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Abstract

There is substantial heterogeneity in the structure of trading relationships in the U.S. overnight interbank lending market: Some banks rely on spot transactions, while most form stable, concentrated borrowing relationships to hedge liquidity needs. As a result, borrowers pay lower prices and borrow more from their concentrated lenders. Exogenous shocks to liquidity supply (days with low GSE lending) lead to marketwide drops in liquidity and a rise in interest rates. However, borrowers with concentrated lenders are almost completely insulated from the shocks, while liquidity transmission affects the rest of the market via higher interest rates and reduced borrowing volumes.

Key words: interbank lending, OTC markets

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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, for which we can obtain detailed information on individual transactions. We analyze how trading relationships in this market are formed and how they affect the pricing and transmission of liquidity shocks across banks. We show that a majority of banks in the interbank market form long-term, stable lending relationships, which have a significant impact on how liquidity shocks are transmitted across the market.

A number of theory papers have proposed models of the OTC markets. 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 (2012a) 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. Importantly, these models assume that counterparties in the OTC market engage in spot transactions and participants in the market have symmetric information about each other's types. They, however, do not allow for the endogenous formation of relationships between counterparties. While we believe that these theories capture some of the fundamental economic forces in the interbank market, our results show that it is of importance to understand the nature of the relationships through which liquidity is provided and shocks spread through the market.

Unlike the OTC markets envisioned in most theory models in which counterparties are randomly matched for spot transactions, we document large and persistent heterogeneity in the extent to which some banks concentrate lending and borrowing across counterparties. First, we show that a significant fraction of banks rely on a small number of dedicated counterparties to fill most of their liquidity needs, while others access the spot market to transact with lenders on an ongoing basis. It appears that banks which have higher demand for hedging their liquidity needs are more likely to rely on concentrated credit relationships: Banks that borrow from a more concentrated and stable set of lenders (we will also call these banks that rely more on relationships) tend to be smaller, borrow smaller amounts and access the market less frequently. In addition, concentrated borrowers have a lower ratio of deposits to assets and more trading assets. After controlling for size and amount borrowed, standard measures for bank opacity (% loans, % opaque assets) were not associated with concentration. This might suggest that relationships are created to mitigate liquidity shocks between counterparties but not to reduce information asymmetry between banks, as might have been suggested by traditional relationship lending models, see for example Rajan (1992) or Boot and Thakor (1994). The liquidity hedging story also seems to be corroborated by the pattern of counterparty matching between lenders and borrowers in the interbank market: Holding constant geographic proximity, counterparties tend to be dissimilar in the timing of their liquidity needs: Counterparties are negatively correlated in customer payment patterns, and in the ratios of non-performing loans.

Second, we look at the role of counterparty concentration in determining borrowers' 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 better interest rates. These findings are consistent with a model where some banks match with lenders whose liquidity needs are negatively correlated with their own and they can thus insure each other against liquidity shocks at favorable rates. Alternatively, the finding could potentially be explained by a model where more opaque borrowers need to form relationships with more informed lenders, which are willing to lend to them at better prices. However, given the prior result that counterparties do not match due to lower transparency, we believe that it is more likely that the observed concentration of relationships reflects the need for liquidity hedging between counterparties.

Third, to understand the role of relationships in the pricing of liquidity and the transmission of supply shocks we look at shocks to the aggregate supply of and idiosyncratic demand for liquidity. We first look at the impact of large unpredicted shocks to the supply of liquidity. Our proxy for supply shocks is days when Government Sponsored Enterprise (GSE) lending is unusually low.[1] Specifically, we identify the ten percent of days in each calendar year where GSEs lend the least. We verify that these days are unrelated to macroeconomic or banking level indicators. According to market participants, incidences of low GSE lending are due to unpredicted changes in mortgage prepayments and other mortgage features. Controlling for borrower and lender fixed effects we find that the GSE supply shocks are transmitted throughout the market: Overall, on days when GSEs lending is unusually low, spreads increase by 2.4 basis points while total borrowing falls for the average borrower in the market. However, it is exactly the banks that borrow the most from GSEs but also have concentrated lenders, which are able to

[1] 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.

expand the amount they borrow from their largest non-GSE lenders without facing significantly higher cost of credit. These results support the idea that lenders provide preferential access to liquidity or liquidity insurance to their concentrated borrowers. Surprisingly, these lenders do not seem to take advantage of their increased bargaining power and demand an interest rate premium for this liquidity insurance. Instead we find that banks which do not have concentrated lenders experience a drop in access to liquidity and an increase in the cost of borrowing on days with low supply of liquidity.

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 which 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. While the results underscore the importance of understanding relationships in this OTC market, 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 want to see if we find similar patterns of transmission for idiosyncratic demand shocks (measured as days where borrowers have the highest 10% largest one day borrowing). We do not find that spreads go up when borrowers have high demand for liquidity. Concentrated counterparties do not seem to take advantage of their increased bargaining power on high demand days. At the same time, borrowers are able to access more liquidity from their most concentrated lenders. This suggests that concentrated lenders provide insurance to banks with volatile liquidity needs. Interestingly, we also see that there is almost no transmission of these idiosyncratic liquidity shocks to other borrowers in the interbank market. Contrary to the findings for aggregate supply shocks, average spreads do not go up and we see no crowding out of liquidity from other borrowers, even for banks with more concentrated lenders. This lack of contagion suggests that borrowers use relationships to obtain liquidity insurance.

One benefit of the overnight interbank market relative to other OTC markets is that we can analyze transactions using estimates on counterparties, prices and amounts extracted from Federal Reserve payments data. Specifically, transactions used in this study are identified as overnight loans from the universe of all Fedwire Funds Service (Fedwire) 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[2] may not be a reliable method of identifying federal funds transactions.[3] 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

[2] 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.

[3] 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.

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.[4]

Overall, our findings support a view that participants in the overnight interbank market concentrate trading partners, especially borrowers that otherwise might find it difficult to access the market, such as smaller banks. Interestingly, lenders provide preferential access to these borrowers and seem to insure them against liquidity shocks. As a result, supply shocks to a subset of borrowers are transmitted to ex ante unaffected parts of the interbank market. These relationships play an important role in pricing and access to liquidity in this market. It is possible that these concentrated relationships may explain some of the stability that we documented in this market after the collapse of Lehman Brothers (Afonso, Kovner and Schoar (2011)).

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, to bargain over the terms of the transaction. Duffie, Gârleanu and Pedersen (2005) are the firsts to introduce search and bargaining characteristics in a model to study trading frictions in OTC markets.[5] Other theoretical contributions propose search-based models to study specific OTC markets. For example, Vayanos and Weill (2008) focuses on the government-bond

[4] 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

[5] 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.

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 (2012a) studies 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 this dynamic setting, when collateral and information acquisition about counterparties are costly, agents rely on a network of relationships to trade in the unsecured market. Similarly to Babus (2012), we find that borrowers with more concentrated lenders get more favorable terms from their most important counterparties. However, unlike in Babus (2012), all transactions are not intermediated by a central counterparty in the US interbank market.

Acharya and Bisin (2010) departs 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) proposes increasing transparency and greater counterparty credit risk management in the market for OTC derivates.

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 the availability of credit and loan terms.[6] Boot and Thakor (1994) studies the gains from durable bank-borrower relationships and shows that upon successful completion of a financed project, loan interest rates and collateral requirements decline. Other theoretical studies predict that loan terms worsen as the relationship

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

lengthens because lenders subsidize borrowers in the early periods and are reimbursed for this subsidy as the relationship matures. Sharpe (1990) and Rajan (1992), for instance, analyze the hold-up problem that may arise from the monopoly power that banks gain as they learn proprietary information about their borrowers. These theories suggest that the bargaining power of lenders increases with the length of time or scale of a bank relationship. Contrary to these predictions, our findings suggest that lenders do not take advantage of their enhanced bargaining power on days with exceptionally low supply of liquidity or unusually high demand for funds.

