Households Rejecting Loan Offers from Banks*

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Abstract

This paper studies a type of mortgage applications in which household applicants reject offers from lenders. We find that less risky applicants with lower loan size to income ratios are more likely to reject loan offers from lenders. Local lenders that operate in a market where they extend the majority of their loans are less likely to be rejected by applicants overall, but are more likely to be rejected by risky applicants specifically. We also find that lenders that are less likely to be rejected by applicants tend to have higher loan acceptance rates and be more active in the jumbo mortgages segment, indicating an information advantage of those banks over the others. The paper adds to the literature by showing that the information advantage of geographically concentrated lenders enables them to have lower probabilities of being denied by applicants, and it also provides a new perspective to look at the relationship between loan borrowers and lenders.

JEL Classification: D14, G14, G21

Key Words: Mortgage Lending, Information Advantage, Concentrated Lender

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1. Introduction

It is commonly accepted that credit is a type of financial resource that is as scarce as many other resources in the world. Due to the scarcity of credit resource, it has long been assumed in banking literature that borrowers will always accept loan offers from lenders as long as the loan applications were completed of the borrowers' own free will (Berger and Udell 2002, Black and Strahan 2002). Indeed, anecdotal evidence and scientific researches both suggest that credit availability is an important issue for firms in real economy, in particular for small and medium sized enterprises (Berger and Udell 2002).

However, very few studies notice that borrowers don't necessarily accept every loan offer from banks even if banks agree to extend them loans with exactly the same condition as they applied for[i]. In the U.S., there are on average about 10% of lender approved mortgage offers end up being rejected by applicants from 2007 to 2012 (see the left panel in Figure 1). The applicant rejection rate was at around 15% in 2007, dropped to 5% in 2009, and came back at about 7% in 2012.

This paper studies this type of home mortgage applications in which household applicants reject loan offers approved by lenders. Our goal in this article is to empirically explore explanations for the following two research questions. First, what type of applicants tends to reject lenders? In particular, we are interested to know the relationship between applicants' riskiness and the probabilities of them rejecting loan offers from lenders. Second, what type of lenders is less likely to be rejected by applicants, and why is that? The main contribution of this paper is to provide a new perspective to look at the relationship between loan borrowers and lenders where borrowers can have more options than previous studies usually assume.

We find that less risky mortgage applicants with lower loan size to income ratios are more likely to reject lenders approved loan offers than risky applicants do. We also

[i] One exception is Collins (2011), in which the author generally views rejecting a lender approved loan offer, together with submitting incomplete paperwork when seeking a mortgage, withdrawing a loan application before the lender makes a credit decision, and accepting a high interest rate loan are mortgage mistakes that happened due to the mortgage applicants' lack of financial literacy.

show that local lenders, defined as lenders operating in a market where they extend the majority of their loans, are less likely to be rejected by applicants. Further, we show that lenders with lower probability of being rejected by applicants tend to have higher loan acceptance rates and be more active in the jumbo mortgages segment. This evidence is in line with previous studies showing that mortgage lenders that concentrate in a few markets are better positioned to price risks and ration credit less and therefore have information advantages over other lenders (Loutshina and Strahan 2011). In light of these studies, we view the information advantage of geographically concentrated lenders as a possible explanation for their low probabilities of being rejected by applicants. It's true that some other factors such as change in house prices and borrower specific characteristics may also play a role in borrowers' decisions on taking the loan or not. Our results confirm that housing price fluctuation and applicant characteristics like race, sex are also crucial factors in borrowers' credit decisions. Henceforth, we claim that information advantage is an explanation that is complementary rather than alternative to other explanations of the variation in applicant rejection rates among lenders.

We obtain our results using an empirical model where, in addition to taking into account changes in economic fundamentals such as housing price index and real GDP growth, we control for changes in lender characteristics such as financial fundamentals and applicant characteristics such as income, race, gender and ethnicity. We employ Home Mortgage Disclosure Act (HMDA) data, which is a very comprehensive database with detailed mortgage application level information. Its classification of loan action types allows us to identify loan offers that are approved by lenders but rejected by applicants on their own free will. The richness of HMDA data guarantees enough variation which enables us to control for unobserved factors, such as MSA * year fixed effects and even lender * year fixed effects. For robustness, we run our model with two alternative definitions of concentrated lenders and a placebo test where we replace local lender with another two substitutive variables.

In this analysis, we outline three potential explanations why household mortgage applicants reject lenders approved loan offers.

First, applicants say no to lenders because they have personal reasons or they are reacting to the change in economic fundamentals. On one hand, it is easy to understand that applicants may reject loan offers if some unexpected accidents happen to them, for example, car accident, heart attack, being fired, divorce, natural disaster, or a breach by house sellers who break the promise and sell the houses to some other people who come late but offer higher bids. On the other hand, applicants' credit decisions may be largely affected by change in economic fundamentals, in particular for the fluctuation in housing prices (Follain 1990). One can easily tell from Figure 1 and Figure 2 that the change in applicant rejection rates and housing price index follow similar pattern between 2007 and 2010. It is reasonable for an applicant to reject a lender approved mortgage offer if he finds that the value of the house he intended to buy has dropped so badly that it is even already below the mortgage value. During housing market downturns, even home mortgage borrowers could choose to strategically default on their loans (Mayer, Morrison, Piskorski and Gupta 2014), let alone mortgage applicants who haven't signed contracts with banks yet. We classify this and similar reasons based on external forces imposed on applicants to reject loan offers as *applicant-based* explanations.

In order to control for the change in housing price and other economic fundamentals, we add the change in housing price index and real GDP growth at MSA level. With regard to applicant specific reasons, even though most of the accidents mentioned above are small-probability events that can be assumed as rarely happen in reality, for robustness, we use accident rates at state level such as layoff rate to control for the probability of residences in that area having an unexpected accident like being fired.

Second, lenders' lending strategy may have an impact on mortgage applicants' credit decisions. More specifically, towards crisis the dramatic decline in applicant rejection rate from 2007 to 2009 (see the left panel in Figure 1) may imply that the loan offers lenders were offering became increasingly so good for mortgage applicants that they stopped rejecting. This could be an indication of banks lowering their lending standards for mortgages when they deliberately change their supplies of mortgage credit due to various potential reasons such as the deterioration of their financial fundamentals, intentions to diversify the risk of their loan portfolios, greater usages of securitization or government financial support programs (Dell'ariccia, Igan and Laeven 2012), and shift in regulation policy (Giovanni and Imbs 2011). Regardless of the reasons, we refer to such explanations that based on the shift in lenders' mortgage lending behaviors as *supply-based* explanations.

We employ a wide range of bank balance sheet variables measuring mortgage lenders' financial situation and lending strategy, as well as lender * year fixed effects, as controls for the impact from supply side.

Third, consumer mortgage shopping behavior may have been responsible for the rejection of lenders approved offers by applicants. In this case, it is almost for sure that shopping around applicants will reject loan offers in the end if they receive more than one approval for their mortgage applications sent to multiple lenders. It doesn't matter what characteristics the lenders have and how well the applicants are doing, rejections on loan offers will happen because mortgage applicants are able to afford only one home mortgage loan for each of their houses[i]. However, the characteristics of applicants and lenders may have an impact on the final credit decisions of those shopping around applicants, i.e. which type of lenders-approved loan offers the applicants would accept. Given that information plays a crucial role in this case where lenders use information about applicants they collected to formulate loan terms, and applicants make credit decisions by comparing loan terms using information they searched for in the shopping period, we refer to explanations based on mortgage applicants shopping behavior as *information-based* hypotheses.

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[i] The assumption is that mortgage applicants don't split their home mortgages into several small mortgages. This is a reasonable assumption because of the following two reasons. First, this action will greatly increase the mortgage application cost for applicants. Second, the probability of an applicant getting enough money for their houses won't be higher if they implement this strategy. Anecdotal evidence also provides supports to the reasonability of this assumption.
Applicants may have multiple home mortgages being paid at the same time if they have several houses and rich enough. But then each mortgage will be completely different from each other in terms of property location, loan size and so on. In these cases, applicants won't be considered as shopping around because the loan products they are shopping for are completely different.

This work is most related to a number of previous papers that study consumer credit shopping behavior (Calem and Mester 1995, Chang and Hanna 1992, Duncan 1999, Fry Mihajilo, Russel and Brooks 2009, Lee and Hogarth 1999 and 2000, Worden and Sullivan 1987). These papers show that search cost affects consumer credit shopping behavior (Calem and Mester 1995). They find that consumers make comparisons between benefits such as better loan terms and costs including opportunity cost of time and financial and mental expenses of searching for credit, and then decide whether to stop shopping around for credit or not (Chang and Hanna 1992). Duncan (1999) finds that four-fifths applicants shop for better "interest rates", rather than the annual percentage rate (APR) disclosed as required by the Truth in Lending Act (TILA). APR is the effective rate of interest rate paid over original term of the loan. It facilitates consumers to compare interest rates under different loan terms (Lee and Hogarth 2000). Additionally, consumer lenders tend to disguise interest rates using "fuzzy math" in order to make consumers underestimate borrowing cost when the real APR is not disclosed (Stango and Zinman 2011). Therefore, lack of financial literacy limits consumers' payoffs from increased search (Fry 2008, Lee and Hogarth 1999). Similarly, Worden and Sullivan (1987) examines the pattern of consumer credit shopping and finds that more educated people with higher financial capability tend to shop more, indicating that financial capability increases consumers' benefits from credit shopping. Consistent with these studies, in this article we find that less risky applicants with lower loan size to income ratios are more likely to reject lenders approved offers than risky applicants. A possible explanation for our finding is that less risky applicants tend to have higher levels of financial literacy, which enables them to benefit more from shopping around and also increases their probabilities of mortgage shopping, therefore increases their tendencies to reject lenders approved loan offers.

This result is also in line with literature of winners' curse in banking market studying the adverse selection problem faced by banks (Broecker 1990, Shaffer 1998). The most relevant part of these papers to our work is that they find risky applicants will stop shopping around once they receive the first loan offers from banks, they will accept the offer immediately and rarely choose to wait because they know their poor credit qualities probably will bring them loan rejections from the subsequent banks. In line with this conclusion, our finding about less risky applicants reject loan offers more can be explained by risky applicants' lack of ability and confidence to reject lenders approved loan offers.

A number of related papers have identified factors that influence lenders' credit decisions (Albertazzi, Bottero and Sene 2014, Dell'ariccia and Marquez 2006, Giovanni and Giannetti 2013, Loutskina and Strahan 2011). Giovanni and Giannetti (2013) find that market concentration affects lenders' perspectives to foreclosure defaulting mortgages. More importantly, a large body of works have shown that information plays an important role, such as in Albertazzi, Bottero and Sene (2014) where the authors empirically test the impact of information spillover on lenders' credit decisions, and Dell'ariccia and Marquez (2006) also provides a theoretical model explaining how private information collection and mitigation on information asymmetry between borrowers and lenders leads to a loosing of lending standards. Loutskina and Strahan (2011) finds that mortgage lenders that concentrate in a few markets have more incentives and are better able to invest in private information collection, therefore they focus more on information intensive high risk borrowers and jumbo mortgage segment because they are better positioned to price risk and thus ration credit less. In consistent with these contemporaneous studies, we also observe a positive relationship between lenders' information advantage and their probabilities of being rejected by applicants.

We find that local lenders, defined as lenders operating in a market where they extend the majority of their loans, are less likely to be rejected by applicants. Further, we show that lenders with lower applicant rejection rates tend to have higher loan acceptance rates and be more active in the jumbo mortgages segment, indicating an information advantage of those lenders with lower applicant rejection rates over the other lenders. This evidence is in line with the conclusions in Loutskina and Strahan (2011).

The rest of the paper is organized as follows. Section 2 provides a small theory model. Section 3 describes the data and hypotheses. Section 4 presents our empirical methodology. Section 5 reports the empirical results and placebo test and section 6 concludes.

2. Theory

In this section we present a simple theoretic model. We use the privately-known-prospects model where borrowers have private information about their probability of success (Tirole, 2006).

A borrower/entrepreneur has no fund to finance a project costing I. The project yields R if the borrower succeeds and 0 if he fails. Both borrowers and lenders are risk neutral, and the interest rate in the economy is normalized to zero. The capital market is competitive and demands an expected rate of return equals to zero.

There are two types of borrower in the economy: a good borrower has a probability of success equals to p_h while a bad borrower has a probability of success equals to p_l, and $p_h > p_l$. Suppose that good borrowers represent α percentage of the whole population and the rest $1 - \alpha$ people are bad borrowers. Notice that in the model we simply remove moral hazard component by ignoring private benefit $B = 0$.

There are also two types of lenders in the economy: a lender who has information about borrowers' creditworthiness, and the other lender who doesn't. Borrowers have private information about their types and they will apply for loans from both two types of lenders and accept the best loans they can have (i.e. loans with the lowest interest rates).

2.1 Lenders with information about borrowers' risks

When the lenders know the prospects of borrowers' projects, they are under symmetric information. Suppose good borrowers ask for R_b^G compensation in the case of success and lenders with information are willing to offer a loan with interest rate r_G to good borrowers. Given that lenders on average will break even:

$$p_h\,(R - R_b^G) = I \text{ and } R - R_b^G = (1 + r_G)\,I$$

Suppose that bad borrowers ask for R_b^B compensation in the case of success and lenders with information offer them loans with interest rate r_B. Likewise,

$$p_l\,(R - R_b^B) = I \text{ and } R - R_b^B = (1 + r_B)I$$

Clearly,

$$R_b^G > R_b^B \; and \; r_G < r_B$$

2.2 Lenders without information about borrowers' risks

When lenders have no information about borrowers' risks, they are under asymmetric information because they don't know whether they face a good borrower or a bad borrower. These lenders' prior probability of success is

$$m = \alpha p_h + (1 - \alpha)p_l$$

Assume that lenders without information can provide only one feasible loan contract to both two types of borrowers. Such contracts necessarily pool the two types of borrowers together and give them compensation R_b and charge them interest rate r_b.These lenders' average profit therefore is

$$m\left(R - R_b\right) - I = [\alpha p_h + (1 - \alpha)p_l]\left(R - R_b\right) - I$$

The borrowers' compensation R_b should be set to make lenders on average break-even:

$$m\left(R - R_b\right) - I = [\alpha p_h + (1 - \alpha)p_l]\left(R - R_b\right) - I = 0$$

Note also that

$$\left(R - R_b\right) = (1 + r_b)\,I$$

This implies that:

$$R_b^G > R_b > R_b^B \; and \; r_G < r_b < r_B$$

Remark 1. Good borrowers accept interest rate r_G from loan offers provided by lenders with information about borrowers' risks, and reject interest rate r_b from loan offers provided by lenders without information.

On the contrary, bad borrowers accept interest rate r_b from loan offers provided by lenders without information about borrowers' risks, and reject interest rate r_B from loans offers provided by lenders with information.

That is to say, lenders with information advantage over other lenders are more likely to be rejected by bad borrowers, while are less likely to be rejected by good borrowers.

Now let us assume that only good borrowers in the economy are creditworthy and bad borrowers are not creditworthy, meaning that $p_l R < I < p_h R$. Therefore,

$$R_b^G > 0 > R_b^B$$

Given that borrowers on average are also break-even:

$$\alpha R_b^G + (1-\alpha) R_b^B = Average\ borrowers'\ efforts > 0$$

Clearly,

$$\alpha > 1/2$$

Remark 2. Lenders with information about borrowers' risks are rejected by bad borrowers who represent $1-\alpha$ percentage of the population. Lenders without information are rejected by good borrowers who are the other α percentage of the population. Henceforth, lenders with information advantage are on average less likely to be rejected by applicants.

3. Data and Summary Statistics

3.1 HMDA Data

We build our database from a comprehensive sample of mortgage applications and originations collected by the Federal Reserve from 2007 to 2012 under the provisions of the Home Mortgage Disclosure Act (HMDA). Regulators use HMDA data to help identify discriminatory lending. All commercial banks, savings institutions, credit unions and mortgage companies with more than $30 million in assets must provide the required information. The HMDA data is a detailed loan application level database including up to 41 million loans applications reported by about 7.5 thousand financial institutions each year, which covers on average over 90% of mortgage dollars issued in the U.S. every year.

HMDA data provides detailed information at loan application level, such as variables capturing institution ID, property location, loan amount, loan purpose, pre-approval status, lien status, applicant characteristics including annual income, sex, race, ethnicity, and the same set of variables for the co-applicant if applicable. A variable that needs to be noted is the loan action type, which contains in total of 8 groups as shown in Table 1. In our sample, we include only loans of action type 1 which are loans originated by mortgage lenders, action type 2 which are applications approved by lenders but not accepted by applicants. 90% of observations in our sample are of action type 1 and action type 2 loans take up the rest 10%. In this paper, we're particularly interested in loans of action types 1 and 2, which presumably are loans of similar credit qualities because they all get approved by lenders.

[Insert Table 1 here]

In addition to the variables listed in Table 1, HMDA data also contains a substantial number of loan characteristics such as loan type (insured by Federal Housing Administration (FHA) or Veterans Administration (VA) et al), property type (one to four-family, multi-family or manufactured housing) and owner occupancy (owner-occupied as a principal dwelling or not). To simplify analysis, we keep only loans that are conventional loans (any loan other than FHA, VA, FSA, or RHS loans), and non-manufacturing housing and owner-occupied as a principal dwelling, which consist about 70% loans from the raw sample.

All variables measuring applicant characteristics are included in regressions as controls for applicant-specific factors that could have an impact on the results, such as sex, race, ethnicity, annual income of applicant and co-applicant if applicable.

One thing needs to be concerned about is the issue of counter offer, which happen when lenders offer to applicants to make the loans on different terms or in a different amount from the terms or amount applied for. But this is not a problem in our data as if a lender offers a counter offer to an applicant, it will be considered as a loan rejection if the applicant turns down the counteroffer or does not respond. If the applicant accepts it, then it will become an originated loan. Put differently, if an applicant decides to reject the counter offer, what he rejects is a loan offer with exactly the same terms as he applied for. This is helpful for us to address the concern that applicants are "forced" to reject lenders approved loan offers in which lenders make the loans on different terms.

We supplement the HMDA information with bank-level balance sheet data published in the Call Report by the Federal Financial Institutions Examination Council (FFIEC), including annual financial fundamentals such as size as measured by total assets, profitability as measured by net income to total asset ratio and yield on total loans and leases, and other general financial profile variables like liquidity ratio, capital ratio, deposit to total asset ratio, real estate loan to gross loans, cost of deposits and so on. We also add Metropolitan Statistical Areas (MSA) level data on economic and social indicators published by federal agencies, including data on housing price index from the FHA; data on layoff rate from the Bureau of Labor Statistics (BLS); annual data on macroeconomic variables, such as real GDP growth from the Bureau of Economic Analysis (BEA); data on demographic characteristics such as population, percentage of minority population, median family income from the Census Bureau; and data on local banking market structure such as the number of deposit taking institutions, total deposit growth, and HHI measuring market competition from Summary of Deposit (SOD) published by the Federal Deposit Insurance Corporation (FDIC) and HMDA. After dropping loans with incomplete control variables, our final sample contains in total of 34,264,401 loans with properties located in 388 MSAs, census tracts, reported by 11,195 mortgage lending institutions owned by 9,548 finance institutions registered at FFIEC during our sample period. Detailed definitions of variables can be found in Table 2.

