Bank Competition, Risk Taking and Their Consequences: Evidence from the U.S. Mortgage and Labor Markets

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January 24, 2014

Preliminary draft. Comments are welcome.

Abstract

Bank competition can induce excessive risk taking due to risk shifting. Using the supply elasticity of local housing as an instrument for the volatility of future house prices, I show that, prior to the recent crisis, U.S. mortgage-issuing banks took significantly more risk in areas where the banking sector had stronger competition. Specifically, I show that mortgage lending standards were substantially lowered in U.S. counties that had more volatile house prices, and this only happened in counties with a competitive banking sector. At the bank level, banks that had main businesses in competitive areas increased their exposure to counties with volatile house prices. Such risk taking pattern implied real economic consequences: in counties where the banking sector had strong bank competition, a one standard-deviation decrease in the supply elasticity of housing (i.e., higher housing volatility) was associated with a 1% increase in the foreclosure rate and a 2-3% increase in the unemployment rate after the crisis. This study provides new evidence supporting the fragility-concentration tension in the bank competition literature.

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1. Introduction

Bank competition is often associated with financial fragility. The U.S. savings and loan crisis in the 1980s and 1990s drew the attention of policymakers on the effect of bank competition on banks' risk taking behavior. According to the 1988 report by the United States League of Savings Institutions, the crisis was concluded to be caused by "decline in the effectiveness of Regulation Q... increased competition on the deposit gathering and mortgage origination sides of the business". History repeats itself. In 2007, a subprime crisis in the U.S. was originated from the housing mortgage market which later led to a severe financial crisis and prolonged economic recession. After the outbreak of this crisis, Ben Bernanke pointed out that "intense competition for subprime mortgage business... may have led to a weakening of standards. In sum, some misalignment of incentives, together with a highly competitive lending environment... likely compromised the quality of underwriting."[1] This time, the crisis brought the attention of academia and policymakers back to exactly the same question that was asked two decades before: did bank competition induce excessive risk taking? This question needs to be carefully reexamined, and it is the thesis of this paper.

In the theoretical literature, the concentration-fragility tension for the banking sector has been widely discussed. The main argument is that banks are subject to the risk shifting problem, as identified by Jensen and Meckling (1976), and Allen and Gale (2004), and bank competition can further induce risk taking. Bank managers have the incentive to engage in risky investments as banks have limited liability and all deposit liabilities are insured. Managers are rewarded if the gamble is successful, but the associated costs are born by deposit insurance funds when the gamble fails. Depositors, who are the debtholders of the bank and are insured against bank failures, have little incentive to monitor bank managers' behavior. With such a payoff structure, the temptation to take on risk is stronger when return volatility is high. A high return volatility generates better payoff for bank managers on the upside while bank managers do not bear the downside of the return. Bank competition can further exacerbate the risk shifting problem because stronger bank competition lowers the expected profit of investments and the franchise value of banks. A lower franchise value induces stronger temptation to take on risk as a higher return volatility may generate higher payoff for bankers under such a payoff structure.

There has been some empirical evidence supporting the concentration-fragility tension. Keeley (1990) famously shows that higher bank competition was indeed associated with riskier capital structures adopted by U.S. banks before the 1990s. He then argues that when the deposit insurance fee is not correctly calculated, bank competition together with deposit insurance can result in excessive risk taking behaviors. Beck, Demirguc-Kunt and Levine (2003) use data on 70 countries during the 1980s and 1990s to show that crises

[1] Speech at the Federal Reserve Bank of Chicago's 43rd Annual Conference on Bank Structure and Competition, 2007.

are less likely to occur in countries with a concentrated banking system.

However, an important empirical challenge in the bank competition literature lies on the measure of risk. The future return volatility of an asset is endogenously determined and highly unobservable. Therefore, very little can be learned from directly investigating the relationship between various risk measures and bank behaviors. Keeley (1990) uses instead the market-value capital-to-asset ratio of a bank to measure how the bank takes risk assuming that all banks are subject to the same risk from the environment. In the paper by Beck, Demirguc-Kunt and Levine (2003), the ex post crisis outcomes are used to infer the amount of risk that banks took ex ante. As it is hard to measure the risk of assets directly and independently, it is difficult to disentangle the risk in the underlying assets and banks' actual risk taking intentions, and thus, the observed empirical correlation alone limits the scope we could answer policy questions. Is it possible to have a direct, independent and observable measure and variation of future return volatility? Would we see that bank competition affects how banks respond to such "volatility shocks"? Moreover, is it possible to make welfare statements? Or, in other words, is it possible to observe and measure the welfare loss associated with bank competition? This paper exactly tries to answer these questions, and the answers are all yes.

The U.S. housing market experienced a boom and bust cycle in the past decade. From 2000 to 2006, the U.S. home price rose by 80%, according to the S&P/Case-Shiller National Composite Home Price Index for the United States (Figure 1). Importantly, there was a large degree of heterogeneity how house prices had evolved. Glaeser, Gyourko, and Saiz (2008) show that the key determinant for the magnitude of house price movement is the supply elasticity of local housing, an indicator measuring geographical constraints and zoning requirements. Areas with inelastic housing supply have less land available for the building of new houses, and therefore, shocks to the local housing market, either temporary or permanent, are reflected in the local house price. On the contrary, areas with elastic housing supply have much fewer land limitations, and thus, the upward price pressure during the boom could be quickly absorbed by the building of new houses. Figure 2 plots the different housing price patterns by quartiles of housing supply elasticity. During the boom and bust cycle in the 2000s, areas with inelastic housing supply experienced a large rise in the house price before 2006 and a drastic fall after the crisis, whereas in the most elastic counties, the house price remained very stable and its growth rate is close to the CPI rate. Therefore, the housing supply elasticity (Saiz (2010)) can serve as a natural instrument for the volatility of the home price which determines banks' profitability. Specifically, the macroeconomic shocks that happened in the background during the first half of the 2000s translate to different degrees of house price volatility, which I call "volatility shocks". High price growth in areas with inelastic housing supply might continue, but might also revert to a more severe price drop than areas with elastic housing supply. The variation in volatility shocks is large: the most inelastic counties in the U.S. double their home from 2001 to 2005 whereas elastic areas had only less than 10% growth, at the level of local CPI. Therefore, these volatility shocks measured by the housing supply elasticity scattered across U.S. counties in a naturally pre-determined way. The research question is how banks in environments with different levels of bank competition responded to these "volatility shocks" of house prices.