Several empirical studies conclude that the existence of bank-borrower relationships enhances availability of financing to small businesses and improves loan contract terms such as loan rates and collateral requirements. Petersen and Rajan (1994) finds that relationships with institutional creditors increase availability of credit while Cole (1998) shows that having a pre-existing relationship increases the probability that a lender extends credit to a firm but that the length of the relationship is unimportant. In Berger and Udell (1995), small firms with longer relationships pay lower rates and are less likely to pledge collateral. Similarly, we find that banks that borrow from a more concentrated set of lenders tend to be smaller and, even though they pay slightly higher rates, get their best terms from their most important lenders.

More recent empirical studies examine the importance of relationships for larger and more transparent firms and show that relationship banking positively affects the terms of lending for large syndicated loans (Dahiya, Saunders and Srinivasan (2003), Bharath, Dahiya, Saunders and Srinivasan (2008, 2007), and Ivashina (2009)). In a competitive market, this suggests that borrowers extract the gains from bank relationships, and should thus pay lower spreads on their high relationship loans.

Most of the literature on relationship banking considers the relationship between firms and financial institutions. While there is an empirical literature on the interbank market,[7] most papers do not consider the role of relationships between banks, with the exception of Cocco, Gomes and Martins (2009). Consistent with our findings in the US interbank market, Cocco, Gomes and Martins 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.

III. Data

a. Estimates of interbank overnight 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).[8] As discussed in the introduction, we cannot determine which of these transactions meet the reserve requirements of depository institutions (Regulation D) definition of fed funds and we will thus refer in this paper to the transactions identified by the Research Group's algorithm simply as interbank loans.

[7] For empirical studies on the US interbank market, see Bech and Atalay (2008), Ashcraft and Duffie (2007), Afonso, Kovner and Schoar (2011) and Afonso and Lagos (2012b), among others.

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

Despite its general appeal, the algorithm may generate error by keeping transactions that are not overnight 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 not to mistakenly include tri-party repo transactions we exclude 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.[9]

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.[10] 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.

[9] 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.

[10] 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 federal funds brokers. The algorithm will also miss negative rates.

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 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, 2006 and end the sample on July 31, 2008 to avoid unusual activity associated with the 2008 financial crisis.

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 100 days from July 2005 through July 2008 (frequent borrowers). These frequent borrowers make up more than two thirds of the banks we observe ever borrowing in this time period. In addition to borrowing more often, frequent borrowers borrow larger amounts, with the mean monthly amount for a frequent borrower of $188 million compared to $2 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 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 449 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

The top panel of Table 1 presents summary statistics with one observation per (frequent) borrower in a month, including only months in which the borrower participated in this market.[11] 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. In a given month the average spread paid by borrowers is 7.4 basis points but there is a remarkable amount of variation in the spreads paid by borrowers within a month. The average standard deviation of spreads in a month for the same borrower is 0.11 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* –

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

the average amount borrowed in a month – with a mean and median average amount borrowed of \$188.3 million and \$115.7 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 57% while the average *Volume Share* for a particular lender is 3%. 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.[12]

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 0.48.[13] As shown in Table A3 in the Appendix, *3-Firm HHI* and the *Volume Share* of the top lender are highly correlated (0.992), but *3-Firm HHI* is not as persistent as the relationship measures *Volume Share* and *Number Share*.

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[12] As shown in Table A2 in the Appendix, *Volume Share* and *Number Share* are highly correlated (0.96), 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*.

[13] Less frequent borrowers have even more concentrated relationships with an average *3-Firm HHI* of 0.945.

IV. Determinants of Counterparty Concentration

Theory offers different ways to think about the concentrated trading patterns that we document. Viewed through the lens of the traditional relationship banking literature, relationships may evolve to reduce the costs of information asymmetry. Since lenders accumulate soft information on their trading partners, opaque banks might seek to build relationships with lenders in order to reduce their cost of capital and facilitate access to the interbank market. Since more opaque banks might find it more difficult to go to new lenders when they have increased liquidity needs, their main lending partners would have increased bargaining power to charge higher spreads during these times. Ex ante it is ambiguous how lenders might use their information advantage: Empirically we might see that lenders insure borrowers over time and across changes in market liquidity, e.g., provide liquidity at favorable rates even when overall liquidity dries up. In return we would expect that borrowers pay an "insurance premium" on average. Alternatively, lenders could resort to charging higher cost of capital in times of increased liquidity needs to exploit their information advantage. Even though the price of capital is going up, it is still a beneficial relationship for the borrowers, since they would not have been able to get any liquidity absent this relationship.

An alternative story for why concentrated lending may evolve relies on the idea that banks have inversely correlated demand for liquidity. The nature of information in the relationship may be the knowledge of a counterparty's liquidity needs. If transaction costs of finding counterparties in the interbank market are high, banks may be engaged in repeated interactions 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. Again, the prediction for the relationship between concentration and pricing is uncertain depending on the extent to which participants value the trading relationship. In this paper we seek to document the relationship between concentration and pricing empirically. But first in this section we aim to understand which types of banks have more concentrated interbank relationships and which borrowers borrow from which lenders.

a. Determinants of concentration

We begin by analyzing 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:

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

where b indexes borrowing banks and t_m indexes time in months. $IB_{b,tcp}$ is a vector of characteristics of the borrower's interbank activity in the control period (July through December 2005) including: *Log Average Amount*, the logarithm of the average daily amount borrowed by the bank; *Log Avg StDev Amount*, the logarithm of the average of the standard deviation of the daily amount borrowed by the bank normalized by the monthly average of daily amount borrowed; and *Frequency*, the number of days that the bank borrowed in the control period.

$X_{b,t-1}$ 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 (see Morgan (2002)) such as: *Assets*, defined as the logarithm of assets; *Publicly Traded*, an indicator variable equal to one if the bank has publicly traded stock; *% Loans*, the proportion of total loans to total assets; *% Trading Assets*, the proportion of trading assets to total assets; *% Transparent Assets*, the proportion of cash, fed funds sold, repos purchased and guaranteed AFS and HTM to total assets; and *% NPL*, the proportion of non-performing loans to total loans. We also examine measures of profitability such as *Tier 1 Ratio* and *ROA* and of stability of funding such as *% 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.[14] Variable definitions are summarized in the Appendix.

The results of these specifications are shown in Table 2. As predicted by traditional relationship banking theory (Petersen and Rajan (1994) among others), larger banks have less concentrated relationships. This is not merely a mechanical function of higher borrowing needs – Even controlling for bank borrowing amount, banks with more assets have less concentrated relationships. 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) seem to have more concentrated trading, although the results are not statistically significant after controlling for bank size and characteristics of their interbank market access. Similarly, banks with less stable funding have more concentrated relationships. This suggests that longer term trading relationships may be valuable because they provide access to funding, and also suggests that banks do not necessarily need to add lenders to meet variable funding needs. Of course, from the cross sectional analysis we cannot rule out a story where better and larger banks borrow more and have access to more lenders because they are more creditworthy. Banks with a higher proportion of trading assets (to total assets) have more concentrated

[14] 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.

relationships. Beyond bank size and trading assets, we do not find consistent, statistically significant results that bank opacity is associated with concentrated relationships. The percentage of loans and the proportion of non-performing loans are negatively associated with HHI, while the percentage of transparent assets is positively associated; neither is statistically significant. Interestingly, it does not seem to matter if banks are publicly traded (column (5)), suggesting that information produced by the equity markets may not be relevant in this market. 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 (3)).

b. Determinants of existing relationships

We next look at which borrowers pair with which lenders. We begin by creating a balanced panel of all possible borrower/lender pairings between 135 frequent borrowers and 449 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 between July 1, 2005 and July 31, 2008. The mean of *Relationship* is 0.047 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:

$$\begin{aligned} Relationship_{b,l} &= \beta(Geography_{b,l}) + \lambda(Difference\ in\ Assets_{b,l}) + \theta(Similarity\ of\ Cash\ Flows_{b,l}) + \\ &+ \delta(X_b) + \chi(Y_l) + \varepsilon_{b,l} \end{aligned} \qquad [2]$$

where b indexes borrowers and l indexes lenders, and $Geography_{b,l}$ is a vector of location characteristics including *Same District* and *Same State*. $Difference\ in\ Assets_{b,l}$ is the difference between the borrower's and lender's assets (in logarithms), normalized by the logarithm of the borrower's assets, measured as of the previous quarter end. *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*. X_b and Y_l are vectors of controls for borrower and lender characteristics, measured as of the previous quarter end, such as *Assets, % NPL* or *Average Net Customer Funds*. Detailed variable definitions are available in the Appendix.

