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Banks' Liability Structure and Mortgage Lending During the Financial Crisis

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Abstract

We examine the impact of banks' exposure to market liquidity shocks through wholesale funding on their supply of credit during the financial crisis in the United States. We focus on mortgage lending to minimize the impact of confounding demand factors that could potentially be large when comparing banks' overall lending across heterogeneous categories of credit. The disaggregated data on mortgage applications that we use allows us to study the time variations in banks' decisions to grant mortgage loans, while controlling for bank, borrower, and regional characteristics. The wealth of data also allows us to carry out matching exercises that eliminate imbalances in observable applicant characteristics between wholesale and retail banks, as well as various other robustness tests. We find that banks that were more reliant on wholesale funding curtailed their credit significantly more than retail-funded banks during the crisis. The demand for mortgage credit, on the other hand, declined evenly across wholesale and retail banks. To understand the aggregate implications of our findings, we exploit the heterogeneity in mortgage funding across U.S. Metropolitan Statistical Areas (MSAs) and find that wholesale funding was a strong and significant predictor of a sharper decline in overall mortgage credit at the MSA level.

JEL Classification Numbers: G01, G21, E50

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Contents Page

I. INTRODUCTION

The years leading to the Global Financial Crisis have witnessed a rapidly changing financial landscape with continuously emerging novel financial practices and instruments. While financial innovations have the potential to improve the efficiency of capital allocation, they also pose challenges to economists, regulators, and market participants in assessing their soundness as well as their impact on overall financial stability.[1] In that regard, the financial crisis offers an opportunity to shed light on whether some of these new practices resulted in an added vulnerability of the financial system.

One important trend that has been emerging in the banking sector is the increased reliance by banks on non-core deposits as their main source of funding (See, e.g. Feldman and Schmidt, 2001; Gatev and Strahan, 2006). These so called wholesale funds are typically raised on a short-term rollover basis. While wholesale market funding offers more flexibility for banks in financing projects it increases their vulnerability to market-wide liquidity shocks.[2] This simply is a result of wholesale financiers being uninsured creditors, and thus, more at risk of realizing losses.[3] In comparison, retail deposits are a more stable source of funding as shown in Gatev and Strahan (2006).

In this paper, we examine the impact of banks' liability structure on their supply of credit following the drying-up of market-wide liquidity during the recent global financial crisis. Our aim is to assess the contribution of wholesale funding to the sharp decline in credit supply during the crisis. Our question is also motivated by a long-standing empirical question regarding the impact of liquidity on credit supply. Evidence on this causality is often confounded by demand factors, since episodes of liquidity shocks are also associated with economic downturns. The comprehensive loan-level disaggregated dataset on mortgage lending that we use allow us to design an empirical strategy that carefully controls for potentially confounding

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[1]For example, an economics literature that has emerged prioir to the crisis has partly attributed the moderation in the volatility of the U.S. GDP (the so-called Great Moderation) to financial innovations.

[2]See, e.g. Allen, Babus, and Carletti (2010); Allen and Gale (2000); Bologna (2011); Brunnermeier (2009); Brunnermeier and Pedersen (2009); Gatev and Strahan (2006); Huang and Ratnovski (2011); IMF (2010); Ivashina and Scharfstein (2010); Raddatz (2010); Rochet and Vives (2004); Yorulmazer and Goldsmith-Pinkham (2010).

[3]For example, preceding its failure in 1984, Continental Illinois National Bank and Trust Company experienced a run from wholesale financiers but not from retail depositors. During the recent crisis, with the exception of Wachovia, runs from retail depositors in the U.S. were rare while wholesale runs became increasingly a threat on the major banks (see, e.g., Johnson, 2009). Even in the U.K, where deposit insurance was only partial, a wholesale bank run on Northern Rock has preceded the infamous run by retail depositors, as documented in Shin (2009).

factors. Our results show a strong and conclusive evidence that the reliance on wholesale funding negatively affected the supply of credit during the crisis.

Our focus on mortgage lending has several motivations. First, a comparison of credit supply by banks based on their overall lending across various credit products could be affected by uneven changes in demand across various sectors in the economy. Such confounding factors could be hard to control for, as banks' portfolios could differ across various dimensions not all of which are easily observable.[4] Thus, by focusing on mortgage lending, specifically new mortgage originations for conventional 1-4 family units, we avoid a potential direct source of bias in our results. Second, the availability of comprehensive data on mortgage applications with information on banks' decisions, as well as loan, borrower, and regional characteristics, is a distinct advantage. They allow us to study the decision by banks to reject a loan while controlling for these characteristics. The change in the rejection rate over time is a better indicator of changes in supply and, in comparison with credit volume, is less likely to be tainted by demand factors. Furthermore, by observing the demand for loan applications at each bank in our sample we are able to distinguish between supply and demand factors.

Our empirical strategy proceeds as follows. Using comprehensive mortgage data from 2005 to 2008 that we match with bank balance sheet data, we examine whether wholesale funded banks decreased their supply of mortgage credit more than retail funded banks. Two sources of identifying variations allow us to answer this question: the time variation in overall market liquidity and the cross-sectional variation in the core deposit to assets ratio, a commonly used measure of the extent to which a bank is funded through retail deposits. We use the data on bank mortgage lending decisions between 2005 and 2008 to fit a linear probability model of rejection rates.

We study bank lending decisions while controlling for loan, borrower, bank and regional characteristics. We control for the characteristics of the borrowers and their loans using the information available from the mortgage data. We also merge the mortgage data with data on bank financials to control for bank characteristics such as size, measures of liquidity, leverage, as well as other factors. We also include fixed-effects for banks, years, and for Metropolitan Statistical Areas (MSAs), as well as the interaction of MSA fixed effects with the crisis dummy to control for unobserved characteristics. We find that the marginal effect of a one standard deviation decrease in the ratio of core deposits to assets is an increase in the rejection rate by around 3 percentage points during the crisis. This result holds both at the

[4]For example, even within mortgage lending one could differentiate between the origination and the refinancing businesses as demand can be heterogenous across this dimension.

U.S. level, controlling for MSA effects interacted with the crisis dummy, as well as in largest MSAs. This result also continues to hold after excluding the largest banks from our sample. Further, we examine and find that this relation holds in a subsample of least risky applications, specifically, those made by higher income applicants for properties located in the MSAs least affected by the collapse in house prices.

While we do control for borrower characteristics in our benchmark estimations, we also address the possibility that these characteristics could be severely unbalanced between banks, which might not be fully addressed by merely including them on the right hand side of a linear regression (See, e.g. Dehejia and Wahba, 2002; Heckman, Ichimura, and Todd, 1998). As argued in Ho and others (2007) and Almeida and others (2009), when control variables have poor distributional overlap, one can improve the estimation of group differences using non-parametric matching methods. We therefore reduce our sample to two subsamples of applicants, at retail and wholesale banks, with almost identical distribution of observable characteristics. Specifically, we divide banks into wholesale and retail groups, and match applications from one group with the other based on applicants' characteristics, namely: gender, race, income, loan to income ratio, and income of the census tract of the applicant. We only match applicants from within the same MSA to control for regional effects. This matching exercise reduces our sample from around 2.6 million to less than 150 thousands observations on characteristically identical pairs of applications. Nevertheless our results also hold in this reduced sample with only trivial changes to the estimate of the marginal impact of bank funding on the rejection rate during the crisis.

Overall our results strongly suggest that the reliance on wholesale funding has led to a sharper contraction in the supply of credit during the crisis. While we argue that the change in rejection rates is a good measure of shifts in supply and is less likely to be affected by shifts in demand compared to overall volume of loans, we nevertheless examine changes in the demand for loans across banks during the crisis. Specifically we check whether the number and volume of loan applications has declined unevenly across banks with various liability structures. We find that the core deposit to asset ratio is not a significant predictor of changes in demand, which we measure by the change in number and volume of mortgage applications. This result helps us further allay concerns of demand driven changes in rejection rates.

We next exploit the variation in the funding of mortgage credit across MSAs, to gauge the aggregate consequences of our earlier findings. While our previous results point to a robust relation between the liability structure of banks and the change in their supply of credit during the crisis, they do not provide a definitive evidence that the reliance on wholesale funding by banks has led to a decline in aggregate credit during the crisis. It is in fact possible that the relative decline in credit by wholesale funded banks was compensated by a relative increase in the supply of retail banks. In other words, one might argue that absent wholesale banks, retail funded banks would have originated less loans. Thus, one way to investigate the aggregate implications of our findings is to examine whether a higher concentration of wholesale funded banks in an MSA was associated with a sharper decline in credit during the crisis. To this end we make use of a panel data of MSA-level observations constructed by collapsing our mortgage data at the MSA level and by merging this data with other MSA-level variables. Our results show a strong negative relation between the MSA's average CD/A ratio and mortgage credit supply during the crisis.

Our paper contributes to several strands of literature in financial economics. First, our paper contributes to a recent literature studying the role of wholesale funding in the credit contraction that occurred during the recent global financial crisis with the aim of understanding the risks from such funding schemes by banks. As pointed out in Huang and Ratnovski (2011), the "dark side" of wholesale funding, i.e. their vulnerability to liquidity shocks, became more visible during the recent crisis. Our paper complements the findings in Ivashina and Scharfstein (2010) and Cornett and others (2011) which also find that bank lending has fallen significantly more at wholesale banks. A salient feature of our approach is the use of comprehensive micro data on a specific credit product which allow us to design an empirical strategy that directly addresses potential confounding factors. In that respect, our paper also adds to a growing literature on the implications of liquidity shocks for credit supply (See, e.g., Khwaja and Mian (2008); Peek and Rosengren (2000), Pravisini (2008) and Puri et al. (2011)). Investigating the link between liquidity shocks and credit (often refereed to as bank lending channel) is challenging due to the fact that events that typically trigger changes in liquidity are also associated with shifts in the demand for loans. In our case, we overcome these challenges by exploiting both time and cross-sectional variation in liquidity using a comprehensive dataset that allows us to distinguish between demand and supply side effects. Finally, our paper contributes to a growing literature that aims to identify factors that have contributed to the severity of the boom-bust cycle with potential implications to macro-prudential policies (See, e.g. Dagher and Fu, 2011; Dell'Ariccia, Igan, and Leaven, 2008; Demyanyk, 2010; Mian and Sufi, 2009; Purnanandam, 2011).

The rest of the paper is organized as follows. Section II describes the data and presents some descriptive statistics and figures. Section III explains the empirical strategy as well as the proposed methodology, and provides the empirical results together with robustness checks. Section IV investigates aggregate supply effects. Section V concludes.

II. Data and Summary Statistics

A. Data

We construct our dataset by merging data on mortgage applications with data on bank financials. The data appendix provides a detailed description of the steps involved in the construction of the dataset.

Our mortgage related data come from a comprehensive sample of mortgage applications between 2005 and 2008 that were collected by the Federal Reserve under the provision of the Home Mortgage Disclosure Act (HMDA). Under this provision, the vast majority of mortgage lenders are required to report.[5] The HMDA data includes information on the year of the application (the data is available on an annual basis), the amount of the loan, the lender's decision, characteristics of the applicant (income, race, gender, location), and the median income in the census tract of the property. The data also provides useful information on the lender, such as the name of the institution, its type, and its regulating agency. We thus can distinguish between banks and their affiliates and other depository (thrifts, credit unions) and non-depository (independent mortgage lenders) institutions. We restrict our attention to mortgage applications made at depository institutions (banks) and their affiliates that are related to owner-occupied home purchases of conventional one-to-four-family properties.