I show in this paper that how banks responded to the volatility shocks was crucially related to how competitive the local banking sector for mortgages was. As described above, with strong local competition, the temptation to take on risk becomes higher and banks only take into account the highest realizations of house prices. One direct consequence is that banks might lower their lending standards, measured by individual borrower's characteristics, as with the highest realizations of house prices, the quality of individual borrowers becomes less important.

Using loan-level data on residential mortgages in the U.S. from 2001 to 2005, I show that banks indeed substantially lowered their lending standards, e.g., loan-to-income and loan-to-population ratios, in areas with inelastic housing supply, and moreover, this only happened in areas with a competitive banking sector (where local bank competition is measured by the Herfindahl-Hirschman Index for accepted loans). In other words, banks in less competitive markets behaved more cautiously and refrained from lowering their lending standards in response to a high volatility shock and housing boom. Figure 3 plots the evolution of the change of average loan riskiness at the U.S. county level from 2000 to 2005. The two solid lines (inelastic and elastic counties) plot the average loan-to-income ratio for accepted loans in high competition areas. One can see that the average loan-to-income ratio in inelastic areas rose by 0.1 higher than elastic counties from 2000-2005. That is to say, if located in a county with strong bank competition, banks lowered their lending standards in response to the house price rise from 2001 to 2005. Next, we move the attention on the two dashed lines plotting the average LTI ratio in low competition areas, again for different levels of housing supply elasticity. One can hardly see any difference between the two lines, meaning that banks did not respond to housing shock if the banking sector is concentrated. Similar results can be obtained if one measures the riskiness of loans alternatively, say in loan-to-population ratio as shown in Figure 4.

The findings described here highlight the role of bank competition in affecting banks' response to return volatility. Banks' responded aggressively to the house price boom before 2005 by lowering lending standards only in areas with high bank competition. With low bank competition, banks behaved much more cautiously. To further confirm these results, I also show that risk shifting was observed at the bank level and that there was a difference in risk taking across bank sizes. Two additional results are confirmed from the data: 1) banks that had main business in competitive areas shifted their portfolio weights of accepted mortgages to inelastic counties; 2) it was the small banks in competitive markets that lowered their lending standards in response to the house price rise, and large banks followed.

Given that banks in a competitive environment "gambled" on the possibility that the house price growth would continue, it is still not clear yet as to whether welfare loss was associated. If it was just the banks who took more risk that suffered later in the crisis, then taking more risk might just be efficiency improving and might not serve as a strong enough reason for policy intervention ex ante. However, if we find that banks that took more risk imposed adverse impact on other sectors as well, especially the real sectors, then regulating risk taking by banks becomes necessary. To address this question, I study how the real economy was affected after the crisis. I look at two real variables at the county level, namely the foreclosure rate and unemployment rate, and investigate whether areas that were the most subject to risk taking experienced worse economic outcomes after the crisis. It appears that, in counties with a concentrated banking sector, there was no significant difference in these real outcomes for areas receiving different housing volatility shocks (inelastic vs. elastic); however, in competitive counties, inelastic counties had much worse outcomes than elastic counties: a one standard-deviation drop in housing supply elasticity was associated with a 1% increase in the foreclosure rate for 2007-2008 and a 2-3% increase in the unemployment rate for the tradable sector[2]. These adverse effects are statistically and economically significant. Therefore, these results suggest that the risk being taken by banks in competitive areas was socially excessive.

This paper tries to shed light on the current debate whether a competitive or concentrated financial sector is preferred from the social welfare point of view. Competition may undermine financial stability as there is the moral hazard problem over deposit insurance. A more concentrated banking sector is, however, subject to the "too-big-to-fail" problem, as systemically important banks might take advantage of the TBTF policy. In the end, the relative importance of the two thoughts in policy making becomes an empirical question and needs to be carefully investigated. In this paper, using the natural variation in housing price volatility in the U.S., I show evidence suggesting that competition encouraged more risk taking and there was real economic consequences were associated.

This project is related to two strands of literature on bank competition. Jensen and Meckling (1976) identify the agency problem that arises when firm managers make overly risky investments maximizing the interests of shareholders while it jeopardizes the value for debtholders. This agency problem is particularly strong for banks as much of the liability of banks is in terms of debt (deposits) insured by deposit insurance funds. Keeley (1990) provides a theoretical framework on the interaction of banking deregulation and deposit insurance. Banking competition undermines banks franchise value and will hence encourage more risk-taking behaviors by bank managers. He also shows empirical evidence that banks in more competitive environments, proxied by the market-to-book asset ratio, adopt riskier capital structures, measured by the market-value capital-to-asset ratio. Hellmann, Murdock, and Stiglitz (2000) show similarly that banks may gamble if the

[2]To tradable industries, these shocks are mainly supply-side shocks. To see the effect on non-tradable industries, local demand factors need to be taken into account. The analysis of non-tradable industries is include in later sections.

required interest rate on deposits is high. Bank competition, however, might force banks to choose a high interest rate to attract deposits. Therefore, it is possible that in a symmetric equilibrium, only gambling is possible. They also show the different effects of capital requirement and deposit ceiling in curbing the gambling behavior. Deposit ceiling may implement the Pareto allocation while capital requirements may further reduce banks franchise value and induce more gambling. Allen and Gale (2004) show that when the supply of deposits is upward sloping, banks in more competitive environments do not internalize the price effect and choose to pay high interest rates to attract deposits. Such high interest rates will lead to more riskier investments due to the risk-shifting problem. A monopoly bank, on the other hand, can internalize the price effect by lowering the interest rate on deposits and be able to make more prudent investments.

Boyd and De Nicolo (2003) challenge the concentration-stability relationship by proposing that banks with greater market power tend to charge higher interest rate on borrowers and this can induce more risk taking behaviors by borrowing firms. They argue that the concentration-stability relationship can go the other way. Another related argument is that "too-big-to-fail" policies that essentially subsidize large banks can intensify risk-taking incentives by these large banks.

On the international scope, Beck, Demirguc-Kunt and Levine (2003) test the two opposing views and find that crises are less likely in countries with more concentrated banking system using data from 79 countries. Their evidence is consistent with the risk shifting idea on bank managers. On the financing of financially-constrained small firms, Petersen and Rajan (1995) propose a theoretical model that creditors are more likely to finance these small firms when they are in a more concentrated banking sector. The key element in their model is that banks in a more concentrated banking sector are able to extract more surpluses as the borrowing firms grow. Therefore, banks ex ante are willing to lower the lending standards to discover the potentially sound firms. They show empirically that in more concentrated credit markets (1) firms are less credit constrained, and (2) financing is less costly for young firms but declined more slowly as the firms grow, relative to those in more competitive markets.

