that captures relationships between German banks by number of past transactions. These results suggest that on average, banks face a supply curve of possible lenders offering different rates, and that borrowers rely more heavily on the lenders that

[17] Month fixed effects control for any seasonality in interbank transactions.

offer them the best rates. An alternative but closely related interpretation is that lenders with whom the bank has a larger relationship give better prices.

Finally, in column (4) we look at the role of symmetry – lenders that also borrow from their counterparty charge slightly lower prices and lend more funds, although the economic magnitude and explanatory power are relatively small. We also investigated the interaction between symmetry and relationship (*Symmetry* x *Volume Share*)(not shown). The estimated coefficient is surprisingly of the opposite sign to the estimated coefficient on *Volume Share*. We conclude from this analysis that low spreads are not driven by banks that insure each other (and that this insurance is not likely to be an unmeasured part of the price paid to relationship lenders).

In columns (5) to (8) we repeat the same set of regressions but use the amount borrowed as the dependent variable. Since our earlier paper (Afonso, Kovner and Schoar (2011)) showed that the interbank market relies more heavily on rationing of loan amounts than prices, this is an important dimension to explore. In column (5) we begin by estimating the relationship between the previous month *Volume Share* and the average amount of credit only controlling for time fixed effects (monthly). We find that the coefficient on lagged *Volume Share* is positive and significant, which means that more concentrated borrowers are able to get larger loans. But even when we include borrower and lender fixed effects in columns (6) and (7), the coefficient stays positive and significant. So a given bank borrows larger amounts from its more important lenders. As we saw in the descriptive statistics, this might suggest that banks which need more liquidity on an ongoing basis and/or find it more difficult to borrow in the interbank market are those that need to establish relationships in this market. Lenders who borrow, however, lend greater amounts to their symmetric counterparties.

VI. The Effects of Supply Shocks

To get a better understanding of the role that concentrated relationships play in this market, we next look at exogenous shocks to the supply of credit. If long-term borrowing relationships facilitate access to credit we should see their most pronounced impact during times of credit tightening in the overall market.

In addition to banks, government sponsored enterprises (GSEs) are large lenders to banks in the overnight market. On average, GSEs comprised more than 40% of overall funding from January 1, 2003 through December 31, 2007. GSE lending is mainly driven by the timing of payments on securitized mortgages and is relatively uncorrelated with liquidity shocks to the US banking system. We use days when the GSEs have large drops in their lending activity (after controlling for known payment patterns) as an instrument for exogenous shocks to the supply of liquidity in this market.

We begin by separately estimating an equation for each GSE of their daily lending. We include as control variables quarterly fixed effects as well as fixed effects for calendar month and day of week and lagged mortgage rates. For the two GSEs with known payment dates, we include fixed effects for those dates and for the preceding two days and subsequent one day. Market participants confirmed the view that, other than the payment dates and end-of-maintenance-period days, unpredictable variation in GSE lending existed. We add up the residuals and identify for each year the smallest 5% of residuals by GSE.

We use the sum of the smallest residuals to identify two types of shock days. The first one is a borrower specific variable, *Counterparty Shock Day*$_{b,t}$, an indicator variable identifying counterparties of the specific GSEs that experience a low residual day. We also identify broader shock days in the market, *GSE Shock Day*$_t$, with an indicator variable equal to 1 on days with the 5% lowest aggregate residuals (i.e. when several individual GSEs are having shocks days). *GSE Shock Days* are plotted in Figure 1. We then examine the relationship between concentration and loan terms on *Counterparty Shock Days* and *GSE Shock Days*. Specifically, we estimate a specification with a loan term (spread, amount or counterparties) as the dependent variable to understand the importance of shocks to counterparties (*Counterparty Shock Day*) and to the broader market (*GSE Shock Day*):

$$Loan\ Term_{b,l,t_d} == \beta(Volume\ Share_{b,t_m-1}) + \delta(GSE\ Shock\ Day_{t_d})(Volume\ Share_{b,t_m-1}) + \lambda(GSE\ Shock\ Day_{t_d}) + \eta(Counterparty\ Shock\ Day_{b,t_d}) + \varphi_b + \gamma_l + \kappa_{t_d} + \varepsilon_{b,l,t_d} \quad [4]$$

where b indexes bank borrowers, l indexes bank lenders, t_m indexes time in months and t_d indexes time in days. *Volume Share*$_{b,l,t_{m-1}}$ is the monthly amount borrowed from a lender divided by the borrower's total borrowing (from all lenders) in that month estimated over the previous month. *GSE Shock Day*$_{t_d}$ is a dummy variable equal to 1 on days with the lowest 5% of aggregated GSE lending residuals when taking into account all GSEs. *Counterparty Shock Day*$_{b,t_d}$ is an indicator variable equal to 1 for banks that borrowed from a GSE that has a residual on the lowest 5% date at any point in the sample. φ_b and γ_l are fixed effects for borrowers and lenders, respectively. κ_{t_d} is a fixed effect for days that are the end of a maintenance period or quarter end. Transactions where a GSE is the lender are excluded from the specifications.

For all specifications in Table 5, the sample excludes all transactions with GSE counterparties. Results are similar if we limit the sample only to those banks that have ever borrowed from

GSEs. The first two columns have as the dependent variable the transaction spread to the fed funds target rate. The coefficient on *Counterparty Shock Day* in column (1) is positive and statistically significant but not the coefficient on the interaction of *Counterparty Shock Day* and lagged *Volume Share.* Thus, on days where there is a lending shortfall from a borrower's GSE counterparty, interest rates rise on average for that borrower, but not disproportionally more from its concentrated lenders (and maybe they even fall). When the counterparty shock day coincides with less supply from other GSEs, we also do not see much statistically significant change in spreads from its concentrated lenders (triple interaction between *Counterparty Shock Day*, lagged *Volume Share* and *GSE Shock Day* in column (2))).