We also limit our study to mortgage originations in counties situated in a Metropolitan Statistical Area (MSA) leaving us with 295 MSAs, which account for around 80% of total HMDA mortgage originations in 2005.[6] To further minimize the noise in the data we focus on banks that were significantly involved in mortgage lending and restrict our attention to banks that originated at least 50 mortgage loans in a given year. A large share of banks account for a small share of originations as they provide mortgage loans occasionally and in small numbers. Lending by these banks is more likely to be affected by idiosyncratic factors that are unrelated to the liquidity crisis. Since our aim is to understand the impact of the crisis on banks' mortgage lending decisions, we are restricted to banks that survived the whole sample period. We therefore balance the sample given the short time span of our data. After imposing these

[5]See Data Appendix for more information about these requirements and the coverage of HMDA.

[6]Restricting our sample to MSAs allows us to control for variables that are otherwise not available, such as measures of house price growth and the housing supply elasticity, and helps us to minimize any noise in the data that could be brought by the inclusion of areas with a small population.

restrictions and excluding loans below $25,000 and above a million, our 2005-2008 sample consists of around 4 million applications at 555 banks.[7]

All regulated depository institutions in the United States are required to file their financial information periodically with their respective regulators. Reports of Condition and Income data are a widely used source of timely and accurate financial data on banks' balance sheets and the results of their operations. Specifically, every national bank, state member bank, and insured non-member bank is required by the Federal Financial Institutions Examination Council (FFIEC) to file a Call Report as of the close of business on the last day of each calendar quarter. The specific reporting requirements depend upon the size of the bank and whether or not it has any foreign offices. The availability of agency specific bank IDs in HMDA (Federal Reserve RSSD-ID, FDIC Certificate Number, and OCC Charter Number) allows us to match HMDA lenders that are depository institutions with their financials from the Call Report. We use the available balance sheet data to capture relevant financial information on banks, including our main variable of interest - the ratio of core deposits to assets. We follow the literature and define core deposits to be the sum of a bank's deposits excluding time deposits over $100,000 (See, e.g. Berlin and Mester, 1999).[8]

B. Summary statistics

Table 1 provides summary statistics on loans in our sample. The first column shows the number of originations in millions of dollars. Over the four years, banks in our sample originated a total of around $898 billion dollars, or more than 19% of the 4.7 trillion of 1-4 family purchase originations reported over the same period by the Mortgage Banker Association (MBA).[9] As expected, and consistent with the MBA numbers, 2005 saw the highest number of originations related to purchases during this period. The volume of originations declined substantially in 2007 with the start of the mortgage crisis and declined by around 46% by 2008 compared to 2005. In the second column of the upper table we show the average rejection rate for banks, which shows an increase of 1.62% during 2008 from 2007. This increase

[7] The original sample includes 4746 banks from which only 555 banks consistently originated more than 50 loans. This restriction on banks reduces the sample from around 5.2 to 4.3 million applications from which around 0.3 million are excluded for being very small or very large loans, to minimize noise from outliers (see e.g. Del'arricia et al. (2008) for similar treatment). Finally, when the data are balanced, the number of observations drops to 4 million applications. Note that these restrictions do not affect our main results in what follows.

[8] Although the limit for insured deposits has been increased to $250,000 in 2008, this does not affect our analysis since we use the lag of the core deposits ratio in each year including in 2008, the last year in our sample.

[9] By focusing on banks we have already excluded from our analysis more than 50% of originations by independent mortgage lenders, saving institutions and credit unions. See Data Appendix for other exclusions.

is substantial compared to relatively stable average rejection rates during the prior years. The last three columns show averages of loan amount, applicant income, and census tract income in thousands of dollars. The increase in all of these measures in 2008 suggest a shift in the composition of accepted applicants, specifically an increase in the share of applicants with higher income. The lower table show a similar trend in the median of these values. Several factors could be at play behind these trends. First, one would expect lower income applicants to be more likely to be affected by the crisis and thus their demand for mortgage loans could have decreased relatively more from previous year. Second, banks could have become more selective during the crisis, due to the shortage in liquidity and the increased risk profile of applicants. The substantial increase in the rejection rate in 2008 suggests that the second factor is likely at play.

We next motivate our empirical analysis by comparing the volume and the rejection rate of banks with different liability structure. We measure the extent of a bank's reliance on insured deposits by the ratio of deposits under $100,000 (core deposits) to total assets (henceforth, CD/A ratio). We divide banks into three categories of low, medium, and high CD/A as of 2005. The category of low CD/A comprises banks with a CD/A below the 33th percentile in 2005, the medium CD/A category comprises banks with a CD/A above this limit but below the 67th percentile, and the higher CD/A comprises the rest of the banks. Figure 1 shows the log of the volume of mortgage credit over the 2005-08 period. We find that, both in mean (upper panel) and in median (lower panel) low CD/A banks experienced a larger contraction in the volume of credit in 2008 compared to banks that relied more on core deposits.[10] Since the bars represent changes in the log of volume we see that the percentage drop in volume of lending in 2008 compared to 2007 is three times larger for the low CD/A group compared to the high CD/A group in means, and more than twice larger in medians.

Figure 2 compares the evolution of the average and median rejection rates of banks in these categories. We also find that relative to 2005 and 2006, the rejection rate has increased substantially more for the low CD/A category than it did for the high CD/A both in mean and in median. Note that rejection rates are on average higher for the low CD/A group. One potential explanation is that mortgage operations could be carried differently between banks with different liability structure. For example, one would expect that banks that aggressively target a large population of potential borrowers would have a higher rejection rates than banks that are less aggressive in their marketing strategy and are more transparent with their qualification

[10]The CD/A ratio is relatively stable over that period, with a slight overall decrease between 2005 and 2007. Thus the choice of the year in which we define the CDA categories has no effect on these patterns. We keep the three sub-samples balanced over the period to enhance comparability and avoid fluctuations due to entry and exit from the sub-samples.

requirements. Investigating this difference is, however, beyond the scope of this paper. Our main interest is whether the patterns shown in Figure 1 and Figure 2 are indeed driven by the difference in CD/A ratio across banks and not by the confounding factors, and the implications of this pattern on the supply of credit during the crisis. In the next section we lay out our empirical strategy to estimate the impact of CD/A on the supply of mortgage credit by banks.

III. Bank Lending During the Crisis

In this section we study the impact of the crisis on lending by banks with a focus on the interaction of the crisis with their funding strategy. We discuss our estimation strategy, present the benchmark empirical results, and then conduct a series of robustness tests.

A. Empirical strategy

Over the recent decades, banks have been increasingly relying on wholesale liabilities to fund and facilitate their operations (See, e.g. Feldman and Schmidt, 2001). The reliance by banks on wholesale funds, typically raised on a short-term rollover basis, has recently received an increasing attention – following the severe liquidity shortages experienced prior and during the Great Recession. Unlike retail deposits, wholesale funds are uninsured liabilities for the banks. This makes them more vulnerable to runs in times of financial stress (See, e.g. Huang and Ratnovski, 2011). This is particularly the case in countries with credible deposit insurance. In fact, absent the risk of devaluation, banks are likely to experience a net inflow of retail deposits during periods of stress in such countries, as suggested for example by evidence in Gatev and Strahan (2006).

With this heterogeneity in mind, the immediate question we ask in this paper is the following: did the vulnerability of wholesale banks to liquidity shocks lead to a sharper decline in their credit supply relative to other banks during the crisis? The overarching objective is to shed light on the impact of liquidity on credit supply. Our empirical methodology allows us to answer this question and provide an insight on the bank lending channel using two sources of identifying variations: time variation in overall market liquidity and the cross-sectional variation in banks' vulnerability to liquidity shortages.

The time variation in market liquidity has been discussed in several recent papers such as Almeida et al (2011), Cornett et al. (2011) and others. One particularly useful indicator used to gauge the extent of the liquidity freeze in the market is the TED Spread, which is the difference between the 3-month LIBOR rate and the 3-month Treasury rate. Increases in the TED spread reflect perceived risk of lending to banks and are widely accepted as indicators of the market squeeze on short term wholesale funding. Figure 3 plots the TED spread between 2005 and 2010. While the TED spread was hovering around 0.43% between 2005 and 2007. It hiked to levels between 1% and 2.4% following August 2007, and has remained above the 1% threshold virtually during all of 2008 reaching its highest level of 5.76% in October 2008. The TED spread has averaged 2.56% during the second half of 2008. These events provide us with a unique opportunity to identify the impact of general market liquidity squeeze on lending by banks of varying liability structure.

Our identification strategy requires two conditions to be met. The first essential requirement for our identification strategy is to have enough variation in banks' reliance on core deposits as a source of funding. Figure 4 depicts the distribution of CD/A and shows a significant variation across banks with a standard error of 11%. The Figure also shows left-skewness in the distribution, with most banks being above the mean CD/A in the sample.

Another requirement that must be satisfied is for the variation in the CD/A to be exogenous to the observed outcomes. To address this issue we use the lag of the CD/A as the explanatory variable and we control for potential confounding factors. There are three broad categories of variables that could be potentially correlated with both our explanatory variable, the CD/A ratio, and the bank's decision on any given application. These are: bank, borrower, and regional characteristics. First, one might worry that the CD/A ratio of a bank might be correlated with other bank specific factors which could in turn be the principal drivers of the changes in rejection rates. To address this issue, we include in our benchmark specification both bank fixed effects as well as a set of time-varying balance sheet information. Second, we control for borrower and loan characteristics with available data from HMDA. Third, there is little doubt that both time non-varying and time-varying regional characteristics are potentially important explanatory factors of mortgage credit supply by banks at the regional level in a given year. We therefore sweep out the impact of these factors using fixed effects and an interaction of the fixed effect with the crisis dummy. We also run regressions at the subnational level, specifically, within the largest MSAs in the U.S. in order to ensure that our results are not driven by a few geographical regions. Finally, we acknowledge that by simply controlling for borrower and regional characteristics on the right hand side of our regression we might not fully address potential problems due to a serious imbalance in the geographical or borrower distribution across banks. Therefore, we address this issue via matching procedures in a robustness section.

B. Model specificatio

Our binary dependent variable reflects the bank's decision of approving or rejecting a mortgage loan application. The objective of our exercise is to test the impact of the liability structure of a bank, specifically the extent of its reliance on core deposits, on its lending decision during the crisis. We use two sources of identifying variations: the time before and after the financial crisis and the variation in the ratio of core deposits to total assets across banks, as a measure of the extent of reliance on retail deposits. Our benchmark model is the following:

$$\begin{aligned} R_{i,k,m,t} &= \alpha_t + \lambda_k + \delta_m + \beta X_{i,t} + \phi Z_{k,t-1} + \gamma(Crisis_t \times CDA_{k,t-1}) \\ &+ \eta\,\delta_m \times Crisis_t + \theta(Crisis_t \times Z_{k,t-1}) + \varepsilon_{i,k,t,m} \end{aligned} \tag{1}$$

Where $R_{i,k,m,t}$ takes the value of one if a loan application i at bank k in year t for a mortgage on a property located in the MSA m has been rejected. The coefficients α_t, λ_k, and δ_m capture time, bank, and MSA fixed effects. $X_{i,t}$ is a vector of variables that captures relevant characteristics that are reported in HMDA for each applicant. These include information on the applicant's income, loan value (which we use to compute loan-to-income ratio), gender, race, and median income of the census tract of the property. We also control for bank characteristics $Z_{k,t-1}$ from the end of the previous period together with their interaction with the crisis dummy. Specifically, we control for: (i) size, captured by the log of total assets, (ii) liquidity, captured by ratio of liquid assets to total assets, (iii) leverage, computed as the ratio of capital to assets, (iv) profitability, captured by the ratio of income to total assets, (v) losses, captured by the ratio of provisions to losses to total assets, (vi) the ratio of unused commitments to total assets which complements our liquidity measure, (vii) the return on equity as a share of total assets, and (vii) the shares of construction loans, loans secured by properties, and commercial and industrial loans to total assets. We interact these financial variables with the crisis dummy ($Crisis_t$), defined in the next section, as their impact on lending could vary with the macroeconomic environment and particularly with overall liquidity in the market. Similarly, to control for the various regional heterogeneities, we also interact the MSA fixed effects with the crisis dummy. While this increases the set of exogenous variable by another 295 variables, we believe that this level of disaggregation is important as even MSAs within a same state could be very differently affected by the crisis and particularly with respect to housing prices. Controlling for regional variation is a critical part of our empirical strategy. Therefore, we also run our benchmark regression at the MSA level for the major MSAs to investigate the robustness of our main results.