[Insert Table 2-1 here]

[Insert Table 2-2 here]

[Insert Table 2-3 here]

Tables 2-1, Table 2-2 and Table 2-3 present definitions and brief summary statistic for all the loan-level, bank-level and market-level variables used in this paper.

Table 2-1 shows that the average applicant earns $ 112,760 every year and applies for a $219,830 mortgage with interest spread set at 4.79%. The average loan size to income ratio is 2.32 for all applicants in our sample.

The average growth rate of housing price is -1.13 between 2007 and 2012. The average total asset of all lenders is $542 million, among which about 10% is capital and 72% is deposits. Real estate loans on average constitute 55% of lenders' gross loans.

For all mortgage lenders in our final sample, the average HHI index of lending across MSAs is 0.23, lower than the threshold at 0.50 where we set to distinguish between concentrated lenders and diversified lenders. In robustness test, we redefine concentrated lenders as those with more than 65% or 75% of their loans lend to properties located in a certain MSA. During our sample period, there are on average 532 lenders in each MSA, among which about 72 lenders (i.e. taking up about 11% of the lender population) are local lenders defined as lenders operating in markets where they extend most of their loans.

Table 3 reports some lender and loan characteristics by lender and loan action types, which provides some descriptive evidence for our hypotheses.

[Insert Table 3 here]

First, our hypothesis of the type of applicants that tends to reject lenders more is:

Hypothesis 1: Relative to risky applicants with higher loan size to income ratios, less risky applicants with lower loan size to income ratios are more likely to reject loan offers from lenders.

As discussed before, this is not only because less risky applicants tend to have more incentive and are better able to shop around due to their higher probabilities of having higher level of financial literacy, but also because relative to risky applicants they have more confidence and higher chances to have another approved loan offer even if they choose to reject the offer at hand.

Second, our hypothesis of the type of lenders that is less likely to be rejected by applicants is:

Hypothesis 2: Relative to diversified lenders, local lenders that operate in a market where they extend the majority of their loans are less likely to be rejected by less risky applicants and are more likely to be rejected by risky applicants due to their information advantage. This information advantage is expected to be represented by higher loan acceptance rates and more active involvement in information intensive jumbo mortgage segment. Overall, local lenders are less likely to be rejected by applicants compared to diversified lenders.

The reason why local lenders' information advantage lowers their probabilities of being rejected is because having more private information about local applicant pool enables lenders to be better positioned to price loans. This doesn't necessarily mean that the interest rates offered by lenders with information advantage will always be lower than the interest rates offered by other lenders. In fact, local lenders with information advantage will charge higher interest rate for risky applicants and lower interest rates for creditworthy applicants, compared to diversified lenders who can only provide a comprised weighted-average interest rate for both two types of borrowers due to the lack of ability to distinguish between them. Therefore, local lenders with information advantage are less likely to be rejected by creditworthy applicants and are more likely to be rejected by risky applicants. Moreover, as the proportion of creditworthy applicants is usually larger than the proportion of risky applicants in a sustainable economy, local lenders are overall less likely to be rejected by applicants than diversified lenders.

The reason why information advantage should be reflected by higher loan acceptance rates and active involvement in jumbo mortgage segment is because in the extreme world when information is complete, all loans should be fairly priced based on their risks and thus no loan will be denied including those risky ones. Moreover, jumbo mortgage is a type of loan that exceeds the two Government Sponsored Enterprises (GSEs) Freddie Mac's and Fannie Mae's loan limit at around 417 million USD. Jumbo mortgages thus are more risky partly due to their excessively large size and partly because of the absence of funding support from GSEs. Only lenders with more information are more incentivized to engage in jumbo mortgage segment. Therefore, lenders with information advantage are expected to have higher loan acceptance rates and more active involvement in jumbo mortgage segment.

The summary statistics in Table 3 show supportive evidence to our second hypothesis. The average applicant rejection rate is 11% for all the lenders in my sample, although this rate is only 6% for local lenders, which is significantly lower than 12% for non-local lenders, meaning that local lenders are less likely to be rejected by applicants relative to non-local lenders.

It is worth noting that the average risk of applicants is 2.01 for local lenders, which is significantly lower compared to 2.38 for non-local lenders. This is helpful to address the concern that selection bias drives the results when local lenders originally have more risky applicants that are less likely to reject lenders approved loan offers. If it is true that local lenders originally have more less-risky customers that are more likely to reject loan offers, then this should go against our story that local lenders are less likely to be rejected by applicants. However, we still observe strong and robust result about the lower applicant rejection rate for local lenders, meaning that selection bias is not an issue in this paper.

3.2 Matching

A disadvantage of the HMDA data is that applicant ID is unavailable, so it is very hard to identify how many loan offers does an applicant receives and which offer does he reject and which offer does he finally choose over the other loan offers rejected by him. In order to solve this problem, we employ a matching method to identify applicants with multiple loan offers, among which they accept one and reject the others. Loan offers will be considered to be received by the same applicant if those offers have exactly the same application year, loan purpose, loan amount, applicant income, applicant ethnicity, race, sex, co-applicant ethnicity, race, sex, and property location at county level. Thus we are able to create the variable of applicant ID to identify multiple loan offers received by the same applicant. Table 4 reports the result of matching based on loan characteristics mentioned above.

[Insert Table 4 here]

During our sample period, there are on average 91.57% applicants received only one mortgage offer, about 6.89% applicants received two mortgage offers, and only 0.28% applicants received more than 4 loan offers. The percentage of applicants with multiple loan offers was low in 2007 and then had a small peak subsequently in 2010 and 2011.

We then create a subsample of loan offers received by applicants with multiple loan offers only, and employ a mixed effects model to test if some lenders do have a lower probability of being rejected by applicants compared to some other lenders when applicants make a comparison of loans offered by all these lenders. We face a challenge to solve the correlated observations issue arising from multiple loan offers received by the same applicants. This is a problem because for an applicant with multiple loan offers, his decisions to accept this one and reject the rest are not completely independent to each other due to the fact that each applicant usually can only accept one mortgage offer for each of their houses. Following Revelt and Train (1998), we use mixed effects model which allows for coefficient estimation when there are repeated choices by the same customers, as occur in our paper.

4. Empirical Methodology

4.1 Type of Applicants that Tend to Reject Lenders Approved Loan Offers

4.1.1 Logit and Linear Probability Model with the Whole Sample

For the analysis of the type of applicants who tend to reject loan offers from lenders, we report regressions with Logit model and linear probability model (LPM) at loan application level with the following specification.

$$\begin{aligned}\boldsymbol{Loan\ Offer\ Rejection_i} = \boldsymbol{\alpha} + \ & \boldsymbol{\beta_1} * \boldsymbol{Loan\ Size\ to\ Income\ Ratio_i} \\ & + \boldsymbol{\gamma_1} * \boldsymbol{Local\ Lender_{jmt}} \\ & + \boldsymbol{\theta} * \boldsymbol{Loan\ Size\ to\ Income\ Ratio_i} * \boldsymbol{Local\ \ Lender_{jt}} \\ & + \boldsymbol{\beta} * \boldsymbol{X_i} + \boldsymbol{\gamma} * \boldsymbol{Y_{jt}} + \boldsymbol{\delta_1} * \boldsymbol{Growth\ HPI_{\ mt}} + \boldsymbol{\delta} * \boldsymbol{Z_{mt}} \\ & + \boldsymbol{Year\ FE} + \boldsymbol{Census\ Tract\ FE} + \boldsymbol{Bank} * \boldsymbol{Year\ FE} + \boldsymbol{\varepsilon_i}\end{aligned} \tag{1a}$$

where the dependent variable $Loan\ Offer\ Rejection_i$ is a dummy which equals to 1 if loan offers are accepted by applicants, otherwise 0. X_i are a vector of loan characteristics for each loan *i*, Y_{jt} is a vector of bank characteristics for each bank *j* at year *t*, and Z_m is a vector of local market characteristics for each MSA *m* where the property is located. The main independent variable is $Loan\ Size\ to\ Income\ Ratio_i$ which measures the riskiness of a mortgage applicant. $Local\ Lender_{jmt}$, defined as a dummy which equals to 1 if the lender is a concentrated lender operating in its biggest market, is another variable that we are interested in. We also add an interaction term between $Loan\ Size\ to\ Income\ Ratio_i$ and $Local\ Lender_{jmt}$ to see the net effect of these two variables. Standard errors are clustered at bank level. Year fixed effects, census tract fixed effects, and bank * year fixed effects are added in regressions. Some regressions have census tract * year fixed effects too.

According to our first hypothesis, β_1 is expected to be negative as risky applicants with higher loan size to income ratios are less likely to reject lenders approved loan offers. Additionally, we expect to observe a negative and significant γ_1 if our second hypothesis is correct, meaning that local lenders are less likely to be rejected by applicants. Thus we are expected to observe a positive θ according to our theory model which predicts that risky applicants are more likely to reject loan offers from lenders with information advantage (i.e. local lenders).

We include loan characteristics such as loan amount, purpose and lien status to control for potential impact drive by fundamental differences across different loan types. X_i also includes applicant characteristics and co-applicants characteristics as we mentioned before, such as ethnicity, race, and gender. They may play a role because applicant from different demographic groups may have different risk preference level, social capital and family ties. Y_{jt} contains bank balance sheet variables such as total assets, liquidity ratio, capital ratio, share of real estate loans in gross loans, deposit to assets ratio, net income to assets ratio, interest costs on deposits and yields on loans and leases. We use these variables to control for bank size, liquidity, capital adequacy, specialization in mortgage market, access and dependency to deposit funding, profitability and efficiency. Z_{mt} includes MSA level GDP growth rate, change in HPI, layoff rate, HHI, number of all mortgage lenders, number of local lenders and share of local lenders. We do so to control for potential effect of market competition, size and macroeconomic prosperity on applicants' loan decisions.

4.1.2 Mixed Effects Logit and Linear Probability Model with Subsample

The next step is to run a mixed effects model using a subsample of loan offers received by applicants with multiple loan offers only.

$$\begin{aligned}
\boldsymbol{Loan\ Offer\ Rejection_{in}} = \boldsymbol{\alpha} + \boldsymbol{\beta_1} * \boldsymbol{Loan\ Size\ to\ Income\ Ratio_i} \\
+ \boldsymbol{\gamma_1} * \boldsymbol{Local\ Lender_{jmt}} \\
+ \boldsymbol{\theta} * \boldsymbol{Loan\ Size\ to\ Income\ Ratio_i} * \boldsymbol{Local\ Lender_{jt}} \\
+ \boldsymbol{\beta} * \boldsymbol{X_i} + \boldsymbol{\gamma} * \boldsymbol{Y_{jt}} + \boldsymbol{\delta_1} * \boldsymbol{Growth\ HPI_{mt}} + \boldsymbol{\delta} * \boldsymbol{Z_{mt}} \\
+ \boldsymbol{Year\ FE} + \boldsymbol{Census\ Tract\ FE} + \boldsymbol{Bank} * \boldsymbol{Year\ FE} + \boldsymbol{\varepsilon_{in}}
\end{aligned} \tag{1b}$$

The specification is shown in equation (1b), which is similar to equation (1a) except that applicant ID is taken into account this time, so in this specification the credit decision applicant i made to the Nth loan offer received by him is represented as $Loan\ Offer\ Rejection_{in}$.

It is expected that mixed effects models shouldn't change our main results, so we hope to observe the same results as in equation (1a), including a negative and significant β_1, a negative and significant γ_1, and a positive and significant θ.

4.2 Type of Lenders that is More Likely to be Rejected by Applicants

The next step is to examine the type of lenders that is more likely to be rejected by applicants. This time we choose to run OLS regressions using panel data with observations at bank * year level, as shown in equation (2a) – (2c).

Equation (2a) aims to test if lenders with information advantage as represented by concentrated lenders are less likely to be rejected by applicants. The dependent variable applicant rejection rate is the percentage of loan offers approved by a lender but not accepted by applicants among all loan offers approved by the lender. The main independent variable is concentrated lender, which equals to 1 if the lender has a HHI of lending across MSAs larger than 0.50. Here we use concentrated lender instead of local lender as we do in Table 5 because concentrated lender is a bank * year level variable while local lender is a bank * MSA* year level variable which requires bank * MSA * year level financial fundamental controls to match. However, controls for bank financial fundamentals are available only at headquarter (i.e. bank * year) level and not available at branch (i.e. bank * MSA * year) level. This shouldn't have a big impact on our results because for a concentrated lender who lends most of his loans in one market, the loans he lends in the other markets shouldn't dominate the lending pattern he applies in his biggest market. In placebo test, we examine whether non-concentrated lenders operating in their biggest markets and concentrated lenders operating in their smaller markets have the same impact as local lenders does on their probabilities of being rejected by applicants. We find that the answer is no, which is in support of our argument that switching from local lender to concentrated lender won't have a major impact on our main results. Standard errors are clustered at bank level. Year fixed effects and bank fixed effects are all included.

$$\begin{aligned}\boldsymbol{Applicant\ Rejection\ Rate_{jt}} &= \boldsymbol{\alpha} + \boldsymbol{\beta_1} * \boldsymbol{Concentrated\ Lender_{j,t}} + \boldsymbol{\gamma} * \boldsymbol{Y_{jt}} + \boldsymbol{Year\ FE} + \boldsymbol{Bank\ FE} \\ &+ \boldsymbol{\varepsilon_{jt}}\end{aligned} \tag{2a}$$

According to our second hypothesis, β_1 in equation (2a) is expected to be negative and significant because concentrated lenders are less likely to be rejected by applicants.

Equation (2b) and (2c) are aiming to test to what extent the information advantage is held by lenders with lower applicant rejection rates over the other lenders.

$$\begin{aligned}\boldsymbol{Loan\ Acceptance\ Rate_{jt}} &= \boldsymbol{\alpha} + \boldsymbol{\beta_1} * \boldsymbol{Applicant\ Rejection\ Rate_{j,t}} \\ &+ \boldsymbol{\beta_2} * \boldsymbol{Concentrated\ Lender_{j,t}} + \boldsymbol{\gamma} * \boldsymbol{Y_{jt}} + \boldsymbol{YearFE} + \boldsymbol{Lender\ FE} \\ &+ \boldsymbol{\varepsilon_{jt}}\end{aligned} \tag{2b}$$

$$\begin{aligned}\boldsymbol{Non-Jumbo\ Mortgage\ Ratio_{jt}} &= \boldsymbol{\alpha} + \boldsymbol{\beta_1} * \boldsymbol{Applicant\ Rejection\ Rate_{j,t}} \\ &+ \boldsymbol{\beta_2} * \boldsymbol{Concentrated\ Lender_{j,t}} + \boldsymbol{\gamma} * \boldsymbol{Y_{jt}} + \boldsymbol{Year\ FE} + \boldsymbol{Bank\ FE} \\ &+ \boldsymbol{\varepsilon_{jt}}\end{aligned} \tag{2c}$$

where the dependent variable $Loan\ Acceptance\ rate_{jt}$ in equation (2b) is the percentage of originated loans among all received loan applications of bank *j* in year *t*, and dependent variable $Non-Jumbo\ Mortgage\ Ratio_{jt}$ in equation (2c) is the percentage of non-jumbo mortgages among all mortgages originated by bank *j* in year *t*. Standard errors are clustered at bank level. Year fixed effects and bank fixed effects are included in regressions.

According to our second hypothesis, we expect to observe a negative and significant β_1 in equation (2b) and a positive and significant β_1 in equation (2c), meaning that lenders with lower applicant rejection rates tend to have information advantage over the other lenders, which is one of the reasons why they are less likely to be rejected by applicants.

4.3 Placebo Test

If our second hypothesis about the impact of information advantage on applicant rejection rate is correct, then lenders without information advantage shouldn't be less likely to be rejected by applicants relative to other lenders, even if they share similar characteristics or have close relationships to lenders with information advantage, such as non-concentrated lenders operating in their biggest markets and concentrated lenders operating in their smaller markets. Given that both two lender types are bank * MSA* year level characteristics that cannot be identified with bank * year level data, we run the following regressions with Logit and LPM models using application level data.

$$\begin{aligned}\boldsymbol{Loan\ Offer\ Rejection_i} = \boldsymbol{\alpha} + \boldsymbol{\beta_1} * \boldsymbol{Loan\ Size\ to\ Income\ Ratio_i} \\ + \boldsymbol{\gamma_1} * \boldsymbol{Non - concentrated\ Lender\ Operating\ in\ Its\ Biggest\ Market_{jmt}} \\ + \boldsymbol{\beta} * \boldsymbol{X_i} + \boldsymbol{\gamma} * \boldsymbol{Y_{jt}} + \boldsymbol{\delta_1} * \boldsymbol{Growth\ HPI_{mt}} + \boldsymbol{\delta} * \boldsymbol{Z_{mt}} \\ + \boldsymbol{Year\ FE} + \boldsymbol{Census\ Tract\ FE} + \boldsymbol{Bank} * \boldsymbol{Year\ FE} + \boldsymbol{\varepsilon_i}\end{aligned} \tag{3a}$$

where we define $Non - concentrated\ Lender\ Operating\ in\ Its\ Biggest\ Market$ as a lender with HHI of lending across MSAs lower than 0.50 operating in its biggest market, and $Concentrated\ Lender\ Operating\ in\ Its\ Smaller\ Markets$ as a concentrated lender operating in markets that are not its biggest market. It is reasonable to believe that these two types of lenders either share similar characteristics or have close relationships with local lenders that are defined as concentrated lenders operating in their biggest markets, but they shouldn't have information advantage over other lenders located in the same area because they don't have as much incentive to collect private information as local lenders do. Therefore, we expect to observe no negative and significant coefficients for these two variables if we regress applicant loan offer rejection dummy on them.

Equation (3a) is the same as equation (1a) except that local lender dummy is replaced by $Non-concentrated\ Lender\ Operating\ in\ Its\ Biggest\ Market$ dummy. To save space, equation with $Concentrated\ Lender\ Operating\ in\ Its\ Smaller\ Markets$ is not shown, which will be the same as equation (3a) except that this dummy variable will replace $Non-concentrated\ Lender\ Operating\ in\ Its\ Biggest\ Market$ dummy. Standard errors are clustered at bank level. Year fixed effects, census tract * year fixed effects, and bank * year fixed effects are added in regressions.

5. Regression Results

5.1 Type of Applicants that Tend to Reject Lenders Approved Loan Offers

5.1.1 Logit and Linear Probability Model with the Whole Sample

Table 5-1 reports regression results with logit model as shown in equation (1a) using our full sample which later reduced to a subsample of about 8 million loans offers approved by more than 4 thousand mortgage lending institutions with available balance sheet information in the U.S. between 2007 and 2012 when we add time variant bank balance sheet controls. The dependent variable is loan offer rejection dummy which equals to 1 if applicant rejects lenders approved loan offer and 0 if applicant accepts the loan offer. The main independent variable is loan size to income ratio which measures the riskiness of a mortgage applicant. Column (1) reports result of base regression with loan level controls, market level controls and MSA fixed effects. In columns (2), (3), (6) and (7), we add bank level controls, which reduce the number of observations to about 7.7 million. MSA fixed effects and year fixed effects are added in all columns except in columns (4) and (7) where MSA * year fixed effects are included. We observe that loan size to income ratio has coefficients that are negative and significant at 1% level in all columns, indicating that the riskiness of an applicant has a negative impact on the probability of him rejecting lenders approved loan offers. Put differently, less risky applicants with lower loan size to income ratios tend to reject lenders more than risky applicants. It is worth noting that the economic significance of the coefficient of loan size to income ratio becomes even stronger when we add more fixed effects. This evidence is in support of our first hypothesis.