Next, we repeat the analysis using the size of the loan as dependent variable. In columns (3) and (4) we use the logarithm of the loan size conditional on a loan being made. The positive coefficient on the interaction of *Counterparty Shock Day* and *L1.Volume Share* suggests that concentrated non-GSE counterparties increase lending on days where GSEs lend less. On days when their GSE counterparties lend less, their borrowers see a bigger drop in loan size, unless they have concentrated lenders. Adding up, borrowers with an HHI greater than 27% are not able to make up the lending. On days with a counterparty shock, an increase in volume share of one standard deviation is associated with an additional $1 million increase in borrowing, which is approximately 10% of average daily borrowing.

When we add the *GSE Shock Day* term in column (4), we see that these concentrated relationships are not as helpful when supply shocks are market-wide. The estimated coefficient on the triple interaction of Counterparty *Shock Day, Volume Share* and *GSE Shock Day* is negative and significant at the 10% level (-0.155). When this is added to the interaction of

Counterparty Shock Day and *Volume Share* the total effect of *Volume Share* on *Counterparty Shock Day* remains positive, but declines from 0.826 to 0.671.

In columns (5) and (6) we repeat these regressions including the latent demand for loans by adding a zero on days where the borrower borrows from at least one of its lenders. This expands our set of observations by a factor of 6. The results in columns (5) and (6) show that there is an increase in the amount of loans by relationship lenders on days of a *GSE Counterparty Shock*: the positive and significant coefficient on the interaction term (*Counterparty Shock Day* x *L1.Volume Share*) increases tenfold, suggesting that the increases in borrowing on shock days appear to come from high concentration lenders.

Finally, in columns (7) and (8) the dependent variable is the logarithm of the number of counterparties of the borrower. Instead of looking at the *Volume Share,* the unit of observation is now one per borrower, and the concentration measure shifts to the borrower's HHI. The number of counterparties increases overall, and we see some differential adjustment for concentrated borrowers, for whom we see a slight fall in counterparties, even for the most affected borrowers, perhaps because their needs have already been met by their relationship counterparties.

Overall, these results suggest relationship lending insures against liquidity shocks. However, this insurance is most effective when shocks are idiosyncratic. When GSE shocks affect the market more broadly, relationship lenders do not increase their lending by as much. Surprisingly, the lenders do not seem to take much advantage of their increased bargaining power over their most affected concentrated borrowers, since prices do increase on these days from their high *Volume Share* lenders. This could suggest that lenders value the ability to place liquidity in a predictable way with a given counterparty and thus do not charge a premium on GSE shock days. Results are similar when calculated at the borrower level, rather than the borrower-lender level – borrowers are disproportionately affected by aggregate supply shocks only when their HHI is greater than 0.27.

VII. The Role of Relationships in the Financial Crisis of 2008

While well identified and plausibly exogenous, the supply shocks we investigate in Section VI are relatively small. One might ask, what happens with lending relationships in the face of a very large shock to the interbank lending market? We build on our previous work (Afonso, Kovner and Schoar (2011)) and examine interbank lending terms on the days following the collapse of Lehman Brothers.[18] We include a fixed effect for borrowers and lenders and track the role of relationships by interacting the indicator variable for the post-crisis variable with our relationship measure (*Volume Share*). This analysis is thus similar in spirit to that done by Affinito (2012) for the Italian interbank market.

In Table 6, we look at the role of relationships and find weak evidence that prices increase and quantities decrease for more concentrated relationships in the week of September 15th, 2008. We begin in the first two columns with the spread as the dependent variable, and as explanatory variables, we include dummy variables for the days immediately following the Lehman failure, but prior to the government intervention on Wednesday, September 17th. We estimate positive, but mostly not statistically significant coefficients on *Volume Share* on Monday and Tuesday and continuing through the end of that week, even while prices begin to fall for the overall market of frequent borrowers starting on Tuesday. In columns (3) through (6) we move to a consideration

[18] We thank the referee for suggesting this analysis to us.

of amounts, looking first at amounts for transactions that occur, and in the next two columns at the full set of possible transactions, including latent demand for loans as measured by zeros. The estimated coefficients on the interaction of *Volume Share* and the dates after Lehman's failure are mostly negative, consistent with reduced volumes, although again the coefficients are often not statistically significant. Overall concentrated relationships do not seem to protect borrowers from large and market wide liquidity shocks, which is consistent with our analysis from the GSE shocks. Unfortunately, the interpretation of these results is complicated because of the endogenous nature of relationships,[19] i.e. the potential that banks' which select into concentrated relationships also change their risk more over the crisis period.

VIII. Conclusion

This is one of the first studies to analyze the role of relationships for access to credit and the transmission of liquidity shocks in an important OTC market, the overnight interbank market. We document that more than half of the banks form stable and persistent trading relationships with borrowers, but that they vary greatly in the intensity with which they rely on their largest lenders. Small banks in particular choose to form more concentrated lending relationships. On average, borrowers seem to match with lenders in the same geography (state and Federal Reserve district), who are otherwise dissimilar from them in terms of their size, as well as in the correlation of their cash flows. While these concentrated borrowers pay higher spreads on average, they borrow more and face significantly lower spreads from their most important

[19] Since lending relationships are endogenously determined and associated with observable bank characteristics, any results would be biased by the fact that banks that are more sensitive to market liquidity shocks, might also tend to choose more concentrated lending relationships.

lenders. This finding suggests relationships between counterparties are very important in this market.

The emergence of repeated trading relationships in our setting could be motivated by the idea that repeated interactions can sustain cooperative equilibria that rely on mutual trust. If cooperation creates long-term value within the relationship, either side can enact punishment strategies in case the other side defects, which can help protect the relationship. See for example Green and Porter (1984), Benjamin and Leffler (1981) or Kreps (1990). A second and related explanation would be that relationships serve purely to reduce the transaction costs of searching. If both sides are perfectly matched in their complementary liquidity needs, e.g. one side always wants to borrow and the other wants to lend, then even in the short run incentives between the two sides are always aligned. So there is no temptation for reneging.