Another related strand of literature is the yardstick competition literature. Faced with more competition, a bank manager's benefits may be more negatively affected by other banks' temporary high profits. This exacerbates the risk shifting incentive for bank managers. In a corporate framework with principal-agent tensions, firm owners or regulators can use a compensation scheme with yardstick competition to induce the optimal efforts if firm owners do not observe the private information of the agent (Shleifer (1985)). However, when a job is finished in a multidimensional fashion and some dimensions are harder to observe, the optimal compensation scheme is different. Holmstrom and Milgrom (1991) show that a fixed-wage compensation scheme (low-powered incentives) is sometimes optimal, especially when there are important aspects of effort taking that are not easily measurable. High-powered incentives may distort the agent's effort towards those more observable ones and reduce overall efficiency. Acemoglu, Kremer, and Mian (2008) show that yardstick competition can lead to suboptimal allocation in a setting similar to Holmstrom-Milgrom. When the performance of the agent is not directly observable and is measured relative to her peers, the "bad" efforts, or manipulating performance, of one agent has negative an externality on her peers. More specifically, a higher level of "unproductive" effort anticipated by the principal makes it harder for the agent to show her ability and efforts, and in equilibrium, this agent would also choose a high level of unproductive effort. In their paper, they also discuss how government regulation can be possible remedies when the government can commit to providing low-powered incentives.

This paper is organized as follows. Section 2 describes a simple theoretical framework and some empirical implications. Sections 3 provides information on the datasets being used and on how various measures are constructed. Sections 4 and 5 show the empirical results and discussions on general equilibrium effects and robustness. Section 6 concludes the papers by discussing some policy implications.

2. Theoretical Framework

In this section, I set up a theoretical framework similar to Keeley (1990) and show how bank competition and risk taking can be associated. I also list the testable implications for the U.S. housing mortgage market from the theoretical framework.

2.1. Environment

Consider an economy where banks need financing for their investment opportunities. Each investment project i has a quality parameter $\theta_i \in [0, 1]$ which is associated with the success probability of that project, which will be specified later. All possible investments form a distribution $G(\theta)$. The higher the value θ_i, the higher quality of project i. Time is discrete with $t = 0, 1, 2$. At time $t = 0$, banks have zero capital and decide to raise deposits D to fund their investment opportunities. The required interest rate for bank deposits is r. In period 1, there is an aggregate shock A affecting the returns on projects. After observing the value of A, bank managers can walk away and declare bankruptcy if they are going to incur negative profits. The associated deposit liabilities will be assumed by deposit insurance funds. If they instead continue to operate, in period 2, they will receive the returns from project investments and repay deposit liabilities.

Each project requires 1 unit of investment in period 0 and yields a return $R > 1$ in period 2 if successful. However, projects are not risk-free and may fail to yield zero returns. There are two factor determining the probability of success for project i, an aggregate shock A in period 1 and project i's quality. More specifically, project i succeeds with probability $\theta_i f(A)$ where f is an increasing function with $f(\infty) = 1, f(0) = 0$. For the purpose of illustration, I assume that there are three values that A can take $A_H = A_M + \epsilon, A_M, A_L = A_M - \epsilon$, for some $\epsilon > 0$. The parameter ϵ describes the variance of the aggregate shock. From the assumption, the expected return increase from 1 to $A_M > 1$ in period 1, but there is some variance over the actual realizations. Given the description above, we have $1 > f(A_H) > f(A_M) > f(A_L) > 0$[3]. I assume that $R < \bar{R}$ for some $\bar{R}$ where at $\bar{R}$ the total project return equals total deposit liabilities when shock A_L hits. Therefore, the success probabilities for project i are $\theta_i f(A_H), \theta_i f(A_M), \theta_i f(A_L)$ for the three realizations of the aggregate shock A_H, A_M, A_L, respectively. In other words, the expected returns from project i to the banker in these three cases are $\theta_i f(A_H)R, \theta_i f(A_M)R, \theta_i f(A_L)R$, respectively.

2.2. Banker's Problem

Suppose that banks have limited liability and deposits are insured[4]. A banker's problem is to choose a subset of projects to invest in at time 0. The optimal strategy for a banker is to choose a threshold $\hat{\theta} \in [0,1]$ and only invest in projects with quality higher than $\hat{\theta}$. The banker maximizes the expected profit given the limited liability condition.

$$\max_{\hat{\theta} \in [0,1]} \sum_A p(A) \left[\int_{\hat{\theta}}^1 R\theta_i f(A) dG(\theta_i) - (1 - \hat{\theta})r \right]^+$$

where $p(A)$ denotes the probability that event A happens. For simplicity, I assume that $p(A_H) = p(A_M) = p(A_L) = \frac{1}{3}$. The expression above is the probability-weighted sum of the banker's payoff over all possible realizations of A. The banker will choose a threshold $\hat{\theta}$ and invest in projects in the range $[\hat{\theta}, 1]$. The expected project return from project i is $R\theta_i f(A)$ in state A. The total costs for investment is $1 - \hat{\theta}$, as the unit cost of investment at $t = 0$ is 1.

Due to limited liability, the banker has the option to walk away and declare bankruptcy. He would choose to do so when the total income from projects is lower than the deposit liabilities. In such cases, the profit to the banker is zero. If the total project return is higher than the deposit liability, the banker will receive the total project return net the costs as profits. I will show later that bank competition which lowers R can potentially increase the range of outcomes A that induce the banker to walk away.

We first discuss what would happen if r is small relative to R. With a sufficiently large returns on projects, the bank would still make profits when A_M occurs. To put it differently, the optimal $\hat{\theta}$ that the banker would choose in absence of limited liability ensures a positive profit for the bank. Then we have the following result.

[3] The main results hold for much weaker assumptions on the f function. It is important that in some states of A, bank obtains total returns lower than its deposit liabilities, i.e., ϵ is large enough.

[4] The insurance fee is assumed to be zero for simplicity.

Proposition 1. Assume that $R < \bar{R}$ is sufficiently large relative to r. Then at time 0, the banker will choose a threshold $\hat{\theta}_1 = \frac{2r}{R(f(A_H)+f(A_M))}$ and invest in projects with $\theta \geq \hat{\theta}_1$. The banker would declare bankruptcy only when shock A_L hits.