The coefficient of interest is γ. It captures the impact of lagged CD/A ratio on bank rejection decision during the crisis. Our stated hypothesis is that banks who relied more on core deposit funding entering the crisis are likely to have curtailed their credit less in comparison with wholesale banks. We therefore expect the coefficient γ to be negative reflecting a smaller increase in the rejection rate by retail banks during the crisis.

We estimate these equations with a linear probability model (LPM) to fit a binary dependent variable. In a panel data setting, the LPM has an important advantage over Probit and Logit models when $N \longrightarrow \infty$ and T is fixed, since the estimates are generally inconsistent in Probit or Logit, but are $\sqrt{N}$ consistent using LPM (Wooldridge, 2002). Nevertheless, for robustness we later also carry a logit estimation.

C. Definitio of the crisis period

HMDA data is available on a yearly basis, without further breakdown at the quarterly or monthly frequency. Thus, we have several options in defining the crisis period. First we can define the crisis year as 2008 assuming 2007 is a non-crisis year. The second possibility is to include both 2007 and 2008 as crisis years. In both of these cases, however, we would be underestimating the effect of the crisis by including a year in the first half of which the funding markets were close to their normal level (in accordance to the TED spread, for example) as either a non-crisis or a crisis year. To avoid this bias, we choose instead to exclude 2007 and thus compare 2008 with 2005 and 2006. Most of our results are, however, robust to including 2007 as crisis year as well as including it as a non-crisis year.

Table 2 helps illustrate this issue and motivate our selection. It shows results from estimating a simplified version of our benchmark model including only crisis-year dummy and the CD/A variable in Panel A and the interaction of these two in Panel B. Our focus is on the coefficient on the crisis dummy. We find that, as one would expect, the coefficient is positive (i.e., higher rejection rate) and that it is larger in magnitude when we drop 2007 and focus on 2008 instead. It is the smallest when we take 2007 to be the crisis year while dropping 2008, and it is somewhere in between when we keep 2007 and assume that it is either a crisis or a non-crisis year. Therefore, it is clear that for a more nuanced comparison between crisis and non-crisis year, we should focus on 2008 excluding 2007 from our sample. We also show in Panel B of Table 2 how the interaction between CD/A and the crisis is negative and significant in all specifications. The results are again in line with our expectations. Specifically, we find that by improperly labeling 2007 as either a crisis year or non-crisis year results in a smaller estimated impact of both the crisis year and the liability structure of the bank, captured by the CD/A ratio, during the crisis year.

Note that in both panels we find that the coefficient on CD/A also implies that an increase in reliance on retail deposits is associated with an increase in the rejection rate in every year, everything else constant. This result echoes the difference in rejection rates reported in Figure 2 and is not necessarily puzzling as the funding structure of banks could also affect their mortgage operations in various ways leading to differences in the volume of applications and in rejection rates.

D. Benchmark results

Table 3 reports results from the estimation of Linear Probability Model in equation (1). We control for bank, MSA, and year fixed effects, as well as for MSA dummies interacted with a crisis dummy in all columns. We use two-way clustering for standard errors and cluster residuals by bank and MSA.[11] In the first column we only regress the rejection decisions on the X variables, which are characteristics of the applications, and on the main variable of interest together with its interaction with the crisis dummy. The coefficients on the X variables are in line with those commonly cited in the literature that studies bank rejection decision in the context of HMDA data. We find that applications by minorities are associated with a higher rejection probability on average, that a higher applicant's income and a higher median income in the census tract of the property are associated with a lower rejection probability, and higher loan to income ratios lead to more rejections on average.[12] The coefficient of interest, γ, on the interaction of CD/A and crisis is negative and significant at the 1% level. In the second column we introduce the Z variables and their interactions with the crisis dummy.[13] We find that by interacting Z variables with the crisis the magnitude of the coefficient γ slightly decreases but remains very significant. The result suggests that a one standard deviation increase in the CD/A ratio (which corresponds to an increase by around 0.11) is associated with a 3% lower probability of rejection of the mortgage application during the crisis, everything else held constant. The coefficient on the interaction between the Z variables and the crisis

[11] See Cameron, Gelbach, and Miller (2006) for details on multi-way clustering.

[12] Note that the coefficient on the minority dummy should not be interpreted as evidence of racial discrimination since variables that could be correlated with both race and creditworthiness that are available to banks were omitted in HMDA (See Munnell et al., 1996).

[13] Given the large set of regress ors we do not report the coefficients for the Z variables but control for them as stated. Since we control for bank fixed effects and due to the small variation in most of the Z variables over the short period of our study, the coefficient on these variables are not of primary importance to us. Instead we show their interaction with the crisis dummy.

are broadly in line with expectations. A higher leverage ratio and a higher liquidity ratio as of end 2007 predict smaller increases in rejection during 2008, while higher provision for losses are associated with a higher rejection rates. We find that banks that had a higher ratio of loans secured by properties continued to lend compared to those banks whose activities were less concentrated in this market. One potential explanation is that banks that were less invested in this market prior to the crisis had more flexibility in retrenching from this sector.

We next examine whether the documented relation also holds for small banks in our sample. The motivation of focusing on small banks is twofold. First, the larger banks originate disproportionally more loans compared to their size and while we do cluster the standard errors by bank and MSA ,one might worry that our results could still be affected by the sheer volume originated by these banks. Second, large banks are complex financial institutions, and controlling for their financial ratios might not fully capture their financial condition at the time of the crisis, including the impact of any potential implicit government guarantees on their lending. Therefore, we reduce our sample to the lower 90% of banks based on their total assets (small banks are commonly defined as such in the literature). The results are shown in column (3). First, we find that the coefficient of interest, γ, is negative and significant, although smaller in magnitude. This comforts us, as it implies that the relation we document is robust, and that the larger banks are unlikely to be outliers but rather strengthen a relation that is already present in the rest of the sample. The result on the X variables are broadly similar to the earlier results, while the interaction between size and crisis now interestingly yields a positive relationship with rejection rates. The coefficients on this interaction in column (2) and (3) could suggest a possibly inverted U curve relation between size and rejection during the crisis. Understanding the drivers of this relation is something that deserves further attention but is beyond the focus of this paper.

There is little doubt that the sharp decline in house prices and the increase in the unemployment rate during the crisis has significantly affected mortgage credit risk since households are more likely to default on their mortgage after losing equity in their homes or after losing a stable source of income. One might therefore wonder how our results should be interpreted against this backdrop of worsening creditworthiness of households. It is important first to clarify that our aim is to understand the implication of the shortage of liquidity on the supply of credit, with no presumptions in mind on the channel or the modality in which this relation holds. Specifically, we make no claims on whether banks that are short of liquidity curtail their credit to conserve liquidity (see e.g. Cornett et al, 2011) or because they become more risk averse. Documenting these channels is indeed worthwhile but is beyond the scope of this paper. Our aim is instead to rigorously examine the impact of liquidity shortages on credit supply ensuring that any potential confounding factors are properly accounted for. To this end it is important to assuage concerns that the increase in credit risk has led to a decline in credit supply due to unobservable factors that happen to be correlated with banks' CD/A ratio. We therefore focus on a subsample of borrowers that are least risky based on income category and geographical location. Specifically we first select a group of MSAs with a high elasticity of housing supply, which are MSAs in which house prices are typically less volatile and less prone to boom bust cycles (See, e.g., Saiz, 2010, and Mian and Sufi, 2009).[14] Figure 5 shows a comparison of the average house price growth in the upper quartile of MSAs ranked by Saiz's housing supply elasticity with the average house price growth in the remaining MSAs. It is clear that MSAs with higher elasticity of housing supply had smaller increases in house prices during the boom period and have had substantially smaller declines in the growth rate in 2007 and 2008. From this subsample we also select households in the upper quartile of the income distribution.The results are shown in column 4. We find that despite decreasing the subsample from 2.7 million to only around 80 thousand observations our results hold with a coefficient that is similar in magnitude to the one in columns (1) and (2). In column (5), instead of selecting MSAs in the upper distribution based on the housing supply elasticity we select MSAs with no drop in house prices and find similar results.[15]

We next run our LPM model in equation (1) at the MSA level for the U.S.'s largest MSAs in order to examine the extent to which the above relation holds across different regions. We select the largest 15 MSAs in our data based on the number of applications. However, since only 12 of these MSAs figure in the top 15 MSAs based on population from census we also include the three remaining MSAs (Boston, Detroit, and Miami). The results are shown in Table 5. All regressions in that table control for the Z variables together with their interaction with the crisis, they also include bank and year fixed effects. We cluster standard errors at the bank level. We find that the documented negative relation between retail funding and the rejection rate during the crisis holds in all MSAs, and that it is significant in 14 out of the top 18 MSAs. Furthermore, we notice that the coefficient lacks significance in the MSAs with the smaller number of applications, particularly in the case of Boston and Detroit.

[14]The elasticity of housing supply are carefully constructed by Edward Saiz based on topological factors. See Data Appendix.

[15]We prefer the specification in column 4 as it makes a selection of MSAs based on a purely exogenous factor.

E. Matching

In the earlier estimations we controlled for applicants characteristics which are available in the HMDA data. However, their mere inclusion in the right hand sand side of a linear regression does not fully address for a potentially serious imbalance resulting from a poor distributional overlap of applicant characteristics across banks.[16] One might argue that characteristics such as income, loan to income, or the median income of the census tract could be correlated with bank characteristics such as their liability structure. Our aim in this section is to reduce such potential imbalance by matching applicants across banks. For this we define two categories of banks, wholesale and retail based on a CD/A cutoff. We chose the cutoff to be equal to 58%, which is the 25th percentile of the distribution. This cutoff value is also motivated by the fact that banks with CD/A above this cutoff are typically classified as traditional retail banks such as Wells Fargo and Bank of America. Further the advantage of such cutoff is that it divides almost equally the volume of applications between wholesale banks (banks with lower CD/A value) and retail banks. Nevertheless we try various similar divisions and find that they don't affect the overall results. Based on this cutoff value of 58%, Panel A of Table 6 compares summary statistics of applicant characteristics across the two group of banks. We find that there are statistically significant differences in the mean (based on the t-test) and in the distribution (based on the Kolmogrov-Smirnov (KS) test) of income, tract income and loan to income across the two groups.

To ensure that this imbalance is not affecting our main results we proceed by matching applicants from the two categories of banks to obtain similar distributions in applicant characteristics in both subsamples. Ho and others (2007) discuss the advantages of non-parametrically pre-processing the data via matching in order to eliminate imbalance. They show that not only does matching eliminate potential bias that could be hard to address with linear regressions but it also makes the subsequent parametric analysis far less dependent on modeling choices and specifications. We use the Abadie and Imbens (2002) exact matching procedure to match applications on: (i) MSA, (ii) census tract income, (iii) applicant income, (iv) loan to income ratio, (v) race, and (vi) gender. The procedure allows for exact matching for discreet variables and allows for approximate matching for continuous variables (Abadie and Imbens, 2002). Nevertheless, the abundance of applicant data in our case allows us to restrict our matching sample to applications where even the continuous variables are matched almost

[16]See, e.g. Heckman, Ichimura, and Todd (1998) and Dehejia and Wahba (2002).

exactly.[17] We perform this matching within each year to reduce the sub-samples into characteristically similar applicants between wholesale and retail banks. We call this the within-year, or one-way matched sample.