[Insert Table 5-1 here]

Local lender, defined as a dummy which equals to 1 if the mortgage lending institution is a concentrated lender operating in its biggest market. We first show results with the definition of local lender based on the volume of mortgages in columns (1) and (2), and then results with the definition of local lender based on the number of mortgages in columns (3) and (4) as robustness test. All columns have year fixed effects and MSA fixed effects. Columns (2) and (4) add interaction term between loan size to income ratio and local lender, and coefficients of interaction terms are positive and significant at 1% level in both columns, meaning risky applicants are more likely to reject loan offers approved by local lenders. This result is also in line with our hypothesis 2 and results in our theoretical model.

Moreover, at bank level control section, we find that in all 4 columns, the variable of log total assets and deposit to asset ratio are positive and significant, liquidity ratio and interest expenses on deposits are negative and significant, indicating that big banks with substantial deposits are more likely to rejected by applicants. A possible reason is that big banks may have more hierarchy which makes it difficult to transmit soft information inside banks and provide competitive and attractive loan products to clients and therefore more likely to be rejected.

Interestingly, we find that applicant demographic characteristics also plays a role. Non-Hispanic or Latino applicant reject bank offers significantly less than applicants with other ethnicities. Women are less likely to reject loan offers from banks than men do. White people are less likely to reject offers than other races. Asian dummy is negative in all 4 columns in Table 5-1, although only two of them show significant coefficients.

But a problem with the logit model is that it takes incredibly long to run a regression with a lot of fixed effects when our full sample has more than 34 million observations. So we turn to the linear probability model (LPM) which allows us to add all the fixed effects as we want.

Table 5-2 reports regression results with linear probability model using a full sample of more than 34 million loans approved by about 11,195 mortgage lending institutions in the U.S. between 2007 and 2012. The dependent variable and independent variable are exactly the same as shown in Table 5-1. The definition of local lender in columns (1) – (3) is based on mortgage volume, while in columns (4) – (6) it is based on the number of mortgages. Columns (1), (2), (4) and (5) report results with bank fixed effects. Bank * year fixed effects are added in columns (3) and (6).

[Insert Table 5-2 here]

Results remain when we switch from logit model to LPM. We still observe negative and significant coefficients for both loan size to income ratio and local lender dummy, although the economic significance of variables in LPM are smaller compared to those in logit model, which is understandable because these two models have different interpretations for the economic meaning of their coefficients. The coefficient of interaction term remains positive and significant as well. This means that the result we observe in Table 5-1 is robust to LPM with bank * year fixed effects and census tract * year fixed effects.

5.1.2 Mixed Effects Logit and Linear Probability Model with Subsample

Table 5-3 reports both logit and linear probability regression results with mixed effects model for a sub-sample of about 521 thousand of loans in the U.S. between 2007 and 2012. Only applicants with multiple loan offers are included in this subsample. The dependent variable and independent variable are exactly the same as in Tables 5-1 and 5-2. Columns (1) and (2) report results with logit model, while columns (3) and (4) report results with linear probability model. Local lender in columns (1) and (3) is determined by the volume of mortgages, while in columns (2) and (4) it is determined by the number of mortgages.

[Insert Table 5-3 here]

Results in Table 5-3 basically remain the same as in the previous two tables. The coefficient of loan size to income ratio is still negative and significant in all 4 columns. The economic significances of the coefficients in the first two columns is even stronger than those in normal logit model and LPM, indicating that our first hypothesis about the higher probability of a less risky applicant rejecting lenders approved offers is correct and robust. Local lender has negative and significant coefficient as usual, which is in line with our second hypothesis. Therefore, we are confident to claim that our results are strong and robust to various models and samples, which provides sufficient supports to our hypotheses.

5.2 Type of Lenders that is More Likely to be Rejected by Applicants

Table 6-1 reports OLS regression results for a sample of about 23 thousand of bank * year observations with 5226 mortgage institutions in the U.S. between 2007 and 2012. The dependent variable is applicant rejection rate which equals to the percentage of loan offers approved by a lender but not accepted by applicants among all loan offers approved by the lender. The main independent variable is concentrated lender, which is determined by the volume of mortgages in columns (1) and (3), while determined by the number of mortgages in columns (2) and (4). All columns in this table have year fixed effects. Columns (2) and (4) add bank fixed effects too. Results show that the coefficient of concentrated lender is negative and significant in all 4 columns, meaning that lenders with information advantage, as represented by concentrated lenders, generally have lower applicant rejection rates. This evidence is in consistent with results in Tables 5-1, 5-2 and 5-3 and our second hypothesis.

[Insert Table 6-1 here]

However, given that we are using a sample in a very sensitive period right after 2007 global financial crisis, one concern is that our results are driven by the pattern in one or a few years between 2007 and 2012 when a particular event or government sponsored program. To address this concern, we decide to run a series of cross sectional regressions in each year with the same specification. The results are shown in Table 6-2.

[Insert Table 6-2 here]

In 11 out of 12 columns, concentrated lender has negative coefficients as expected, except for one where the coefficient is close to zero. It indicates that the negative impact of being a concentrated lender on applicant rejection rate is not driven or affected by any particular event happened between 2007 and 2012. In 7 out of 12 specifications, coefficients remain significant, which shows that the result is robust across years and provides convincing evidence for our second hypothesis.

Table 7 reports OLS regression results using the model shown in equation (2b) and (2c) with the same sample as in Table 6. The dependent variables are lender loan acceptance rate in columns (1) – (2) and non-jumbo mortgage ratio in columns (3) – (4). Lender loan acceptance rate is the percentage of loan applications approved by a lender among all applications received by the lender. Non-jumbo mortgage ratio is the percentage of non-jumbo mortgages among all mortgages originated by the lender. The main independent variable is applicant rejection rate, which is the same as the dependent variable in Tables 6-1 and 6-2. Applicant rejection rate measures the probability of a lender's offers being rejected by applicants. Concentrated lender is added in all columns as a control for the impact of lenders' geographical concentration. Applicant rejection rate and concentrated lender in columns (1) and (3) are determined by the volume of mortgages, while in columns (2) and (4) they are determined by the number of mortgages. All columns have bank fixed effects and year fixed effects.

[Insert Table 7 here]

In the first two columns where the dependent variable is lender loan acceptance rate, the coefficient of applicant rejection rate is negative and significant at 1% level, suggesting that lenders with lower applicant rejection rates tend to have higher loan acceptance rates than the other lenders. This is a sign of information advantage owned by lenders with lower applicant rejection rates over the others with higher applicant rejection rates. Similarly, we find a positive and significant coefficient of applicant rejection rate in column (3) where the dependent variable is non-jumbo mortgage ratio, meaning that lenders with higher applicant rejection rate tend to be more active in non-jumbo mortgage segment. Coefficient of applicant rejection rate in column (4) is negative but insignificant. This is an indication of information disadvantage for those lenders that are more likely to be rejected by applicants. Results in Table 7 are in consistent with previous studies about information advantage of geographically concentrated lenders, and provide strong evidence in support of our second hypothesis.

5.3 Placebo Test

Table 8 reports OLS regression results for the placebo test as shown in equation (3a). The dependent variable is loan offer rejection which is the same dummy as in Tables 5-1, 5-2 and 5-3. The two main independent variables are non-concentrated lender operating in its biggest market dummy, which equals to 1 if it is a lender with HHI of lending across MSAs lower than 0.50 operating in its biggest market; and concentrated lender operating in its smaller market dummy, which equals to 1 if it is a concentrated lender operating in markets that are not its biggest market. Both two independent variables in columns (1), (2), (5) and (6) are determined by the volume of mortgages, while in columns (3), (4), (7) and (8) are determined by the number of mortgages. All columns have bank level controls, loan level controls and year fixed effects. Columns (1) – (4) report results with linear probability model while columns (5) – (8) report results with logit model.

[Insert Table 8 here]

We observe the coefficient of loan size to income ratio remains negative and significant at at least 5% level in all 8 columns, which is in line with our results in Tables 5-1, 5-2 and 5-3, meaning that our first hypothesis remains correct and robust. More importantly, for the other two independent variables that we are interested in: non-concentrated lender operating in its biggest market dummy and concentrated lender operating in its smaller market dummy, we don't observe negative and significant coefficients as we do with local lender dummy in Tables 5-1, 5-2 and 5-3. Moreover, we observe positive and significant coefficients for concentrated lender operating in its smaller market dummy in 3 out of the 4 columns, meaning that concentrated lenders operating in their smaller markets are more likely to be rejected by applicants than their peers. This result is reasonable because concentrated lenders normally have little incentive to invest in collecting local information for their branches operating in their smaller markets where they lend only a small fraction of their loans. This may lead to an information disadvantage of concentrated lenders' branches operating in their smaller markets relative to the other lenders in the same market, which increases their probability of being rejected by applicants, as shown by the positive and significant coefficient we observe in columns (2), (4), and (6).

Nevertheless, neither non-concentrated lender operating in its biggest market dummy nor concentrated lender operating in its smaller market dummy have negative and significant coefficient as local lender does, even if they share similar characteristics and have close relationships with local lenders. This result suggests that it is truly information advantage, rather than any other lender-level characteristics, enables geographically concentrated lenders to be rejected by applicants less than their peers.

5.4 Robustness Test

In all 7 tables from Table 5-1 to Table 8, both results with variables' definitions based on mortgage volume and results with variables' definitions based on mortgage numbers are shown. The mortgage numbers based results are usually shown next to the mortgage volume based results. Results remain the same when we switch from volume-based variables to number-based variables.

We also try two alternative definitions of concentrated lender: lenders with more than 65% or 75% of their originated mortgages lend to a certain MSA. We find results don't change[i] too.

[i] Results are not shown due to limited space, but they are available upon request.

6. Conclusion

In this paper, using a comprehensive dataset with detailed loan application level information, we study a particular type of home mortgage applications in which household applicants reject lenders approved loan offers. We find that less risky mortgage applicants with lower loan size to income ratios are more likely to reject lenders approved loan offers than risky applicants. We also find that local lenders, defined as lenders that operate in a market where they extend most of their loans, are more likely to be rejected by risky applicants and less likely to be rejected by creditworthy applicants. Overall, local lenders are found to be less rejected by applicants compared to diversified lenders. Moreover, we find that lenders with lower applicant rejection rates tend to have higher loan acceptance rates and be more active in the jumbo mortgages segment. This evidence is in consistent with previous studies of information advantage of geographically concentrated lenders showing that mortgage lenders that concentrate in one or a few markets are better positioned to price risks and ration credit less. Therefore, we are confident to claim that information plays an important role in affecting both borrowers' and lenders' credit decisions, and explains the variations in the probabilities of applicants rejecting lenders approved loan offers, as well as the variation in the probabilities of lenders being rejected by applicants.

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Appendix

Figure 1 Applicant Rejection Rate and Lender Geographical HHI 2007 – 2012

The figure shows *applicant rejection rate* and *lender geographical HHI* for all mortgage lending institutions that report HMDA data in the U.S. between 2007 and 2012. *Applicant rejection rate* equals to the percentage of loan offers approved by mortgage lending institution but not accepted by applicants among all loan applications approved by the mortgage lending institutions. The left panel reports the average a*pplicant rejection rate* weighted by the total number of originated mortgages for each lender. *Lender geographical HHI* equals to the Herfindahl-Hirschman Index calculated using the volume based share of originated mortgages at each MSA by the mortgage lending institution. The right panel shows the average *lender geographical HHI* weighted by the total number of originated mortgages for each lender.

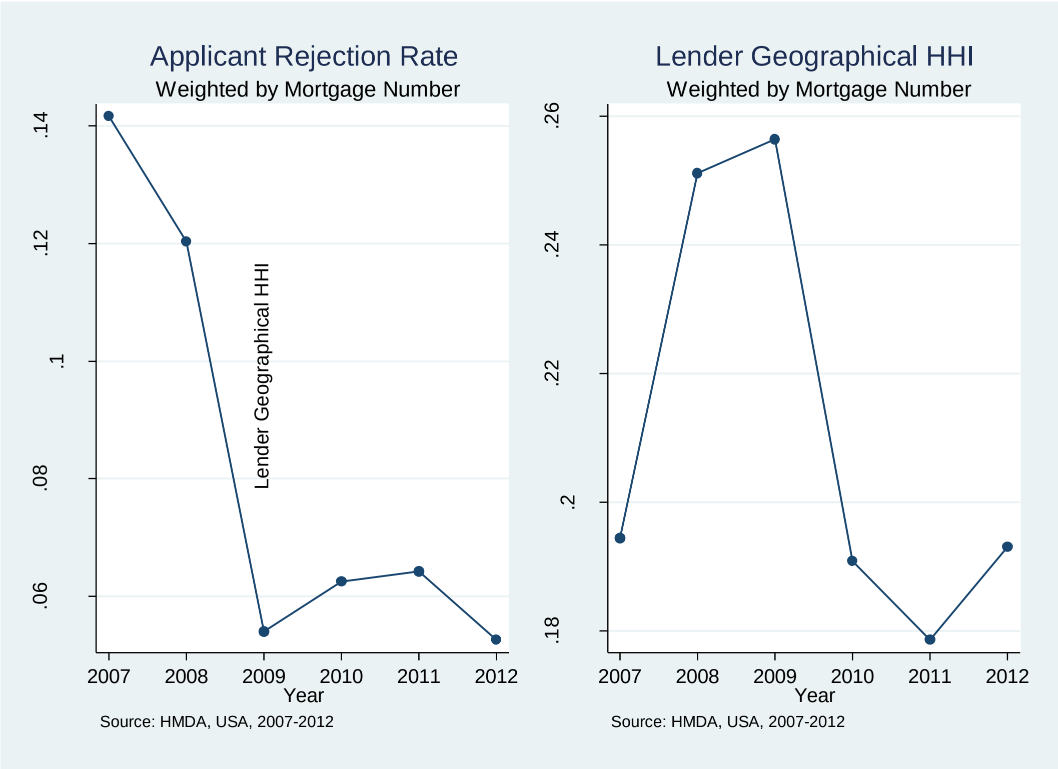

Figure 2 Housing Price Index 2007 – 2012

The figure shows *housing price index* in the U.S. between 2007 and 2012. *Housing price index* at MSA level is collected from Federal Housing Agency (FHA). The graph reports the un-weighted average housing price index..

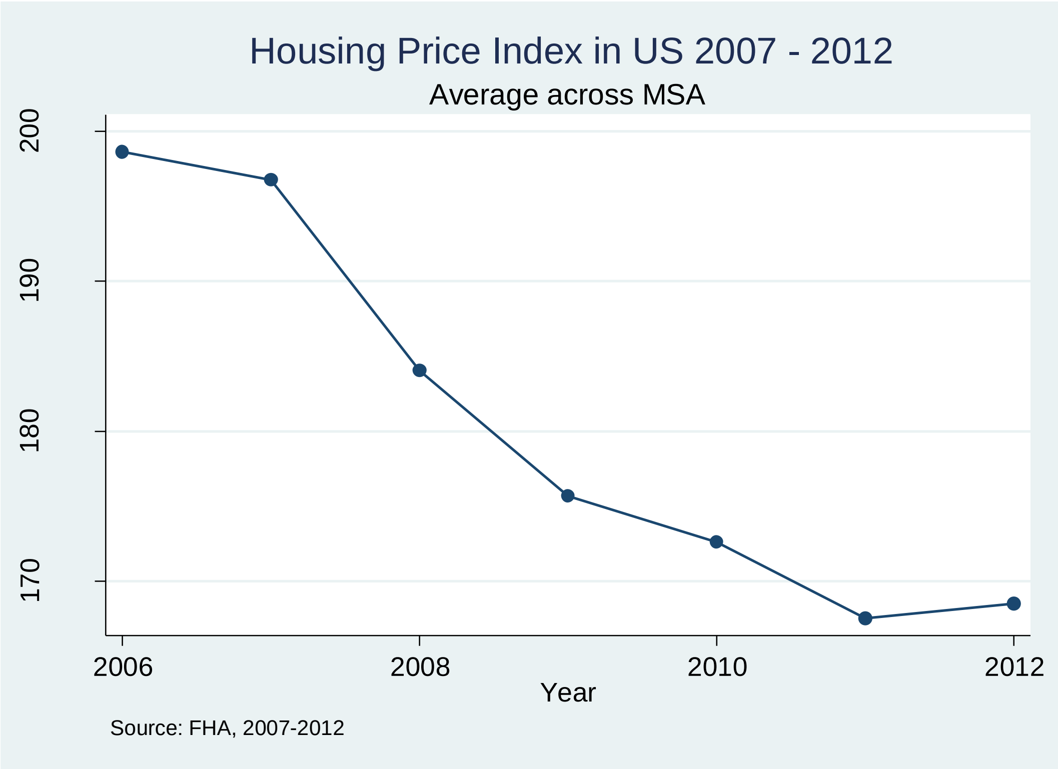

Table 1 HMDA Loan Action Type

The table shows all 8 action types of loans reported in HMDA data between 2007 and 2012. We are interested in only the following two action types: loan action type 1 which is loan originated by financial institution, loan action type 2 which is application approved by mortgage lending institution but not accepted by applicant. These two types of loan represent about 90%, 10% of observations respectively in our final sample.

Loan Action Type	**Percentage in HMDA**	**Percentage in Sample**
1 -- Loan originated by mortgage lending institution	39%	90%
2 -- Application approved by mortgage lending institution but not accepted by applicant	7%	10%
3 -- Application denied by mortgage lending institution	22%	
4 -- Application withdrawn by applicant before mortgage lending institution makes decision	9%	
5 -- File closed for incompleteness	3%	
6 -- Loan purchased by the institution	18%	
7 -- Preapproval request denied by mortgage lending institution	1%	
8 -- Preapproval request approved by mortgage lending institution but not accepted by applicant (optional reporting)	1%	

Source: HMDA.

Table 2-1 Loan Level Descriptive Statistics

The table reports loan level summary statistics. Loan amount is rounded to the nearest thousand. Loans of less than $500 are not reported. Applicant income is the total gross revenue a mortgage lending institution relied on in making the credit decision. Loan rate spread is reported as the difference between the annual percentage rate (APR) and the applicable average prime offer rate if the spread is equal to or greater than 1.5 percentage points for first-lien loans and 3.5 percentage points for subordinated-lien loans.