We use these different measures of the similarity of banks (geography, regulatory, size, risk, and cash flow patterns) to understand whether banks choose to trade with similar or different counterparties. In columns (1)-(4) of Table 3 we add each control consecutively. Specification (4) of Table 3 includes all the measures of banks' businesses, and we find that banks are more than 80% more likely to pair with banks in the same district and on top of that more than 67% more likely to contract with banks in the same state. While banks pair with other banks in the same geography, they are matching with otherwise dissimilar banks. A one standard deviation higher correlation in borrower/lender NPLs makes the probability of trading 8% lower. Banks also choose dissimilar counterparties in terms of size: the higher the difference in assets the more likely is trade between these two banks. 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 which may have more excess cash precisely when their own liquidity needs are higher.

Next we look at a borrower's top lender to understand if the relationship with the top lender is different or not from the borrower's other relationships. We estimate a probit model where the variable of interest is now *Maximum Relationship,* which is an indicator variable equal to one for the lender who lent the most funds to the borrower. Results are summarized in columns (5)-(8) in

Table 3. We see a similar pattern in banks' top counterparties (column (8)). 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).

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. However, geographic considerations appear to be important. Lending to close by banks could reflect monitoring (it is easier to monitor close by 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. Of course, to the extent that the algorithm 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.

V. The Effects of Concentration on Interbank Loan Terms

We next test to see 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:

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

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. 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}). Due to computational limitations, instead of including dummy variables, the proxy used for fixed effects is the average spread or amount for the borrower, lender or day. Specifically, we estimate how counterparty concentration is correlated with spread (or amount) controlling for

(1) The average spread (or amount) that this borrower pays on average,
(2) The average spread (or amount) this lender lends to its counterparties, and
(3) The average spread (or amount) of lending in the overall market on that date.

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 rows (1)-(3) the term of the loan is the spread between the loan rate and the target rate while in rows (4)-(6) the term is the amount borrowed. In row (1) we report the results of regressing the interest rate spread on *Volume Share* only controlling for calendar month fixed effects.[15] 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. In rows (2) and (3) we successively add borrower fixed effects, lender fixed effects and month fixed effects. Interestingly, in row (2) we see that once we add our proxy for a borrower fixed effect to

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

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. 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 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.

In rows (4) to (6) 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 row (4) 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 rows (5) and (6) 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.

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 idiosyncratic shocks to the demand for credit and 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 32.4% of overall funding from July 1, 2005 through July 31, 2008. GSE lending is 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 as an instrument for exogenous shocks to the supply of liquidity in this market. There do not appear to be seasonal or other patterns in days with low GSE lending and thus they are unlikely to be anticipated by borrowers. We ran a number of tests trying to predict whether the low GSE lending dates are predicted by macroeconomic indicators, credit spreads or other variables that could be correlated with activities in the mortgage markets. But we do not find any explanatory power for any of the variables. We also talked to a few participants in the fed funds market and they suggested that these days are random and participants are not likely to foresee them. Each year we identify the smallest 10% of GSE lending days, and create a dummy variable equal to 1 on these *GSE Shock* days. We examine the relationship between concentration and loan terms on *GSE Shock* days. Specifically, we estimate a specification with a loan term (spread, amount or counterparties) as the dependent variable, estimating the importance of *GSE Shock* days and adding an indicator variable identifying banks for which a GSE is a top lender (*GSE Top Lender*), for whom these shocks may be particularly important:

$$\begin{aligned} Loan\,Term_{b,l,t_d} &= \beta(Volume\ Share_{b,l,t_m-1}) + \delta(GSE\ Shock_{t_d})(Volume\ Share_{b,l,t_m-1}) + \\ &+ \lambda(GSE\ Shock_{t_d}) + \eta(GSE\ Top\ Lender_b) + \varphi_b + \gamma_l + \kappa_{t_d} + \varepsilon_{b,l,t_d} \end{aligned} \quad [4]$$

where b indexes bank borrowers, l indexes bank lenders, t_m indexes time in months and t_d indexes time in days. $Volume\ Share_{b,l,t_m\text{-}1}$ 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. $GSE\ Shock_{t_d}$ is a dummy variable equal to 1 on days with the lowest 10% of GSE lending of the calendar year, calculated only for borrowers with GSE access. $GSE\ Top\ Lender_b$ is an indicator variable equal to 1 for banks for whom a GSE is their top lender in the control period (July through December 2005). φ_b and γ_l are fixed effects for borrowers and lenders, respectively. Due to computational limitations, instead of including dummy variables, the proxy used for fixed effects is the average spread, amount or counterparties for the borrower and lender. κ_{td} 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.

The first two columns of Table 5 have as the dependent variable the transaction spread to the fed funds target rate. The coefficient on *GSE Shock* is positive (0.024) and significant at the 1% level. Thus, on days where there is a shortfall in GSE liquidity, interest rates rise on average in the market. When we include an interaction term of *GSE Shock* and a dummy indicating if the GSE was the top lender to this bank (*GSE Top Lender*) in column (2), we see that there is an additional impact on those banks of almost 1 basis point (this is economically important since the average spread is 0.12 basis points). This means that banks that are directly affected by the absence of the GSE lenders since they are large borrowers from the GSEs, see an even larger increase in the cost of funding.

Next, we repeat the results 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. While the average loan size seems to drop on days of GSE shocks, the positive coefficient on the triple interaction suggests that borrowers for which the GSEs are the main lenders see a bigger drop in loan size unless they have concentrated lenders. In columns (5) and (6) we repeat these regressions including the latent demand for loans by including 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 5. The results in columns (5) and (6) show that there is a significant reduction in the amount of loans that are provided on days of a *GSE Shock*: the average loan size is 2% smaller. There seems to be an even bigger effect for the borrowers for which the GSEs are their main lenders. But interestingly, the positive and significant coefficient on the triple interactions term (*Volume Share* x *GSE Top Lender* x *GSE Shock*) suggests that the increases in borrowing on shock days appear to come from high concentration lenders. In contrast, most of the drop in lending happens at the extensive margin (when we include zeros for the loans that did not happen).

Finally, in columns (7) and (8) the dependent variable is the logarithm of the number of counterparties of the borrower. While the number of counterparties increases overall, we do not see differential adjustment for concentrated borrowers, perhaps because their need have already been met by their relationship counterparties.

Overall these results suggest that in contrast to idiosyncratic liquidity shocks, GSE shocks are transmitted throughout the market in the form of higher spreads and smaller loans even to banks that do not borrow from the GSEs. Surprisingly, while spreads increase significantly on GSE shock days, the lenders do not seem to take much advantage of their increased bargaining power over their concentrated borrowers (column (1)), and in fact they are likely expanding borrowing from their high *Volume Share* lenders. Results are similar when calculated at the borrower level, rather than the borrower-lender level – highly concentrated borrowers are not disproportionately affected by aggregate supply shocks.

VII. The Effects of Concentration on Loan Terms in the Presence of Demand Shocks

Overnight interbank markets are one of banks' last recourses for funding in response to liquidity shocks. Therefore it is possible that relationships in this market play a special role in maintaining access to funding when banks suffer idiosyncratic demand shocks. However, these may also be precisely the times at which borrowers' bargaining power is the lowest. In this section, we examine what happens to borrowers with concentrated lenders when they need liquidity.