We believe that the rationale for repeat relationships that we see in the interbank lending market is a combination of these last two models. Repeated counterparties are matched based on complementary liquidity needs (negative correlation between counterparty payment shocks) and lenders providing the best rates to their repeat borrowers. The value created in the repeat relationships may be that some counterparties value the assurance that they can receive (or place) liquidity when they need to. In addition, we find that banks which rely on repeat relationships with their lenders, can borrow more when confronted with market liquidity shocks (GSE shocks) without incurring increased prices. These results are consistent with the idea that these banks are engaged in a trust game. However, we cannot rule out that pure reduction of search costs is also part of the explanation.

Going forward it would be very interesting to understand how these dynamics might change in OTC markets where transactions are secured by collateral, such as repo markets. While concerns about counterparty risks might be negligible in regular times compared to the unsecured market, the disruptions in these markets could be much more dramatic once there are doubts about the value of the collateral. One might even conjecture that this could explain why repo markets seem to have faced much larger dislocations than the interbank market during the financial crisis.

TABLE 1, PANEL A: SUMMARY STATISTICS

	Obs.	Mean.	StDev.	25%	50%	75%
One Observation per Borrower / Month						
Monthly Wght. Avg. Spread	5,256	0.061	0.113	0.002	0.033	0.123
StDev. Spreads	4,253	0.085	0.091	0.032	0.063	0.103
Monthly Avg. Amount ($mil)	5,256	326.6	365.1	63.9	202.0	454.7
StDev. Monthly Amount	5,193	796.7	1,219.4	122.7	397.6	952.4
Volume Share, All Lenders	220,453	0.024	0.100	0.000	0.000	0.005
Volume Share, Top Lender	5,256	0.530	0.319	0.238	0.469	0.849
3 Firm-HHI	5,256	0.434	0.359	0.102	0.339	0.742
Counterparties	5,256	18.064	30.804	2.000	5.000	18.000
One Observation per Borrower						
Assets ($bn)	141	40.621	174.311	1.710	4.302	13.331
Log Assets (log $th)	141	15.496	1.735	14.314	15.273	16.400
NPL (% of loans)	141	0.007	0.007	0.004	0.006	0.008
Deposits (% of assets)	141	0.710	0.109	0.665	0.726	0.782
Publicly Traded	141	0.674	0.471	0.000	1.000	1.000
Average Amount ($mil)	141	17,599	49,001	366	1,167	7,908
StDev Average Amount	141	7,867	20,937	269	840	5,174
One Observation per Lender						
Assets ($bn)	394	15.467	105.749	0.386	0.891	3.060
Log Assets (log $th)	394	14.043	1.763	12.864	13.697	14.914
NPL (% of loans)	394	0.009	0.013	0.003	0.006	0.011

Note: The sample ranges from 1/1/2003 to 12/31/2007 and includes all *frequent* borrowers that borrow in the interbank market over this time period and file a Call Report or Y9-C. A *frequent* borrower is defined as a bank that borrows 50 days or more in the interbank market within the calendar year. *Monthly Wght. Avg. Spread* is the monthly average weighted spread to the target fed funds rate, in percentage points. *StDev. Spreads* is the standard deviation of the monthly weighted spread a borrower receives from each of its lenders. *Monthly Avg. Amount* is the average monthly amount (in U.S. $ million) a bank borrows from each of its lenders. *StDev. Monthly Amount* is the standard deviation of the monthly average amounts a bank borrows from each of its lenders. *Volume Share, All Lenders* is the monthly amount borrowed from a particular lender divided by the borrower's total borrowing in that month and is observed once per borrower / lender / month. *Volume Share, Top Lender* is the largest value of *Volume Share* for a borrower in a month, where *Volume Share* is the amount borrowed in a month from a given lender divided by the total amount borrowed in the month. *3 Firm-HHI* is the sum of the squared value of the percentage of total monthly borrowing from a borrower's three largest relationships. *Counterparties* is the average number of counterparties the borrower trades with each month. *Assets* is the bank assets (in U.S. $ billions). *Log Assets* is the natural log of bank assets (in U.S. $ thousands) measured using Call Report or Y-9C as of the previous year-end, averaged over the months each bank is in the sample. *NPL* is total non-performing loans divided by total loans. *Deposits* is total deposits divided by assets. *Publicly Traded* is an indicator variable equal to one if a bank has publicly traded stock. *Average Amount* is the average across active months of the average monthly amount. *StDev Average Amount* is the average across active months of the standard deviation of the average monthly amount borrowed.

TABLE 1, PANEL B: SYMMETRY SUMMARY STATISTICS

	N	mean	sd
Equal Weighted by Counterparty			
Lender only lends	11,805	14%	24%
Lender borrow and lends	11,805	86%	24%
% of lenders that borrow from bank i	11,805	34%	40%
% of lenders that borrow from bank I, of lenders that borrow	11,340	38%	40%
Weighted by Amount			
Lender only lends	11,805	11%	24%
Lender borrow and lends	11,805	89%	24%
% of lenders that borrow from bank i	11,805	35%	42%
% of lenders that borrow from bank i, of lenders that borrow	11,340	38%	42%
Frequent Borrowers			
Equal Weighted by Counterparty			
Lender only lends	5,302	24%	23%
Lender borrow and lends	5,302	76%	23%
% of lenders that borrow from bank i	5,302	19%	22%
% of lenders that borrow from bank i, of lenders that borrow	5,057	24%	25%
Weighted by Amount			
Lender only lends	5,302	18%	26%
Lender borrow and lends	5,302	82%	26%
% of lenders that borrow from bank i	5,302	21%	27%
% of lenders that borrow from bank i, of lenders that borrow	5,057	25%	29%
Top Lender ONLY			
Equal Weighted by Counterparty			
Lender only lends	1,151	18%	38%
Lender borrow and lends	1,151	82%	38%
% of lenders that borrow from bank i	1,151	45%	50%
% of lenders that borrow from bank i, of lenders that borrow	944	54%	50%