Proof: When R is sufficiently large relative to r, profit is positive for $A = A_M$ or A_H. Therefore, one can rewrite the objective function as

$$\max_{\hat{\theta}\in[0,1]} \sum_{A=A_H,A_M} p(A) \left[\int_{\hat{\theta}}^{1} R\theta_i f(A) dG(\theta_i) - (1-\hat{\theta})r \right]^{+}$$

The first-order condition with respect to $\hat{\theta}$ is given by

$$\tfrac{1}{3} R\hat{\theta}[f(A_H) + f(A_M)] = \tfrac{2}{3} r.$$

The above equations yields $\hat{\theta}_1 = \frac{2r}{R(f(A_H)+f(A_M))}$. $\square$

The proposition above suggests that, when R is sufficiently large relative to r (high franchise value for banks), the banker earns positive profits when A_H or A_M shock hits. Then the optimal choice for him is to choose a threshold $\hat{\theta}_1$ taking into account the possible returns in these two states. More specifically, for every one dollar of deposit (which need to be repaid $\frac{2}{3}$ of the time), the expected profit generated from this one dollar in A_H or A_M states must be $\frac{2}{3}r$.

Perhaps a more interesting question is how banks respond to return volatility, i.e., changes in ϵ. The following Corollary summarizes the result.

Corollary 1. Assume that $R < \bar{R}$ is sufficiently large relative to r. An increase in ϵ, the variance of house price movements, would imply a lower threshold value. In other words, $\eta_1 \equiv \frac{\partial\hat{\theta}_1}{\partial\epsilon} < 0$.

Proof: An increase in ϵ increases A_H without changing other parameters. $f'(A) > 0$ implies that $\eta_1 \equiv \frac{\partial\hat{\theta}_1}{\partial\epsilon} < 0$. $\square$

One can see directly from the expression for $\hat{\theta}_1$ that a higher ϵ, i.e., an increase in A_H, would lead to a drop in the value of $\hat{\theta}_1$. Intuitively, because banks have limited liability, a mean-preserving spread in returns would induce banks to take more risk ex ante due to the problem of risk shifting. With a higher volatility in returns, banks do not bear the cost of extremely low returns, but can gain from the better returns on the upside. Therefore, higher volatility in returns induces more risk taking behavior.

2.3. Bank Competition

Bank competition that lowers the interest rate R relative to r can potentially change the optimal strategy for the banker[5]. This lower value of R/r lowers the franchise value of banks in the local market. This corresponds to the banking competition literature that higher competition can induce riskier investment behaviors by bank managers investing on behalf of bank equity holders. When R is sufficiently small, we have the following result.

Proposition 2. Assume that $R > \frac{r}{f(A_H)}$ is sufficiently small relative to r due to high bank competition. Then at time 0, the banker will choose a threshold $\hat{\theta}_2 = \frac{r}{Rf(A_H)}$ and invest in projects with $\theta \geq \hat{\theta}_2$. Moreover, for a given value ϵ, we have $\hat{\theta}_1 > \hat{\theta}_2$.

Proof: Condition $R > \frac{r}{f(A_H)} \geq r$ guarantees that by optimally choosing $\hat{\theta}$, the banker makes positive profit when shock A_H hits. To see this, suppose that R is small such that neither A_M or A_L yields a positive return for the banker, so the banker will default in these two cases. Then the banker can choose a very small value $\hat{\theta} = 1 - \xi$ where $\xi \to 0^+$, i.e., invest in the highest quality project. The expect income in state A_H is $p(A_H)Rf(A_H)$ while the cost is $p(A_H)r$. Therefore, the banker makes a positive profit in state A_H. The optimization problem for the banker becomes

$$\max_{\hat{\theta}\in[0,1]} p(A_H)\left[\int_{\hat{\theta}}^{1} R\theta_i f(A_H)dG(\theta_i) - (1-\hat{\theta})r\right]^+$$

The first-order condition gives $\hat{\theta}_2 = \frac{r}{Rf(A_H)}$. $\square$

The proposition above shows that when the franchise value for banks is low (R/r is low), then banks would default when A_M or A_L shock hits, and only profits from the high A_H shock. If this is the case, the only relevant information that the bank needs to consider is the profitability in the highest A_H state. A low franchise value exacerbates the risk shifting idea and induces riskier investment behavior

[5]Sunderam and Scharfstein (2013) show that local bank competition significantly lowers the financing costs for home mortgages.

by bankers. Moreover, bankers in this environment have higher temptation to take advantage of return volatility, which is summarized in the Corollary below.

Corollary 2. Assume that R/r is sufficiently small due to high bank competition. An increase in ϵ, the variance of house price movements, would also imply a lower threshold value. Moreover, $\eta_2 \equiv \frac{\partial \hat{\theta}_2}{\partial \epsilon} < \eta_1 < 0$.

Proof: From the expression $\hat{\theta}_2 = \frac{r}{Rf(A_H)}$, one can see that a unit increase in A_H lowers $\hat{\theta}_2$ more than $\hat{\theta}_1$. Therefore, $\eta_2 \equiv \frac{\partial \hat{\theta}_2}{\partial \epsilon} < \eta_1 < 0$. □

Corollary 2 states that when bank competition is high, bankers have higher temptation to take risk when volatility is high. Moreover, bankers respond to volatility shocks more aggressively than when competition is low. The intuition is that when the bank has a higher franchise value, the banker would take into account some worse states (than the highest state) as well, i.e., the intermediate state A_M. A lower threshold $\hat{\theta}$ hurts more in the intermediate state A_M than in the highest state A_H. So taking into account the intermediate state in investment decisions curbs the risk taking behavior by the banker.

2.4. Empirical Implications

In the context of the U.S. housing mortgage market, one can think of θ_i as the quality of individual borrowers (e.g., loan-to-income/loan-to-value ratios) and A as the local house price that affects each individual's default decision. The theorems and corollaries above can be then interpreted as the following empirical implications.

1. Counties with inelastic housing supply should experience a larger decline in loan quality, relative to high elasticity counties. Moreover, this effect should be mainly in areas with a competitive banking sector.

2. Banks that had their main business in competitive counties should shift their weights of mortgage portfolio towards inelastic areas.

3. Real economic outcomes after the crisis should increase as the elasticity of housing supply. This effect should be mainly in areas with a competitive banking sector. The real variables I look at are foreclosure and unemployment rates in particular.