Variable	Labels	Mean	Std. Dev.	Observations	Min	Max
	Loan Characteristics					
Loan Amount	Mortgage amount, in thousand USD	219.83	212.27	34,264,401	1	98,400
Applicant Income	Applicant annual income, in thousand USD	112.76	135.82	34,264,401	1	9,998
Loan Size to Income Ratio	Loan amount / Applicant income	2.32	5.48	34,264,401	0.08	9,197
Loan Rate Spread	in %, difference between APR and applicable average prime offer rate, only available for a small part of originated loans	4.79	1.89	2,084,916	1.5	99.99
Loan Purpose	1 if Home purchase; 2 if Home improvement; 3 if Refinance	2.38	0.89	34,264,401	1	3
Preapproval	1 if Preapproval was requested, 2 if not, 3 if not applicable.	2.83	0.44	34,264,401	1	3
Lien Status	1 if Secured by a first lien, 2 if Secured by a subordinate lien, 3 if Not secured by a lien, 4 if Not applicable (purchased loans)	1.11	0.35	34,264,401	1	3
Applicant Ethnicity	1 if Hispanic or Latino, 2 if not, 3 if Information not provided by applicant, 4 if not applicable	2.04	0.42	34,264,401	1	4
Applicant Race	1: American Indian or Alaska Native, 2: Asian, 3: Black, 4: Native Hawaiian or Other Pacific Islander, 5: White, 6: Information not provided by applicant, 7: Not applicable	4.82	0.94	34,264,401	1	7
Applicant Sex	1 if Male, 2 if Female, 3 if Information not provided by applicant in mail, Internet, or telephone application, 4 if Not applicable.	1.39	0.60	34,264,401	1	4
Co-Applicant Ethnicity	Code 1- 4 are the same as Applicant Ethnicity, 5 if no co-applicant	3.41	1.49	34,264,401	1	5
Co-Applicant Race	Code 1- 7 are the same as Applicant Race, 8 if No co-applicant	6.31	1.69	34,264,401	1	8
Co-Applicant Sex	Code 1- 4 are the same as Applicant Sex, 5 if No co-applicant.	3.33	1.57	34,264,401	1	5

Source: HMDA.

Table 2-2 Bank Level Descriptive Statistics

The table reports bank level summary statistics. Annual change in TIER 1 Capital is determined by subtracting the account balance as of the corresponding reporting period in the previous year from the current period account balance and dividing the result by the previous year balance. HHI of lending across MSA is the Herfindahl-Hirschman Index calculated using the volume-based share of originated mortgages at each MSA of a mortgage lending institution. Concentrated lender is a bank * year level dummy which equals to 1 if the lender's HHI of lending across MSAs is larger than 0.5. Local lender is a bank * MSA * year level dummy which equals to 1 if the lender is a concentrated lender operating in its biggest market.

Variable	Labels	Mean	Std. Dev.	Observations	Min	Max
	Bank Characteristics					
Total Assets	Total Assets, in thousand USD	5.42E+08	5.91E+08	16,216,665	8,691	1.81E+09
Liquidity Ratio	(Federal Funds Sold & Re-sales + Trading Account Assets + Held-to-Maturity Securities + Available-for-Sale Securities + Total Earning Assets) / Average Total Assets	25.54	13.18	16,216,665	0.0441	97.8434
Intangible Assets / TA	Intangible Assets / Total Assets	0.03	0.03	16,216,665	0	0.59
Total Deposits / TA	Total Deposits / Total Assets	0.72	0.13	18,579,958	0	1.04
Equity Capital / TA	Equity Capital / Total Assets	0.10	0.03	18,579,958	-0.08	0.93
Net Income / TA	Net Income / Total Assets	0.01	0.01	18,579,958	-0.27	0.18
Real Estate Loans / GL	Real Estate Loans / Gross Loans	55.07	25.87	18,573,727	0	100
Yield on Total Loans and Leases	Yield on Total Loans and Leases	2.56E+07	1.85E+08	18,573,726	0	2.47E+09
Cost of Total Interest Bearing Deposits	Cost of Total Interest Bearing Deposits	295,637	2,823,338	18,566,243	0	7.19E+07
Annual Change in TIER 1 Capital	Annual change in TIER 1 Capital	23.95	67.15	16,167,481	-296.55	5,128.53
HHI of Lending across MSAs	Calculated based on volume of originated mortgages	0.23	0.30	34,264,346	0	1
Concentrated Lender	D:1 if HHI of lending across MSAs is larger than 0.5.	0.18	0.39	34,264,346	0	1
Local Lender	D:1 if mortgage lending institution is a concentrated lender operating in its biggest market	0.16	0.37	34,264,346	0	1
Lender Acceptance Rate	Percentage of loan applications approved by a mortgage lending institution among all loan applications received by the institution.	0.78	0.16	34,264,341	0	1
Non-Jumbo Mortgage Ratio	Percentage of non-jumbo mortgage among all mortgages originated by an lender	0.88	0.12	34,262,536	0	1

Applicant Rejection Rate	Percentage of loan offers approved by a mortgage lending institution but not accepted by applicants among all loan offers approved by the institution	0.11	0.12	34,264,401	0	1

Source: Call Report, HMDA.

Table 2-3 Market Level Descriptive Statistics

The table reports market level summary statistics. HHI of all lenders in a MSA is the Herfindahl-Hirschman Index calculated using volume-based share of mortgages of originated by each mortgage lending institutions in a MSA. Growth rate of Housing Price Index, layoff rate and real GDP are determined by subtracting the number as of the corresponding reporting period in the previous year from the current period number and dividing the result by the previous year number.

Market Characteristics						
Variable	**Labels**	**Mean**	**Std. Dev.**	**Observations**	**Min**	**Max**
Number HMDA Lenders	Number of mortgage lending institutions reporting HMDA in a MSA	532.02	254.17	34,264,401	22	1121
Number Local Lenders	Number of local lenders in A MSA. Local lender is a concentrated lender (i.e. HHI of lending across MSAs is larger than 0.5) operating in its biggest market	72.03	76.25	34,264,401	0	286
% Local Lenders	Percentage of local lenders among all mortgage lending institutions in a MSA.	0.11	0.09	34,264,401	0	0.74
HHI of All Lenders	Herfindahl-Hirschman Index calculated using volume-based share of mortgages of originated by each mortgage lending institutions in a MSA.	0.05	0.02	34,264,401	0.02	0.33
Growth Housing Price Index	Housing Price Index[t] / Housing Price Index[t-1] -1	-1.13	6.31	23,100,123	-45.30	22.48
Growth Layoff Rate	Layoff Rate[t] / Layoff Rate[t-1] -1	0.14	0.38	25,624,143	-0.72	1.94
Growth Real GDP	ln(Real GDP)[t] - ln(Real GDP)[t-1]	0.01	0.03	34,096,719	-0.45	0.35

Source: HMDA, FHA, BLS, Census Bureau, BEA.

Table 3 Lender and Loan Characteristics by Lender Types

The table reports lender and loan characteristics by lender and loan action types between 2007 and 2012. The two lender types are *local lenders* that are concentrated lenders operating in their biggest markets, and *non-local lenders* that are lenders other than local lenders. Definitions of the two variables can be found in Table 2. The two columns "Difference t-test" in the table report t-statistics for differences in means between the two bank types or loan action types and indicate significance at the 1%, 5%, and 10% levels with ***, **, *.

Variable Names	Non-local Lender		Local Lender		Difference
	Mean	Std. Err.	Mean	Std. Err.	t-test
Lender Characteristic					
Average Applicant Rejection Rate	0.12	0	0.06	0	0.057***
Loan Characteristic					
Average Loan Size to Income Ratio	2.38	0.001	2.01	0.004	0.371***
Average Loan Amount	227.47	0.038	180.31	0.104	47.160***
Average Applicant Income	114.11	0.026	105.81	0.052	8.298***

Table 4 Matching based on Loan Characteristics

The table reports the result of matching based on loan characteristics. The aim of matching is to find loan offers that are received by the same applicant in order to identify how many offers does an applicant receives and which offer does he reject and which offer does he finally choose to accept over the other loan offers. Loan offers will be considered to be received by the same applicant if they have exactly the same loan amount, loan purpose, application year, applicant income, applicant ethnicity, race, sex, co-applicant ethnicity, race, sex and county level property location. Matching results are represented by the distribution of applicants with various number of mortgage offers. All mortgage applicants are grouped into 2 groups: *applicants with single mortgage offer* are those people who received only one mortgage offer from a HMDA reporting financial institution; *applicants with multiple mortgage offers* are people who received more than one mortgage offers from HMDA reporting financial institutions. Moreover, *applicants with multiple mortgage offers* are further categorized into 4 subgroups based on the number of mortgage offers received by them. Matching results are shown by year and aggregated in all 6 years.

		2007	**2008**	**2009**	**2010**	**2011**	**2012**	**2007-2012**
Percentage of Applicants with Single Mortgage Offer		89.91%	92.52%	90.81%	92.32%	93.64%	91.79%	91.57%
Percentage of Applicants with Multiple Mortgage Offer	2 Offers	8.13%	6.11%	7.17%	6.42%	5.54%	6.80%	6.89%
	3 Offers	1.32%	0.82%	1.14%	0.84%	0.59%	0.98%	1.00%
	4 Offers	0.36%	0.23%	0.33%	0.21%	0.12%	0.25%	0.26%
	More than 4 Offers	0.29%	0.32%	0.56%	0.21%	0.11%	0.18%	0.28%

Table 5-1 Who are the Applicants that Reject Lenders? (Logit Model)

The table reports regression results with logit model as shown in equation (1a) using a subsample of about 8 million loans offers approved by more than 4 thousand mortgage lending institutions with available balance sheet information in the U.S. between 2007 and 2012. The dependent variable is *loan offer rejection* dummy which equals to 1 if applicant rejects lenders approved loan offers and 0 if applicant accepts the loan offers. The main independent variable is *loan size to income ratio* which measures the riskiness of a mortgage applicant. *Local lender*, defined as a dummy which equals to 1 if the mortgage lending institution is a concentrated lender operating in its biggest market. We first show results with the definition of *local lender* based on the volume of mortgages in columns (1) and (2), and then results with the definition of *local lender* based on the number of mortgages in columns (3) and (4) as robustness test. All columns have year fixed effects and MSA fixed effects. Columns (2) and (4) add interaction term between *loan size to income ratio* and *local lender*. Standard errors are clustered at bank level. P-values are presented in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10%.

	(1)	(2)	(3)	(4)
	Loan Volume		Loan Number	
Variables of Interest				
Loan Size to Income Ratio	-0.057***	-0.094***	-0.056***	-0.096***
	(0.001)	(0.000)	(0.001)	(0.000)
Local Lender	-0.283***	-0.391***	-0.267***	-0.379***
	(0.001)	(0.000)	(0.002)	(0.000)
Loan Size to Income Ratio * Local Lender		0.334***		0.348***
		(0.000)		(0.000)
Bank level control				
Log Total Assets	0.064*	0.065*	0.068**	0.069**
	(0.058)	(0.054)	(0.043)	(0.041)
Liquidity Ratio	-0.035***	-0.035***	-0.035***	-0.035***
	(0.000)	(0.000)	(0.000)	(0.000)
Intangible Assets / Total Assets	-2.389	-2.496	-2.444	-2.562
	(0.389)	(0.370)	(0.379)	(0.359)
Total Deposits / Total Assets	1.055**	1.056**	1.047**	1.050**
	(0.017)	(0.018)	(0.019)	(0.019)
Equity Capital / Total Assets	2.358	2.280	2.384	2.297
	(0.325)	(0.341)	(0.320)	(0.339)
Net Income / Total Assets	-1.759	-1.756	-1.760	-1.721
	(0.654)	(0.654)	(0.657)	(0.664)
Real Estate Loans / Gross Loans	-0.000	-0.001	-0.000	-0.001
	(0.920)	(0.902)	(0.938)	(0.916)
Yield on Total Loans and Leases	0.049	0.047	0.049	0.048
	(0.449)	(0.457)	(0.446)	(0.454)
Cost of Total Interest Bearing Deposits	-0.339***	-0.340***	-0.340***	-0.341***
	(0.004)	(0.004)	(0.004)	(0.004)
Annual change in TIER 1 Capital	0.000	0.000	0.000	0.000
	(0.303)	(0.382)	(0.298)	(0.381)
Loan level control				
Log Loan Amount	0.057**	0.053**	0.054**	0.050**
	(0.013)	(0.019)	(0.018)	(0.027)

Loan Purpose - Home Improvement	0.177**	0.198**	0.179**	0.202**
	(0.036)	(0.019)	(0.035)	(0.017)
Loan Purpose - Refinance	0.041	0.055	0.042	0.056
	(0.518)	(0.389)	(0.519)	(0.378)
No Preapproval Requested	0.284***	0.298***	0.284***	0.299***
	(0.000)	(0.000)	(0.000)	(0.000)
Preapproval Request not Applicable	0.388***	0.385***	0.389***	0.385***
	(0.001)	(0.001)	(0.001)	(0.001)
Applicant not Hispanic or Latino	-0.220***	-0.222***	-0.219***	-0.222***
	(0.000)	(0.000)	(0.000)	(0.000)
Applicant Ethnicity Information Missing	-0.003	-0.007	-0.002	-0.005
	(0.944)	(0.885)	(0.968)	(0.905)
Applicant Ethnicity Information not Applicable	-15.216***	-15.199***	-15.213***	-15.195***
	(0.000)	(0.000)	(0.000)	(0.000)
Applicant Asian	-0.089*	-0.082	-0.087*	-0.080
	(0.081)	(0.108)	(0.086)	(0.116)
Applicant Black	0.011	0.015	0.012	0.017
	(0.786)	(0.701)	(0.765)	(0.673)
Applicant Native Hawaiian or Other Pacific Islander	-0.039	-0.036	-0.038	-0.036
	(0.452)	(0.479)	(0.459)	(0.485)
Applicant White	-0.296***	-0.294***	-0.294***	-0.292***
	(0.000)	(0.000)	(0.000)	(0.000)
Applicant Race Information Missing	-0.199***	-0.192***	-0.200***	-0.193***
	(0.006)	(0.007)	(0.005)	(0.007)
Applicant Race Information not Applicable	12.030***	11.993***	12.035***	11.997***
	(0.000)	(0.000)	(0.000)	(0.000)
Applicant Female	-0.051***	-0.052***	-0.051***	-0.052***
	(0.000)	(0.000)	(0.000)	(0.000)
Applicant Gender Information Missing	0.022	0.013	0.021	0.012
	(0.812)	(0.882)	(0.814)	(0.889)
Applicant Gender Information not Applicable	1.047	1.068	1.048	1.070
	(0.175)	(0.167)	(0.173)	(0.164)
Secured by a Subordinate Lien	0.510***	0.529***	0.512***	0.530***
	(0.000)	(0.000)	(0.000)	(0.000)
Not Secured by a Lien	0.389*	0.361*	0.388*	0.361*
	(0.068)	(0.084)	(0.069)	(0.084)
Co-applicant Not Hispanic or Latino	-0.122***	-0.120***	-0.122***	-0.120***
	(0.000)	(0.000)	(0.000)	(0.000)
Co-applicant Ethnicity Information Missing	-0.115***	-0.114***	-0.117***	-0.115***
	(0.000)	(0.000)	(0.000)	(0.000)
Co-applicant Information not Applicable	-0.472*	-0.464*	-0.456*	-0.448*
	(0.080)	(0.086)	(0.092)	(0.097)
No co-applicant	-0.210***	-0.205***	-0.210***	-0.205***
	(0.000)	(0.000)	(0.000)	(0.000)
Co-applicant Asian	-0.045	-0.046	-0.044	-0.045
	(0.298)	(0.287)	(0.304)	(0.288)

Co-applicant Black	-0.088***	-0.088***	-0.088***	-0.088***
	(0.001)	(0.001)	(0.001)	(0.001)
Co-applicant Native Hawaiian or Other Pacific Islander	0.022	0.024	0.023	0.026
	(0.696)	(0.662)	(0.680)	(0.643)
Co-applicant White	-0.177***	-0.174***	-0.177***	-0.175***
	(0.000)	(0.000)	(0.000)	(0.000)
Co-applicant Race Information Missing	-0.125***	-0.126***	-0.125***	-0.126***
	(0.000)	(0.000)	(0.000)	(0.000)
Co-applicant Race Information not Applicable	-1.708***	-1.739***	-1.715***	-1.749***
	(0.001)	(0.001)	(0.001)	(0.001)
Co-applicant Female	-0.185***	-0.184***	-0.183***	-0.182***
	(0.000)	(0.000)	(0.000)	(0.000)
Co-applicant Gender Information Missing	-0.300***	-0.295***	-0.297***	-0.292***
	(0.000)	(0.000)	(0.000)	(0.000)
Co-applicant Gender Information not Applicable	1.005***	1.014***	1.017***	1.028***
	(0.001)	(0.001)	(0.001)	(0.001)
Market level control				
Lag Percent Local Lenders in MSA	5.271***	5.136***	6.129***	5.993***
	(0.000)	(0.000)	(0.000)	(0.000)
Lag HHI	-0.855	-0.883	-1.854*	-1.884*
	(0.195)	(0.181)	(0.056)	(0.053)
Log Total Population in Tract	-0.034***	-0.034***	-0.034***	-0.034***
	(0.000)	(0.000)	(0.000)	(0.000)
Minority Population %	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Log HUD Median Family Income	0.231	0.217	0.167	0.151
	(0.274)	(0.298)	(0.399)	(0.442)
Tract to MSA/MD Median Family Income Percentage	-0.002***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Lag Growth Housing Price Index	-0.007	-0.007	-0.007	-0.007
	(0.148)	(0.146)	(0.165)	(0.162)
Lag Growth Real GDP	0.295	0.290	0.265	0.258
	(0.283)	(0.290)	(0.336)	(0.347)
Lag Layoff Rate	0.010	0.011	0.017	0.018
	(0.878)	(0.871)	(0.791)	(0.784)
Constant	-4.183	-3.955	-3.504	-3.235
	(0.117)	(0.134)	(0.164)	(0.194)
Observations	8,573,866	8,573,866	8,571,639	8,571,639
Year FE	yes	yes	yes	yes
MSA FE	yes	yes	yes	yes

Table 5-2 Who are the Applicants that Reject Lenders? (Linear Probability Model)

The table reports regression results with linear probability model using a sample of about 34 million loans approved by about more than 10 thousand mortgage lending institutions in the U.S. between 2007 and 2012. The dependent variable is *loan offer rejection* dummy which equals to 1 if applicant rejects lenders approved loan offers and 0 if applicant accepts the loan offers. The main independent variable is *loan size to income ratio* which measures the riskiness of a mortgage applicant. *Local lender*, defined as a dummy which equals to 1 if the mortgage lending institution is a concentrated lender operating in its biggest market. The definition of *local lender* in columns (1) – (3) is based on mortgage volume, while in columns (4) – (6) it is based on the number of mortgages. Columns (1), (2), (4) and (5) report results with census tract * year fixed effects and bank fixed effects. Bank * year fixed effects are added in columns (3) and (6). In columns (2), (3), (5) and (6), an interaction term between *loan size to income ratio* and *local lender* is added. Standard errors are clustered at bank level. P-values are presented in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10%.