We first identify days on which borrowers have high demands for funds, identifying *High Demand* with a dummy variable equal to one on days where the bank's borrowing is at the top 10% highest of days in the calendar year. While these high demand days are more likely to occur on the first trading day of the week and in December, the correlation across banks of *High Demand* days is relatively low. We also repeat the analysis excluding maintenance days, quarter-end days, Mondays and December and find similar results. On average, eight banks experience a *High Demand* day on a single day, with ten banks experiencing a *High Demand* day on the same day at the 75th percentile. While some individual pairs of banks have correlated *High Demand* days, we do not find systematic correlations in these days for banks by asset size. We therefore interpret the *High Demand* days as incidences where a given bank has an idiosyncratic shock to the *demand* for liquidity. Absent a truly exogenous instrument for liquidity one could worry that these are days of especially high *supply* rather than demand. However, our estimated effects on price and number of counterparties strongly suggest that these are demand effects as we will show in the following tables.

We examine the relationship between concentration and loan terms on *High Demand* days, estimating a specification similar to equation [3], where we add *High Demand* and an interaction between previous month *Volume Share* and the *High Demand* dummy variable:

$$\begin{aligned} Loan\,Term_{b,l,t_d} = {} & \beta(Volume\ Share_{b,l,t_m-1}) + \delta(High\ Demand_{b,t_d})(Volume\ Share_{b,l,t_m-1}) + \\ & + \lambda(High\ Demand_{b,t_d}) + \varphi_b + \gamma_l + \kappa_{t_d} + \varepsilon_{b,l,t_d} \end{aligned} \qquad [5]$$

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. $High\ Demand_{b,t_d}$ is an indicator variable equal to one on days where the bank's borrowing is at the top 10% highest of days in the calendar year. φ_b and γ_l are fixed effects for borrowers and lenders, respectively. As before, the proxy used for fixed effects is the average spread, amount or counterparties for the borrower and lender. κ_{td} is a fixed effect for days that are the end of a maintenance period or quarter end.

Table 6 summarizes our results. The first two columns have as dependent variable the transaction spread to the target rate. Column (1) regresses the spread on *High Demand* days and a control for the previous month's *Volume Share*. As before we control for borrower and lender fixed effects as well as time period effects. In line with the findings of Table 3 the coefficient on previous month *Volume Share* is negative and significant. But the coefficient on *High Demand* days is insignificant and very close to zero. This suggests that borrowers with idiosyncratic high demand do not face a higher spread on these days. This is in contrast to our results for the market wide supply shock presented in Section VI. However, when we interact *High Demand* and *Volume Share* in column (2) we see that the coefficient on the interaction is positive (0.018) although not significant. This suggests that at worst, some of the pricing advantage offered by concentrated lenders recedes on days in which borrowers have higher demand.

We repeat these specifications but change the dependent variable to the logarithm of the amount borrowed for all transactions in columns (3) and (4), and in columns (5) and (6) we expand the observations to include borrower-lender pairs with no transactions (filled in as 0s) on days where the borrower borrows from at least one of its lenders. This increases our sample size by a factor of five since we include each possible lender that a borrower had interacted with in the past. The idea is to capture latent supply that did not get transacted. Columns (3) and (4) show that on days where a borrower has an idiosyncratic demand shock for liquidity, affected banks borrow an additional 14%, on average. They particularly ramp up lending from their main lenders, borrowing an additional 7% for each 10% increase in concentration. A similar pattern holds in columns (5) and (6) when we include possible supply from past lenders to a given borrower.

Finally, the dependent variable in specifications (7) and (8) is the logarithm of the number of counterparties of the borrower. To create this variable we have to collapse the sample to one observation per borrower day. Column (7) shows that borrowers increase the number of their counterparties by about 38% percent on high demand days. This effect is economically large and statistically significant, since the average borrower in the sample has 2 lenders. In column (8) we now interact high demand and volume share to see the effect of concentration and find that the coefficient on the interaction term is positive (0.039) although not significant. This result suggests that banks with concentrated lenders may disproportionately add more counterparties on days where they have excess liquidity needs.

While on average borrowers receive better terms and more liquidity from their concentrated lenders, on days when borrowers have high idiosyncratic liquidity demands, they fill the liquidity need through a combination of borrowing more from their main lender but also adding more counterparties. These results suggest that trading relationships have an important role in access to liquidity in this market.

VIII. Transmission of Idiosyncratic Demand Shocks

We now want to understand if idiosyncratic liquidity shocks to one bank affect other banks in the market and how these shocks might spread through the market. We begin with the dates on which we identify borrowers as experiencing high demand days. We identify the borrower's top lender and then look at the banks that borrow from that same top lender. We drop borrowers on their high demand dates from the sample, and identify the other counterparties of that lender. The dummy variable *Residual Shock* is thus equal to one on days when a lender to a given borrower is affected by excess demand (i.e. a *High Demand* day) from one of its other borrowers. Since we are interested in measuring the transmission of shocks, we only include shocks where the borrower is important to that lender, i.e. where the high demand borrower constitutes more than 4% of the lender's amount lent (above the median).

Consider the following example. Suppose there are four potential borrowers: Bank X, Y, Z and Q, and two lenders: Lender A and B. On June 4, only three banks borrow from Lender A: Bank X, Y and Z. Suppose that on June 4 Bank X is having a demand shock (*High Demand=1*). We identify Lender A as the *Max Lender* of Bank X. *Residual Shock* is then equal to one for Banks Y and Z who also borrow from Lender A on June 4. On June 4, *Residual Shock* is equal to zero for Bank Q because it does not borrow from Lender A on that day. On June 5, when Bank X is not having a *High Demand* day, *Residual Shock* is equal to 0 for banks X, Y, Z and Q. Observations for *High Demand* borrowers (Bank X on June 4, for example) are dropped from the analysis altogether.

We estimate equation [5] but replacing *High Demand* with *Residual Shock*, and including only banks that are not experiencing *High Demand* shocks:

$$\begin{aligned} Loan\,Term_{b,l,t_d} &= \beta(Volume\ Share_{b,l,t_m-1}) + \delta(Residual\ Shock_{b,t_d})(Volume\ Share_{b,l,t_m-1}) + \\ &+ \lambda(Residual\ Shock_{b,t_d}) + \varphi_b + \gamma_l + \kappa_{t_d} + \varepsilon_{b,l,t_d} \end{aligned} \qquad [6]$$

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. $Residual\ Shock_{b,t_d}$ is an indicator variable equal to one on days when a borrower's lender is the maximum lender for another bank that is experiencing a high demand day. High demand days are identified as the days when the bank's borrowing is at the top 10% highest in the calendar year. φ_b and γ_l are fixed effects for borrowers and lenders, respectively. Due to computational limitations, instead of including dummy variables, the proxy used for fixed effects is the average spread or amount for the borrower and lender. κ_{t_d} is a fixed effect for days that are the end of a maintenance period or quarter end.

Results are reported in Table 7. Column (1) of Table 7 shows the specification using spread to target as the dependent variable. The coefficient on *Residual Shock* is insignificant and very close to zero (-0.001). When we add the interaction of *Volume Share* with the *Residual Shock* in column (2) the coefficient on *Residual Shock* remains unchanged and the coefficient on the interaction term is insignificant and close to zero as well. In column (3) we include a control for the logarithm of the amount lent, but the results are unchanged. These results suggest that an idiosyncratic liquidity shock to one bank does not affect the interest rates of the rest of the banks that borrow from that lender.