In addition to the within-year matching, we also match applicants across years, and thus ensuring that the characteristics of the borrowers are not only similar across banks, but also across bank-years. This two-way matching serves as a stringent robustness test that helps minimize concerns of changes in applicant characteristics over time and the potential implications this would have on our estimation. Note that we deflate income variable by the county's nominal income growth in the case of the two-way matching. We therefore reduce our sample from around 2.7 million applications to 0.68 million with the within year matching, and 0.13 million applications with the two-way matching.

Matching itself is not an estimation method and is typically followed by a difference in difference matching estimation or by a regression analysis. Given the various banking and geographical variables that we need to control for we chose to follow the matching by the same regressions as in Table 3.

1. Balancing tests

Upon completion of the matching estimation we conduct balancing tests. The objective of these tests is to to check the effectiveness of the matching and ensure that the distribution of the applicant's characteristics does not significantly differ across groups in the matched sample. We use the Kolmogorov-Smirnov (KS) test of *distributional* differences as well as t-test to compare the means (See, e.g. Almeida and others, 2009). The comparison of the samples post matching are shown in panels B and D of Table 6. We can see that neither the t-test nor the KS test can reject the equality of the mean or the distribution of the variables, respectively. In general, and following the literature, our aim is to have p-values for the t-test and the KS test above 10%. Our tables show that this threshold is far exceeded and that the wealth of data allowed us to implement a strict matching leading to almost identical distributions between applicant characteristics across groups. For example a quick comparison of the mean and median income between Wholesale and Retail banks we find that they are almost exactly the same with a difference at the third decimal point. This contrasts with the difference in the

[17] After one to one matching of applicants between the two categories of banks we drop matches which are too far apart, using a variant of *caliper matching* (Cochran and Rubin, 1973). Specifically, we drop matched pairs with distance in the upper 25^{th} percentile in each matching group.

original sample shown in the panels A and C of the same table. Overall the results of the balancing tests give us comfort that the matching achieved its goal.

2. Regressions on the matched sub-samples

We next proceed by fitting equation (1) to our matched sample and show the results in Table 4. For comparison purposes we show in columns 1 and 2 the results from our earlier benchmark model. In columns (3) and (4) we show the results from the LPM regression on the One-Way matched sample, that is the sample in which the matching was done across banks but not across years. It is clear from the coefficients on the interaction between CD/A and crisis in columns (1) and (3), and the coefficients on the interaction between the retail and crisis dummies in columns (2) and (4) that our results remain unchanged both qualitatively and quantitatively. The coefficients on the other variables also remain largely in line with the benchmark results. Columns (5) and (6) show the results from the estimation on the smaller Two-Way matched sample. We find that while some coefficients lose their significance in this smaller sample, such as the coefficient on loan to income, the coefficient on the interaction of interest remain remarkably stable. The reason that some coefficients have a reduced significance in our matched sample could be due the fact that the matching exercise is likely matched observations from the more dense areas of the distribution, since observations on the thinner tails are harder to match across banks. Finally we follow our LPM regressions on the matched sample with a Logit estimation on the One-Way matched sample. The LPM has an important advantage over Probit and Logit models when $N \longrightarrow \infty$ and T is fixed, since the estimates are generally inconsistent in Probit or Logit, but are $\sqrt{N}$ consistent using LPM (Wooldridge, 2002). Nevertheless we show the Logit results for robustness and find that the coefficient on the interaction between CD/A and the crisis dummy remains significant at the 1% level.

F. Demand for credit

The main objective of this paper is to test whether wholesale lenders decreased their *supply* of credit more during the crisis. Our empirical strategy has thus focused on controlling for demand related effects that could confound our analysis by, for example, focusing on one type of loan, and by carefully controlling for regional and borrower characteristics across banks. Further, we have chosen our dependent variable to be the rejection rate, a variable that is less likely to be affected by shifts in demand in comparison for example with credit volume. This empirical strategy makes us confident that changes in the rejection rate are reflecting changes in the supply of credit. In this section we turn to examine how the demand for loans was affected by the crisis and to further address concerns related to the potential implications of uneven changes in demand between wholesale and retail banks. Note that in our earlier estimations we have controlled for variations in demand facing banks that are due to banks' heterogeneous geographical distribution. Therefore the only remaining concern would be regarding potential heterogeneity in demand shifts between wholesale and retail banks *within the same MSAs*. We aggregate the number and dollar volume of applications at the bank-MSA level and proceed with the following estimations:

$$A_{k,m,t} = \alpha_t + \lambda_k + \delta_m + \gamma(Crisis_t \times CDA_{k,t-1}) + \eta\,\delta_m \times Crisis_t + \varepsilon_{k,t,m} \tag{2}$$

$$V_{k,m,t} = \alpha_t + \lambda_k + \delta_m + \gamma(Crisis_t \times CDA_{k,t-1}) + \eta\,\delta_m \times Crisis_t + \varepsilon_{k,t,m} \tag{3}$$

where $A_{k,m,t}$ is the log of the number of loan applications at bank k, in MSA m, in year t. Similarly, $V_{k,m,t}$ is the ratio of the dollar volume of applications made at bank k in MSA m to the total assets of the bank. We control as usual for time, bank and MSA effects and interact the crisis dummy with the lagged ratio of core deposits to total assets. The coefficient γ captures the relation between a banks' CD/A and demand for loans at these banks in the crisis year. We do not control for other time varying bank characteristics, since arguably these are of little relevance to demand.[18]

The results are shown in Table 7. We first estimate equations (2) and (3) in columns (1) and (3) without including the interaction between MSA and the Crisis dummy to show the impact of the crisis on the overall number and dollar volume of applications. The regressions otherwise include bank, MSA and year fixed effects. We cluster the residuals at MSA and bank level. We find that the crisis has led to a significant decline in the demand for mortgages. Indeed, one would expect that the recession together with the sharp decline in house prices would have led to a decline in the demand for mortgages. The coefficient on the interaction between CD/A is, however, not statistically significant. The results are also similar in columns (2) and (4) where we control for the interaction of MSA dummies with the crisis. Therefore, we can conclude from this exercise that while demand for mortgages has significantly declined during the crises, it did so relatively evenly across our partition scheme, i.e., between retail and wholesale banks. One plausible interpretation of the positive coefficient

[18]We nevertheless do run variations on these regression by including these controls, without showing them here, and find that they do not affect our main results.

on the interaction term could be that the increased rejection rate by wholesale banks has led applicants to seek loans from retail banks, but not to a significant extent as the coefficient are not statistically significant. These result further strengthen our claims that our earlier findings are capturing shifts in the supply of credit.[19]

IV. Aggregate Supply Effects

In this section we examine whether the relation between wholesale funding and lending during the crisis was consequential to aggregate lending during the crisis. To this end, we exploit cross-regional variation in banks' liability structure.

A. Motivation and empirical strategy

Our previous findings from loan level data show that lending by wholesale funded banks was more affected by the crisis. Based on these findings alone, however, one cannot conclude that the reliance on wholesale funding by banks has led to a lower overall mortgage credit in the economy. This is because it is possible that the relative increase in credit supply by retail funded banks went to compensate the relative decline in credit supply by wholesale banks. One way to investigate whether the shortage of credit supply from wholesale funded banks was consequential to the ability of households in obtaining credit is to exploit the geographical heterogeneity in banks' liability structure. The heterogeneity in banks' liability structure (shown previously in Figure 4) together with the heterogeneity in their market share across regions would suggest that there could be a measurable diversity in the way mortgages are funded across regions. Figure 6 shows a histogram of the distribution of the weighted average ratio of core deposits to assets across Metropolitan Statistical Areas (MSAs). The ratio is weighted by the share of each bank in the total number of mortgages originated in a given MSA. We find that the CD/A ratio varies between 0.5 and 0.7 across MSAs. We therefore estimate the following two regressions to investigate the relation between the liability structure

[19]One could worry, for example, that the volume of applications at wholesale banks has decreased less during the crisis compared to the volume of applications at retail banks, and that this *relative* increase in demand from wholesale banks has led to a relative increase in their rejection rate. However unlikely this scenario could be, as mortgage applicants are unlikely to choose banks based on their liability structure, the results in this section help us put such concerns to rest.

of banks in the region, proxied by the weighted CD/A, and credit supply during the crisis:

$$\begin{aligned} V_{m,t} =& \alpha_t + \delta_m + \beta V_{m,t-1} + \gamma Crisis_t \times \overline{CDA}_{m,t-1} + \\ & \phi \overline{Z}_{m,t-1} + \theta Crisis_t \times \overline{Z}_{m,t-1} + \rho M_{m,t-1} + \varepsilon_{m,t} \end{aligned} \tag{4}$$

$$\begin{aligned} \triangle V_{m,t} =& \alpha_t + \delta_m + \beta \triangle V_{m,t-1} + \gamma Crisis_t \times \overline{CDA}_{m,t-1} + \\ & \phi \overline{Z}_{m,t-1} + \theta Crisis_t \times \overline{Z}_{m,t-1} + \rho M_{m,t-1} + \varepsilon_{m,t} \end{aligned} \tag{5}$$

where $V_{m,t}$ stands for the log of dollar value of total mortgage originations in MSA m at time t. $\overline{CDA}_{m,t}$ and $\overline{Z}_{m,t}$ are the average bank characteristics within MSA, weighted by the total number of originations by each bank in MSA m at time t.[20]. In addition to the interaction of the lag CD/A with the dummy for the crisis year, we also include its interaction with the dummy variable for the year of 2007. This is done to eliminate the effect of year 2007, which, as discussed previously, cannot be considered as either crisis or non-crisis year . $M_{m,t}$ is a set of MSA characteristics such as change in house prices, their interaction with crisis dummy, and GDP per capita. We estimate the equations in (4) and (5) with methods fit for dynamic panel also to control for unobserved group and time effects. For robustness we show estimation output from several methods. Specifically, we first run a static fixed-effect estimation neglecting the lag of the dependent variable. We then add to our estimation the lagged dependent variable to account for possible persistence and mean-reverting dynamics in the volume of loans. However, with such estimation method we could run into potential problems that are well discussed in the empirical literature: the time-invariant Bank-MSA characteristics might be correlated with with the lagged dependent variable leading to problems of bias and inconsistency that are more likely to arise in dynamic panels with short time component and a large cross-section. We thus tackle this issue in three different ways. We first employ a fixed-effect two-stage least squares estimator, and then we use the Arellano and Bond (1991) difference GMM and the Arellano and Bond system GMM estimators which employ a matrix of instruments obtained from levels and first differences of lagged endogenous variables in addition to exogenous variables.

B. Results

The results are shown in Table 8. The results for the static fixed-effect estimation are shown in column (1). They show a positive and significant effect of average CDA during the years

[20]For example, $\overline{CDA}_{m,t} = \sum_k CDA_{k,t} \frac{\sum_i I(R_{i,k,m,t}=0)}{\sum_k \sum_i I(R_{i,k,m,t}=0)}$, where I is an indicator function.

2008 and 2007 on both the level and change of loans.[21] We find, in the second column, that these results also hold when including the lagged dependent variable in both changes and levels. In column (3), we use fixed-effect two-stage least squares estimator, employing the lag of all the RHS variables as instruments for the lagged dependent variable. The high F statistics from the first stage regressions (13.83 and 6.65) comfort us as they suggest that our instruments are not weak.[22] Finally, in columns (4) and (5), we employ the Arellano and Bond (1991) difference GMM and the Arellano and Bond system GMM estimators, which use a matrix of instruments obtained from levels and first differences of lagged endogenous variables in addition to exogenous variables. The post-estimation diagnostic test for serial correlations (AR(2)) rejects the presence of autocorrelation of order higher than one, and the Hansen J test implies that the overidentifying restrictions implied by this GMM procedure are not rejected in any of the specifications. Moreover, the fact that th p-value from the Hansen J test are not very high (above 0.9) is sometimes used as an indication that the instruments are not weak, as discussed in Roodman (2009). The Sargan test also fails to reject the overidentifying restrictions for the GMM in all specifications, thus we are assured in the exogeneity of our instruments.