The first implication states that, observing a high volatility shock, banks would lower their lending standards if they are situated in a competitive environment. The intuition is that banks in a competitive market take into account only the highest realizations of the housing price, so the characteristics of individual borrowers are less important in determining the profit for banks. Therefore, we should see a deterioration in the observed lending standards by these banks. For banks in a concentrated market, banks take into account all realizations of the housing price. Therefore, banks should not respond to housing volatility by lowering their lending standards.

The second implication indicates that banks in competitive areas should have higher temptation to take on risk. The intuition is straightforward. With a natural variation in the riskiness of different assets (mortgages in different counties), banks that faced high competition should have a higher temptation to take on risk, and therefore, should shift their portfolio towards inelastic areas.

The third prediction focuses on the real consequences and indicates that the risk taking before the crisis was associated with worse real outcomes after the crisis. If there is evidence on the real economic consequence, we can infer that the risk being taken by banks was socially excessive. It then can shed light on the policy question whether bank competition undermines financial stability.

The main measure I use for the housing volatility shock is the land-topology based housing supply elasticity, constructed by Saiz (2010). This elasticity index measures the geographical and zoning constraints in 818 U.S. counties, and can be regarded as a measure how easily new houses can be built in response to price shocks.

3. Data

I list the main datasets that I use in this paper and also discuss the advantages and disadvantages that each dataset has. The way that various measures are constructed is described in this section as well.

3.1. Home Mortgage Disclosure Act (HMDA)

The main dataset for U.S. housing mortgages that I use is the Home Mortgage Disclosure Act (HMDA) dataset, available starting from 1980 and maintained by the Federal Financial Institutions Examination Council (FFIEC). Required by Regulation C, most mortgage-issuing institutions need to report the information on the mortgage application they receive each year. The coverage of depository institutions is very broad, including commercial banks, savings and loan associations, credit unions, and other types of institutions. In the recent decade, for each year, the number of reporting institutions has been between 7,500 and 9,000 with a total number of reported loan applications of 15 to 42 millions.

An important feature of the HMDA dataset is that it contains detailed loan-level information, such as acceptance status, location, lender ID and borrower characteristics. Moreover, the dataset includes information on the type of issuer (e.g., commercial bank, thrift, credit union) and whether each accepted loan has been purchased by GSE or private securitization institutions. Such information allows me to study how each institution has changed their lending standards, e.g., loan-to-income ratio, in a particular U.S. county over time. Specifically, in this project, I measure the riskiness of loans by constructing the average loan-to-income ratio, large-LTI-loan fraction, loan-to-population ratio and the denial rate at the bank and county levels and for each year. The main object that I focus on is how measures of riskiness of loans evolved during the house price from 2001 to 2005

Another advantage of this dataset is that I can construct the local Herfindahl-Hirschman Index (HHI) using the market share for each institution in the mortgage market. As mentioned above, the U.S. mortgage market is relatively competitive, with thousands of relatively small and local institutions competing with large banks. There is also a large degree of heterogeneity in how competitive different markets are, mainly due to government regulation and historical presence of local banks. Local competition matter for the mortgage market in the U.S. and empirical evidence suggests that households typically shops mortgages within 25 miles of their residence (Amel, Kennickell, and Moore (2008)). The HHI, measuring the competition level of the local market, has been very sticky. The relative HHI ranking of counties has not changed very much after the branching deregulation in the 1980s and has been quite stable from 1995 to 2005 (Figure 3). In this project, I take the local HHI index for 2001 as given and assume that this measure does not change significantly from 2001 to 2005. Various robustness checks and discussions are included in later sections.

There are also limitations of this dataset. For example, this dataset does not contain loan-level information on the loan-to-value ratio of accepted loans, nor does it provide information on the performance of each loan. Therefore, I use alternative measures and datasets to address these issues.

3.2. County Business Patterns (CBP)

The dataset that I use for employment outcomes is the County Business Patterns (CBP) dataset maintained by the United States Census Bureau. This dataset contains detailed employment and wage information for each county at the 6-digit NAICS industry level.

An advantage of this dataset is that I can identify which industries are tradable or non-tradable industries. Tradable industries include the mining industries, the manufacturing of chemical products, machinery, automobile, apparel and etc. These tradable products are nationally demanded and are usually transported and sold to other areas. On the contrary, non-tradable industries include bakery shops, restaurants, the sales department of tradable goods and other local service sectors. These industries highly depend on local demand and other local factors. According to the findings by Mian and Sufi (2013), the collapse of local households' balance sheet was the main cause of the rise in the unemployment rate for non-tradable sectors, whereas for tradable sectors, employment was nearly unaffected by local factors.

Based on their results, I focus my attention on tradable sectors as local supply shocks have significant impact. More discussion on non-tradable sectors is included in later sections.

3.3. Other Data Sources

I also use other publicly available data sources for information on wage income, population, debt-to-income, county foreclosure rate and etc. These data sources include the New York Fed database, IRS database, Housing and Urban Department, and Zillow.com. These datasets provide additional county-level information and are used in many other works in this field.

4. Empirical Results

According to the empirical implications listed in previous sections, I perform test to show whether there is evidence supporting these predictions. Specifically, I try to show whether bank competition indeed induced more risk taking by banks, whether banks shift risk by increasing their exposure to inelastic counties, and whether real economic outcomes are worse for those counties who were subject to excessive risk taking.

4.1. Riskiness of Loans

In this section, I show empirical evidence on the lowering of lending standards associated with high bank competition. As mentioned above, I use the local supply elasticity as the measure for the variation in house price volatility. The prediction from the previous section suggests that the responsiveness to the volatility shock depends on how competitive the local mortgage market is. The more competitive the local banking sector is, the more aggressively banks respond to volatility shocks by lowering lending standards. Therefore, the regression model can be described

(1) $y_i = \beta_1 Elas_i + \beta_2 Elas_i \times HHI_i + \beta_3 HHI_i + X_i^{'}\beta_4 + \epsilon_i$

where y_i is the 2001-2005 change in county-average loan riskiness for county i, $Elas_i$ the housing supply elasticity, HHI_i the Herfindahl index for the mortgage market in 2001, and X_i a list of county controls.