	(1)	(2)	(3)	(4)	(5)	(6)
	Loan Volume			Loan Number		
Loan Size to Income Ratio	-0.005***	-0.008***	-0.009***	-0.005***	-0.008***	-0.009***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Local Lender	-0.011***	-0.018***	-0.017***	-0.008***	-0.016***	-0.013***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Loan Size to Income Ratio * Local Lender		0.020***	0.015***		0.021***	0.015***
		(0.000)	(0.000)		(0.000)	(0.000)
Observations	16,153,748	16,153,748	34,264,346	16,150,606	16,150,606	34,251,288
R-squared	0.092	0.092	0.159	0.092	0.092	0.159
Bank level control	yes	yes	yes	yes	yes	yes
Loan level control	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes
Bank FE	yes	yes	no	yes	yes	no
Bank*Year FE	no	no	yes	no	no	yes
Census Tract*year FE	yes	yes	yes	yes	yes	yes

Table 5-3 Who are the Applicants that Reject Lenders? (Mixed Effect Model)

The table reports both logit and linear probability regression results with mixed effects model for a sub-sample of about 521 thousand of loans in the U.S. between 2007 and 2012. Only applicants with multiple loan offers are included in this subsample. The dependent variable is *loan offer rejection* dummy which equals to 1 if applicant rejects lenders approved loan offers and 0 if applicant accepts the loan offers. The main independent variable is *loan size to income ratio* which measures the riskiness of a mortgage applicant. *Local lender,* defined as a dummy which equals to 1 if the mortgage lending institution is a concentrated lender operating in its biggest market. Columns (1) and (2) report results with logit model, while columns (3) and (4) report results with linear probability model. Local lender in columns (1) and (3) is determined by the volume of mortgages, while in columns (2) and (4) it is determined by the number of mortgages. Standard errors are clustered at bank level. P-values are presented in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10%.

	(1)	(2)	(3)	(4)
	Logit Model		Linear Probability Model	
	Loan Volume	Loan Number	Loan Volume	Loan Number
Loan Size to Income Ratio	-0.143***	-0.144***	-0.050***	-0.051***
	(0.002)	(0.002)	(0.000)	(0.000)
Local Lender	-0.307***	-0.281**	-0.027**	-0.026**
	(0.007)	(0.014)	(0.019)	(0.028)
Number of offers received by applicants	-0.007	-0.007		
	0.342	0.356		
Observations	521,410	521,303	521,421	521,314
Bank level control	yes	yes	no	no
Loan level control	yes	yes	yes	yes
Market level control	yes	yes	yes	yes
Year FE	yes	yes	yes	yes
State FE	yes	yes	no	no

Table 6-1 Which Lenders are Likely to be Rejected by Applicants? (Panel)

The table reports OLS regression results for a sample of about 23 thousand bank-year observations from 4,230 banks that lend mortgage loans in the U.S. between 2007 and 2012. The dependent variable is *applicant rejection rate* which equals to the percentage of loan offers approved by a lender but not accepted by applicants among all loan offers approved by the lender. The main independent variable is *concentrated lender*, which equals to 1 if the lender has a HHI of lending across MSAs larger than 0.5. *Concentrated lender* in columns (1) and (3) is determined by the volume of mortgages, while in columns (2) and (4) it is determined by the number of mortgages. All columns in this table have year fixed effects. Columns (2) and (4) add bank fixed effects too. Standard errors are clustered at bank level. P-values are presented in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10%.

	(1)	(2)	(3)	(4)
	Loan Volume		Loan Number	
Variables of Interest				
Concentrated Lender	-0.012***	-0.015***	-0.015***	-0.022***
	(0.001)	(0.004)	(0.000)	(0.000)
Bank level control				
Log Total Assets	0.011***	0.006	0.011***	0.002
	(0.000)	(0.403)	(0.000)	(0.769)
Liquidity Ratio	-0.000*	-0.000	-0.000**	-0.000
	(0.062)	(0.558)	(0.027)	(0.859)
Intangible Assets / Total Assets	0.043	0.353**	0.047	0.374**
	(0.592)	(0.030)	(0.518)	(0.011)
Total Deposits / Total Assets	0.009	0.013	-0.001	-0.004
	(0.605)	(0.641)	(0.968)	(0.865)
Equity Capital / Total Assets	0.005	-0.054	0.016	-0.062
	(0.894)	(0.422)	(0.606)	(0.291)
Net Income / Total Assets	-0.286***	0.235**	-0.311***	0.129
	(0.001)	(0.042)	(0.000)	(0.190)
Real Estate Loans / Gross Loans	0.000***	0.000	0.000**	0.000
	(0.009)	(0.119)	(0.015)	(0.147)
Yield on Total Loans and Leases	0.003**	-0.002	0.003**	-0.001
	(0.034)	(0.439)	(0.016)	(0.533)
Cost of Total Interest Bearing Deposits	-0.001	0.005	-0.001	0.005*
	(0.633)	(0.145)	(0.702)	(0.067)
Annual change in TIER 1 Capital	-0.000	-0.000	-0.000	-0.000
	(0.960)	(0.683)	(0.567)	(0.328)
Constant	-0.110***	-0.046	-0.100***	0.020
	(0.000)	(0.652)	(0.000)	(0.810)
Observations	23,242	23,242	23,242	23,242
R-squared	0.021	0.004	0.029	0.008
Number of hmid2	5,226	5,226	5,226	5,226
Year FE	yes	yes	yes	yes
Bank FE	no	yes	no	yes

Table 6-2 Which Lenders are Likely to be Rejected by Applicants? (Cross-Sectional)

The table reports both OLS regression results for a sub-sample of about four thousand bank * year observations from 4,230 banks that lend mortgage loans in the U.S. each year between 2007 and 2012. The dependent variable is *applicant rejection rate* which equals to the percentage of loan offers approved by a mortgage lending institution but not accepted by applicants among all loan offers approved by the institution. The main independent variable is *concentrated lender*, which equals to 1 if the lender has a HHI of lending across MSAs larger than 0.5. *Concentrated lender* in columns (1) - (6) is determined by the volume of mortgages, while in columns (7) - (12) it is determined by the number of mortgages. All 12 columns have bank level controls. Standard errors are clustered at bank level. P-values are presented in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10%.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	2007	2008	2009	2010	2011	2012	2007	2008	2009	2010	2011	2012
	Loan Volume						Loan Number					
Variables of Interest												
Concentrated Lender	-0.017**	-0.004	0.000	-0.020**	-0.025***	-0.008	-0.020***	-0.010*	-0.003	-0.020***	-0.029***	-0.010
	(0.018)	(0.462)	(0.945)	(0.020)	(0.003)	(0.231)	(0.004)	(0.070)	(0.600)	(0.009)	(0.000)	(0.117)
Observations	4,008	4,059	4,015	3,851	3,696	3,613	4,008	4,059	4,015	3,851	3,696	3,613
R-squared	0.027	0.049	0.031	0.018	0.015	0.009	0.038	0.060	0.041	0.024	0.025	0.012
Bank level control	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year FE	no	no	no	no	no	no	no	no	no	no	no	no
Bank FE	no	no	no	no	no	no	no	no	no	no	no	no

Table 7 Lenders with Lower Applicant Rejection Rate Show Information Advantage over Others

The table reports OLS regression results using the model shown in equation (2b) and (2c) with the same sample as in Table 6. The dependent variables are *lender loan acceptance rate* in columns (1) – (2) and *non-jumbo mortgage ratio* in columns (3) – (4). *Lender loan acceptance rate* is the percentage of loan applications approved by a lender among all applications received by the lender. *Non-jumbo mortgage ratio* is the percentage of non-jumbo mortgages among all mortgages originated by the lender. The main independent variable is *applicant rejection rate*, which equals to the percentage of loan offers approved by a mortgage lending institution but not accepted by applicants among all loan offers approved by the institution. *Applicant rejection rate* measures the probability of a lender's offers being rejected by applicants. *Concentrated lender* is added in all columns as a control for the impact of lenders' geographical concentration. *Applicant rejection rate* and *concentrated lender* in columns (1) and (3) are determined by the volume of mortgages, while in columns (2) and (4) they are determined by the number of mortgages. All columns have year fixed effects and bank fixed effects. Standard errors are clustered at bank level. P-values are presented in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10%.

	(1)	(2)	(3)	(4)
	Lender Loan Acceptance Rate		Non-jumbo Mortgage Ratio	
	Loan Volume	Loan Number	Loan Volume	Loan Number
Applicant Rejection Rate	-0.353***	-0.379***	0.116***	-0.022
	(0.000)	(0.000)	(0.000)	(0.252)
Concentrated Lender	0.001	0.013***	0.001	-0.003
	(0.790)	(0.009)	(0.843)	(0.502)
Observations	23,240	23,240	23,202	23,202
R-squared	0.082	0.094	0.015	0.007
Number of banks	5,226	5,226	5,222	5,222
Bank level control	yes	yes	yes	yes
Year FE	yes	yes	yes	yes
Bank FE	yes	yes	yes	yes

Table 8 Placebo Test

The table reports OLS regression results for a sample of about 34 million loans in the U.S. between 2007 and 2012. The dependent variable is *loan offer rejection* which equals to 1 if applicant rejects loan offer approved by lenders and 0 if applicant accepts the loan offer. The main independent variable is *loan size to income ratio* which measures the risk level of a mortgage applicant. The other two main independent variables are dummy variable *non-concentrated lender operates in its biggest market*, which equals to 1 if it is a lender with HHI of lending across MSAs lower than 0.50 operating in its biggest market; and dummy variable *concentrated lender operates in its smaller market*, which equals to 1 if it is a concentrated lender operating in markets that are not its biggest market. Both two independent variables in columns (1), (2), (5) and (6) are determined by the volume of mortgages, while in columns (3), (4), (7) and (8) are determined by the number of mortgages. All columns have bank level controls, loan level controls and year fixed effects. Columns (1) – (4) report results with linear probability model while columns (5) – (8) report results with logit model. Standard errors are clustered at bank level. P-values are presented in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10%.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Linear Probability Model				Logit Model			
	Loan Volume		Loan Number		Loan Volume		Loan Number	
Loan Size to Income Ratio	-0.005***	-0.007***	-0.005***	-0.007***	-0.050**	-0.049**	-0.049**	-0.049**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.020)	(0.020)	(0.020)	(0.020)
Non-Concentrated Lender Operating in Its Biggest Market	-0.001		-0.001		-0.051		-0.045	
	(0.797)		(0.753)		(0.232)		(0.309)	
Concentrated Lender Operating in Its Smaller Market		0.010***		0.010***		0.129*		0.077
		(0.000)		(0.000)		(0.078)		(0.223)
Observations	16,153,748	34,264,346	16,153,748	34,264,346	12,598,889	12,598,889	12,598,889	12,598,889
Bank level control	yes	yes	yes	yes	yes	yes	yes	yes
Loan level control	yes	yes	yes	yes	yes	yes	yes	yes
Market level control	no	no	no	no	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes	yes	yes
Bank FE	yes	no	yes	no	no	no	no	no
Bank*Year FE	no	yes	no	yes	no	no	no	no
MSA FE	no	no	no	no	yes	yes	yes	yes
Census Tract*year FE	yes	yes	yes	yes	no	no	no	no

The value of relationship banking:

Evidence from interbank liquidity crunch in China

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The value of relationship banking:

Evidence from interbank liquidity crunch in China

Abstract

Using an event study of the interbank liquidity crunch in June 2013 in China, we investigate how lending relationships affect the market reactions of the borrowing firms during the interbank liquidity crunch. We find that firms with lending relationships with banks (i.e. firms whose largest lender of long-term loans are banks) outperform others in the stock market. Lending relationships with local banks are associated with lower firm CARs, while lending relationships with big 4 banks do not have any significant effect. We also find a positive correlation between firms' stock performances and their banks' stock performances, as well as banks' liquidity in interbank market, in particular for those firms whose largest lenders of long-term loans are big 4 banks. (119 words)

Key words: lending relationship, interbank liquidity crunch, local banks

JEL classification: G30, G140, G210.

1. Introduction

The role of relationship banking has been widely examined in the literature (Chava and Purnanandam, 2011; Ongena, Smith, and Michalsen, 2003). However, the identification is often based on a mixed link with accounting performance, or the event studies during the financial crisis, which affects both the credit supply of lenders and credit demand of borrowers. We use the interbank liquidity crunch in June 2013 in China as a natural experiment to evaluate the value of bank-firm relationship in the eyes of investors. Interbank liquidity crunch could increase the funding cost for all participants in the interbank market, e.g. banks, non-bank financial institutions, and non-financial firms. The interbank market liquidity dry-up in June 2013 had a direct negative impact on the credit supply of lenders during the event, while it did not directly affect firms' access to finance as it only lasted for a couple of days.

The interbank market crunch in China is an ideal setting to examine bank-firm relationship as it is "artificially" made by the central bank, i.e. *People's Bank of China* (PBOC). The PBOC often intervenes the interbank market whenever there is a signal of liquidity dry-up. However, the new leadership that came to power in March 2013 tried to change the role of *PBOC* in the interbank market, which ended up in an unexpected liquidity dry-up on June 20th 2013. The unique characteristics make it a clean setting to evaluate the bank-firm relationship for the borrowing firms.

There are two main contributions of this paper. On the one hand, we document a new setting to test the value of relationship banking. Unlike the standard way of the event study of loan announcements when bank-firm relationships are newly established or renewed, we test the value of relationship banking at the moment when banks suffer exogenous liquidity shocks, which end up in a clean identification of the value of relationship banking for the borrowing firms. On the other hand, we also provide evidence on the policy interventions of central banks. We provide evidence on the market reactions to an unexpected change of central banks' policy in the interbank market, which may help understand the effectiveness of the policies of central banks.

The paper is organized as follows. Section 2 provides an introduction of the Chinese credit market and the interbank liquidity crunch in June 2013. Section 3 surveys the literature, develops the hypotheses, and shows the empirical methodology. In section 4, we describe the data and provide summary statistics. Section 5 shows the regression results. Section 6 concludes the paper.

2. Credit market and interbank liquidity crunch in China

2.1 Credit market in China

China's capital markets comprise a bond market and an equity market. The bond market remains under-developed, although corporate bonds were first issued already in 1986. The market value of newly issued bonds in China was only 1.74 percent of GDP at the end of 2012, and corporate bond issuance accounts for only 11.19 percent of total bond issuance in China. In contrast, the newly established *Shanghai Stock Exchange* and *Shenzhen Stock Exchange* have enjoyed rapid expansion since their inceptions in 1990, which ranked in the world's top ten exchanges at the end of 2011 by total market capitalization. Moreover, the two stock exchanges were established so as to provide a new source of funding to state-owned enterprises (SOEs) and to reduce the financial burden of government bailouts. Up until 2005, about 80 percent of the (more than 1,100) listed enterprises were converted from SOEs in China.

The Chinese credit market is dominated by commercial banks (Allen, Qian and Qian, 2005), with a bank credit to GDP ratio of 1.11. Banks provided half of the total financing for Chinese firms in 2013 (National Bureau of Statistics of China). Most of the bank credit is extended by state-owned banks to SOEs or to large private firms. The capital market is relatively underdeveloped and a majority of listed firms are ultimately owned / controlled by the government. Thus, a majority of credit is channeled to the SOEs and large private firms.

2.2 Interbank liquidity crunch in China

Market liquidity dry-ups in the interbank market have been a relatively recent phenomenon in the country. The PBOC typically injects liquidity into the market whenever there is a dry-up, which creates a moral-hazard problem for the banks. Under a context of decreasing deposit and increasing legal depository rate, the 4 state-owned banks, i.e. *Industrial and Commercial Bank of China*, *China Construction Bank*, *Bank of China*, and *Agricultural Bank of China*, still hold a large amount of liquid assets (e.g. cash), while the medium-sized and small banks tend to rely more on interbank market for liquidity. Due to an expectation that the PBOC will inject liquidity in case of dry-ups, banks adopted aggressive loan strategies in June 2013 in order to meet the semi-annual performance goals. The newly loans increased by 863 billion in June 2013, i.e. a 28.89% increase from the month before. Moreover, the PBOC initiated the issuance of bills again in May 2013, which further aggravates the liquidity dry-up. All these factors precipitated the interbank liquidity crunch on June 20th 2013.

The interbank market has already witnessed several negative news since the beginning of the month (see Appendix 1 for an overview of major events). The bond issuance of *Agriculture Development Bank of China* failed to attract enough subscriptions on June 5th, 2013, which brought a pessimistic atmosphere to the interbank market (i.e. the overnight interbank interest rate rose to 4.62% on that day from about 3% a week before). On June 6th, a rumor flies in the market: *China Everbright Bank* couldn't repay more than 100 billion RMB loans back to *China Industrial Bank*. Although the two banks denied the loan default, the panic in the interbank market had arisen when the interbank market delayed its closing time due to the widespread default rumor. On June 7th, rumors flew that the *PBOC* would inject 150 billion RMB into the interbank market. However, the *PBOC* turned out to fail to meet the rumors at the end of the day. As a result, the interbank rate hiked to 9.58% on June 8th 2013 while it reversed back to a normal level subsequently.

On June 14th, the issuance of treasury bonds failed to attract enough subscription, which aggravated the panic in the interbank market. On June 18th, the Chairman of *China Banking Regulatory Commission* issued a warning against the financial innovations that make arbitrage of the financial regulations. On June 19th, Premier *Keqiang Li* expressed a determination for the financial reform by the government. The interbank rate hiked to 7.66% on that day, which delayed the closing time of the interbank market by 30 minutes. The PBOC talked privately with several big banks (e.g. China Post Savings Bank), and made these banks inject about 400 billion RMB and meet the funding gap of the interbank market.

On June 20th, the panic had spread to the whole interbank market. However, the PBOC insisted on the issuance of bills, which further extract liquidity from the interbank market. A rumor flew that the *Bank of China* was in default in the interbank market. The overnight interest rate hiked to more than 10% at the opening of the interbank market and surpassed 13% at the end of the day.

On June 21st, the PBOC supplied 50 billion RMB to *Industrial and Commercial Bank of China* in order to alleviate the liquidity dry-up. On June 23rd, several branches of the *Industrial and Commercial Bank of China* in *Beijing* and *Shanghai* closed unexpectedly, which was believed to be caused by the liquidity crunch in the interbank market. While the *Industrial and Commercial Bank of China* and *Bank of China* denied these rumors afterwards, the panic had already spread further to the whole market.

On June 24th, the stock market suffered a crash, i.e. *Shanghai Stock Exchange* composite index decreased by about 5%. In particular, the stock prices decreased by about 10% for *China Minsheng Bank*, *China Industrial Bank*, and *Ping An Bank*.

However, the PBOC still kept a neutral attitude and announced that the market liquidity was sufficient. A lot of financial institutions were forced to sell other assets in order to meet their liquidity needs, which substantially enhanced banks' liquidity and dragged the overnight interbank interest rate to 5.74%. On June 25th, the *PBOC* suspended the issuance of bills and supplied liquidity support for certain financial institutions. On June 26th, the overnight interbank interest rate decreased to 5.55%, which indicated that the liquidity crunch was over and the panics in the money market were alleviated substantially.

The liquidity crunch in June 2013 served as a warning tool to the banks' loan strategy, i.e. the newly issued loans only recovered to a comparable level of June 2013 seven months after the liquidity crunch. On June 29th, the Chairman of the *China Banking Regulatory Commission* pointed out that some commercial banks face problems in liquidity and risk management, which needs further enhancement afterwards. On July 1st, the President of the *PBOC* said that the liquidity crunch pushed these banks to improve their liquidity management and adjust asset structures, e.g. banks' incentives to extend more loans in order to meet the semi-annual performance goals. Five months after the liquidity crunch, Premier *Keqing Li* said in Nov 2013 that the central government tried to keep the neutrality of the PBOC during the liquidity crunch in June 2013 even when he was concerned about the panics from the rumors at that time.

3. Hypothesis and methodology

3.1 Hypothesis

Our paper is related to three strands of literature: firstly, the benefits of relationship banking; secondly, the heterogeneity of bank performance in the Chinese banking market; and thirdly, the mechanism of the interbank market liquidity crunch.