We observe that MSAs with higher reliance on mortgage lending by retail funded banks experienced a smaller decrease in credit, everything else equal. The coefficient of 1.91 in column (4) of panel A, which is our preferred specification for level equations, implies about 2% increase in volume of mortgage originations when the average CD/A in an MSA increases by 1%. If we compare two MSA in the lower and upper quartiles of CD/A distribution (57% and 62%, respectively), then the fall in the volume of originations was about 10% steeper in the MSA with more wholesale funded banks. These results strongly suggest that the decline in credit supply by wholesale funded banks was consequential to aggregate mortgage credit during the crisis.

V. Conclusion

We examined the impact of banks' exposure to market liquidity risk through wholesale funding on their supply of credit during the financial crisis using comprehensive loan-level data on mortgage lending. We found that wholesale funded banks increased their rejection rate sig-

[21] All the estimations in Table 8 control for MSA and time fixed effects.

[22] See Staiger and Stock (1997) and Stock and Yogo (2005) for the discussion of rule of thumb, where the F-statistics being less than 2 is a sign of weak instruments, while F-statistics greater than 10 is a sign of non-weak instruments.

nificantly more than retail banks during the crisis, controlling for a large set of potential confounding factors. Our methodology addressed potential confounding factors by controlling for regional factors, including by running regressions within Metropolitan Statistical Areas. To address the heterogeneity in applicant characteristics between banks and their potential impact our results, we also match sub-samples of statistically indistinguishable applicants between retail and wholesale banks thus reducing our sample by more than 95 percent and find that our main results remain strong. We also confirm that while *supply* of credit has been more severely affected in the wholesale sample during the crisis, both categories of banks faced a similar decline in *demand*. The aggregate consequences of our results are illustrated in an empirical exercise showing that regions where mortgage credit was to a larger extent funded through wholesale operations suffered a larger contraction, everything else constant.