Note: The sample ranges from 2003 to 2007. The unit of observation is one per borrower / month, with statistics representing means for the borrower in a month, weighted either equally by lender, or value weighted by transaction amount. The sample includes frequent borrowers only, where frequent borrowers are defined as banks that borrow 50 days or more in the interbank market within the calendar year. *Lender only lends* is the mean by borrower/month of an indicator variable equal to one when the lender bank does not borrow in the previous twelve months. *Lender borrows and lends* is the mean by borrower/month of an indicator variable equal to one when the lender bank both borrows and lends in the previous twelve months. *% of lenders that borrow from bank i* is the mean by borrower/month of an indicator variable equal to one when the lender bank borrows in the previous twelve months from bank *i*. *% of lenders that borrow from bank i* is the mean by borrower/month of an indicator variable equal to one when the lender bank borrows in the previous twelve months from bank *i* calculated from the subset of bank i's lenders that both borrow and lend.

TABLE 1, PANEL C: PERSISTENCE AND CORRELATIONS IN RELATIONSHIP MEASURES

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1)	Volume Share	1.000							
(2)	L1.Volume Share	0.908	1.000						
(3)	L2.Volume Share	0.875	0.907	1.000					
(4)	L3.Volume Share	0.851	0.874	0.907	1.000				
(5)	Number Share	0.952	0.874	0.845	0.826	1.000			
(6)	L1.Number Share	0.872	0.952	0.873	0.845	0.916	1.000		
(7)	L2.Number Share	0.842	0.871	0.952	0.873	0.886	0.916	1.000	
(8)	L3.Number Share	0.821	0.842	0.871	0.952	0.866	0.886	0.916	1.000

Note: The unit of observation for variables (1) - (8) is one per borrower / lender / month. *Volume Share* is the amount borrowed in a month from a given lender divided by the total amount borrowed in the month. *Number Share* is the number of days a bank borrows from a particular lender in a month, divided by the number of total borrower / lender / days in the month. *L1-L3* variables are monthly lags of *Volume Share* and *Number Share*. All results are statistically significant at the 1% level.

TABLE 2: DETERMINANTS OF RELATIONSHIP CONCENTRATION

3 Firm-HHI	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log Average Amount	-0.110***	-0.147***	-0.151***	-0.158***	-0.147***	-0.147***	-0.135***	-0.151***
	(0.010)	(0.015)	(0.014)	(0.015)	(0.017)	(0.015)	(0.016)	(0.014)
Log Avg. StDev Amount	-0.475***	-0.594***	-0.642***	-0.658***	-0.580***	-0.594***	-0.526***	-0.588***
	(0.112)	(0.116)	(0.109)	(0.111)	(0.117)	(0.116)	(0.112)	(0.101)
Frequency	-0.332***	-0.271***	-0.287***	-0.261**	-0.289***	-0.271***	-0.314***	-0.307***
	(0.104)	(0.101)	(0.100)	(0.102)	(0.098)	(0.101)	(0.093)	(0.094)
Lent Last Year	-0.048	-0.045	-0.058**	-0.047	-0.048*	-0.046	-0.020	-0.044
	(0.033)	(0.031)	(0.028)	(0.031)	(0.029)	(0.031)	(0.032)	(0.028)
Log Assets		0.045**	0.043	0.057***	0.040**	0.045**	0.025	0.018
		(0.017)	(0.035)	(0.018)	(0.018)	(0.017)	(0.019)	(0.038)
<u>*Opacity*</u> (Morgan 2002)								
Publicly Traded			-0.021					-0.013
			(0.033)					(0.027)
Log Loans			0.003					0.005
			(0.012)					(0.014)
Log Trading Assets			0.003					0.007**
			(0.003)					(0.003)
Log Cash and Deposits			0.026					0.015
			(0.020)					(0.020)
Log Fixed Assets and Premises			-0.032**					-0.019
			(0.013)					(0.015)
Tier 1 Ratio (-)			-0.355					-0.241
			(0.235)					(0.283)
<u>*Financial Characteristics*</u>								
%NPL				-2.479*				-1.373
				(1.322)				(1.282)
Rolling 8Q SD ROA				-4.896				-12.292**
				(4.493)				(4.778)
<u>*Funding Stability*</u>								
%Deposits					-0.273*			-0.232
					(0.146)			(0.143)
<u>*Competitiveness*</u>								
District Ratio						0.111	0.081	0.069
						(0.080)	(0.066)	(0.068)
District FEs	No	No	No	No	No	No	Yes	Yes
Constant	1.771***	1.352***	1.474***	1.280***	1.631***	1.351***	1.563***	2.018***
	(0.072)	(0.183)	(0.246)	(0.195)	(0.262)	(0.183)	(0.217)	(0.368)
Observations	5,256	5,256	5,256	5,139	5,256	5,256	5,256	5,139
Adjusted R^2	0.657	0.666	0.677	0.675	0.673	0.666	0.686	0.707

Note: The sample ranges from 1/1/2003 to 12/31/2007 and includes *frequent* borrowers only, where *frequent* borrowers are defined as banks that borrow 50 days or more in the interbank market within the calendar year. The data comprises 141 *frequent* borrowers and 414 lenders. The dependent variable is *3-Firm HHI*, the sum of the squared value of the percentage of total monthly borrowing from a borrower's three largest relationships. *Log Average Amount* is the logarithm of the average monthly amount borrowed in the previous year. *Log Avg. StDev. Amount* is the logarithm of the monthly average of the standard deviation of the daily amount borrowed, by bank, normalized by the monthly average of daily amount borrowed in the previous year. *Frequency* is the fraction of days we observe banks borrowing in the interbank market per month averaged over the number of months the bank is in the sample. *Lent Last Year* is an indicator variable for whether the borrower lent within the last calendar year, rolling over the sample. *Assets* is the logarithm of bank assets (in US $ millions). *Publicly Traded* is an indicator variable equal to one if a bank has publicly traded stock. *Log Loans* is logarithm of total loans. *Log Trading Assets* is logarithm of total trading assets. *Log Cash and Deposits* is logarithm of total cash and deposits. *Log Fixed Assets and Premises* is logarithm of total fixed assets and premises. Tier 1 Ratio is tier 1 risk based capital divided by risk weighted assets. *%NPL* is total non-performing loans divided by total loans. *Rolling 8Q SD ROA* is the rolling 8 quarter standard deviation of ROA, where ROA is defined as net income divided by assets. *%Deposits* is total deposits divided by assets. *District Ratio* is the number of borrowers divided by the number of lenders in a bank's Federal Reserve district calculated on a monthly basis. Bank characteristics are measured using the Call Report or Y-9C on a quarterly basis. Standard errors are clustered at the bank level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