Firstly, the benefits of relationship banking have well been documented in the literature. Relationship banking can add value as it facilitates the information exchange and production, i.e. firms are incentivized to disclose more information and banks are also motivated to invest more in acquiring proprietary information (Ongena and Smith, 2000; Boot, 2000). Empirical works also find supportive evidence. James (1987) and Lummer and McConnell (1989) find positive market reactions of bank loan announcements from firms' perspective while Megginson et al (1995) find heterogeneous market reactions from banks' perspective. Solvin et al (1992) find that small and less prestigious firms have benefits from screening and monitoring services associated with bank loans.

Moreover, the quality, organizational structure, and the origin of lender also matter for market reactions (Slovin et al, 1988; Billet et al, 1995; Ongena and Roscovan, 2013). However, there is some evidence against the benefits of relationship banking though. Maskara and Mullineaux (2011) find that self-selection bias affects the positive announcement effect in existing research. Fields et al (2006) finds that the general advantages of bank-firm relationships have disappeared since 1980s, although relationship banking are still beneficial for smaller and poorly performing firms or during the period of high credit spreads. However, since the recent financial crisis in 2007, banks' role in certifying corporate borrowers has been revitalized, as documented in Li and Ongena (2014).

Secondly, domestic banks in China can often be categorized into three groups (Chong et al, 2013): 4 state-owned banks (i.e. national banks), 12 joint-stock banks (i.e. regional banks), and other small and medium-sized banks including city / rural commercial banks, urban / rural credit cooperatives, rural cooperative banks, village-town banks (i.e. local banks). We denote the 4 state-owned banks that dominate the Chinese banking sector as *Big 4 banks*, i.e. *Industrial and Commercial Bank of China*, *China Construction Bank*, *Bank of China*, and *Agricultural Bank of China*. Big 4 banks extend a large proportion of credit to the state-owned and large private firms, while they show less interests in SMEs financing due to their organization structures (Berger et al, 2005) and soft budget problems. Berger et al (2009) show that the *Big 4 banks* are the least efficient banks in China. Lin and Zhang (2009) show that the *Big 4 banks* are less profitable, less efficient, and have worse asset quality than other banks.

Local banks in the China are found to have better performance than state-owned banks. Using a survey of 20 city commercial banks in China, Ferri (2009) shows that the local economic growth has a spillover effect on the performance of local banks, while their corporate governance structures are no better than the state-owned banks.

Thirdly, our paper is also related to the literature on the mechanism of the interbank market liquidity crunch. Michaud and Upper (2008) show that risk premiums are mainly driven by factors related to the funding liquidity in the short-term, i.e. the ability to convert assets into cash by individual banks. Besides, lending relationship among banks is also an important determinant of banks' ability to access liquidity in the interbank market (Cocco et al, 2009).

We will show the effect of a liquidity crunch in the interbank market on the performance of firms that have lending relationships with banks. Generally speaking, a liquidity crunch in the interbank market negatively affect credit supply, which will lead to a more tightening credit constraint of the borrowing firms, thus a negative market reaction for listed firms. Thus our first hypothesis is:

Hypothesis 1: the cumulative abnormal returns (CARs) of the listed firms during the liquidity crunch is negative.

Banks may acquire information through a long-term relationship with a firm. A relationship bank may help alleviate the credit constraints and survive a liquidity shocks in the interbank market than otherwise (i.e. no relationship bank). If the largest lender of the long-term loans is a bank (versus non-bank financial institutions and nonfinancial firms), we define that this firm has a relationship bank. If a listed firm has a relationship bank, it may suffer less from a liquidity crunch in the interbank market. The reason is that the relationship banks have incentives to keep lending to customers with whom they have relationships, and may reallocate lending by reducing lending to other customers with whom they have no relationships during liquidity shocks. Our second hypothesis is:

Hypothesis 2: Firms that have relationship banks have higher CARs than firms that have no relationship banks.

The national and regional banks typically have more financing flexibility than local banks due to their diversification in deposit and other funding sources. In addition, local banks have less support from the governments, e.g. PBOC often supports the national banks and regional banks but not the local banks during liquidity crunches, which make local banks more fragile to external shocks. Furthermore, the Big 4 banks often receive more support from the regulatory authority, which enable them with more financial flexibility during the liquidity crunches. Thus, a listed firm may face higher credit constraints during a liquidity crunch if their relationship bank is a local bank instead of a national or regional bank, while lower credit constraints if with a national bank. Our third and fourth hypothesis is:

Hypothesis 3: Firms whose relationship banks are local banks have lower CARs than firms whose relationship banks are national or regional banks.

Hypothesis 4: Firms whose relationship banks are big 4 banks have higher CARs than firms whose relationship banks are non-big-4 banks.

Firms will suffer less if their relationship banks hold more liquid assets before a liquidity crunch. Put differently, the market reactions of listed banks can also capture the soundness of the banks during the liquidity crunch. Thus, we use the interbank market liquidity position (i.e. liquid assets / liquid liabilities in the interbank market) and the CARs of listed banks to measure the soundness of the banks. Our fifth hypothesis is:

Hypothesis 5: Firms whose relationship banks experience higher CARs or have more interbank market liquidity, have higher CARs.

3.2 Methodology

A standard market model (James, 1987) is used to estimate the benchmark returns and then to calculate the abnormal returns. In order to measure market returns, we use the market return weighted by the market value for the Chinese stock market (A-shares) from the *China Stock Market & Accounting Research* (CSMAR) database. We define June 20th 2013 as the event date "day 0", (i.e. when the overnight interbank interest rate hiked to 13.44%). We run a daily market model for the firms over the estimation window of [-120, -21]. Specifically, the abnormal return for firm *i* on day *t* is defined as:

$$AR_{it} = R_{it} - (\alpha_i + \beta_i R_{mt}) \quad (1)$$

where R_{it} is the rate of return for firm *i* on day *t*, R_{mt} is the rate of return for the market index weighted by market value of the Chinese stock market (A-shares) on day *t*. The coefficients α_i and β_i are estimates of firm *i*'s market model parameters for the period from 120 trading days to 21 trading days before June 20th 2013.

The average abnormal return on event day *t* for a sample of size *N* is:

$$AR_t = \frac{1}{N}\sum_i^N AR_{it} \quad (2)$$

The significance tests are based on standardized abnormal returns:

$$SAR_{it} = \frac{AR_{it}}{S_{it}} \quad (3)$$

where

$$S_{it} = \left[V_i^2\left[1 + \frac{1}{M} + \frac{(R_{mt}-R_m)^2}{\sum_j^M (R_{mj}-R_m)^2}\right]\right]^{1/2} \quad (4)$$

and V_i^2 is the residual variance of the market model for firm i; M is the number of days used in the market model regression; R_m is the average market return over the estimation window.

Cumulative abnormal returns, i.e. $CAR[T_1, T_2]_i$, are the summation of abnormal returns over the event window $[T_1, T_2]$ for firm *i*. The average CAR for a sample size

N is:

$$CAR[T_1, T_2] = \frac{1}{N} \sum_{i=1}^{N} \sum_{t=T_1}^{T_2} AR_{it} \tag{5}$$

The statistic for the significance test of $CAR[T_1, T_2]$ is:

$$Z_{(T_1, T_2)} = \frac{1}{\sqrt{N}} \sum_{i=1}^{N} \sum_{t=T_1}^{T_2} SAR_{it} / (\sqrt{T_2 - T_1 + 1}) \tag{6}$$

The Chinese stock market has imposed restrictions on the daily price ceiling and floor since 1996. Based on the previous trading day's closing price, the ceiling and the floor for the stock prices are set at ten percent for all stocks and five percent for stocks that are labeled for special treatment (i.e. "ST"). Thus, the stock price may continue to react after the event day, which makes CAR[-1, 1] a more informative measure to capture a full market reaction besides the standard CAR[-1,0]. We also report results for various event windows (e.g., CAR[-2, 2], etc.) to check the robustness.

Finally we link the CARs to bank-firm relationship, firm and bank level characteristics in a regression equation:

$$CAR[-1,1]_i = \gamma_0 + \gamma_1 Bank - firm\ relationship_i + \gamma_2 Firm_i + \gamma_3 Bank_i + \gamma_4 Industry_i + \epsilon_i \tag{7}$$

We include bank-firm relationship variables in the regression, i.e. *Bank, Local bank, and Big 4 bank*, which indicate whether the largest lender of long-term loans for a listed firm is a bank (versus non-bank financial institutions and non-financial firms), local bank (versus regional, national and foreign banks), or big 4 bank (versus all other banks except for the largest four banks in China, *ICBC*, *BOC*, *CCB*, and *ABC*).

In addition, we include a set of firm variables: state-owned, firm size (Total assets), leverage, profitability (EBIT), and Tobin's Q. We further include bank level variables, such as interbank market liquidity, bank CAR, bank total assets, bank liquidity ratio, and bank equity ratio. Finally, we include the industry fixed effects in the regression, and the standard errors are clustered at the industry level.

4. Data and summary statistics

We collect data on *SHIBOR* (*Shanghai Interbank Offered Rate*) from *National Interbank Funding Center*. As shown in Figure 1 that the overnight *SHIBOR* peaked to 13.44% on June 20th 2013, we then define June 20th 2013 as the event day for the liquidity crunch in the interbank market.

[Insert Figure 1 here]

Our sample consists of all firms traded on the Chinese stock market, including the *Shanghai* and *Shenzhen Stock Exchange*. After excluding firms with missing stock returns within the [-5, 5] window around the event day, we reach a sample of 2,355 firms, including 42 financial firms and 2,313 nonfinancial firms.

We then identify firms' largest lender of long-term loans using the top-five outstanding long-term loans disclosed by firms' annual reports in 2012. The *China Securities Regulatory Commission* (*CSRC*) requires the disclosure of the top-five outstanding long-term loans in annual reports, i.e. lender name, outstanding loan volume in the beginning and end of the fiscal year, start-date and end-date of the loan, interest rate, and loan type. Given that a lender could appear multiple times in a firm's top-five long-term loans, we aggregate lenders at headquarter level and add up loan volumes by each lender. We take an average of loan volume in the beginning and end of the year, and then identify the largest lender of long-term loans.

Half of the listed firms (i.e. 1,021) disclose long-term loan information in their 2012 annual reports, which makes it difficult to identify their relationship bank. We cross-check it with the data of firms' long-term debts from *Datastream*, and find that firms who don't disclose long-term loans in the annual reports are mostly with zero long-term debt.

We collect stock prices and market indexes from *CSMAR*, a widely used database for the Chinese stock market. We calculate stock return as the daily growth rate of stock closing price and market return as the growth rate of market index weighted by the firms' total capitalization. We also use dividend-adjusted stock return to test the robustness of our results. We choose four symmetric windows [-1, 1], [-2, 2], [-3, 3], [-5, 5] around the event day, and another four asymmetric windows [-1, 0], [0, 1], [-1, 2], and [0, 2] to capture the market reactions for the interbank liquidity crunch. Descriptive statistics of CARs for the eight event windows for all listed firms is shown in Table 1-1.

[Insert Table 1-1 here]

We supplement the *CSMAR* corporate stock data with firm balance sheet data at the end of 2012 from *Wind* database, i.e. firm size, profitability, leverage, and Tobin's

Q. We add firm ownership information from *CSMAR* and create a state-owned firm dummy variable which equals 1 if the firm's ultimate controller is a state-owned entity.

We then add bank balance sheet data from *Bankscope*, i.e. bank total asset, bank liquidity ratio, and bank equity ratio. Among all 78 banks that serve as listed firms' largest lenders of long-term loans, 46 banks have balance sheet information in *Bankscope*, which covers about 95% of firms with banks as their largest lender of long-term loans in our sample.

We compile a dataset of bank and firm characteristics that may be associated with firm CARs for the event of interbank liquidity crunch. Variable definitions and summary statistics are in Table 1-2.

[Insert Table 1-2 here]

To examine general market reactions to the interbank liquidity crunch, Table 2 reports a brief descriptive statistics of CARs in six event windows for all 2,313 non-financial listed firms. All eight CARs are negative, while seven out of six CARs are significant and four of them are significant at 1% level. For example, CAR [-1, 1] equals -0.003 that is significant at 1% level, i.e. the stock price decrease abnormally by 0.3% for all non-financial firms in the market within the three days around the event day. This results is economically significant given that the average CARs of bank loan announcement before 2007 is around 0.5% (Li and Ongena, 2014). Among all eight rows, CAR[-2, 2] and CAR[-3, 3] are the highest, which may show the reversion after the liquidity crunch. Notice that CAR[-1, 0] is insignificant and its standard error is also much higher than other CARs. However, CAR[0, 1] is significantly negative, and its economic significance is about half of those of CAR[-2, 2] and CAR[-3, 3], indicating that the main market reactions are on the day after SHIBOR reached its peak of 13.44%. In a word, Table 2 shows that interbank liquidity crunch have significantly negative impact on the stock prices of listed firms.

[Insert Table 2 here]

We further categorize the listed firms by the types of their relationship banks (i.e. their largest lenders of long-term loans) in order to examine the role of relationship banks during the interbank liquidity crunch. *Bank* equals 1 if a firm's largest lender of long-term loans is a bank at the end of 2012, 0 otherwise, i.e. whether they have a relationship bank or not.

Among the 1,021 firms with long-term loans information, 714 firms borrow the largest proportion from 78 banks, while others borrow the largest proportion from non-bank institutions. The first panel of Table 3 shows the firm CARs in eight event windows between the two groups of firms. Although almost all CARs are negative except for one, firms borrowing from non-bank institutions are clearly more negative than others borrowing from banks, i.e. the differences are positive and significant in all eight event windows. It indicates that investors believe that banks tend to continue supporting customers with prior lending relationships during interbank liquidity crunch and it benefits firms who have lending relationships with banks.

[Insert Table 3 here]

Furthermore, we categorize firms by the types of their largest lender bank of long-term loans. *Big 4 banks* are *Agricultural Bank of China* (ABC), *Bank of China* (BOC), *China Construction Bank* (CCB) and *Industrial and Commercial Bank of China* (ICBC). The *Big 4 banks* dominate the Chinese banking market ever since the 1980s, which are often considered as the safest banks with implicitly government guarantees. Therefore, we propose that firms with relationships with *Big 4 Banks* may perform better in the stock market during the interbank liquidity crunch.

Among the 714 firms whose largest lenders of long-term loans are banks, 167 of them borrow the largest proportion from the *Big 4 banks* while the other firms borrow from the other 74 banks. The second panel of Table 3 shows CARs in eight event windows between these two groups of firms. None CARs are positive for firms which borrow from other banks, while three CARs are either positive or equal to zero for firms which borrow from *Big 4 banks*. The differences in CARs between these two groups of firms are positive though only about half of them are significant. This evidence suggests that *Big 4 banks* may have slight but not much advantage over other banks during interbank liquidity crunch.

We further categorize banks into local banks, regional banks, and national banks. We define *local banks* as city / rural commercial banks, urban / rural credit cooperatives, rural cooperative banks, and village-town banks, i.e. small and medium-sized banks. Local banks may be quite different from national and regional banks in terms of geographical presences, organizational structures, business orientations, and also the legal reserve requirement ratio. Local banks have lower legal reserve requirement ratio which incentivizes them to finance SMEs, e.g. since May 2012, the legal reserve requirement ratio is 20% for national and regional banks and 16.5% for local banks.

Among 714 firms whose largest lenders of long-term loans are banks, 216 firms borrow the largest proportion from 38 local banks, while the other 498 firms borrow from 40 national and regional banks. The third panel of Table 3 shows CARs in eight event windows between these two groups of firms. All CARs are negative except for one, and the differences between these two groups of firms are negative and mostly statistically significant. Firms whose largest lenders of long-term loans are local banks may perform worse than others during interbank liquidity crunch. Investors seem to believe that local banks suffer the most from interbank liquidity crunch, thus firms that have lending relationships with local banks witness more negative market reactions to this event than other firms.

The last panel of Table 3 compares CARs in eight event windows between 853 firms that have long-term loans and 1,502 firms that don't. The differences between these two groups of firms are largely insignificant. Only two out of eight columns show significant CARs: event windows [-3, 3] and [-5, 5]. This indicates that these two groups of firms don't behave significantly different during the interbank liquidity crunch. The significant differences in CAR[-3, 3] and CAR[-5, 5] could be due to the fact that these two long event windows captures some long-term effect of long-term loans on firms' stock performances.

5. Results

5.1 Firms whose largest lender of long-term loans are banks

Table 4-1 and 4-2 show whether having a bank as the largest lender of long-term loans makes any difference on firm's market reactions during the interbank liquidity crunch in general. The table shows regression results of an OLS model for 2,355 Chinese firms listed in *Shanghai* and *Shenzhen Exchanges*. The dependent variables are CARs in eight event windows, which are calculated from firm daily stock returns and market index weighted by firms' total market capitalization. *Bank* equals 1 if a firm's largest lender of long-term loans is a bank, and 0 otherwise. Firm characteristics such as state ownership, size, profitability, Tobin's Q, the largest lender's share in top 5 long-term loans, share of top 5 long-term loans in total long-term loans, and share of long-term loans in total liability are included in the specification as control variables.

[Insert Table 4-1 here]

The coefficients of *Bank* are positive and statistically significant at conventional levels. For example, the coefficient is 0.01 when the dependent variable is CAR [-1, 1] in column (1), i.e. firms with a largest lender of long-term loans as a bank tend to have 1% higher stock returns than otherwise. During interbank liquidity crunch, banks tend to continue extending credit to firms with prior lending relationship. Therefore, firms with lending relationships with banks may still have access to bank credit when banks are suffering from interbank liquidity crunch. Adding *Long-term Loan* dummy to control for whether a firm has long-term loan or not, doesn't change the results. The *Long-term Loan* dummy is insignificant in most cases, indicating that having long-term loans doesn't affect market reactions to interbank liquidity crunch. This result is consistent with the summary statistics in the last panel of Table 3.

The results are robust to including firm characteristics as control variables. *Leverage* has negative coefficients in all columns and four of them are also significant, i.e. firms with higher leverage perform worse than other firms during interbank liquidity crunch. The largest lender's share in top 5 long-term loans captures how important the largest lender of long-term loans is to a firm, or in other words, firms' dependency on its largest lender of long-term loans. Share of top 5 long-term loans in total long-term loans represents how much share the top 5 long-term loans take up in total long-term loans, or alternatively, how well disclosed the long-term loan data. Share of long-term loans in total liability measures how important long-term loans to a firm, or in other words, a firm's dependency on long-term loans. All three variables are largely insignificant, indicating that none of them affect market reactions during the interbank liquidity crunch. However, both the largest lenders' share in top 5 long-term loans and the share long-term loans in total liability show negative coefficients, indicating that a firm's dependency on its largest lender of long-term loans and long-term loans may have some negative impacts on its stock performance during interbank liquidity crunch.