According the the previous predictions, a high volatility shock should imply a higher change in loan riskiness, so coefficient β_1 should be negative. Moreover, the responsiveness to the volatility shock should be strongest in counties with high competition (low HHI), so coefficient β_2 should be positive. In this exercise, county controls include the growth in wages, population, share of mortgages securitized, commercial bank share, higher orders of variables, state fixed effects, and etc. In this exercise, I also control for HHI^2 to address the concern that the realized volatility might be higher than what the elasticity index predicts for competitive counties. Different measures for loan riskiness are constructed (e.g., loan-to-income ratio, loan-to-population ratio, large-LTI fraction, denial rates), and the results are shown in Tables 2 and 3.

From Tables 2 and 3 for different measures of loan riskiness, one can see that the coefficients on elasticity and the interaction term are highly significant, both statistically and empirically. Lower elasticity implies a substantial increase in the riskiness of loans, and this effect is the strongest for counties with a competitive banking sector. A more straightforward presentation of this result is shown in Figures 5-6. The solid lines in both panels are for competitive counties and dashed lines for non-competitive counties. For competitive counties, the effect of volatility shock is significant: loan quality in inelastic counties dropped a lot more than elastic counties. However, this effect is not present for non-competitive counties. The main message from this figure is that loan quality deteriorated when the county experienced a high volatility shock in housing price, but the effect is mainly in competitive counties, conforming to the first prediction from the theoretical framework.

4.2. Bank Risk Shifting

One can test the risk shifting effect at the bank level. According to the theoretical model and the second prediction, if a bank is located in an area where bank competition is strong, then the bank should have a higher temptation than other banks to take on risk. In the context of mortgage issuance, such banks should shift their portfolio weights towards inelastic areas where housing volatility is high. In other words, these banks should increase their exposure to highly volatile counties. On the contrary, banks that are located in less competitive areas should behave more prudently by limiting the exposure to volatile counties.

To formally show this result, I construct a few measure for each bank. For each bank j, I compute the average Herfindahl index HHI_j for 2001 according to bank j's portfolio weights over counties. I compute similarly the average elasticity for bank j's mortgage business in 2001 and 2005 by averaging out the elasticity for the business of bank j in these two years, which I call $Elas_j^{01}$ and $Elas_j^{05}$, respectively. A testable implication from the theoretical model is whether banks that faced stronger competition (lower HHI_j) should reduce the average elasticity of their mortgage portfolio. Hence, I consider the following regression model.

(2) $Elas_j^{05} - Elas_j^{01} = \beta_1 HHI_j + X_j' \beta_2 + \epsilon_j$

where $Elas_j$ and HHI_j are defined for bank j as described above, and X_j is a list of controls for bank j, including various bank size measures, fraction of loans securitized by the bank, bank type (e.g. commercial bank, thrift, credit union), headquarter state and etc.. If the bank risk shifting effect is significant, one would expect to see that coefficient $\beta_1 > 0$.

The regression results are shown in Table 4 and Figure 7. One can see that β_1 is estimated around 2 and is statistically significant with the inclusion of various controls. There may be concerns that national banks might behave differently from local/state banks. I perform the same test on the subsamples of single-state banks and thrift banks, and similar results are obtained.

In sum, I show in this section that banks that had their main business in competitive regions increased their exposure to more volatile counties by increasing the portfolio weights for inelastic areas. This result confirms the second empirical implication and shows results consistent with the risk shifting of banks.

4.3. Evolution of Loan Riskiness

A potentially interesting object to study and result that confirms how bank competition exacerbated risk shifting is the evolution of loan riskiness, especially across bank sizes. The risk shifting incentive should be the strongest for small banks in competitive areas. For large banks competing in the same region, they might in fact be forced to lower their lending standards just not to lose business to local small banks. Therefore, I look at the evolution of loan riskiness over time across bank sizes.

In this section, I define two types of banks as "small" and "large" banks for each county. For each county, I look at

1. banks that had fewer than 2,000 mortgage loans in 2001 and had this county account for more than 10% of their total business; and
2. banks that had more than 20,000 mortgage loans in 2001 and had this county account for less than 5% of their total business.

The first type of banks are defined as "small banks" and the second type as "large banks". Intuitively, the local market structure and conditions should be more relevant for small banks than for large banks. Therefore, one should expect to see that in competitive counties where banks responded more to housing volatility, small banks should be more aggressive in lowering lending standards, and large banks perhaps followed but behaved more cautiously.

Figure 8 plots the time evolution of loan riskiness, measured in bank's average loan-to-income ratio, for inelastic counties from 1998 to 2005. These counties experienced a higher housing volatility shock during the boom period. The two solid lines (large and small banks) represent competitive counties and dashed lines (large and small banks) are for non-competitive counties. The solid lines show that in a county with a competitive banking sector receiving a high volatility shock, small banks led the way in lowering their lending standards. Large banks followed small banks in these counties, and behaved more cautiously, especially towards the crisis period. On the contrary, in non-competitive counties shown in dashed lines, small and large banks behaved very similarly. If one looks at elastic counties (Figure 9), there was little difference between the evolution of lending standards for large and small banks, except large banks raised their lending standards towards the crisis period.

The results described here show that in competitive counties, small banks were the ones that behaved so aggressively. For small banks, their franchise values are largely determined by local competition, and higher competition implies a lower franchise value and hence more aggressive risk taking behaviors.

4.4. Real Consequences: Post-Crisis Outcome

In previous sections, we see that banks in competitive environment responded more to volatility shocks by taking more housing risk and lowering lending standards. A natural question then arises: why is such risk taking socially excessive? If it was just the banks that took more risk suffered in the crisis, then regulating such risk taking behavior might be unnecessary. To address this question, one has to look at the real economic outcomes after the crisis. If worse real outcomes were associated with higher risk taking temptation of banks and areas that had more risk taking were hit harder in the crisis, then we find a rationale to ex ante spend effort preventing excessive risk taking from happening. The two real outcomes that I focus on are foreclosure and unemployment rates.

4.4.1. Foreclosure Rate

The U.S. experienced a wave of foreclosures after the subprime crisis in 2007, also with some degree of heterogeneity across U.S. counties. In this section, I show that the pattern of foreclosure rates is linked to banks' risk taking behavior prior to the crisis. Specifically, I show that foreclosure rate is increasing in the magnitude of the housing volatility shock prior to the crisis, and this effect is mainly in competitive counties. In other words, counties that suffered from the risk shifting of banks experienced higher foreclosure rates in the crisis. To formally test this, I consider the following regression model.