TABLE 3: DETERMINANTS OF EXISTING RELATIONSHIPS

	Relationship				Max Relationship		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Probit	Probit	Probit	Probit	Probit	Probit	Probit
Same District	0.142***	0.142***	0.130***	0.361***	0.088	0.088	0.091
	(0.030)	(0.030)	(0.030)	(0.040)	(0.138)	(0.138)	(0.139)
Same State	0.217***	0.218***	0.230***	0.434***	0.431**	0.430**	0.429**
	(0.044)	(0.044)	(0.044)	(0.057)	(0.194)	(0.194)	(0.194)
Geographic Distance	-0.030***	-0.030***	-0.043***	-0.031**	0.042	0.041	0.041
	(0.009)	(0.009)	(0.010)	(0.015)	(0.051)	(0.052)	(0.052)
Difference in Assets	-2.494***	-2.502***	-2.545***	-0.693*	-0.282	-0.306	-0.306
	(0.065)	(0.065)	(0.066)	(0.366)	(0.265)	(0.270)	(0.270)
Symmetry	0.930***	0.930***	0.922***	0.834***	0.483***	0.484***	0.485***
	(0.028)	(0.028)	(0.028)	(0.034)	(0.101)	(0.101)	(0.101)
Correlation of %NPL		-0.018	-0.011	-0.032*		-0.036	-0.036
		(0.014)	(0.014)	(0.019)		(0.075)	(0.075)
Correlation of Net Customer Funds			-0.489***	-0.710***			-0.099
			(0.047)	(0.058)			(0.245)
No. of Counterparties					-0.018**	-0.018**	-0.018**
					(0.008)	(0.008)	(0.008)
Constant	-2.750***	-2.746***	-2.678***	-3.684***	-0.700	-0.678	-0.685
	(0.302)	(0.302)	(0.303)	(0.368)	(1.031)	(1.034)	(1.039)
Borrower Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender Fixed Effects	No	No	No	Yes	No	No	No
Observations	118,449	118,449	118,449	111,263	5,415	5,415	5,415
Pseudo R2	0.329	0.329	0.331	0.544	0.287	0.287	0.288

Note: The unit of observation is one per borrower / lender / year, excluding years in which either the borrower or lender is not active. The sample in regressions (1) - (4) includes the set of borrower-lender-year groupings between 140 frequent borrowers and 420 lenders from 2003-2007 for which all variables are populated. Frequent borrowers are defined as banks that borrow 50 days or more in the interbank market within the calendar year. The dependent variable in regressions (1) - (4) is *Relationship*, an indicator variable equal to one if the borrower borrows from the lender in that year. The dependent variable in regressions (5) - (7) is *Max Relationship*, an indicator variable equal to one if the lender is the borrower's most important relationship, in terms of value, in that year. The sample in regressions (5) - (7) includes only observations for which *Relationship* is equal to one. *Same District* is an indicator variable equal to one if the borrower is located in the same Federal Reserve district as the lender. Same State is an indicator variable equal to one if the borrower is located in the same state as the lender. *Geographic Distance* is the Haversine distance between the regulatory headquarters of the borrower and lender, measured in log miles. *Difference* *in Assets* is equal to the difference between the borrower and lender's assets, divided by the borrower's assets, where borrower and lender's assets are in logarithmic form. *Symmetry* is an indicator variable equal to one if the borrower has lent to the lender in the previous year. *Correlation of %NPL* is the correlation coefficient between the borrower and lender's %NPL in the previous 2 years, where %NPL is total non-performing loans divided by total loans. *Correlation of Net Customer Funds* is the correlation coefficient between the borrower and lender's net customer transfers over Fedwire during March, June, September, and December of the previous year. *No. of Counterparties* is the number of lenders per borrower per year. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

TABLE 4: BANK RELATIONSHIPS AND INTERBANK LOAN TERMS

	Spread				Amount			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
L1.Volume Share	0.028	-0.065***	-0.069***	-0.069***	8.547***	12.063***	9.625***	9.504***
	(0.023)	(0.016)	(0.009)	(0.009)	(0.726)	(0.903)	(0.603)	(0.605)
Symmetry				-0.006**				0.531***
				(0.002)				(0.091)
Borrower FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Lender FE	No	No	Yes	Yes	No	No	Yes	Yes
Time FE	No	No	Yes	Yes	No	No	Yes	Yes
Month FE	Yes	Yes	No	No	Yes	Yes	No	No
Observations	92,675	92,675	92,675	92,675	213,603	213,603	213,603	213,603
Adjusted R^2	0.0807	0.152	0.299	0.299	0.0702	0.156	0.396	0.399

Note: The sample ranges from 1/1/2003 to 12/31/2007. The unit of observation is one per borrower / lender / month (one observation per relationship / month). The sample includes *frequent* borrowers only, where *frequent* borrowers are defined as banks that borrow 50 days or more in the interbank market within the calendar year. *Spread* is the monthly weighted average spread between the banks' loans and the target rate, by relationship. *Amount* is the logarithm of the monthly amount borrowed in the interbank market (in US $ millions), by relationship. *L1.Volume Share* is the previous month's value of *Volume Share*. *Symmetry* is an indicator variable equal to one if the borrower has ever lent to the to the lender in the previous twelve months. Regressions include controls for the logarithm of monthly amount borrowed. Standard errors are clustered at the bank level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