Figure 1. Volume of originations

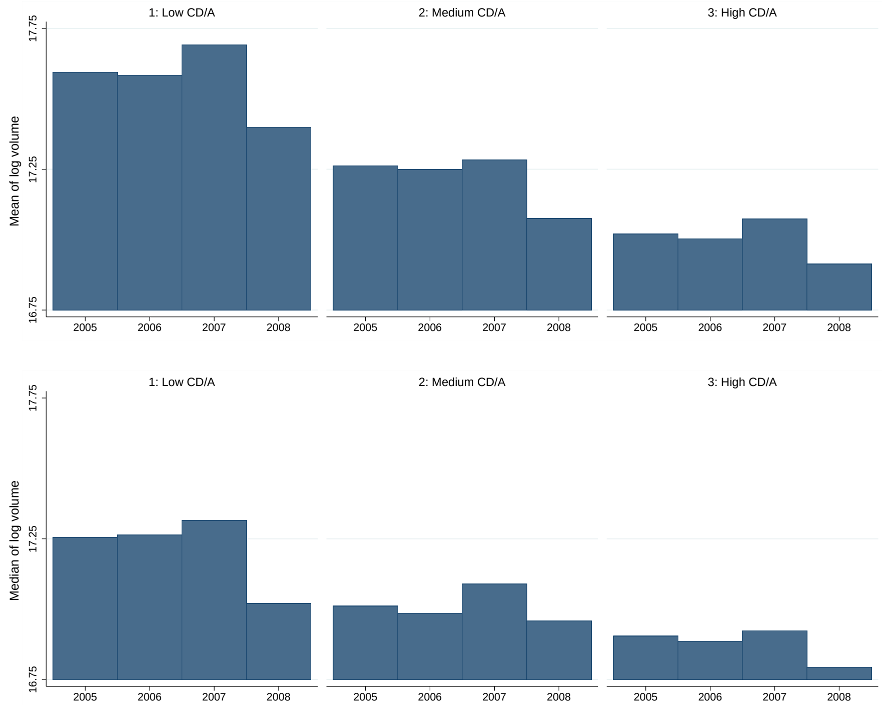

Figure 2. Rejection rates

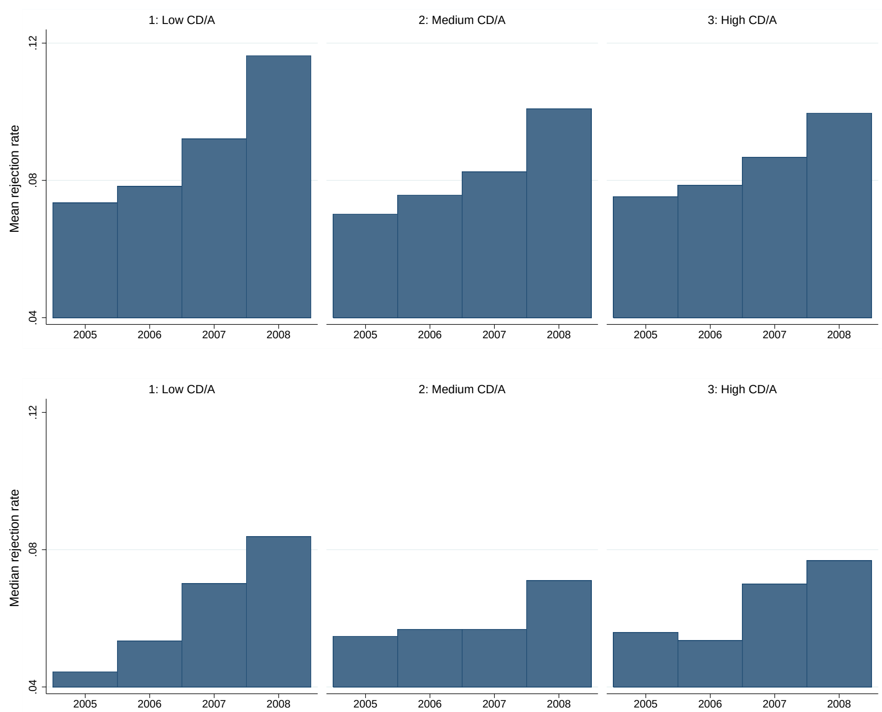

Figure 3. TED spread

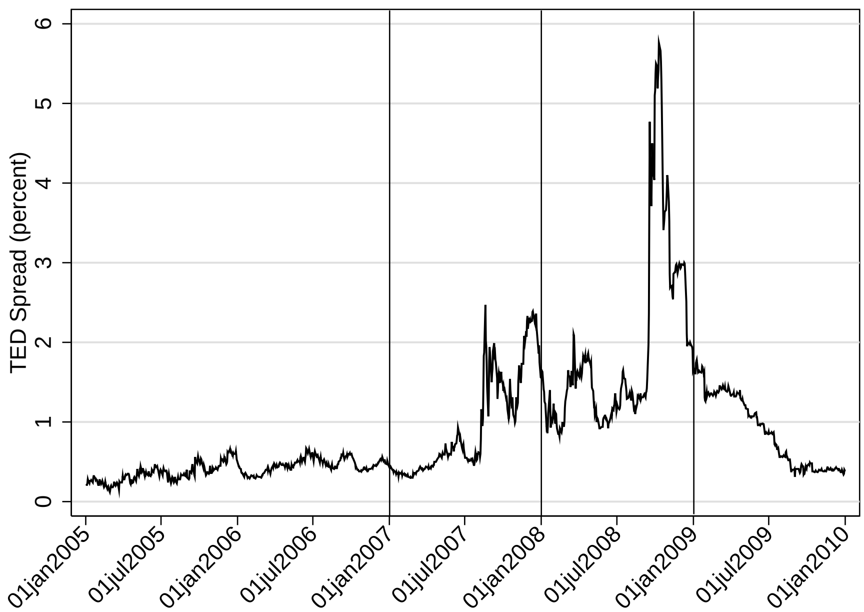

Figure 4. Distribution of CD/A in 2005 across banks

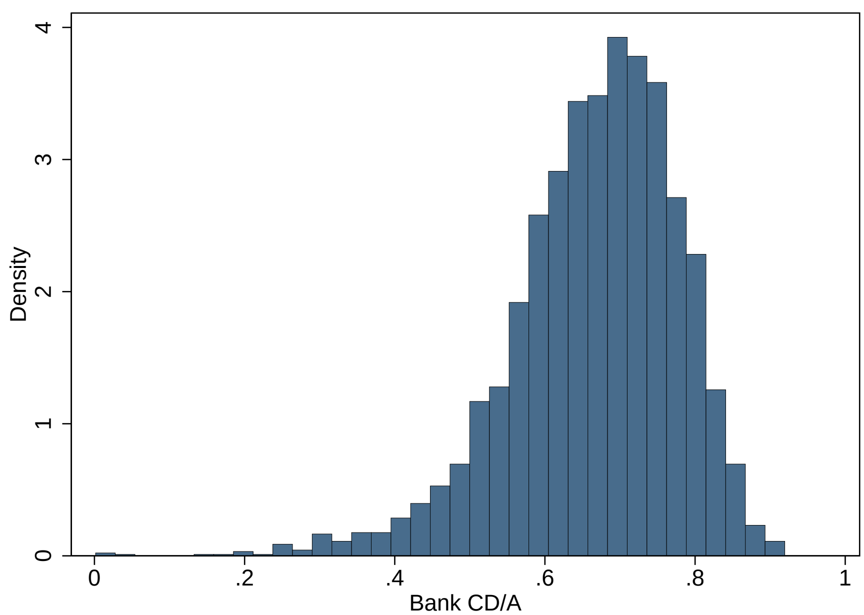

Figure 5. House prices and housing supply elasticity

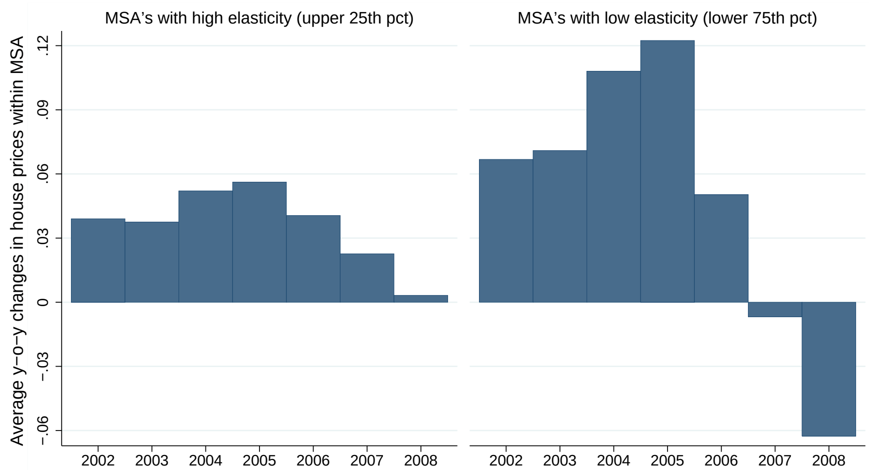

Figure 6. Distribution of average CD/A in 2005 across MSAs

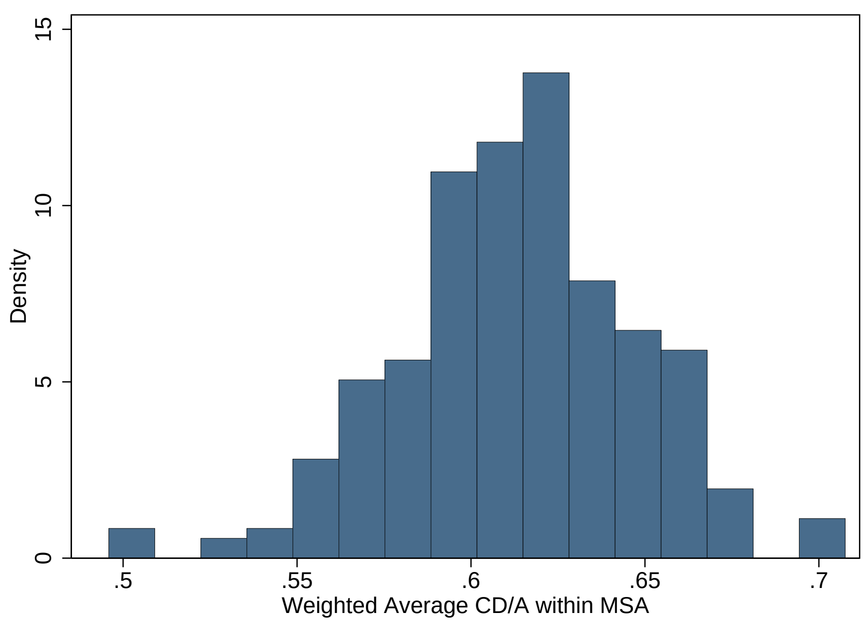

Table 1. Summary statistics

	Total	Average			
	originations (in Mils $)	rejection rate	loan amount (in Thous $)	income (in Thous $)	tract income (in Thous $)
2005	259927	14.39%	207.93	99.81	72.88
2006	259128	14.62%	202.18	107.21	73.76
2007	239442	14.40%	211.77	108.10	73.64
2008	139597	16.02%	236.40	114.52	80.08
			Median		
2005			160.0	77.0	68.9
2006			152.0	82.0	69.6
2007			165.0	81.0	69.4
2008			197.0	84.0	75.3

Notes: This table presents the volume of mortgage originations in 295 MSAs in the U.S. The sample is limited to conventional mortgages for purchases of owner-occupied one-to-four family properties during the 2005-2008 period. Rejection rate is the ratio of rejected applications to the total number of approved and rejected ones irrespective of the actual origination.

Table 2. Selecting the crisis year, 2007 vs. 2008

	Panel A: Without CD/A × crisis interaction			
	Crisis is 08	Crisis is 07 and 08	Crisis is 08 dropping 07	Crisis is 07 dropping 08
Crisis	0.0405***	0.0357***	0.0504***	0.0278***
	(0.0004)	(0.0003)	(0.0005)	(0.0004)
Core Deposit/Asset	-0.4197***	-0.4177***	-0.4019***	-0.3867***
	(0.0013)	(0.0013)	(0.0016)	(0.0014)
Constant	0.3647***	0.3535***	0.3444***	0.3356***
	(0.0008)	(0.0008)	(0.0010)	(0.0008)
R-squared	0.0269	0.0278	0.0255	0.0252
	Panel B: With CD/A × crisis interaction			
	Crisis is 08	Crisis is 07 and 08	Crisis is 08 dropping 07	Crisis is 07 dropping 08
Crisis	0.1998***	0.1256***	0.2357***	0.0894***
	(0.0024)	(0.0015)	(0.0024)	(0.0016)
Core Deposit/Asset	-0.3873***	-0.3424***	-0.3424***	-0.3424***
	(0.0014)	(0.0018)	(0.0018)	(0.0018)
Core Deposit X Crisis	-0.2725***	-0.1555***	-0.3173***	-0.1071***
	(0.0040)	(0.0026)	(0.0041)	(0.0028)
Constant	0.3460***	0.3101***	0.3101***	0.3101***
	(0.0008)	(0.0011)	(0.0010)	(0.0010)
R-squared	0.0280	0.0286	0.0276	0.0257
Observations	4,011,233	4,011,233	2,799,288	3,360,756

We estimate the probability of a bank rejecting a mortgage application given its liability structure. The dependent variable is equal to one when a loan application is rejected. We use a linear probability model for the estimation. These benchmark estimations do not include any control variables, and serve only descriptive properties. Ordinary standard errors are shown in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 3. LPM baselines and robustness

VARIABLES	(1) Benchmark Estimates	(2) Full Model	(3) Small Banks	(4) High income High elasticity	(5) High income No price drop
X: Male	-0.0020	-0.0024	-0.0044	-0.0162***	-0.0216***
	(0.0036)	(0.0033)	(0.0028)	(0.0048)	(0.0045)
X: Hispanic	0.0566***	0.0564***	0.0458***	0.0297***	0.0431***
	(0.0073)	(0.0074)	(0.0094)	(0.0089)	(0.0119)
X: Balck	0.0855***	0.0845***	0.0886***	0.0472***	0.0858***
	(0.0060)	(0.0063)	(0.0107)	(0.0116)	(0.0171)
X: Census tract income	-0.0452***	-0.0451***	-0.0475***	-0.0425***	-0.0412***
	(0.0032)	(0.0031)	(0.0088)	(0.0067)	(0.0058)
X: Applicant income	-0.0320***	-0.0319***	-0.0338***	0.0135**	0.0187***
	(0.0063)	(0.0064)	(0.0042)	(0.0056)	(0.0065)
X: Loan-to-income	0.0057***	0.0057***	0.0052***	0.0081	0.0109
	(0.0015)	(0.0015)	(0.0016)	(0.0064)	(0.0080)
Core deposits X crisis	-0.3119***	-0.2814***	-0.1559***	-0.3177***	-0.2415***
	(0.0884)	(0.0465)	(0.0368)	(0.0773)	(0.0661)
Size X crisis		-0.0072*	0.0118***	-0.0053	-0.0061*
		(0.0041)	(0.0040)	(0.0036)	(0.0036)
Profitability X crisis		0.5742	0.1819	2.4140	0.6301
		(2.1092)	(1.3445)	(4.4501)	(2.7740)
Leverage X crisis		-0.6118**	-0.0760	-0.3161	-0.2080
		(0.2552)	(0.1849)	(0.4292)	(0.2425)
Liquidity X crisis		-0.1239*	0.0371	-0.1995**	-0.2330***
		(0.0695)	(0.0491)	(0.0923)	(0.0750)
Losses X crisis		5.2255***	1.3795	0.4818	2.1445
		(1.5922)	(1.3215)	(2.0456)	(1.8821)
Construction loans X crisis		-0.2930***	-0.0373	-0.2309**	-0.3120***
		(0.0790)	(0.0562)	(0.0957)	(0.1022)
Unused commitments X crisis		-0.0013	-0.1059***	0.0277	0.0401
		(0.0550)	(0.0328)	(0.0433)	(0.0473)
Loans secured by properties X crisis		-0.3281***	0.0438	-0.0147	-0.2195***
		(0.0571)	(0.0376)	(0.0788)	(0.0635)
Consumer and industrial loans X crisis		-0.2788***	0.0852	-0.0511	-0.3455***
		(0.1017)	(0.0762)	(0.1081)	(0.1060)
Return on equity to assets X crisis		-0.0924	0.1583	-0.1858	-0.1123
		(0.2709)	(0.1806)	(0.4002)	(0.2793)
Constant	0.8835***	1.3876***	1.0363***	1.1132*	0.8188***
	(0.0840)	(0.3165)	(0.1849)	(0.5746)	(0.3045)
Observations	2,694,272	2,694,272	312,855	80,652	168,879
R-squared	0.0898	0.0917	0.2720	0.1086	0.1013
Z variables	CD/A only	YES	YES	YES	YES
Bank fixed effects	YES	YES	YES	YES	YES
MSA fixed effects	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES
MSA X Crisis	YES	YES	YES	YES	YES
Cluster Bank	YES	YES	YES	YES	YES
Cluster MSA	YES	YES	YES	YES	YES

Notes: We estimate the probability of a bank rejecting a mortgage application given its liability structure, while controlling for borrower, lender, and geographical characteristics. The dependent variable is equal to one when a loan application is rejected. We use a linear probability model for the estimations. Heteroscedasticity consistent standard errors clustered at bank and MSA level are show in parentheses. All estimations include bank, MSA, and year fixed effects as well as the interaction of MSA fixed effects with crisis dummy. All the bank variables (Z) and their interactions are included in columns (2)-(5) but only the interaction estimates are shown to conserve space. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 4. LPM and Logit for the matched sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Full	Discreate	One Way Matched		Two Way Matched		Logit
VARIABLES	Model	CD/A					
X: Male	-0.0024	-0.0024	-0.0048*	-0.0049*	-0.0072*	-0.0073*	-0.0501***
	(0.0033)	(0.0038)	(0.0027)	(0.0027)	(0.0041)	(0.0041)	(0.0098)
X: Hispanic	0.0564***	0.0566***	0.0570***	0.0570***	0.0708***	0.0709***	0.4128***
	(0.0074)	(0.0079)	(0.0074)	(0.0071)	(0.0111)	(0.0111)	(0.0262)
X: Balck	0.0845***	0.0842***	0.0897***	0.0898***	0.1034***	0.1036***	0.6537***
	(0.0063)	(0.0068)	(0.0083)	(0.0083)	(0.0131)	(0.0130)	(0.0338)
X: Census tract income	-0.0451***	-0.0452***	-0.0481***	-0.0481***	-0.0438***	-0.0437***	-0.4128***
	(0.0031)	(0.0032)	(0.0040)	(0.0040)	(0.0054)	(0.0053)	(0.0357)
X: Applicant income	-0.0319***	-0.0313***	-0.0158*	-0.0156*	-0.0169*	-0.0168*	-0.1823***
	(0.0064)	(0.0074)	(0.0093)	(0.0092)	(0.0087)	(0.0087)	(0.0310)
X: Loan-to-income	0.0057***	0.0057***	0.0065*	0.0065*	0.0030	0.0030	0.0565***
	(0.0015)	(0.0017)	(0.0037)	(0.0037)	(0.0033)	(0.0033)	(0.0090)
Core deposits X crisis	-0.2814***		-0.2975***		-0.2638***		-1.1829***
	(0.0465)		(0.0435)		(0.0441)		(0.1893)
Retail 25th pct X crisis		-0.0637***		-0.0634***		-0.0605***	
		(0.0148)		(0.0136)		(0.0139)	
Size X crisis	-0.0072*	-0.0041	-0.0063	-0.0048	-0.0051	-0.0038	-0.0938***
	(0.0041)	(0.0040)	(0.0045)	(0.0044)	(0.0052)	(0.0053)	(0.0220)
Profitability X crisis	0.5742	2.8650	2.7610	3.6313	1.6219	2.4018	-3.3764
	(2.1092)	(2.4329)	(2.5612)	(2.5565)	(2.5122)	(2.6307)	(16.7210)
Leverage X crisis	-0.6118**	-0.5509*	-0.8041***	-0.5533*	-0.4898	-0.2767	-4.7521***
	(0.2552)	(0.2942)	(0.3104)	(0.2999)	(0.3084)	(0.3119)	(1.5332)
Liquidity X crisis	-0.1239*	-0.0969	-0.2026**	-0.1363	-0.2900**	-0.2185*	-1.9064***
	(0.0695)	(0.0879)	(0.0992)	(0.1041)	(0.1151)	(0.1226)	(0.5446)
Losses X crisis	5.2255***	5.8102***	1.5825	3.9203*	-0.3688	2.2330	-6.2433
	(1.5922)	(1.8212)	(2.1481)	(2.2312)	(2.0932)	(1.9570)	(11.1012)
Construction loans X crisis	-0.2930***	-0.3845***	-0.3861***	-0.4182***	-0.4118***	-0.4322***	-3.1118***
	(0.0790)	(0.1123)	(0.0975)	(0.1230)	(0.1057)	(0.1176)	(0.6656)
Unused commitments X crisis	-0.0013	-0.0210	-0.0625	-0.0408	-0.0683	-0.0447	-0.5018**
	(0.0550)	(0.0564)	(0.0611)	(0.0615)	(0.0631)	(0.0649)	(0.2298)
Loans secured by properties X crisis	-0.3281***	-0.3333***	-0.4442***	-0.3794***	-0.4861***	-0.4198***	-4.0202***
	(0.0571)	(0.0683)	(0.0762)	(0.0785)	(0.0783)	(0.0818)	(0.4668)
Consumer and industrial loans X crisis	-0.2788***	-0.1460	-0.2786***	-0.0998	-0.3255***	-0.1556	-2.9826***
	(0.1017)	(0.1398)	(0.1018)	(0.1421)	(0.1079)	(0.1297)	(0.5636)
Return on equity to assets X crisis	-0.0924	-0.2527	-0.3681	-0.3209	-0.2229	-0.1716	1.7821
	(0.2709)	(0.2927)	(0.3601)	(0.3492)	(0.3318)	(0.3313)	(1.7886)
Constant	1.3876***	2.6277***	1.8500***	2.6278***	2.0013***	2.6373***	14.3512***
	(0.3165)	(0.4955)	(0.4935)	(0.5201)	(0.4702)	(0.5218)	(2.4554)
Observations	2,694,272	2,566,429	688,570	688,570	138,249	138,249	687,209
R-squared	0.0917	0.0914	0.0968	0.0966	0.1145	0.1144	0.1052
Z variables	YES	YES	YES	YES	YES	YES	YES
Bank fixed effects	YES	YES	YES	YES	YES	YES	YES
MSA fixed effects	YES	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES	YES
MSA X Crisis	YES	YES	YES	YES	YES	YES	YES
Cluster Bank	YES	YES	YES	YES	YES	YES	YES
Cluster MSA	YES	YES	YES	YES	YES	YES	YES