(3) $FC_i^{07-08} = \beta_1 Elas_i + \beta_2 Elas_i \times HHI_i + \beta_3 HHI_i + X_i' \beta_4 + \epsilon_i$

where FC_i^{07-08} is the foreclosure rate for county i from 2007Q1 to 2008Q2[6].

[6]Longer time horizon is included with more data availability.

The regression results are shown in Table 5 and in Figure 10. Very similar to the pattern that banks took risk before the crisis, higher volatility was associated with worse economic outcomes, but this effect was only present in counties with a competitive banking sector. Figure 10 shows this result graphically. A one standard-deviation fall in housing supply elasticity (i.e., higher volatility) was associated with a 1% higher foreclosure rate in competitive counties. This effect was not significant in non-competitive areas.

4.4.2. Unemployment Rate: Tradable Sectors

Perhaps a more important real economic variable that describes how hard each county was hit through the banking sector during the crisis is employment, especially tradable sectors. Tradable sectors include the production of chemicals and minerals and the manufacturing of machinery, automobiles, apparel and etc., whereas non-tradable industries include restaurants, the sales of some tradable products, and other local service industries. These products are demanded nationally and are minimally affected by local demand factors (Mian and Sufi (2013)). Tradable sectors, however, are subject to shocks to the local banking sectors, as these local factors affect the supply side of these sectors. I perform a similar test as the previous section and show whether local competition was associated with how hard the county was hit during the crisis. Similar to Mian and Sufi (2013), in measuring employment outcomes, I use the change in local tradable employment from 2007 to 2009. In later sections, non-tradable sectors are discussed as well.

Table 6 demonstrates the regression results. One can see clearly that in competitive counties, lower employment outcome is associated with higher housing volatility shocks (i.e., lower elasticity). This pattern, however, does not appear for non-competitive counties. In other words, high housing price volatility does not necessarily imply worse employment results, but it does when the mortgage market was competitive and banks behaved aggressively in lowering lending standards. This result confirms the argument that the risk taking behavior by banks in competitive markets due to risk shifting was indeed socially excessive.

5. General Equilibrium Effects and Robustness

In this section, I discuss the potential general equilibrium effects associated and provide some robustness checks.

5.1. General Equilibrium Effect: Non-Tradable Sectors

In the previous sections, tradable sectors are discussed and shown to have been affected by bank competition in the mortgage market and banks' risk taking patterns prior to the crisis. But was it the case that those jobs lost in the tradable sectors all moved into non-tradable sectors? If it were the case, then this general equilibrium effect undermines the conclusion we drew earlier. Therefore, one has to see if non-tradable employment offset the findings above.

Table 7 shows the results for non-tradable employment. Mian and Sufi (2013) show that non-tradable sectors, including bakery, restaurants, sales of tradable products, and other local services, depend crucially on local demand factors. Therefore, the inclusion of meansures for local demand is important in this exercise. The first two columns of Table 7 show the regression results for the sample of all counties. The coefficient on debt-to-income is highly significant both statistically and economically, consistent with the results of Mian and Sufi (2013). Taking subsamples according to the top and bottom one third of counties by the level of competition, one can see a clearer picture. Columns (3)-(4) are for competitive counties only and columns (5)-(6) include non-competitive counties alone. The coefficients on elasticity in both samples are positive even after controlling for local demand, i.e., debt-to-income 2006. This suggests that general equilibrium effects do no offset the findings for tradable sectors and, in fact, non-tradable sectors are similarly affected. Another observation is that, for competitive counties shown in columns (3)-(4), the coefficients on elasticity are very significant, whereas for non-competitive counties, the coefficients are much less significant. This observation is consistent with the pattern we earlier see for tradable sectors, suggesting that similar effects are present for non-tradable sectors as well.

5.2. Loan Demand

Apart from the supply side effect studied here, demand factors may also play a role. As financial innovation began to prosper in the 1990s and early 2000s, especially after the American Dream Downpayment Assistance Act of 2003, households might find it easier to borrow money from banks to finance their purchase of home. Therefore, the demand from the borrower side is important in the mortgage market.

One such factor is that potential borrowers might want to take advantage of the housing price growth. And in fact, if default penalties are low, households may also have the incentive to bet on the housing price to continue to grow. Households can enjoy the capital gain in the value of their house if the home price continues to grow, but do not bear all the costs if the home price collapses. Therefore, given a loose monetary environment, households might find it attractive to borrow despite the risk in the housing price, which was not uncommon during the housing price boom in the U.S..

This households gambling, however, would not change the supply effect discussed previously. A higher demand to reach for yield in areas with volatile housing prices should force potential borrowers to put a higher down payment. Therefore, absent supply effects, a higher demand in counties that received a high volatility shock should impose a downward pressure on the observed characteristics of loan riskiness in those counties. What we observe in the data is that high volatility areas experienced a worsening of observed loan quality. If demand factors are important, then our results are underestimates for the true supply effect.

5.3. Bank Competition

A potential concern is the endogeneity of bank competition that areas with higher volatility attracted banks to compete, and therefore, the level of bank competition might change over time. To address this issue, in the exercises mentioned above, the 2001 competition measure is used to study the change of loan quality from 2001 to 2005. For robustness checks, the 1999, 1997 and 2006 measures are used to show that one can obtain similar effects. In fact, local bank competition has been quite sticky over time, especially after the branching deregulation in the 1980s. Figure 3 plots the 2005 ranking of large counties (left) and CBSAs (right) by the level of bank competition against the 1995 ranking. One can see that over this ten-year period, competitive banks mainly remained to be competitive, and non-competitive banks largely remained to be non-competitive. Moreover, the plot is highly symmetric, meaning that there was not a systematic shift in the background that previously concentrated areas became more competitive. Therefore, we can take the 2001 level bank competition as given in the exercises above.

Another issue arises if the realized housing volatility differs from what the elasticity predicts and is higher for higher competition. This is plausible as bank competition might have some price effects on the housing market. To address this issue, one needs to include some higher order terms of the level of bank competition (i.e., HHI^2) in the loan riskiness regression. Results shown in Table 2 suggest that higher orders of HHI does not affect the estimates on the coefficients for housing volatility. I plot the realized home price by the median elasticity and HHI in Figure 12. One can see that even if counties are split using the median level of bank competition, the local housing supply elasticity is still a good predictor of housing price movement. Therefore, the systematic deviation of realized housing volatility from its predicted values is less of a concern.