TABLE 5: THE IMPACT OF GSE FUNDING CHANGES

	Spread		Log Amount		Log Amount, Filled		Counterparties	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Counterparty Shock Day	0.002***	0.002*	-0.039***	-0.039***	-0.062***	-0.062***	0.064***	0.067***
	(0.001)	(0.001)	(0.006)	(0.006)	(0.010)	(0.010)	(0.018)	(0.018)
L1.Volume Share	-0.040***	-0.040***	0.889***	0.889***	5.339***	5.339***	-1.098***	-1.098***
	(0.007)	(0.007)	(0.125)	(0.125)	(0.342)	(0.342)	(0.094)	(0.094)
Counterparty Shock Day x	0.004	0.005	0.809***	0.826***	6.601***	6.736***	-0.296***	-0.295***
L1.Volume Share	(0.010)	(0.010)	(0.226)	(0.231)	(1.275)	(1.300)	(0.087)	(0.088)
GSE Shock Day		0.002*		0.032***		0.040***		-0.008
		(0.001)		(0.009)		(0.013)		(0.009)
Counterparty Shock Day x		0.007***		-0.017*		-0.041**		-0.025
GSE Shock Day		(0.002)		(0.010)		(0.016)		(0.025)
Counterparty Shock Day x		-0.014		-0.155*		-1.320***		-0.006
L1.Volume Share x GSE Shock Day		(0.009)		(0.089)		(0.402)		(0.066)
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes		
Maintenance Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter End FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	593,251	593,251	593,251	593,251	3,730,479	3,730,479	80,928	80,928
Adjusted R^2	0.243	0.243	0.750	0.750	0.239	0.239	0.849	0.849

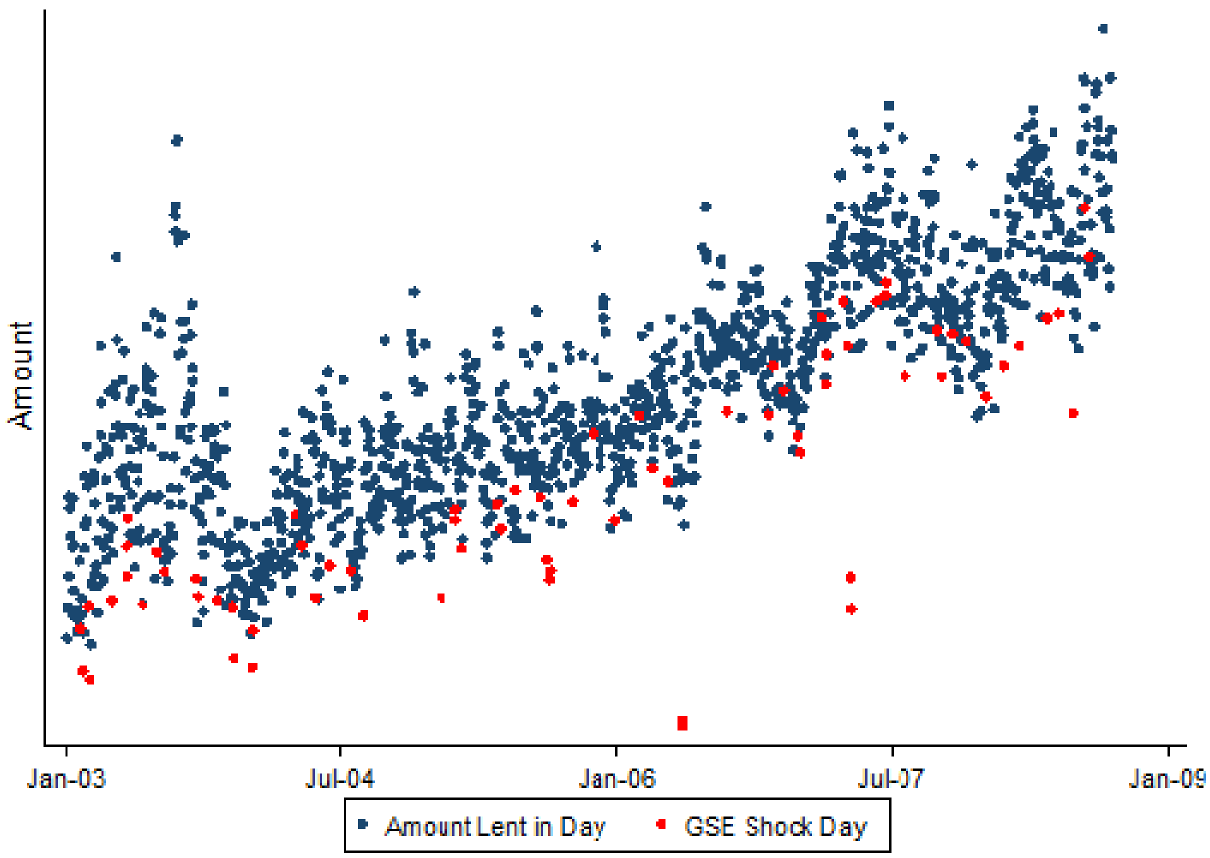
Note: The sample ranges from 1/1/2003 through 12/31/2007.The unit of observation for regressions (1) to (6) is one per borrower / lender / day (one observation per relationship / day) and the unit of observation in regressions (7) to (12) is one per borrower / day. The sample includes *frequent* borrowers only, where a *frequent* borrower is defined as a bank that borrows 50 days or more in the interbank market within the calendar year. The sample excludes any relationships where the lender is a GSE. *Spread* is the daily weighted average spread between the banks' interbank loans and the target rate, by relationship. *Log Amount* is the logarithm of the daily amount borrowed in the interbank market, by relationship. *Log Amount*, *Filled* is *Log Amount* filled in with 0's on days where the borrower borrows from at least one of its lenders. *Counterparties* is the number of counterparties the borrower transacted with on that day. *Weighted Average Spread* is the average monthly *Spread*, weighted by amount. *Counterparty Shock Day* is an indicator variable, equal to one on a given borrower-day if one of the borrower's GSE lenders from any point in the sample is having a 5% lowday. In specifications (1) to (6), L1.Volume Share is the previous month's value of Volume Share. In specifications (7) to (12), L1.Volume Share is equal to the previous month's value of 3-Firm HHI, the sum of the squared value of the percentage of total monthly borrowing from a borrower's three largest relationships. *GSE Shock Day* is an indicator variable, equal to one on days of low GSE lending, where low GSE lending is defined as the bottom 5% of residuals across the sample in a regression with controls for anticipated low days. Standard errors are clustered at the bank level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