In columns (4) and (5) we repeat these specifications but use the logarithm of the amount borrowed as the dependent variable, and in (6) and (7) we fill in 0s on days where the borrower borrows from at least one of its lenders. The results in column (4) show that the coefficient on *Residual Shock* is negative, although insignificant. This suggests that on average the negative transmission from a shock to a lender onto the other borrowers of the lender is relatively small. But when we interact *Residual Shock* with previous month *Volume Share* in column (5) we see that there is an interesting asymmetry: the coefficient on the direct effect of *Residual Shock* becomes negative (-0.102) and significant at the 1% level, but the coefficient on the interaction term is large and positive (0.368), and also significant at the 1% level. Therefore, we see that there is some transmission of the liquidity shock, since the other borrowers of the affected lender see a decrease in liquidity by about 10%. However, if these other borrowers have a more concentrated set of lenders they seem to be insulated against the *Residual Shock*. In fact, they are able to make up the decrease in liquidity without any increase in their spread.

IX. Conclusion

This is one of the first studies to analyze the importance of concentration in facilitating access to credit and transmitting 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. 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 risk profiles (NPLs) and of cash flows. Small banks in particular choose to form more concentrated lending relationships.

While these concentrated borrowers pay higher spreads on average, they borrow more and face significantly lower spreads from their most important lenders. Similarly, we find that concentrated borrowers are able to expand their access to credit disproportionally during times when they have idiosyncratic demand shocks.

This finding suggests relationships between counterparties are very important in this market. While these patterns are consistent with a market in which search costs are high, we do not find that lenders take advantage of their most concentrated customers by increasing prices on days with market supply shocks. This unwillingness to exploit temporary liquidity needs of the borrower, suggests that the lender's bargaining power might de facto not increase much on these days. Perhaps this is because the search costs for lenders are just as high as for borrowers and they do not want to risk the relationship, or because borrowing banks, even concentrated ones, are able to access additional counterparties when they need to.

These findings could have important implications for other OTC markets where search costs may be high for both borrowers and lenders and where the assessment of counterparty risk is important. On the one hand we find that in such a market relationships seem to form to accommodate idiosyncratic liquidity shocks without disturbing the larger market. While on the other hand, the risk of mutual hold up during times of high liquidity needs is low, since the lender seems to be concerned with maintaining the relationship.

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: SUMMARY STATISTICS

	Obs.	Mean	StDev.	25%	50%	75%
One Observation per Borrower / Month						
Monthly Wght. Avg. Spread	3,540	0.074	0.150	0.002	0.043	0.151
StDev. Spreads	2,706	0.110	0.125	0.038	0.073	0.135
Monthly Avg. Amount	3,540	188.3	210.4	34.0	115.7	272.1
StDev. Monthly Amount	3,359	428.3	677.4	62.9	220.1	509.0
Volume Share, All Lenders	118,572	0.030	0.117	0.000	0.000	0.008
Volume Share, Top Lender	3,540	0.567	0.334	0.239	0.534	0.981
3 Firm-HHI	3,540	0.480	0.377	0.106	0.429	0.963
Counterparties	3,540	16.815	29.870	2	4	17
One Observation per Borrower						
Assets	135	5.196	0.006	1.297	4.347	13.771
%NPL	135	0.006	0.006	0.003	0.004	0.008
%Deposits	135	0.714	0.124	0.679	0.739	0.792
Publicly Traded	135	0.704	0.458	0.000	1.000	1.000
Average Amount	135	262.473	34.278	27.667	286.017	5250.849
Avg. StDev. Amount	135	1.284	1.193	1.081	1.319	1.446
One Observation per Lender						
Assets	449	1.026	0.007	0.284	0.734	2.736
%NPL	449	0.008	0.011	0.001	0.005	0.011

Note: The sample ranges from 1/1/2006 to 7/31/2008 and includes all *frequent* borrowers that borrow in the interbank market over this time period and file a Call Report or Y9-C. *Frequent* borrowers are defined as banks that borrow 100 days or more in the interbank market from 7/1/2005 through 7/31/2008. *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. *Assets* is bank assets (in U.S. $ billions), measured using Call Report or Y-9C as of 12/31/2005. *%NPL* is total non-performing loans divided by total loans. *%Deposits* is total deposits divided by assets as of 12/31/2005. *Publicly Traded* is an indicator variable equal to one if a bank has publicly traded stock. *Average Amount* is the average monthly amount borrowed in the control period (7/2005 – 12/2005). *Avg. StDev. Amount* is 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 control period (7/2005 – 12/2005).

TABLE 2: DETERMINANTS OF RELATIONSHIP CONCENTRATION

3 Firm-HHI	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)	
Log Average	-0.052	***	-0.025	***	-0.026	***	-0.026	***	-0.025	***	-0.026	***	-0.027	***	-0.021	**
Amount	*(0.008)*		*(0.009)*		*(0.009)*		*(0.010)*		*(0.009)*		*(0.010)*		*(0.009)*		*(0.009)*	
Log Avg. StDev	0.082		0.006		0.006		0.007		0.019		0.008		0.031		0.043	
Amount	*(0.105)*		*(0.106)*		*(0.105)*		*(0.106)*		*(0.104)*		*(0.107)*		*(0.100)*		*(0.097)*	
Frequency	-0.001	***	-0.001	***	-0.001	***	-0.001	***	-0.001	***	-0.001	***	-0.001	***	-0.001	***
	(0.000)		*(0.000)*		*(0.000)*		*(0.000)*		*(0.000)*		*(0.000)*		*(0.000)*		*(0.000)*	
Opacity																
Assets			-0.057	***	-0.055	***	-0.057	***	-0.068	***	-0.056	***	-0.060	***	-0.063	***
			(0.015)		*(0.014)*		*(0.015)*		*(0.017)*		*(0.016)*		*(0.014)*		*(0.016)*	
Publicly Traded					-0.022											
					(0.037)											
%Loans							-0.046									
							(0.126)									
%Trading Assets									1.181	***						
									(0.412)							
%Transparent									0.028							
Assets									*(0.130)*							
%NPL											-0.055					
											(1.088)					
Profitability																
Tier 1 Ratio											0.017					
											(0.356)					
ROA											0.688					
											(2.383)					
Funding Stability																
%Deposits													-0.275	*		
													(0.145)			
Competitiveness																
District Ratio															0.120	**
															(0.059)	
Observations	3,540		3,540		3,540		3,540		3,540		3,540		3,540		3,540	
Adj R-squared	0.61		0.64		0.64		0.64		0.65		0.64		0.65		0.65	