[Insert Table 4-2 here]

One concern about the empirical strategy is that all firms react to the event on the same day while the standard event study methodology requires independently distributed observations. It is a problem because we would get biased standard errors if observations are correlated with each other. To address this issue, we perform the bootstrapping exercise to generate 50 randomly generated portfolios of firms with and without relationship banks, and run regressions using these random samples to test if our result still holds (Chava and Purnanandam, 2011). The bootstrapping regression results are shown in Table 4-2. Although the statistical significances of the coefficient of *Bank* dummy decline in bootstrapping results, it remains positive for all 8 event windows in all 10 columns and significant in 7 out of 10 regressions. Thus we are confident to say that our results are robust and firms whose largest lender of long-term loans are banks outperform other firms during the interbank liquidity crunch.

5.2 Firms whose largest lender of long-term loans are local and big 4 banks

Table 5 examines whether having a *Big 4 bank* as the largest lender of long-term loans makes any difference on firm's stock performance during interbank liquidity crunch. The table reports regression results of an OLS model using a sample of 2,233 Chinese listed firms. In column (2), we use a subsample of 675 firms whose largest lender of long-term loans are banks and the balance sheet information of those banks are available. Firm liquidity ratio which equals to the cash to total asset ratio is added in all other columns and reduce the number of observations to 1,476 firms. The dependent variables are firm CARs in eight event windows, using daily stock returns and market index weighted by firms' total market capitalization. *Local bank* and *Big 4 bank* equals 1 if a firm's largest lender of long-term loans is a local bank or a big 4 bank respectively, and 0 otherwise. All regressions include firm characteristics such as state ownership, size, profitability, Tobin's Q, the largest lender's share in top 5 long-term loan; share top 5 long-term loan in total long-term loan; and share long-term loan in total liability as control variables. Given that our sample also contains firms that have no relationship banks and firms that have no long-term loans, we add *Bank* dummy and *Long-term Loan* dummy in all columns to rule out that *Local bank* simply captures the effect of having a relationship bank or having long-term loans, except for in column (2) where we use a subsample of firms with relationship banks only.

[Insert Table 5 here]

In the first column with the full sample of 2,233 firms, the coefficient of *Local bank* is -0.7% and significant at 1% level. The coefficient rise to -0.8% when we use a subsample of firms whose largest lenders of long-term loans are banks and the balance sheet information is available for the banks. The results are also robust to bank level control variables because *local bank* has negative coefficients which are significant at 5% level in all 7 regressions. The results are qualitatively similar for the other 4 event windows, as well as for the rest 3 event windows which are suppressed for brevity and available upon request.

The negative coefficients of *Local bank* show that firms whose largest lender of long-term loans are local banks tend to perform worse in the stock market during interbank liquidity crunch. Local banks are often more fragile in the interbank market due to their small sizes and limited funding sources, which expose them more to the interbank liquidity crunch. Henceforth, firms having lending relationships with local banks are more likely to suffer from the interbank liquidity crunch than other firms that have lending relationships with regional and national banks.

Interestingly, we don't observe a clear difference in the stock performance between firms who borrow the largest proportion of long-term loans from *Big 4 banks* and otherwise. *Big 4 bank* is positive but only marginally significant in a few occasions in columns (8) – (11) with a subsample of 1,476 firms that have available liquidity ratio data. The coefficients of *Big 4 bank* are significant at 10% level only in columns (8) – (11) and not significant in other event windows not shown in Table 5. Investors may show more confidences in the big 4 banks but not so significant than other banks. The new leadership of China has released signals of withdrawing government intervention in the real economy after March 2013, i.e. 3 months before the interbank liquidity crunch. Investors may have already adjusted their expectation on the role of the big 4 banks well before the interbank liquidity crunch.

5.3 Heterogeneity across bank CARs

Table 6 reports regression results of an OLS model using a sample of 465 listed firms whose largest lender of long-term loans is a listed bank. The dependent variables are

CARs in six event windows. We control for firm characteristics and bank balance sheet variables in all specifications and bank fixed effects in 6 out of 12 specifications.

[Insert Table 6 here]

Column (1) of Table 6 shows that the interaction terms between *Local bank* and *Bank CAR* are positive and statistically significant, and the coefficients of *Local bank* are mainly negative as in Table 5. The result is robust to including bank balance sheet control variables, as well as bank fixed effects. If a firm's largest lender of long-term loans is a local bank, the firm will have a higher market reaction if this local bank has a higher CAR during the interbank liquidity crunch. Investors seem to believe that firms do not suffer much during the interbank liquidity crunch, if their relationship banks also suffer little from exogenous the liquidity shock.

5.4 Heterogeneity across interbank market liquidity

Table 7 reports regression results of an OLS model using a sample of 443 Chinese listed firms whose largest lender of long-term loans is a bank and the interbank market liquidity data of the bank is available in *Bankscope*. The dependent variables are CARs in five event windows. The interbank market liquidity equals interbank assets over interbank liability in the second quarter of 2013, i.e. a value over 100% indicates that the bank has a higher liquidity in the interbank market. We propose that a higher liquidity of a bank in the interbank market is associated with a lower shock to the stock prices of firms which have lending relationship with the bank. Due to a limited coverage of interbank market liquidity among local banks, we only create an interaction term between *Big 4 bank* with the *interbank market liquidity*. All columns includes firm characteristics and bank balance sheet variables.

[Insert Table 7 here]

We find that the coefficient of the interaction term between *Big 4 bank* and *interbank market liquidity* is positive in all 15 columns, and significant in all but one columns. Columns (3), (6), (9), (12) and (15) add bank fixed effects and results basically remain the same. The positive and largely significant coefficient of the interaction term indicates a positive relationship between firms' stock performance during the interbank liquidity crunch and their relationship banks' interbank market liquidity position. Put differently, if a firm's largest lender of long-term loans is a big 4 bank, the firm's stock price will perform better if this big 4 bank has higher liquidity in the interbank market.

6. Conclusion

We conduct an event study on the interbank liquidity crunch in China in June 2013 in order to evaluate the bank-firm relationship. We find that lending relationships with banks are associated with better stock performance for the borrowing firms during the interbank liquidity crunch. In addition, the effect of lending relationships varies across different types of banks. Firms whose largest lender of long-term loans are local banks tend to perform worse in the stock market than firms whose largest lender of long-term loans are regional and national banks or firms that have no long-term loans. However, firms whose largest lender of long-term loans are big 4 banks don't perform substantially better than otherwise. We also find a positive correlation between firms' stock performance and their relationship banks' stock performance, as well as their relationship banks' liquidity position in the interbank market.

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Table 1-1: Descriptive statistics of CARs

The table reports descriptive statistics of the dependent variable: cumulative abnormal return (CAR). Market index weighted by market value and daily stock returns at each trading day are used to calculate CAR in eight different event windows. Data source: *CSMAR*.

	Mean	Std. Dev	Obs.	Min.	Max.
CAR [-1, 1]	0.00	0.04	2,355	-0.26	0.26
CAR [-2, 2]	-0.01	0.06	2,355	-0.27	0.37
CAR [-3, 3]	-0.01	0.08	2,355	-0.25	0.45
CAR [-5, 5]	0.00	0.10	2,355	-0.28	0.54
CAR [-1, 0]	0.00	0.03	2,355	-0.24	0.21
CAR [0, 1]	0.00	0.03	2,355	-0.13	0.20
CAR [-1, 2]	-0.01	0.06	2,355	-0.25	0.36
CAR [0, 2]	-0.01	0.05	2,355	-0.18	0.28

Table 1-2: Definitions and descriptive statistics for bank relationship, firm and bank level variables

The table reports definition and descriptive statistics of bank-firm relationship, firm and bank characteristics. The data is sourced from *CSMAR*, *BankScope*, and *Wind*.

Variable name	Definition	Mean	Std. Dev	Obs.	Min.	Max.
	Bank-firm relationship variables					
Bank	Equals 1 if a firm's largest lender of long-term loans is a bank in 2012, 0 otherwise	0.303	0.460	2,355	0	1
Local bank	Equals 1 if a firm's largest lender of long-term loans is a local bank in 2012, i.e. city / rural commercial banks, urban / rural credit cooperatives, rural cooperative banks, village-town banks, etc.	0.092	0.289	2,355	0	1
Big 4 bank	Equals 1 if a firm's largest lender of long-term loans is one of the "big 4" banks in China, i.e. Agricultural Bank of China, Bank of China, China Construction Bank, and Industrial and Commercial Bank of China	0.071	0.257	2,355	0	1
Long-term loan	Equals 1 if a firm disclose long-term loan information in annual report	0.362	0.481	2,355	0	1
	Firm level variables					
State-owned	Equals 1 if the firm's ultimate controller is state owned at the end of 2012, 0 otherwise	0.141	0.348	2,275	0	1
Total assets	Total assets at the end of 2012, in 1,000 RMB	5.08E+07	6.34E+08	2,355	6.78E+03	1.75E+10
Leverage	Total liability over total asset at the end of 2012	0.436	0.233	2,355	0.040	0.947
EBIT	Industry adjusted EBIT at the end of 2012	0.057	0.051	2,355	-0.105	0.242
Tobin's Q	Book value of total liabilities plus the market value of total equity over the book value of total assets at the end of 2012	1.888	1.083	2,355	0.548	7.079

	Bank level variables					
The largest lender’s share in top 5 long-term loans	Total value of long-term loans from a firm's largest lender over the total value of top 5 long-term loans	0.265	0.382	2,355	0	1
Share top 5 long-term loan in total long-term loans	Total value of top 5 long-term loans over the total value of long-term loans of a firm	0.296	0.654	2,355	0	1
Share long-term loans in total liability	Total value of long-term loans over total liability of a firm	0.108	0.174	2,355	0	0.728
Interbank market liquidity	Interbank assets over interbank liabilities of a bank that is a firm's largest lender in the second quarter of 2013, while a value over 100% indicates a higher liquidity in the interbank market.	0.723	0.318	447	0.273	1.157
Bank CAR	The CAR[-1, 1] of the bank which is the largest lender of long-term loans of a firm at the end of 2012	-0.028	0.040	469	-0.098	0.025
Bank total assets	The book value of total assets (in 1,000 RMB) of the bank which is the largest lender of the long-term loans	1.41E+09	9.33E+08	679	3.92E+06	2.79E+09
Bank liquidity ratio	Liquid asset over total assets at the end of 2012 of the bank which is the largest lender of the long-term loans	0.262	0.085	679	0.130	0.495
Bank equity ratio	Total equity over total assets at the end of 2012 of the bank which is the largest lender of the long-term loans	5.856	1.744	679	1.290	8.320

Table 2: Firm CARs

The table reports the CARs for a sample of 2,313 non-financial listed firms in China in 2013, which are calculated in eight event windows using daily stock returns and market index weighted by market value. Mean and standard deviation of CARs are reported for various event windows. ***, **, and * indicate significance at the 1%, 5%, and 10%.

	Mean	Std.Err	# of Obs.
CAR [-1, 1]	-0.003***	(0.001)	2,313
CAR [-2, 2]	-0.008***	(0.001)	2,313
CAR [-3, 3]	-0.008***	(0.002)	2,313
CAR [-5, 5]	-0.004*	(0.002)	2,313
CAR [-1, 0]	-0.000	(0.001)	2,313
CAR [0, 1]	-0.004***	(0.000)	2,313
CAR [-1, 2]	-0.006***	(0.001)	2,313
CAR [0, 2]	-0.007***	(0.001)	2,313

Table 3 Firm CARs sorted by firm types

The table reports the mean and standard deviation for the CARs in eight event windows sorted by firm types. The CARs are calculated using the returns of the daily stock price and market index weighted by market value. Three bank-firm relationship variables, i.e. Bank, Big 4 bank, Local bank, and a firm balance sheet variable (i.e. Long-term Loan) categorize the listed firms into respective groups, whose definitions are listed in Table 1-2. T-statistics for the differences of the means between bank types are reported, and significance indicated at the 1%, 5%, and 10% levels respectively with ***, **, and *.

Firm types		CAR [-1, 1]	CAR [-2, 2]	CAR [-3, 3]	CAR [-5, 5]	CAR [-1, 0]	CAR [0, 1]	CAR [-1, 2]	CAR [0, 2]
Bank = 1	Mean	0.000	-0.007	-0.011	-0.030	0.002	-0.001	-0.005	-0.005
	Std. Dev.	0.002	0.002	0.003	0.007	0.001	0.001	0.002	0.002
Bank = 0	Mean	-0.008	-0.018	-0.021	-0.014	-0.003	-0.009	-0.018	-0.018
	Std.Dev.	0.004	0.005	0.006	0.004	0.003	0.003	0.005	0.004
Difference T-test		0.008**	0.012**	0.010**	0.016**	0.004**	0.008***	0.013***	0.013***
Big 4 bank = 1	Mean	0.003	-0.002	-0.006	-0.015	0.005	0.000	-0.001	-0.004
	Std.Dev.	0.003	0.005	0.006	0.007	0.002	0.002	0.004	0.004
Big 4 bank = 0	Mean	-0.003	-0.010	-0.014	-0.017	0.000	-0.002	-0.008	-0.008
	Std.Dev.	0.002	0.002	0.003	0.004	0.001	0.001	0.002	0.002
Difference T-test		0.006**	0.008*	0.008*	0.002	0.005**	0.003	0.007*	0.004
Local bank = 1	Mean	-0.005	-0.014	-0.020	-0.023	-0.002	-0.003	-0.012	-0.009
	Std.Dev.	0.003	0.004	0.004	0.006	0.002	0.002	0.004	0.003
Local bank = 0	Mean	0.000	-0.007	-0.010	-0.015	0.002	-0.002	-0.005	-0.007
	Std.Dev.	0.002	0.002	0.003	0.004	0.001	0.001	0.002	0.002
Difference T-test		-0.005**	-0.007**	-0.010**	-0.008	-0.004**	-0.001	-0.006**	-0.003
Long-term loans = 1	Mean	-0.002	-0.009	-0.012	-0.017	0.001	-0.002	-0.007	-0.007
	Std. Err.	0.001	0.002	0.002	0.003	0.001	0.001	0.002	0.002
Long-term loans = 0	Mean	-0.003	-0.007	-0.005	0.004	0.000	-0.004	-0.004	-0.005
	Std. Err.	0.001	0.002	0.002	0.003	0.001	0.001	0.002	0.001
Difference T-test		0.001	-0.001	-0.008***	-0.021***	0.001	0.002	-0.003	-0.002

Table 4-1: Firms with a bank as the largest lender of long-term loans

The table reports regression results with an OLS model using a sample of 2,233 Chinese firms listed in Shanghai and Shenzhen exchanges. The dependent variables are CARs in eight event windows, calculated using daily stock return and market index weighted by market value. Bank equals 1 if a firm's largest lender of long-term loans is a bank, 0 otherwise. Long-term loan equals to 1 if a firm disclose long-term loan information in its 2012 annual report. The largest lender's share in top 5 long-term loans equals to the total value of long-term loans from a firm's largest lender of long-term loans over the total value of top 5 long-term loans. Share top 5 long-term loan in total long-term loans equals to the total value of top 5 long-term loans over the total value of long-term loans of a firm. Share long-term loans in total liability equals to the total value of long-term loans over total liability of a firm. State-owned equals 1 if the firm's ultimate controller is state owned at the end of 2012, 0 otherwise; Log total assets is the logarithm of total assets at the end of 2012 in 1,000 RMB; Leverage is total liabilities over total assets at the end of 2012; EBIT is the industry adjusted EBIT at the end of 2012; Tobin's Q is the book value of total liabilities plus the market value of total equity over the book value of total assets at the end of 2012. All regressions in this table have industry fixed effects and standard errors are clustered at industry level. P-values are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10%.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	CAR [-1,1]		CAR [-2,2]		CAR [-3,3]	CAR [-5,5]	CAR [-1,0]	CAR [0,1]	CAR [-1,2]	CAR [0, 2]
Variables of interest										
Bank	0.009***	0.007***	0.012***	0.009**	0.007	0.024**	0.003*	0.006***	0.010***	0.010**
	(0.000)	(0.001)	(0.004)	(0.030)	(0.251)	(0.037)	(0.092)	(0.000)	(0.004)	(0.014)
Firm controls										
Long-term loan	-0.003	-0.000	0.006	0.007	0.008	-0.022	0.003	-0.003	0.002	-0.001
	(0.730)	(0.993)	(0.611)	(0.601)	(0.566)	(0.123)	(0.411)	(0.550)	(0.821)	(0.936)
The largest lender's share in top 5 long-term loans	-0.002	-0.005	-0.018	-0.021	-0.021	-0.006	-0.004	-0.002	-0.012	-0.010
	(0.828)	(0.691)	(0.234)	(0.235)	(0.249)	(0.671)	(0.538)	(0.739)	(0.382)	(0.311)
Share top 5 long-term loans in total long-term loans	-0.002	-0.002*	-0.002	0.000	0.003	0.007**	-0.001	-0.000	-0.002	-0.000
	(0.167)	(0.072)	(0.367)	(0.775)	(0.143)	(0.044)	(0.299)	(0.866)	(0.193)	(0.870)
Share long-term loans in total liability	-0.007	-0.005	-0.016***	-0.010	-0.012	0.003	0.000	-0.004	-0.006	-0.004
	(0.217)	(0.359)	(0.008)	(0.224)	(0.228)	(0.806)	(0.980)	(0.324)	(0.426)	(0.448)
State-owned firm	-0.001	-0.004*	-0.002	-0.005**	-0.007*	-0.016***	-0.002	-0.002	-0.005*	-0.003
	(0.393)	(0.062)	(0.288)	(0.030)	(0.051)	(0.009)	(0.284)	(0.235)	(0.051)	(0.166)

Log total asset	-0.000	0.000	-0.000	0.001	0.001	-0.000	-0.001	0.001	0.001	0.001
	(0.905)	(0.766)	(0.996)	(0.724)	(0.807)	(0.875)	(0.395)	(0.523)	(0.602)	(0.430)
Leverage	-0.001	-0.001	-0.013	-0.006	-0.020	-0.047***	-0.004	-0.001	-0.010	-0.009
	(0.828)	(0.888)	(0.155)	(0.525)	(0.152)	(0.000)	(0.387)	(0.856)	(0.328)	(0.179)
Industry adjusted EBIT	-0.022	-0.006	0.018	0.048	0.059	0.061	-0.006	-0.000	0.062	0.067*
	(0.247)	(0.813)	(0.500)	(0.255)	(0.199)	(0.136)	(0.654)	(0.986)	(0.110)	(0.069)
Market value of asset	-0.002	-0.002	-0.006*	-0.007*	-0.008**	-0.007*	-0.003	-0.002	-0.006*	-0.007**
	(0.354)	(0.493)	(0.060)	(0.060)	(0.017)	(0.066)	(0.183)	(0.209)	(0.085)	(0.013)
Cash to total asset ratio		-0.005		0.007	0.032***	0.082***	-0.009*	-0.006	0.007	0.007
		(0.479)		(0.608)	(0.004)	(0.000)	(0.052)	(0.312)	(0.453)	(0.350)
Constant	0.009	-0.004	0.005	-0.018	-0.009	-0.001	0.024	-0.009	-0.029	-0.034
	(0.820)	(0.918)	(0.942)	(0.778)	(0.904)	(0.984)	(0.271)	(0.664)	(0.597)	(0.365)
Observations	2,233	1,476	2,233	1,476	1,476	1,476	1,476	1,476	1,476	1,476
R-squared	0.026	0.021	0.049	0.054	0.077	0.175	0.027	0.037	0.042	0.054
Industry FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Cluster	Industry	Industry	Industry	Industry	Industry	Industry	Industry	Industry	Industry	Industry