TABLE 6: THE IMPACT OF IDIOSYNCRATIC DEMAND SHOCKS

	Spread		Log Amount		Log Amount, Filled		Counterparties	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
L1.Volume Share	0.011	-0.018	1.198***	1.201***	6.582***	6.626***	-1.080***	-1.080***
	(0.035)	(0.034)	(0.213)	(0.214)	(0.447)	(0.450)	(0.181)	(0.181)
1 week pre-Lehman (9/5-9/11)	0.055***	0.062***	0.019	-0.014	0.107*	0.080	0.123***	0.193**
	(0.009)	(0.010)	(0.020)	(0.022)	(0.057)	(0.059)	(0.044)	(0.076)
Friday (9/12)	0.145***	0.149***	0.001	0.019	0.053	0.046	0.107**	0.196**
	(0.009)	(0.011)	(0.039)	(0.039)	(0.070)	(0.072)	(0.054)	(0.091)
Monday (9/15)	0.270*	0.222	-0.065*	-0.072*	-0.074	-0.028	-0.039	0.034
	(0.152)	(0.180)	(0.038)	(0.040)	(0.076)	(0.077)	(0.062)	(0.087)
Tuesday (9/16)	-0.155**	-0.230***	0.016	0.006	-0.052	-0.043	0.033	0.095
	(0.071)	(0.084)	(0.026)	(0.031)	(0.060)	(0.060)	(0.061)	(0.089)
Post-AIG, Pre-IOR (9/17-10/8)	-0.368***	-0.426***	-0.029*	-0.010	-0.053	-0.022	-0.008	-0.050
	(0.050)	(0.057)	(0.017)	(0.019)	(0.049)	(0.048)	(0.040)	(0.068)
L1.Volume Share x		-0.054**		0.259***		0.650**		-0.163
1 week pre-Lehman (9/5-9/11)		(0.023)		(0.085)		(0.283)		(0.112)
L1.Volume Share x		-0.027		-0.141		0.150		-0.208
Friday (9/12)		(0.024)		(0.160)		(0.370)		(0.130)
L1.Volume Share x		0.413		0.057		-1.129***		-0.179
Monday (9/15)		(0.309)		(0.169)		(0.388)		(0.157)
L1.Volume Share x		0.633***		0.084		-0.237		-0.156
Tuesday (9/16)		(0.163)		(0.167)		(0.497)		(0.152)
L1.Volume Share x Post-AIG,		0.495***		-0.166		-0.793***		0.110
Pre-IOR (9/17-10/8)		(0.101)		(0.102)		(0.229)		(0.108)
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes		
Maintenance Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter End FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Assets x Time Period Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	101,485	101,485	101,485	101,485	507,885	507,885	15,692	15,692
Adjusted R^2	0.213	0.216	0.743	0.743	0.241	0.241	0.788	0.788

Note: The sample ranges from 4/1/2008 through 2/28/2009. The unit of observation in specifications (1) to (6) is one per borrower / lender / day (one observation per relationship / day) and the unit of observation in specifications (7) and (8) is one per borrower / day. The sample includes frequent borrowers only, where a frequent borrower is defined as a bank that borrows 50 days or more in the interbank market within the calendar year. *Spread* is the daily weighted average spread between banks' loan rates and the target rate, by relationship. *Log Amount* is the logarithm of the daily amount borrowed in the interbank market (in U.S. $ millions), by relationship. *Log Amount*, *Filled* is *Log Amount* filled in with 0's on days where the borrower borrows from at least one of its lenders. *Counterparties* is the logarithm of the daily number of a bank's unique counterparties. *Weighted Average Spread* is the average monthly Spread, weighted by amount. In specifications (1) to (6), *L1.Volume Share* is the previous month's value of *Volume Share*. In specifications (7) and (8), *L1.Volume Share* is the previous month's value of *3-Firm HHI*, the sum of the squared value of the percentage of total monthly borrowing from a borrower's three largest relationships. *1 week pre-Lehman*, *Friday, Monday,Tueday, and Post-AIG, Pre-IOR* are indicator variables, equal to one on the specified days in 2008. Standard errors are clustered at the bank level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

FIGURE 1: GSE LENDING AND SHOCK DAYS



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APPENDIX

VARIABLE	DEFINITION
Average Amount	Average daily amount borrowed by the bank in U.S. $ millions
Avg StDev Amount	Average of the standard deviation of the daily amount borrowed by the bank normalized by the monthly average of daily amount borrowed
Volume Share	Monthly amount borrowed from a lender divided by the borrower's total borrowing (from all lenders) in that month estimated calculated over the previous month
Number Share	The number of days a bank borrows from a particular lender in a month, divided by the number of total borrower / lender / days in the month
3-Firm HHI	The sum of the squared value of the percentage of total monthly borrowing from a borrower's three largest relationships
Frequency	The fraction of days we observe banks borrowing in the interbank market per month averaged over the number of months the bank is in the sample.
Lent Last Year	Indicator variable for whether the borrower lent within the last calendar year, rolling over the sample.
Log Assets	Logarithm of bank assets in U.S. $ billions
Publicly Traded	Indicator variable equal to one if the bank has publicly traded stock
Log Loans	Logarithm of total loans
Log Trading Assets	Logarithm of trading assets
Log Cash and Deposits	Logarithm of total cash and deposits
Log Fixed Assets and Premises	Logarithm of total fixed assets and premises
Tier 1 Ratio	Tier 1 risk based capital divided by risk weighted assets
% NPL	Proportion of non-performing loans to total loans, measured as of the previous quarter
Rolling 8Q SD ROA	Rolling 8Q Standard Deviation of ROA, defined as net income divided by assets
% Deposits	Total deposits divided by assets, measured as of the previous quarter
District Ratio	Ratio between the monthly average number of borrowers that borrowed in a bank's Federal Reserve district and the monthly average number of lenders in the same district.