Note: The sample ranges from 1/2006 to 7/2008. The sample includes *frequent* borrowers only, where *frequent* borrowers are defined as banks that borrow 100 days or more in the interbank market from 7/1/2005 through 7/31/2008. 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 control period (7/05 – 12/05). *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. *Frequency* is the number of days we observe banks borrowing in the interbank market from 7/1/2005 through 7/31/2008. *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. *%Loans* is total loans divided by assets. *%Trading Assets* is total trading assets divided by assets. *%Transparent Assets* is total transparent assets divided by assets, where transparent assets are comprised of cash, federal funds sold, securities purchased under agreements to resell, and guaranteed available-for-sale as well as held-to-maturity securities. *%NPL* is total non-performing loans divided by total loans. *Tier 1 Ratio* is tier 1 risk based capital divided by risk weighted assets. *ROA* is 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)	(8)
Model	Probit	Probit	Probit	Probit	Probit	Probit	Probit	Probit
Same District	0.249 ***	0.252 ***	0.246 ***	0.248 ***	-0.036	-0.034	-0.033	-0.029
	(0.036)	*(0.036)*	*(0.036)*	*(0.036)*	*(0.150)*	*(0.150)*	*(0.151)*	*(0.151)*
Same State	0.219 ***	0.215 ***	0.220 ***	0.217 ***	0.552 ***	0.581 ***	0.551 ***	0.576 ***
	(0.051)	*(0.052)*	*(0.052)*	*(0.052)*	*(0.179)*	*(0.181)*	*(0.179)*	*(0.182)*
Difference in Assets	0.983 ***	0.924 ***	0.924 ***	0.874 ***	1.599 **	1.729 **	1.579 **	1.731 **
	(0.165)	*(0.166)*	*(0.165)*	*(0.166)*	*(0.795)*	*(0.803)*	*(0.801)*	*(0.810)*
Assets, Borrower	0.250 ***	0.261 ***	0.248 ***	0.257 ***	-0.539 ***	-0.545 ***	-0.533 ***	-0.541 ***
	(0.014)	*(0.014)*	*(0.014)*	*(0.014)*	*(0.106)*	*(0.106)*	*(0.106)*	*(0.107)*
Assets, Lender	0.293 ***	0.293 ***	0.285 ***	0.284 ***	0.253 ***	0.272 ***	0.251 ***	0.274 ***
	(0.018)	*(0.018)*	*(0.018)*	*(0.019)*	*(0.095)*	*(0.096)*	*(0.095)*	*(0.097)*
Correlation of %NPL		-0.097 ***		-0.070 ***		-0.143		-0.156
		(0.022)		*(0.022)*		*(0.107)*		*(0.109)*
%NPL, Borrower		-9.252 ***		-7.655 ***		7.504		7.312
		(1.568)		*(1.539)*		*(5.308)*		*(5.323)*
%NPL, Lender		1.178		1.215		8.082		8.085
		(1.005)		*(1.007)*		*(5.606)*		*(5.637)*
Correlation of Net			-0.446 ***	-0.461 ***			0.026	-0.020
Customer Funds			*(0.121)*	*(0.121)*			*(0.279)*	*(0.281)*
Average Net Customer			-0.057 ***	-0.054 ***			0.007	0.010
Funds, Borrower			*(0.005)*	*(0.005)*			*(0.017)*	*(0.019)*
Average Net Customer			-0.033 ***	-0.032 ***			0.002	0.003
Funds, Lender			*(0.009)*	*(0.008)*			*(0.013)*	*(0.014)*
Fixed Effects	No	No	No	No	No	No	No	No
Observations	60,615	60,615	60,615	60,615	2,832	2,832	2,832	2,832
Pseudo R-squared	0.27	0.27	0.27	0.27	0.26	0.26	0.26	0.26

Note: The unit of observation is one per borrower / lender pair. The sample in regressions (1) - (4) includes the set of all possible borrower / lender pairings between 135 *frequent* borrowers and 449 lenders, where *frequent* borrowers are defined as banks that borrow 100 days or more in the interbank market from 7/1/2005 through 7/31/2008. The dependent variable in regressions (1) - (4) is *Relationship*, an indicator variable equal to one if the borrower borrows from the lender between 7/1/2005 and 7/31/2008. The dependent variable in regressions (5) - (8) is *Max Relationship*, an indicator variable equal to one if the lender is the borrower's most important relationship, in terms of value, from 7/1/2005 through 7/31/2008. The sample in regressions (5) - (8) 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. *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. *Assets* is the logarithm of bank assets (in U.S. $ millions), measured using the Call Report or Y-9C as of the previous quarter on a quarterly basis. *Correlation of %NPL* is the correlation coefficient between the borrower and lender's *%NPL,* measured as of the previous quarter and on quarterly basis from September 30, 2005 to June 30, 2008, 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 2006. *Average Customer Funds* is the average customer funds transfers over Fedwire (in U.S. $ billions) during March, June, September, and December 2006. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

TABLE 4: BANK RELATIONSHIPS AND INTERBANK LOAN TERMS

	Dependent	L1.Volume Share		Borrower FE Proxy		Lender FE Proxy		Time FE Proxy		Monthly Fixed Effects	Obs.	Adjusted R-Squared
1.	Spread	0.036								Yes	59,084	0.08
		(0.029)										
2.	Spread	-0.038	***	1.058	***					Yes	59,084	0.14
		(0.013)		*(0.023)*								
3.	Spread	-0.045	***	0.784	***	0.700	***	1.109	***	Yes	59,084	0.22
		(0.009)		*(0.036)*		*(0.043)*		*(0.084)*				
4.	Amount	6.072	***							Yes	117,139	0.06
		(0.534)										
5.	Amount	7.669	***	0.819	***					Yes	117,139	0.11
		(0.569)		*(0.048)*								
6.	Amount	6.110	***	0.825	***	0.710	***	0.971	***	Yes	117,139	0.29
		(0.414)		*(0.108)*		*(0.049)*		*(0.192)*				

Note: The sample ranges from 1/2006 through 7/2008. 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 100 days or more in the interbank market from 7/1/2005 through 7/31/2008. *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*. The *Borrower Fixed Effect Proxy* is average *Spread* and average *Amount* by borrower, respectively. The *Lender Fixed Effect Proxy* is average *Spread* and average *Amount* by lender, respectively. The *Time Fixed Effect Proxy* is average *Spread* and average *Amount* by month, respectively. Regressions (1) – (3) 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		Amount		Amount, Filled		Counterparties	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GSE Shock	0.024 ***	0.025 ***	-0.022 ***	-0.015 *	-0.023 **	-0.020 *	0.041 ***	0.044 *
	(0.002)	*(0.003)*	*(0.008)*	*(0.009)*	*(0.011)*	*(0.012)*	(0.011)	(0.023)
L1.Volume Share	-0.034 ***	-0.034 ***	0.170	0.174	4.170 ***	4.163 ***	-0.186 ***	-0.187 ***
	(0.006)	*(0.006)*	*(0.114)*	*(0.114)*	*(0.260)*	*(0.259)*	(0.057)	(0.058)
L1.Volume Share x		-0.004		-0.057		-0.102		-0.005
GSE Shock		*(0.005)*		*(0.048)*		*(0.108)*		(0.029)
GSE Top Lender	-0.003	-0.003	-0.119 **	-0.120 **	0.035	0.034	-0.003	-0.002
	(0.002)	*(0.002)*	*(0.054)*	*(0.054)*	*(0.075)*	*(0.075)*	(0.022)	(0.022)
GSE Top x	0.008	0.006	-0.009	-0.064 ***	-0.040	-0.089 ***	-0.093 *	-0.068
GSE Shock	*(0.005)*	*(0.006)*	*(0.015)*	*(0.021)*	*(0.031)*	*(0.028)*	(0.048)	(0.044)
L1.Volume Share x		0.074		2.363 **		6.297 **		-0.427
GSE Top x GSE Shock		*(0.051)*		*(0.924)*		*(2.862)*		(0.266)
Borrower F/E Proxy	0.665 ***	0.664 ***	0.394 ***	0.395 ***	0.298 ***	0.299 ***	0.936 ***	0.935 ***
	(0.030)	*(0.030)*	*(0.041)*	*(0.041)*	*(0.053)*	*(0.053)*	(0.020)	(0.020)
Lender F/E Proxy	0.719 ***	0.719 ***	0.825 ***	0.824 ***	0.303 ***	0.301 ***		
	(0.044)	*(0.044)*	*(0.037)*	*(0.037)*	*(0.034)*	*(0.035)*		
Maintenance Day F/E	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter End F/E	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	366,067	366,067	366,067	366,067	2,036,740	2,036,740	14,217	14,217
Adjusted R-squared	0.16	0.16	0.64	0.64	0.15	0.15	0.91	0.91