Notes: The dependent variable is equal to one when a loan application is rejected. Retail 25th pct is an indicator variable which is equalt to one for banks with CD/A higer than 25th percentile (retail banks). In columns (1)-(6) we use linear probability model for the estimations and heteroscedasticity consistent standard errors clustered at bank and MSA level are show in parentheses. In column (7), logistic regression is used and errors are clustered at bank by MSA level. All estimations include bank, MSA, and year fixed effects as well as the interaction of MSA fixed effects with crisis dummy. All the bank variables (Z) and their interactions are included but only the interaction estimates are shown to conserve space. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 5. MSA level estimations

Variable/MSA ID Number	(1) New York Wayne White Plains 35644	(2) Los Angeles Long Beach Glendale 31084	(3) Chicago Naperville Joliet 16974	(4) Dallas Fort Worth Arlington 19124	(5) Philadelphia Camden Wilmington 37964	(6) Houston Baytown Sugar Land 26420	(7) Washington Arlington Alexandria 47894	(8) Miami Miami Beach Kendall 33124	(9) Atlanta Sandy Springs Marietta 12060
X: Male	0.0034*	-0.0026	-0.0017	-0.0096**	0.0035	-0.0101	-0.0002	0.0010	0.0045
	(0.0018)	(0.0048)	(0.0024)	(0.0046)	(0.0028)	(0.0082)	(0.0054)	(0.0025)	(0.0030)
X: Hispanic	0.0505***	0.0501***	0.0665***	0.0763***	0.0454***	0.0479***	0.0671***	0.0091	0.0724***
	(0.0065)	(0.0132)	(0.0060)	(0.0076)	(0.0138)	(0.0101)	(0.0047)	(0.0068)	(0.0215)
X: Black	0.0701***	0.0785***	0.1192***	0.1026***	0.074***	0.0933***	0.086***	0.0753***	0.0942***
	(0.0059)	(0.0130)	(0.0084)	(0.0124)	(0.0136)	(0.0125)	(0.0084)	(0.0155)	(0.0154)
X: Census tract income	-0.0399***	-0.042***	-0.0456***	-0.0502***	-0.0622***	-0.039***	-0.0158**	-0.0328***	-0.0434***
	(0.0036)	(0.0062)	(0.0068)	(0.0054)	(0.0069)	(0.0084)	(0.0067)	(0.0042)	(0.0036)
X: Applicant income	-0.0009	-0.0174**	-0.021***	-0.0264***	-0.0184***	-0.0459***	-0.0256***	-0.0269	-0.0376***
	(0.0155)	(0.0080)	(0.0043)	(0.0096)	(0.0060)	(0.0095)	(0.0062)	(0.0178)	(0.0088)
X: Loan-to-income	0.0103***	0.0062*	0.0022*	0.012***	0.0139***	0.0142***	0.0076**	0.015***	0.0051***
	(0.0024)	(0.0036)	(0.0013)	(0.0018)	(0.0019)	(0.0012)	(0.0032)	(0.0023)	(0.0016)
Core deposits X Crisis	-0.3361***	-0.1933**	-0.2711***	-0.0880	-0.0946	-0.3371***	-0.4972***	-0.6622***	-0.5138***
	(0.1216)	(0.0933)	(0.0837)	(0.0946)	(0.1184)	(0.1198)	(0.1149)	(0.1660)	(0.0579)
Observations	98,900	70,699	101,623	57,104	42,923	79,138	70,686	36,869	72,306
R-squared	0.0811	0.1008	0.0975	0.0856	0.0957	0.1113	0.0729	0.0928	0.0966

Variable/MSA ID Number	(10) Boston Quincy 14484	(11) Oakland Fremont Hayward 36084	(12) Detroit Livonia Dearborn 19804	(13) Riverside San Bernar. Ontario 40140	(14) Phoenix Mesa Scottsdale 38060	(15) Seattle Bellevue Everett 42644	(16) Minneapolis St. Paul Bloomington 33460	(17) Tampa St. Petersburg Clearwater 45300	(18) Baltimore Townson 12580
X: Male	0.0100**	-0.0021	-0.0029	-0.0176*	0.0030	-0.0017	-0.0034	-0.0016	0.0017
	(0.0039)	(0.0037)	(0.0061)	(0.0096)	(0.0044)	(0.0035)	(0.0025)	(0.0037)	(0.0031)
X: Hispanic	0.0564***	0.0583***	-0.0031	0.0526***	0.0687***	0.0566***	0.0751***	0.0675***	0.0485***
	(0.0103)	(0.0107)	(0.0280)	(0.0098)	(0.0125)	(0.0130)	(0.0172)	(0.0069)	(0.0067)
X: Black	0.0899***	0.0844***	0.1083***	0.0629***	0.065***	0.0449***	0.1007***	0.0729***	0.0788***
	(0.0105)	(0.0088)	(0.0135)	(0.0131)	(0.0115)	(0.0102)	(0.0181)	(0.0095)	(0.0061)
X: Census tract income	-0.0211***	-0.0361***	-0.1656***	-0.0417***	-0.0316***	-0.0342***	-0.0305***	-0.0397***	-0.0528***
	(0.0040)	(0.0049)	(0.0090)	(0.0140)	(0.0060)	(0.0079)	(0.0052)	(0.0056)	(0.0072)
X: Applicant income	-0.0261***	-0.0066*	0.0086	-0.0172	-0.0349***	-0.0326***	-0.0204***	-0.0441***	-0.0189**
	(0.0044)	(0.0039)	(0.0131)	(0.0156)	(0.0068)	(0.0122)	(0.0041)	(0.0096)	(0.0086)
X: Loan-to-income	0.012***	0.0154***	0.0231***	0.0087***	0.0014	0.0016	0.003***	0.0074***	0.0055***
	(0.0030)	(0.0051)	(0.0048)	(0.0002)	(0.0011)	(0.0011)	(0.0008)	(0.0013)	(0.0015)
Core deposits X Crisis	-0.0615	-0.3326*	-0.1609	-0.1606**	-0.5822***	-0.1601***	-0.4402***	-0.6343***	-0.2642**
	(0.0634)	(0.1963)	(0.2709)	(0.0799)	(0.0755)	(0.0569)	(0.0606)	(0.1548)	(0.1238)
Observations	23,042	39,768	10,571	49,391	54,659	50,050	55,675	41,291	36,996
R-squared	0.0863	0.0884	0.1698	0.0899	0.0966	0.0779	0.1271	0.0815	0.0618
Z variables	YES	YES	YES	YES	YES	YES	YES	YES	YES
Z variables X crisis	YES	YES	YES	YES	YES	YES	YES	YES	YES
Bank fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Cluster Bank	YES	YES	YES	YES	YES	YES	YES	YES	YES

Notes: The dependent variable is equal to one when a loan application is rejected. We use linear probability model for each of the biggest 18 MSAs in the country in terms of their population and the size of the sample in our data. Heteroscedasticity consistent standard errors clustered at bank level are show in parentheses. All estimations include bank, MSA, and year fixed effects as well as the interaction of MSA fixed effects with crisis dummy. All the bank variables (Z) and their interactions are included but only the interaction estimates are shown to conserve space. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 6. Balancing tests for two way matching

	Retail matched with wholesale									
	Wholesale			Retail			T-Test		KS-test	
	Mean	Median	St.Dev	Mean	Median	St.Dev	Stat	P-Val	Stat	P-Val
	A: Pre Matching									
Log Income	11.23	11.20	0.66	11.27	11.26	0.66	-51.08	0.00	0.04	0.00
Log Tract Income	11.07	11.08	0.38	11.12	11.14	0.38	-105.05	0.00	0.06	0.00
Loan to income	2.25	2.21	2.64	2.47	2.36	2.50	-61.90	0.00	0.08	0.00
Male	0.64			0.66			-26.49	0.00	0.02	0.00
Black	0.15			0.10			101.19	0.00	0.05	0.00
Hispanic	0.09			0.06			66.79	0.00	0.02	0.00
	B: Post Matching									
Log Income	11.24	11.24	0.48	11.24	11.24	0.48	-0.00	1.00	0.00	1.00
Log Tract Income	11.14	11.15	0.28	11.14	11.15	0.28	-0.03	0.98	0.00	1.00
Loan to income	2.42	2.45	0.96	2.42	2.45	0.96	-0.22	0.82	0.00	1.00
Male	0.66			0.66			0.00	1.00	0.00	1.00
Black	0.09			0.09			0.00	1.00	0.00	1.00
Hispanic	0.05			0.05			0.00	1.00	0.00	1.00
	Pre crisis matched with post crisis (wholesale)									
	Pre Crisis			Post Crisis			T-Test		KS-test	
	Mean	Median	St.Dev	Mean	Median	St.Dev	Stat	P-Val	Stat	P-Val
	C: Pre Matching									
Log Income	11.24	11.21	0.64	11.20	11.17	0.70	22.58	0.00	0.05	0.00
Log Tract Income	11.07	11.08	0.38	11.06	11.08	0.40	9.84	0.00	0.02	0.00
Loan to income	2.13	2.11	2.52	2.70	2.56	2.98	-73.00	0.00	0.18	0.00
Male	0.64			0.66			-15.09	0.00	0.02	0.00
Black	0.16			0.10			64.44	0.00	0.06	0.00
Hispanic	0.10			0.06			46.54	0.00	0.03	0.00
	D: Post Matching									
Log Income	11.24	11.24	0.48	11.24	11.24	0.48	0.16	0.88	0.01	0.82
Log Tract Income	11.14	11.15	0.28	11.14	11.15	0.28	1.15	0.25	0.01	0.43
Loan to income	2.42	2.45	0.96	2.42	2.45	0.96	0.13	0.89	0.01	0.86
Male	0.66			0.66			0.00	1.00	0.00	1.00
Black	0.09			0.09			0.00	1.00	0.00	1.00
Hispanic	0.05			0.05			0.00	1.00	0.00	1.00

Note: This table illustrates the effectiveness of our matching procedure by comparing the distribution of observable borrower characteristics across the two dimensions: Panels A and B compare the distributions for retail and wholesale banks while panels C and D perform the comparison between pre and post-crisis periods (2005 and 2006 versus 2008, only for wholesale banks. The results are similar for the retail banks but not shown here.). These results are from two-way matching, where the nominal figures are deflated by the county-level GDP growth. KS-test stands for Kolmogorov-Smirnov equality of distribution test, where rejection (small p-value) implies unequal distributions. T-test is the usual equality of means test. The MSA, gender, and race variables are matched exactly.