Same District	Dummy variable equal to one if the borrower and lender are headquartered in the same Federal Reserve district
Same State	Dummy variable equal to one if the borrower and lender are headquartered in the same state
Geographic Distance	The Haversine distance between the regulatory headquarters of the borrower and lender, measured in log miles.
Difference in Assets	Difference between the borrower’s and lender’s assets (in U.S. $ billions), normalized by the borrower’s assets, and measured as of the previous quarter
Symmetry	Indicator variable equal to one if the borrower has lent to the lender in the previous year
Correlation of %NPL	The correlation coefficient between the borrower and lender’s %NPL in the previous 2 years, where %NPL is total non-performing loans divided by total loans
Correlation of Net Customer Funds	The correlation coefficient between the borrower and lender’s net customer transfers over Fedwire during March, June, September, and December of the previous year.
Average Net Customer Funds	The average customer funds transfers over Fedwire (in U.S. $ billions) during March, June, September, and December of the previous year.
Counterparty Shock Day	Indicator variable, equal to one on a given borrower-day if one of the borrower's GSE lenders from any point in the sample is having a 5% lowday.
GSE Shock Day	Indicator variable, equal to one on days of low GSE lending, where low GSE lending is defined as the bottom 5% of residuals across the sample in a regression with controls for anticipated low days.

TABLE A1: SUMMARY STATISTICS

	Obs.	Mean	StDev.	25%	50%	75%
One Observation per Possible Relationship						
Relationship	119,700	0.057	0.232	0.000	0.000	0.000
Same District	119,700	0.118	0.323	0.000	0.000	0.000
Same State	119,700	0.047	0.211	0.000	0.000	0.000
Log Geographic Distance	119,700	6.597	1.096	6.165	6.735	7.357
Difference in Assets	119,700	0.095	0.152	0.006	0.110	0.201
Symmetry	119,700	0.030	0.171	0.000	0.000	0.000
Correlation of %NPL	119,700	0.067	0.487	-0.303	0.023	0.464
Correlation of Net Customer Funds	119,700	0.009	0.147	-0.074	0.000	0.086
One Observation per Relationship						
Max Relationship	6,825	0.038	0.190	0.000	0.000	0.000
Same District	6,825	0.156	0.363	0.000	0.000	0.000
Same State	6,825	0.073	0.260	0.000	0.000	0.000
Log Geographic Distance	6,825	6.373	1.218	5.959	6.551	7.130
Difference in Assets	6,825	0.126	0.184	0.030	0.156	0.258
Symmetry	6,825	0.243	0.429	0.000	0.000	0.000
Correlation of %NPL	6,825	0.138	0.536	-0.275	0.125	0.617
Correlation of Net Customer Funds	6,825	0.001	0.153	-0.087	0.000	0.091

Note: The unit of observation is one per borrower / lender / year, excluding years in which either the borrower or lender is not active. The sample in the upper statistics includes the set of borrower-lender-year groupings between 140 frequent borrowers and 420 lenders from 2003-2007 for which all variables are populated. Frequent borrowers are defined as banks that borrow 50 days or more in the interbank market within the calendar year. The sample in the lower statistics includes only observations for which Relationship is equal to one. *Relationship* is an indicator variable equal to one if the borrower borrows from the lender in that year. *Max Relationship* is an indicator variable equal to one if the lender is the borrower's most important relationship, in terms of value, in that year. *Same District* is an indicator variable equal to one if the borrower is located in the same Federal Reserve district as the lender. *Same State* is an indicator variable equal to one if the borrower is located in the same state as the lender. *Log Geographic Distance* is the Haversine distance between the regulatory headquarters of the borrower and lender, measured in log miles. *Difference in Assets* is equal to the difference between the borrower and lender's assets, divided by the borrower's assets, where borrower and lender's assets are in logarithmic form. *Symmetry* is an indicator variable equal to one if the borrower has lent to the lender in the previous year. *Correlation of %NPL* is the correlation coefficient between the borrower and lender's %NPL in the previous 2 years, where %NPL is total non-performing loans divided by total loans. *Correlation of Net Customer Funds* is the correlation coefficient between the borrower and lender's net customer transfers over Fedwire during March, June, September, and December of the previous year.

TABLE A2: PERSISTENCE AND CORRELATIONS IN RELATIONSHIP MEASURES

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1)	3 Firm-HHI	1.000							
(2)	L1.3 Firm-HHI	0.918	1.000						
(3)	L2.3 Firm-HHI	0.892	0.918	1.000					
(4)	L3.3 Firm-HHI	0.873	0.893	0.919	1.000				
(5)	Max Volume Share	0.990	0.910	0.886	0.865	1.000			
(6)	L1.Max Volume Share	0.908	0.990	0.910	0.886	0.913	1.000		
(7)	L2.Max Volume Share	0.883	0.908	0.990	0.910	0.887	0.912	1.000	
(8)	L3.Max Volume Share	0.863	0.884	0.909	0.990	0.866	0.888	0.913	1.000

Note: The unit of observation for variables (1) - (8) is one per borrower / month. *3 Firm-HHI* is the sum of the squared value of the percentage of total monthly borrowing from a borrower's three largest relationships. *Max Volume Share* is the maximum of a borrower's *Volume Share* in a month. L1-L3 variables are monthly lags of *3 Firm-HHI* and *Max Volume Share*. All results are statistically significant at the 1% level.