Note: The sample ranges from 1/1/2006 through 7/31/2008. The unit of observation is one per borrower / lender / day (one observation per relationship / day). The sample includes *frequent* borrowers only, where *frequent* borrowers are defined as banks that borrow 100 days or more in the interbank market from 7/1/2005 through 7/31/2008. 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. *Amount* is the logarithm of the daily amount borrowed in the interbank market (in U.S. $ millions), by relationship. *Amount, Filled* is *Amount* filled in with 0's on days where the borrower borrows from at least one of its lenders. *L1.Volume Share* is the previous month's value of *Volume Share*. *GSE Shock* is an indicator variable, equal to one on day of low GSE lending. Low GSE lending is defined as the bottom 10% of days, per year, on which GSE lending was lowest. *GSE Top Lender* is an indicator variable, equal to one for borrowers whose most important relationship in the control period, in terms of *Volume Share,* was with a GSE. The *Borrower Fixed Effect Proxy* is average *Spread, Amount,* and *Amount Filled,* respectively, by borrower. The *Lender Fixed Effect Proxy* is average *Spread, Amount,* and *Amount Filled,* respectively, by lender. 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		Amount		Amount, Filled		Counterparties	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High Demand	-0.001	-0.002	0.143 ***	0.100 ***	0.405 ***	0.335 ***	0.376 ***	0.359 ***
	(0.007)	*(0.008)*	*(0.011)*	*(0.013)*	*(0.023)*	*(0.020)*	*(0.016)*	*(0.026)*
L1.Volume Share	-0.028 ***	-0.029 ***	0.346 ***	0.299 ***	4.695 ***	4.479 ***	-0.172 ***	-0.175 ***
	(0.006)	*(0.006)*	*(0.115)*	*(0.114)*	*(0.314)*	*(0.293)*	*(0.062)*	*(0.063)*
L1.Volume Share x High Demand		0.018		0.692 ***		3.411 ***		0.039
		(0.020)		*(0.083)*		*(0.381)*		*(0.055)*
Borrower F/E Proxy	0.640 ***	0.640 ***	0.469 ***	0.470 ***	0.383 ***	0.385 ***	0.933 ***	0.933 ***
	(0.031)	*(0.031)*	*(0.040)*	*(0.040)*	*(0.076)*	*(0.075)*	*(0.021)*	*(0.021)*
Lender F/E Proxy	0.730 ***	0.730 ***	0.819 ***	0.819 ***	0.289 ***	0.288 ***		
	(0.046)	*(0.046)*	*(0.054)*	*(0.054)*	*(0.040)*	*(0.040)*		
Maintenance Day F/E	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter End F/E	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	434,955	434,955	434,955	434,955	2,307,340	2,307,340	14,685	14,685
Adjusted R-squared	0.14	0.14	0.68	0.68	0.16	0.17	0.93	0.93

Note: The sample ranges from 1/1/2006 through 7/31/2008. 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) and (8) is one per borrower / day. The sample includes *frequent* borrowers only, where *frequent* borrowers are defined as banks that borrow 100 days or more in the interbank market from 7/1/2005 through 7/31/2008. *Spread* is the daily weighted average spread between banks' loan rates and the target rate, by relationship. *Amount* is the logarithm of the daily amount borrowed in the interbank market (in U.S. $ millions), by relationship. *Amount, Filled* is *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. In regressions (1) to (6), *L1.Volume Share* is the previous month's value of *Volume Share*. In regressions (7) and (8), *L1.Volume Share* is equal to the previous month's value of *Volume Share* for the borrower's largest relationship, in terms of volume. *High Demand* is an indicator variable, equal to one on days of high demand. *High Demand* is defined as the top 10% of days, per year, on which each bank's borrowings in the interbank market was highest. The *Borrower Fixed Effect Proxy* is average *Spread, Amount, Amount Filled,* and *Counterparties,* respectively, by borrower. The *Lender Fixed Effect Proxy* is average *Spread, Amount, Amount Filled,* and *Counterparties,* respectively, by lender. Standard errors are clustered at the bank level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

TABLE 7: THE RESIDUAL IMPACT OF BORROWER DEMAND SHOCKS

	Spread			Amount		Amount, Filled	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Residual Shock	-0.001	-0.000	-0.001	-0.041	-0.102 ***	-0.012	-0.053
	(0.002)	*(0.002)*	*(0.002)*	*(0.030)*	*(0.032)*	*(0.040)*	*(0.039)*
L1.Volume Share	-0.017 **	-0.016 **	-0.016 **	0.513 ***	0.470 ***	4.276 ***	4.211 ***
	(0.007)	*(0.007)*	*(0.007)*	*(0.109)*	*(0.110)*	*(0.282)*	*(0.278)*
L1.Volume Share x		-0.004	-0.005		0.368 ***		0.598 **
Residual Shock		*(0.007)*	*(0.007)*		*(0.101)*		*(0.256)*
Amount			0.009 **				
			(0.004)				
Borrower F/E Proxy	0.643 ***	0.643 ***	0.721 ***	0.805 ***	0.802 ***	0.740 ***	0.739 ***
	(0.033)	*(0.033)*	*(0.045)*	*(0.044)*	*(0.044)*	*(0.124)*	*(0.124)*
Lender F/E Proxy	0.658 ***	0.658 ***	0.617 ***	0.624 ***	0.625 ***	0.255 ***	0.255 ***
	(0.052)	*(0.052)*	*(0.050)*	*(0.060)*	*(0.060)*	*(0.040)*	*(0.040)*
Maintenance Day F/E	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter End F/E	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	165,875	165,875	165,875	165,875	165,875	577,955	577,955
Adjusted R-squared	0.14	0.14	0.15	0.63	0.63	0.17	0.17

Note: The sample ranges from 1/1/2006 through 7/31/2008. The unit of observation is one per borrower / lender / day (one observation per relationship / day). The sample includes *frequent* borrowers only, where *frequent* borrowers are defined as banks that borrow 100 days or more in the interbank market from 7/1/2005 through 7/31/2008. *Spread* is the daily weighted average spread between the banks' loans and the target rate, by relationship. *Amount* is the logarithm of the daily amount borrowed in the interbank market (in U.S. $ millions), by relationship. *Amount, Filled* is *Amount* filled in with 0's on days where the borrower borrows from at least one of its lenders. *Residual Shock* is equal to one for banks who borrow from another borrower's max lender on days where the other borrower is experiencing a shock, and who have lagged *Volume Share* greater than the median lagged *Volume Share*. *L1.Volume Share* is the previous month's value of *Volume Share*. *Amount* is the logarithm of the daily amount borrowed in the interbank market (in US $ millions), by relationship. The *Borrower Fixed Effect Proxy* is average *Spread, Amount,* and *Amount Filled,* respectively, by borrower. The *Lender Fixed Effect Proxy* is average *Spread, Amount,* and *Amount Filled,* respectively, by lender. Standard errors are clustered at the bank level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

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APPENDIX

VARIABLE	DEFINITION
Average Amount	Average daily amount borrowed by the bank
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
Frequency	Number of days that the bank borrowed in the control period (July through December 2005)
Assets	Bank assets in U.S. $ billions
Publicly Traded	Dummy variable equal to one if the bank has publicly traded stock
% Loans	Proportion of total loans to total assets
% Trading Assets	Proportion of trading assets to total assets
% Transparent Assets	Proportion of cash, fed funds sold, repos purchased and guaranteed AFS and HTM to total assets
% NPL	Proportion of non-performing loans to total loans, measured as of the previous quarter
Tier 1 Ratio	Tier 1 risk based capital divided by risk weighted assets
ROA	Net income divided by assets
% Deposits	Total deposits divided by assets, measured as of the previous quarter

VARIABLE	DEFINITION
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
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
Correlation of %NPL	Correlation between the borrower's and lender's proportion of non-performing loans (over total loans) measured as of the previous quarter
Correlation of Net Customer Funds	Correlation between the borrower's and lender's net customer transfers over Fedwire estimated in March, June, September and December of 2006
Average Net Customer Funds	Average customer funds transfers over Fedwire in March, June, September and December of 2006
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
GSE Shock	Dummy variable equal to 1 on days with the lowest 10% of GSE lending of the calendar year only for borrowers with GSE access
GSE Top Lender	Dummy variable equal to 1 for banks for whom a GSE is their top lender in the control period (July through December 2005)
High Demand	Dummy variable equal to one on days where the bank's borrowing is at the top 10% highest of days in the calendar year
Residual Shock	Dummy variable equal to one on days when a borrower's lender is the maximum lender for another bank that is experiencing a high demand day. High demand days are identified as the days when the bank's borrowing is at the top 10% highest in the calendar year