Table 4-2: Firms with a bank as the largest lender of long-term loans (Bootstrapping)

The table reports bootstrapping regression results with an OLS model using a sample of 2,233 Chinese firms listed in Shanghai and Shenzhen exchanges. The dependent variables are CARs in eight event windows, calculated using daily stock return and market index weighted by market value. Bank equals 1 if a firm's largest lender of long-term loans is a bank, 0 otherwise. Long-term loan equals to 1 if a firm disclose long-term loan information in its 2012 annual report. The largest lender's share in top 5 long-term loans equals to the total value of long-term loans from a firm's largest lender of long-term loans over the total value of top 5 long-term loans. Share top 5 long-term loan in total long-term loans equals to the total value of top 5 long-term loans over the total value of long-term loans of a firm. Share long-term loans in total liability equals to the total value of long-term loans over total liability of a firm. State-owned equals 1 if the firm's ultimate controller is state owned at the end of 2012, 0 otherwise; Log total assets is the logarithm of total assets at the end of 2012 in 1,000 RMB; Leverage is total liabilities over total assets at the end of 2012; EBIT is the industry adjusted EBIT at the end of 2012; Tobin's Q is the book value of total liabilities plus the market value of total equity over the book value of total assets at the end of 2012. All regressions in this table have industry fixed effects and standard errors are clustered at industry level. P-values are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10%.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	CAR [-1,1]		CAR [-2,2]		CAR [-3,3]	CAR [-5,5]	CAR [-1,0]	CAR [0,1]	CAR [-1,2]	CAR [0, 2]
Variables of interest										
Bank	0.009*	0.007*	0.012*	0.009	0.007	0.024***	0.003	0.006*	0.010*	0.010*
	(0.063)	(0.088)	(0.068)	(0.127)	(0.310)	(0.006)	(0.342)	(0.056)	(0.077)	(0.059)
Firm controls										
Long-term loan	-0.003	-0.000	0.006	0.007	0.008	-0.022	0.003	-0.003	0.002	-0.001
	(0.718)	(0.995)	(0.571)	(0.601)	(0.563)	(0.270)	(0.593)	(0.723)	(0.859)	(0.953)
The largest lender's share in top 5 long-term loans	-0.002	-0.005	-0.018*	-0.021*	-0.021	-0.006	-0.004	-0.002	-0.012	-0.010
	(0.772)	(0.569)	(0.081)	(0.065)	(0.146)	(0.795)	(0.397)	(0.736)	(0.262)	(0.318)
Share top 5 long-term loans in total long-term loans	-0.002	-0.002	-0.002	0.000	0.003	0.007	-0.001	-0.000	-0.002	-0.000
	(0.165)	(0.417)	(0.400)	(0.879)	(0.439)	(0.129)	(0.506)	(0.890)	(0.490)	(0.919)
Share long-term loans in total liability	-0.007	-0.005	-0.016**	-0.010	-0.012	0.003	0.000	-0.004	-0.006	-0.004
	(0.240)	(0.485)	(0.035)	(0.404)	(0.349)	(0.827)	(0.981)	(0.631)	(0.615)	(0.715)
State-owned firm	-0.001	-0.004	-0.002	-0.005	-0.007	-0.016**	-0.002	-0.002	-0.005	-0.003
	(0.667)	(0.218)	(0.536)	(0.200)	(0.170)	(0.028)	(0.332)	(0.523)	(0.194)	(0.416)

Log total asset	-0.000	0.000	-0.000	0.001	0.001	-0.000	-0.001	0.001	0.001	0.001
	(0.795)	(0.678)	(0.990)	(0.596)	(0.721)	(0.864)	(0.346)	(0.579)	(0.465)	(0.404)
Leverage	-0.001	-0.001	-0.013	-0.006	-0.020	-0.047***	-0.004	-0.001	-0.010	-0.009
	(0.821)	(0.922)	(0.133)	(0.571)	(0.116)	(0.005)	(0.489)	(0.922)	(0.398)	(0.343)
Industry adjusted EBIT	-0.022	-0.006	0.018	0.048	0.059	0.061	-0.006	-0.000	0.062*	0.067**
	(0.253)	(0.848)	(0.527)	(0.259)	(0.283)	(0.375)	(0.770)	(0.986)	(0.096)	(0.040)
Market value of asset	-0.002**	-0.002	-0.006***	-0.007***	-0.008***	-0.007***	-0.003**	-0.002*	-0.006***	-0.007***
	(0.036)	(0.122)	(0.000)	(0.000)	(0.000)	(0.002)	(0.012)	(0.052)	(0.000)	(0.000)
Cash to total asset ratio		-0.005		0.007	0.032*	0.082***	-0.009	-0.006	0.007	0.007
		(0.617)		(0.645)	(0.052)	(0.000)	(0.230)	(0.518)	(0.603)	(0.555)
Constant	0.009	-0.004	0.005	-0.018	-0.009	-0.001	0.024	-0.009	-0.029	-0.034
	(0.636)	(0.877)	(0.866)	(0.675)	(0.857)	(0.982)	(0.179)	(0.664)	(0.454)	(0.336)
Observations	2,233	1,476	2,233	1,476	1,476	1,476	1,476	1,476	1,476	1,476
R-squared	0.026	0.021	0.049	0.054	0.077	0.175	0.027	0.037	0.042	0.054
Industry FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Cluster	Industry	Industry	Industry	Industry	Industry	Industry	Industry	Industry	Industry	Industry

Table 5: Firms with a largest lender of long-term loans as a local bank or a big 4 bank

The table reports regression results with an OLS model using a sample of 2,233 Chinese firms listed in Shanghai and Shenzhen exchanges. The dependent variables are CARs in five event windows, calculated using daily stock returns and market index weighted by market value. Local bank and Big 4 bank equal 1 if a firm's largest lender of long-term loans is a local bank or a big 4 bank respectively, 0 otherwise. Columns (1) uses the full sample of 2,233 listed firms, with the Bank dummy to control the general effect of having a bank as the largest lender of long-term loans. Column (2) adds bank balance sheet controls, which reduce the sample to 675 firms whose largest lender of long-term loans is a bank. Other columns use a subsample of firms whose cash to total asset information is available, i.e. 1,476 firms. All regressions control for firm characteristics at the end of 2012, including: state-owned dummy, 0 otherwise; log total assets in 1,000 RMB; leverage is total liabilities over total assets; the industry adjusted EBIT; Tobin's Q (i.e. the book value of total liabilities plus the market value of total equity over the book value of total assets); the largest lender's share in top 5 long-term loan; share top 5 long-term loan in total long-term loan; and share long-term loan in total liability. Bank balance sheet controls are characteristics of the bank which is the largest lender of the long-term loans at the end of 2012, including the book value of total assets (in 1,000 RMB) of the bank; bank liquidity ratio which is the liquid asset over total assets; and bank equity ratio which is the total equity over total assets. All regressions in this table have industry fixed effects and standard errors are clustered at industry level. P-values are presented in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10%.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
				Local Bank					Big 4 Bank		
		CAR		CAR	CAR	CAR	CAR	CAR	CAR	CAR	CAR
		[-1, 1]		[-2, 2]	[-3, 3]	[-1, 0]	[0, 1]	[-1, 1]	[-2, 2]	[-3, 3]	[-1, 0]
Variables of interest											
Local Bank	-0.007***	-0.008**	-0.008***	-0.015***	-0.018***	-0.006**	-0.005***				
	(0.009)	(0.018)	(0.009)	(0.005)	(0.004)	(0.027)	(0.010)				
Big 4 Bank								0.008*	0.013*	0.015*	0.006**
								(0.079)	(0.094)	(0.084)	(0.036)
Bank	0.011***		0.010***	0.013***	0.012*	0.004**	0.008***	0.006***	0.006	0.003	0.002
	(0.000)		(0.000)	(0.004)	(0.058)	(0.017)	(0.000)	(0.005)	(0.158)	(0.560)	(0.338)
Long-term loan	-0.003		-0.000	0.006	0.008	0.003	-0.003	-0.000	0.006	0.008	0.003
	(0.703)		(0.957)	(0.632)	(0.599)	(0.449)	(0.534)	(0.952)	(0.624)	(0.592)	(0.435)
Observations	2,233	675	1,476	1,476	1,476	1,476	1,476	1,476	1,476	1,476	1,476
R-squared	0.028	0.042	0.023	0.057	0.081	0.029	0.039	0.023	0.056	0.079	0.028

Firm level controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Firm liquidity control	no	no	yes	yes	yes	yes	yes	yes	yes	yes	yes
Bank Balance sheet controls	no	yes	no	no	no	no	no	no	no	no	no
Industry FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Cluster	Industry	Industry	Industry	Industry	Industry	Industry	Industry	Industry	Industry	Industry	Industry

Table 6: Heterogeneity across bank CARs

The table reports regression results with an OLS model using a sample of 465 Chinese listed firms whose largest lender of long-term loans is a listed bank. The dependent variables are CARs in six event windows, calculated using daily stock returns and market index weighted by market value. Local bank equals 1 if a firm's largest lender of long-term loans is a local bank. Bank CAR is the CAR of the bank which is the largest lender of long-term loans of a firm using daily stock returns and market index weighted by market value. All regressions control for firm characteristics at the end of 2012, including: state-owned dummy, 0 otherwise; log total assets in 1,000 RMB; leverage is total liabilities over total assets; the industry adjusted EBIT; Tobin's Q (i.e. the book value of total liabilities plus the market value of total equity over the book value of total assets); the largest lender's share in top 5 long-term loan; share top 5 long-term loan in total long-term loan; and share long-term loan in total liability. Bank balance sheet controls are characteristics of the bank which is the largest lender of the long-term loans at the end of 2012. All regressions have bank balance sheet controls, including the book value of total assets (in 1,000 RMB) of the bank; bank liquidity ratio which is the liquid asset over total assets; and bank equity ratio which is the total equity over total assets. All regressions have industry fixed effects and standard errors are clustered at industry level. P-values are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10%.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	CAR[-1, 1]		CAR[-2, 2]		CAR[-3, 3]		CAR[-5, 5]		CAR[0, 1]		CAR[0, 2]	
Local Bank * Bank CAR	0.284*	0.056	0.314***	0.213***	0.336***	0.208*	0.431*	0.258**	0.121**	0.107***	0.190*	0.248***
	(0.072)	(0.558)	(0.000)	(0.008)	(0.000)	(0.050)	(0.061)	(0.049)	(0.011)	(0.005)	(0.051)	(0.005)
Local Bank	-0.005	-0.089	-0.003	0.015	-0.009	0.267*	-0.022	0.008	-0.004	-0.228***	-0.005	-0.355***
	(0.276)	(0.502)	(0.748)	(0.921)	(0.351)	(0.091)	(0.108)	(0.973)	(0.154)	(0.007)	(0.430)	(0.009)
Bank CAR	-0.190	-0.003	-0.051	0.002	-0.092	-0.009	-0.058	-0.010	-0.073*	0.003	-0.085	0.004
	(0.200)	(0.718)	(0.538)	(0.901)	(0.362)	(0.522)	(0.852)	(0.586)	(0.078)	(0.522)	(0.477)	(0.567)
Observations	288	465	288	465	288	465	288	465	288	465	288	465
R-squared	0.132	0.134	0.132	0.105	0.102	0.078	0.146	0.117	0.169	0.152	0.138	0.115
Firm level controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Bank balance sheet controls	yes	yes	yes	yes	yes	yes	no	no	no	no	no	no
Bank FE	no	yes	no	yes	no	yes	no	yes	no	yes	no	yes
Industry FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Cluster	Industry	Industry	Industry	Industry	Industry	Industry	Industry	Industry	Industry	Industry	Industry	Industry

Table 7: Heterogeneity across interbank market liquidity

The table reports regression results with an OLS model using a sample of 443 Chinese listed firms whose largest lender of long-term loans is a bank and the interbank market liquidity data is available for the bank. The dependent variables are CARs in five windows, calculated using daily stock returns and market index weighted by market value. Big 4 bank equals 1 if a firm's largest lender of long-term loans is a big 4 bank. The Interbank market liquidity is the interbank assets over interbank liability in the second quarter of the 2013. All regressions control for firm characteristics at the end of 2012, including: state-owned dummy, 0 otherwise; log total assets in 1,000 RMB; leverage is total liabilities over total assets; the industry adjusted EBIT; Tobin's Q (i.e. the book value of total liabilities plus the market value of total equity over the book value of total assets); the largest lender's share in top 5 long-term loan; share top 5 long-term loan in total long-term loan; and share long-term loan in total liability. Bank balance sheet controls are characteristics of the bank which is the largest lender of the long-term loans at the end of 2012. All regressions have bank balance sheet controls, including the book value of total assets (in 1,000 RMB) of the bank; bank liquidity ratio which is the liquid asset over total assets; and bank equity ratio which is the total equity over total assets. All regressions have industry fixed effects and standard errors are clustered at industry level. P-values are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10%.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
		CAR[-1, 1]			CAR[-2, 2]			CAR[0, 1]			CAR[-1, 2]			CAR[0, 2]	
BIG 4 * Bank Interbank Position	0.012*	0.011*	0.008	0.029***	0.026***	0.021***	0.012**	0.011***	0.009**	0.025***	0.022**	0.020**	0.024**	0.021**	0.021**
	(0.080)	(0.088)	(0.127)	(0.000)	(0.001)	(0.003)	(0.019)	(0.006)	(0.041)	(0.005)	(0.032)	(0.032)	(0.019)	(0.049)	(0.041)
Bank Interbank Position	-0.005	-0.004	0.013	-0.007	-0.004	-0.031*	-0.003	-0.002	0.025**	-0.007	-0.004	0.013	-0.005	-0.002	0.025*
	(0.521)	(0.596)	(0.234)	(0.563)	(0.751)	(0.090)	(0.484)	(0.638)	(0.018)	(0.500)	(0.749)	(0.398)	(0.547)	(0.843)	(0.085)
BIG 4	-0.004	-0.004	-0.001	-0.017*	-0.014	-0.010	-0.008	-0.009*	-0.006	-0.014	-0.011	-0.009	-0.018*	-0.015*	-0.014
	(0.378)	(0.327)	(0.825)	(0.075)	(0.118)	(0.376)	(0.147)	(0.054)	(0.274)	(0.157)	(0.247)	(0.388)	(0.098)	(0.092)	(0.164)
Observations	443	443	443	443	443	443	443	443	443	443	443	443	443	443	443
R-squared	0.064	0.066	0.077	0.065	0.065	0.073	0.109	0.114	0.124	0.057	0.058	0.065	0.082	0.083	0.089
Firm level controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Bank balance sheet controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Bank FE	no	no	yes	no	no	yes	no	no	yes	no	no	yes	no	no	yes
Industry FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Cluster	Industry	Industry	Industry	Industry	Industry	Industry	Industry	Industry	Industry	Industry	Industry	Industry	Industry	Industry	Industry

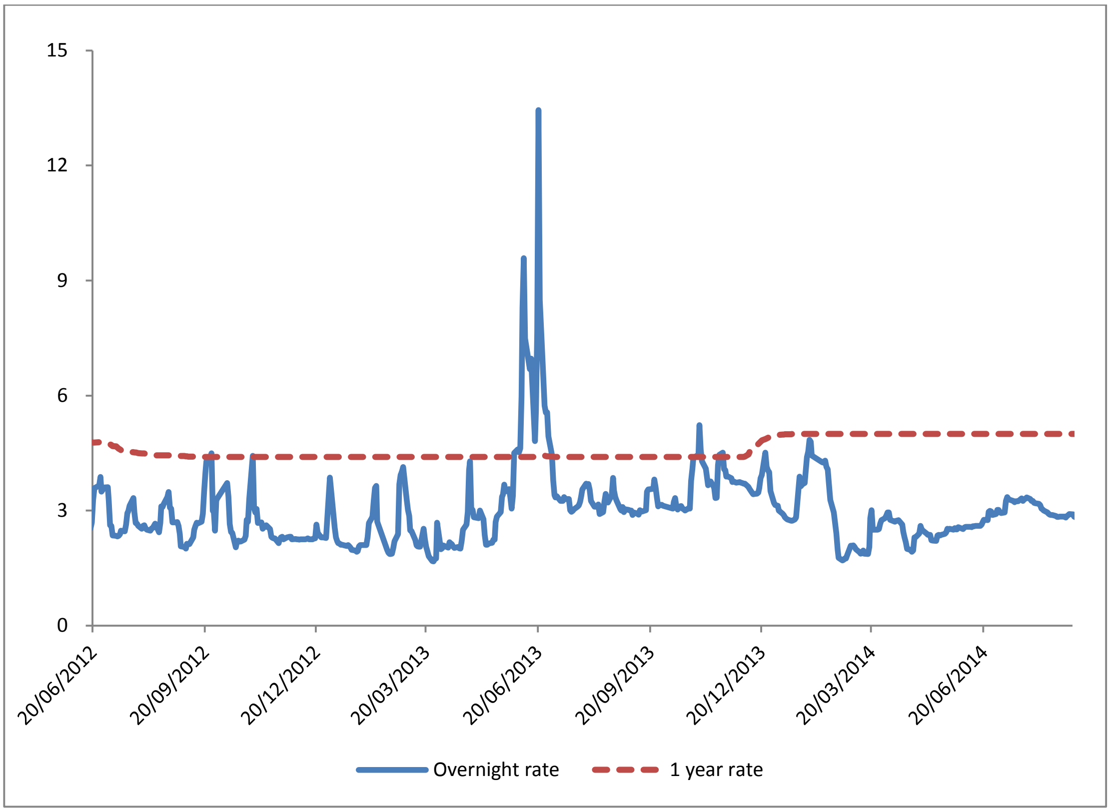

Figure 1: the interbank interest rate from 1-year before and till 1-year after the liquidity crunch of June 20, 2013.

Appendix 1: Major events around the interbank liquidity crunch on June 20th, 2013 in China.

2013/6/5

The bond issuance of *Agriculture Development Bank of China* failed to attract enough subscriptions.

2013/6/14

The issuance of treasury bonds failed to attract enough subscription.

2013/6/19

Premier *Keqiang Li* expressed a determination for the financial reform by the government. The overnight rate increases to 7.66%, i.e. an increase of about 200 basis points. The *PBOC* talked privately with several big banks, which made these banks inject about 400 billion RMB. The interbank market delayed the closing time by 30 minutes.

2013/6/20

The overnight rate hikes to 13.44%, i.e. an increase of 578 basis points. The PBOC initiated the issuance of bills, which extracted liquidity from the interbank market. A Rumor flies that the *Bank of China* was in default in the interbank market.

2013/6/21

The *PBOC* supplied 50 billion RMB to *Industrial and Commercial Bank of China*. The overnight interbank interest rate dropped to 8.49%, i.e. a decrease about 500 basis points from the previous day.

2013/6/23

Several branches of the *Industrial and Commercial Bank of China* in *Beijing* and *Shanghai* closed unexpectedly

2013/6/24

The stock prices of the banks crashes, i.e. *Shanghai Stock Exchange* composite index decreased by about 5%, and the stock prices of *Ping An Bank*, *China Minsheng Bank*, and *China Industrial Bank* falls about 10%.

2013/6/25

The *PBOC* suspended the issuance of bills and supplied liquidity support for certain financial institutions.

2013/6/26

The overnight interbank interest rate decreased to 5.55%