Table 7. Demand for mortgages, 2005-2008

VARIABLES	(1)	(2)	(3)	(4)
	Number (log)		Volume / Assets (log)	
Crisis (2008 dropping 2007)	-1.0877**		-0.9215***	
	(0.4652)		(0.3466)	
Core deposits / Assets	-3.2485**	-3.3234**	-2.5746*	-2.7102**
	(1.4031)	(1.4235)	(1.4519)	(1.5054)
CDA x Crisis	1.1646	1.2022	0.5423	0.5746
	(0.7801)	(0.7720)	(0.5806)	(0.5643)
Constant	2.4691***	2.416***	-3.4854***	-3.5594***
	(0.6206)	(0.5953)	(0.6309)	(0.6148)
Observations	11,412	11,412	11,412	11,412
R-squared	0.4489	0.4540	0.6795	0.6827
Bank fixed effects	YES	YES	YES	YES
MSA fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
MSA X Crisis	NO	YES	NO	YES
Cluster Bank	YES	YES	YES	YES
Cluster MSA	YES	YES	YES	YES

Notes: The dependent variable in columns (1) and (2) is the log of number of applications to each bank in each MSA, which we use to capture the demand for loans. In columns (3) and (4) we use the log of dollar value of applications divided by the value of assets of each bank, for the same purpose. OLS estimation is used and heteroscedasticity consistent standard errors clustered at bank and MSA level are show in parentheses. All estimations include bank, MSA, and year fixed effects as well as the interaction of MSA fixed effects with crisis dummy. The coefficient of CDA x Crisis is insignificant in all four specifications, which signals that, the demand was not correlated by the liability structure of a bank during the crisis. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 8. Aggregate Supply, 2005-2008

VARIABLES	Static Fixed-effects	Dynamic Fixed-effects	Dynamic FE-2SLS	Dynamic A-B GMM	Dynamic A-B system GMM
	Panel A: Log volume of originations in MSA				
Log value of originations in MSA (t-1)		0.0224**	0.3881**	0.0549	0.9577***
		(0.0101)	(0.1795)	(0.0768)	(0.0626)
Change in house prices in MSA (t-1)	1.0081***	0.9973***	0.3826*	0.5665***	0.1870
	(0.1214)	(0.1214)	(0.2248)	(0.1361)	(0.4798)
Change in house prices in MSA (t-1) X Crisis	0.9074***	0.8621***	0.4878	0.5196*	-0.0902
	(0.2767)	(0.2774)	(0.3577)	(0.2835)	(0.8031)
Change in GDP per capita in MSA (t-1)	0.2236	0.2321	-0.0834	0.3772	0.7677
	(0.3096)	(0.3014)	(0.3279)	(0.2897)	(0.9029)
Average CD/A	-0.0602	-0.0427	-0.1372	0.0000	-1.0136
	(0.4048)	(0.4017)	(0.4780)	(0.4171)	(1.6038)
Average CD/A X Crisis	1.1520**	1.2062**	1.5092***	2.0592***	3.0824**
	(0.5238)	(0.5172)	(0.5298)	(0.5022)	(1.3015)
Average CD/A X 2007	0.6958*	0.7942**	0.3257	0.8759*	2.2977*
	(0.3920)	(0.3969)	(0.4899)	(0.4838)	(1.3474)
Time effect F test p-value	0.0000	0.0002	0.8574	0.0022	0.0000
R-squared (within)	0.7464	0.7485	0.8035		
F-stat from first stage			13.09		
AR(2) test p-value				0.5370	0.2190
Sargan Test p-value				0.6760	0.8520
Hansen J test p-value				0.6520	0.3950
Number of Instruments				23	25
	Panel B: Change in log volume of originations in MSA				
Change in log value of originations in MSA (t-1)		-0.2987***	-0.0839***	-0.0409	-0.0078
		(0.0483)	(0.0320)	(0.0392)	(0.0308)
Change in house prices in MSA (t-1)	0.5268	0.6540	-0.1084	0.2109	0.2325
	(0.5316)	(0.4744)	(0.1976)	(0.4763)	(0.5134)
Change in house prices in MSA (t-1) X Crisis	-1.1089	-0.8565	-0.0351	-0.4336	-0.2541
	(1.6095)	(1.1382)	(0.4200)	(1.6800)	(0.9423)
Change in GDP per capita in MSA (t-1)	0.6054	0.5994	0.1090	0.4825	0.9691
	(0.9772)	(0.7202)	(0.4183)	(0.9440)	(0.9894)
Average CD/A	0.7190	1.5338	0.4518	0.5829	-0.6939
	(2.4031)	(1.5257)	(0.5831)	(2.6022)	(1.7420)
Average CD/A X Crisis	3.5687**	2.7799**	2.0330***	3.5076**	2.9060**
	(1.4166)	(1.2894)	(0.6707)	(1.5917)	(1.4398)
Average CD/A X 2007	5.0827**	3.8614**	0.5640	3.3103*	2.2010
	(2.1543)	(1.9342)	(0.6416)	(1.8228)	(1.6418)
Time effect F test p-value	0.0176	0.0000	0.5551	0.0066	0.0000
R-squared (within)	0.3967	0.5499	0.7494		
F-stat from first stage			6.89		
AR(2) test p-value				0.5550	0.2810
Sargan Test p-value				0.8110	0.8520
Hansen J test p-value				0.5410	0.6810
Number of Instruments				23	25
Observations	1,076	1,076	807	807	1,076
Number of MSAs	269	269	269	269	269

Notes: The dependent variable is the log and the log-difference of total volume of mortgage originations in each MSA in panels A and B, respectively. The sample is a balanced panel with 269 MSAs, for the period of four years from 2005 to 2008. Year dummies are included in all regressions and the joint significant is tested using the F test. All regressions include the MSA weighted averages of other bank characteristics, weighted by the number of mortgage originations within an MSA, as well as their interaction with the crisis dummy. Crisis is defined as the year 2008. Fixed-effect OLS regressions without lagged dependent variable are reported in column (1) with MSA dummies and robust standard errors clustered by MSA in parentheses. Column (2) adds the lagged dependent variable to the estimation to account for possible persistence with conventional robust standard errors in parentheses. Column (3) uses fixed-effect 2SLS model and instruments the lagged dependent variable by the lag of all other independent variables. Column (4) and (5) present the result from Arellano and Bond (1991) GMM and Arellano and Bower (1995) system GMM estimation, respectively, with robust standard errors from the two step estimation clustered at bank level.

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Data Appendix

HMDA Data

We use a comprehensive sample of mortgage applications and originations that have been collected by the Federal Reserve under the provision of the Home Mortgage Disclosure Act (HMDA). Under this provision, the vast majority of mortgage lenders are required to report data about their house-related lending activity.[23] HMDA data covered around 95% of all mortgage originations in 2005 (See, e.g. Dell'Ariccia, Igan, and Leaven, 2008), and has a better coverage within MSAs due to stricter reporting requirements in these areas.

The HMDA data provide information on the year of the application (the data is available on an annual basis), the amount of the loan, the lender's decision, and the income of the applicant. The data also provide information on the gender and race of the applicant, as well as other information on the census tract of the property such as the median income and share of minority households.

The raw HMDA data in our sample covering the sample period 2005 to 2008 period contains around 5.2 million applications that are either approved or denied (Action code 1, 2, and 3), after we restrict our loan types to be conventional (we exclude Federal Housing Agency, Veterans Administration, Farm Service Agency or Rural Housing Service), the property types to be one to four-family, the loan purpose to be home purchase only (excluding home improvement, refinancing purposes), and the occupancy status to be owner-occupied as principal dwelling.

We distinguish between the type of lenders based on information available from HMDA on their regulatory agencies. Depository institutions and their affiliates (which we refer to as banks) are listed under the following agencies: Federal Deposit Insurance Corporation, Federal Reserve System, Office of the Comptroller of the Currency, Office of Thrift and Super-

[23]Lenders are required to report if they meet certain criteria related to size, geographical location, the extent of housing-related lending activity, and regulatory status. Regarding size, a depository institution is subject to HMDA reporting requirements if it has assets of $34 million or more, as of December 31, 2004. In 2010, the Board raised this threshold to $40 million. For a non depository institution, total assets must exceed $10 million, as of December 31 of the preceding year, taking into account the assets of any parent corporation. Regarding the geographical location, lenders must report if they have offices in a Metropolitan Statistical Area (MSA) or if they are non-depository institutions with lending activities on properties located in an MSA. Lenders must also report if they are depository institutions with at least one home purchase loan or if they are non-depository institutions and they originate 100 or more home-purchase and refinancing loans. As for the regulatory status, lenders must report if they are non-depository institutions or if they are depository institutions that are federally insured or regulated.

vision, and National Credit Union Administration. Non-bank mortgage originators (independents) are listed under the Department of Housing and Urban Development.

We restrict our study to mortgage originations by depository institutions in counties situated in an Metropolitan Statistical Area (MSA) for which HMDA has better coverage and data on house prices and on house supply elasticity are available. This leaves us with 773 counties. These counties cover around 80% of total mortgage originations in HMDA in 2005.

Call Report data

All regulated depository institutions in the United States are required to file their financial information periodically with their respective regulators. Reports of Condition and Income data are a widely used source of timely and accurate financial data regarding banks' balance sheets and the results of their operations. Specifically, every national bank, state member bank and insured non-member Bank is required by the Federal Financial Institutions Examination Council (FFIEC) to file a Call Report as of the close of business on the last day of each calendar quarter. The specific reporting requirements depend upon the size of the bank and whether or not it has any foreign offices. The availability of agency specific bank IDs in HMDA (Federal Reserve RSSD-ID, FDIC Certificate Number, and OCC Charter Number) allows us to match HMDA lenders that are depository institutions with their financials from the Call report.

Federal Housing Finance Agency: House Prices

House Price Index (HPI) is a quarterly data published by the U.S. Federal Housing Finance Agency, an entity created in 2008 from the merging of the U.S. Office of Federal Housing Enterprise Oversight and the U.S. Federal Housing Board. As a weighted, repeated sales index, the HPI measures average price changes in repeat sales or refinancing on single family properties with mortgages that have been purchased or securitized by Fannie Mae or Freddie Mac. The HPI includes indexes for all nine Census Divisions, the 50 states and the District of Columbia, and every Metropolitan Statistical Area (MSA) in the U.S., excluding Puerto Rico. Compared to S&P/Case-Shiller indexes, the HPI offers a more comprehensive coverage of housing price trends in the U.S. metropolitan areas. We use the HPI data at MSA level (most disaggregated level that is available for this variable) and compute the year on year changes as a measure of house price growth in a given MSA.

Housing Supply Elasticity

Saiz (2010) provides a measure of housing supply elasticity at the MSA level computed based on topological factors. These factors are exogenous to house market conditions and population growth and are computed using both water and land slope constraint information obtained using Geographic Information System (GIS), United State Geographic Service (USGS), and USGS Digital Elevation Model (DEM). The data covers 269 Metropolitan areas using the 1999 county-based MSA or NECMA definitions. The geographic data is calculated using the principal city in the MSA, i.e., the first one on the list of a MSA name.