TABLE A1: SUMMARY STATISTICS

	Obs.	Mean	StDev.	25%	50%	75%
One Observation per Possible Relationship						
Relationship	60,615	0.047	0.211	0.000	0.000	0.000
Same District	60,615	0.114	0.318	0.000	0.000	0.000
Same State	60,615	0.047	0.212	0.000	0.000	0.000
Difference in Assets	60,615	0.165	0.284	0.013	0.211	0.367
Correlation of %NPL	60,615	0.278	0.480	-0.075	0.335	0.696
Correlation of Net Customer Funds	60,615	0.000	0.039	0.000	0.000	0.000
One Observation per Relationship						
Max Relationship	2,832	0.036	0.185	0.000	0.000	0.000
Same District	2,832	0.148	0.355	0.000	0.000	0.000
Same State	2,832	0.070	0.256	0.000	0.000	0.000
Difference in Assets	2,832	0.201	0.331	0.054	0.271	0.439
Correlation of %NPL	2,832	0.390	0.506	0.000	0.528	0.838
Correlation of Net Customer Funds	2,832	0.000	0.170	-0.091	0.000	0.099

Note: The sample ranges from 1/1/2006 to 7/31/2008 and includes all *frequent* borrowers that borrow in the interbank market over this time period and file a Call Report or Y9-C. *Frequent* borrowers are defined as banks that borrow 100 days or more in the interbank market from 7/1/2005 through 7/31/2008. *Relationship* is an indicator variable, equal to one if the borrower borrows from the lender between July 1, 2005 and July 31, 2008. *Max Relationship* is an indicator variable, equal to one if the lender is the borrower's most important relationship, in terms of value, from July 1, 2005 through July 31, 2008. *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. *Difference in Assets* is equal to the difference between the borrower's and lender's assets, divided by the borrower's assets, where borrower and lender's assets are in U.S. $ billions, measured using the Call Report as of 12/31/2005. *Correlation of %NPL* is the correlation coefficient between the borrower and lender's *%NPL,* measured quarterly from 9/30/2005 to 6/30/2008. *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 2006.

TABLE A2: PERSISTENCE AND CORRELATIONS IN RELATIONSHIP MEASURES

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1)	Volume Share	1.000							
(2)	L1.Volume Share	0.895 ***	1.000						
(3)	L2.Volume Share	0.862 ***	0.895 ***	1.000					
(4)	L3.Volume Share	0.843 ***	0.862 ***	0.895 ***	1.000				
(5)	Number Share	0.959 ***	0.868 ***	0.838 ***	0.820 ***	1.000			
(6)	L1.Number Share	0.867 ***	0.960 ***	0.868 ***	0.837 ***	0.904 ***	1.000		
(7)	L2.Number Share	0.837 ***	0.867 ***	0.960 ***	0.868 ***	0.873 ***	0.904 ***	1.000	
(8)	L3.Number Share	0.820 ***	0.837 ***	0.867 ***	0.960 ***	0.854 ***	0.873 ***	0.904 ***	1.000

Note: The unit of observation for variables (1) - (8) is one per borrower / lender / month (one observation per relationship / 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*.

TABLE A3: 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	0.683 ***	1.000						
(3)	L2.3 Firm-HHI	0.630 ***	0.679 ***	1.000					
(4)	L3.3 Firm-HHI	0.597 ***	0.629 ***	0.678 ***	1.000				
(5)	Max Volume Share	0.992 ***	0.772 ***	0.729 ***	0.703 ***	1.000			
(6)	L1.Max Volume Share	0.781 ***	0.992 ***	0.769 ***	0.731 ***	0.919 ***	1.000		
(7)	L2.Max Volume Share	0.750 ***	0.779 ***	0.992 ***	0.770 ***	0.899 ***	0.919 ***	1.000	
(8)	L3.Max Volume Share	0.731 ***	0.747 ***	0.777 ***	0.992 ***	0.886 ***	0.899 ***	0.919 ***	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*.

TABLE A4: CORRELATIONS OF BANK RELATIONSHIP AND BORROWER CHARACTERISTICS

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1)	Mean Volume Share	1.000													
(2)	Mean Spread	0.150 ***	1.000												
(3)	Mean Amount	0.104 ***	-0.003	1.000											
(4)	StDev of Volume Share	0.594 ***	0.200 ***	0.074 ***	1.000										
(5)	StDev of Spread	-0.088 ***	-0.331 ***	-0.043 ***	-0.087 ***	1.000									
(6)	StDev of Amount	0.086 ***	-0.006	0.908 ***	0.090 ***	-0.022	1.000								
(7)	ROA	0.010	0.041 ***	-0.012	0.073 ***	-0.015	-0.015	1.000							
(8)	%NPL	-0.022	-0.008	0.056 ***	-0.024	0.021	0.072 ***	-0.279 ***	1.000						
(9)	Assets	-0.354 ***	-0.324 ***	0.118 ***	-0.395 ***	0.152 ***	0.149 ***	-0.099 ***	0.269 ***	1.000					
(10)	Tier 1 Ratio	0.144 ***	0.138 ***	-0.040 ***	0.223 ***	-0.038 **	-0.048 ***	0.554 ***	-0.091 ***	-0.355 ***	1.000				
(11)	%Deposits	0.169 ***	0.130 ***	-0.097 ***	0.135 ***	-0.077 ***	-0.099 ***	-0.017	-0.355 ***	-0.647 ***	0.003	1.000			
(12)	Loan Concentration	0.041 ***	0.011	-0.005	0.104 ***	-0.007	0.004	0.194 ***	0.095 ***	0.043 ***	0.036 **	-0.128 ***	1.000		
(13)	SdDev of ROA	-0.009	0.025	0.022	0.082 ***	0.032 *	0.019	0.248 ***	0.185 ***	0.118 ***	0.311 ***	-0.321 ***	0.190 ***	1.000	
(14)	GSE Access	-0.387 ***	-0.304 ***	0.070 ***	-0.436 ***	0.102 ***	0.085 ***	-0.049 ***	0.063 ***	0.564 ***	-0.241 ***	-0.180 ***	-0.203 ***	0.003	1.000
(15)	First Borrow	-0.119 ***	0.040 ***	-0.146 ***	-0.057 ***	0.032 *	-0.154 ***	0.041 ***	0.034 **	-0.098 ***	0.091 ***	0.009	0.047 ***	0.044 ***	-0.177 ***

Note: The unit of observation for variables (1) - (6) is one per borrower / lender (one observation per relationship). The sample includes *frequent* borrowers only, where *frequent* borrowers are defined as banks that borrow 100 days or more in the interbank market from 7/1/2005 through 7/31/2008. *Volume Share* is the monthly amount borrowed in a particular relationship, as a percent of the borrower's total borrowing. *Mean Volume Share* is the average of the monthly *Volume Share* from 1/2006 through 7/2008. *Mean Spread* and *Mean Amount* are the average monthly weighted spread and monthly amount by relationship, respectively. *StDev of Volume Share, StDev of Spread,* and *StDev of Amount* are the standard deviation of *Volume Share, Spread* and *Amount,* respectively, from 1/2006 through 7/2008. Variables (7) - (13) are borrower characteristics, measured using the Call Report on a quarterly basis. *ROA* is net income divided by assets. *%NPL* is total non-performing loans divided by total loans. *Assets* is the logarithm of bank assets (in US $ millions). *Tier 1 Ratio* is tier 1 risk based capital divided by risk weighted assets. *%Deposits* is total deposits divided by assets. *Loan Concentration* is a Herfindahl Index of the bank's residential real estate, consumer, commercial real estate and C&I loans, relative to the total loan portfolio. *StDev of ROA* is the standard deviation of *ROA* over Q1 2006 through Q4 2007. *GSE Access* is an indicator variable equal to one if a bank borrows from a GSE at least once from 7/1/2005 to 12/31/2005. *First Borrow* is number of days elapsed from when we first observe a bank borrow to the time it first borrows in a particular relationship, divided by the number of days elapsed from the first time a bank borrows to the end of the sample. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level, respectively.