6. Conclusion

The boom of the U.S. mortgage market in the early 2000s and the subsequent collapse of the housing market has drawn much attention of academia and policymakers to the competition on the mortgage origination side of business. In fact, it is often impossible to ex ante distinguish excessive risk taking from improving efficiency. Therefore, it seems that there is so far still limited evidence in favor of a more concentrated banking sector. For policymakers, the rationale to regulate bank competition needs justification.

In this paper, I use a quasi-natural experiment in the U.S. housing market which naturally generates a variation in the housing price risk. I show that competition indeed played an important role how banks responded to the housing risk. Stronger temptation to take risk was associated with stronger bank competition, and small local banks behaved more aggressively than larger banks. Moreover, counties with strong bank competition and volatile housing prices incurred greater loss in real economic performance after the crisis. It suggests that the risk taking pattern for banks in a competitive environment is excessive.

There are also policy implications with respect to bank competition. Competition, in general, reduces the markup between investment returns and funding costs, which improve efficiency of the economy. However, bank competition might not be the case especially when risk is involved. Deposit insurance reduces significantly the incentive for depositors to monitor banks' risk taking behavior, and therefore, any miscalculation in the deposit insurance fee might well imply bad incentives for banks. The risk shifting problem, as has been identified by various authors, is the strongest for smaller banks. Small and local banks have a higher temptation to take on risk when the market is competitive. The design for deposit insurance fees for these banks is itself a dilemma: an under-priced deposit insurance fee subsidizes risky investment, but an over-priced deposit insurance fee might hurt the franchise value of banks and encourage unwanted risk taking behaviors. Such a dilemma is very typical for a banking system like the United States with a large degree of heterogeneity in the characteristics of banks. Therefore, limiting the degree of competition in the banking sector might be a more practical approach to alleviate this problem.

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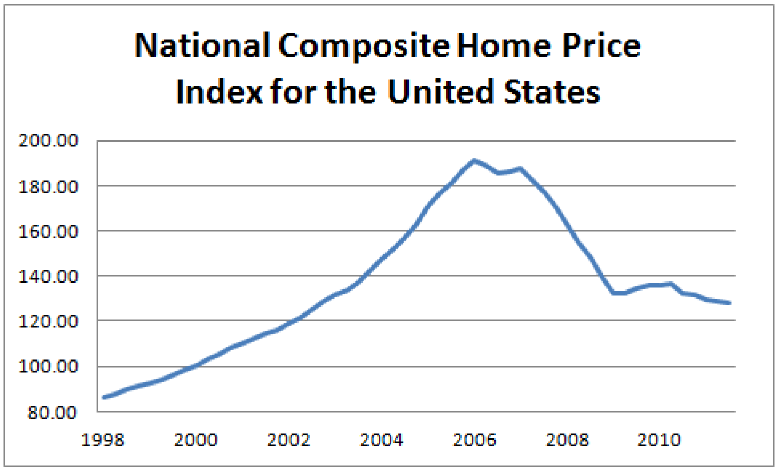
Figure 1

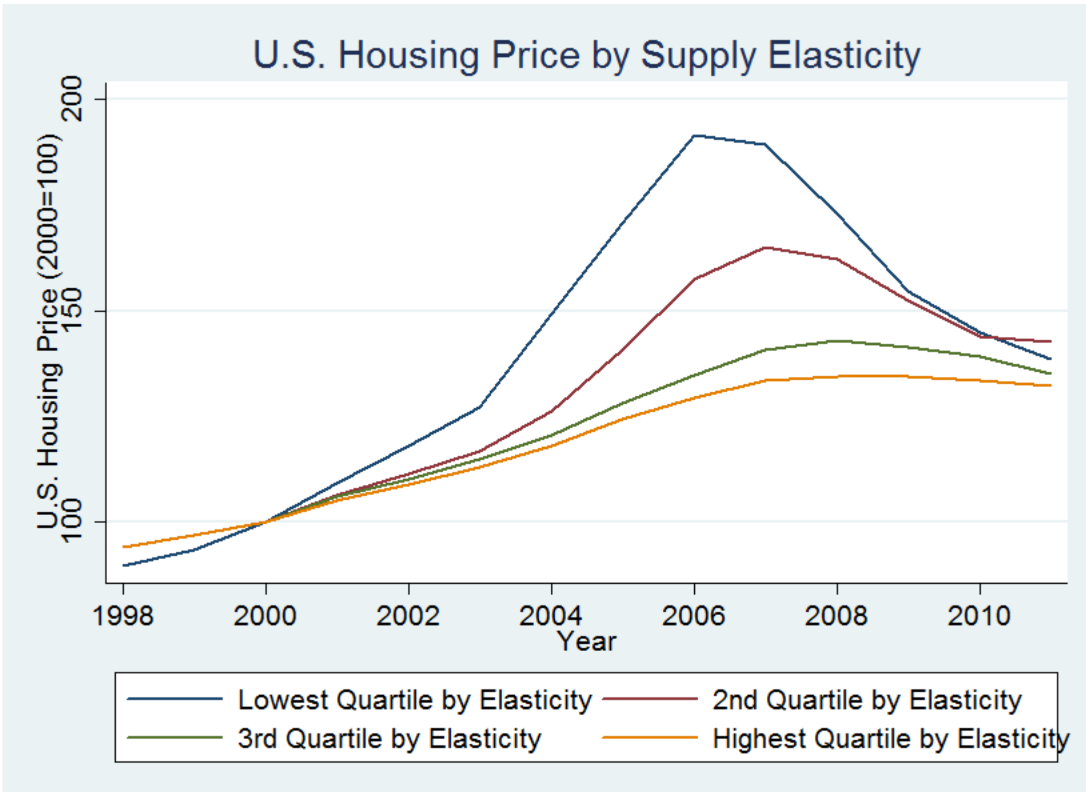
National Composite Home Price Index for the United States from 1998 to 2012.



Data Source: S&P/Case-Shiller.

Figure 2

This figure plots U.S. Home Price Index by housing supply elasticity (Saiz (2010)).



Data Source: S&P/Case-Shiller.

Figure 3

This figure plots the 1995 ranking of the county Herfindahl index against the 2005 ranking. The left panel is for large U.S. counties (top 450) and the right panel is for CBSAs.

Data Source: S&P/Case-Shiller.

Figure 4

This figure plots the county-average riskiness of loans from 2000 to 2005 and by housing supply elasticity. The left panel is the county-average loan-to-income ratio for newly approved home-purchase loans by the housing supply elasticity. The right panel is the county-average loan-to-population ratio by the housing supply elasticity.

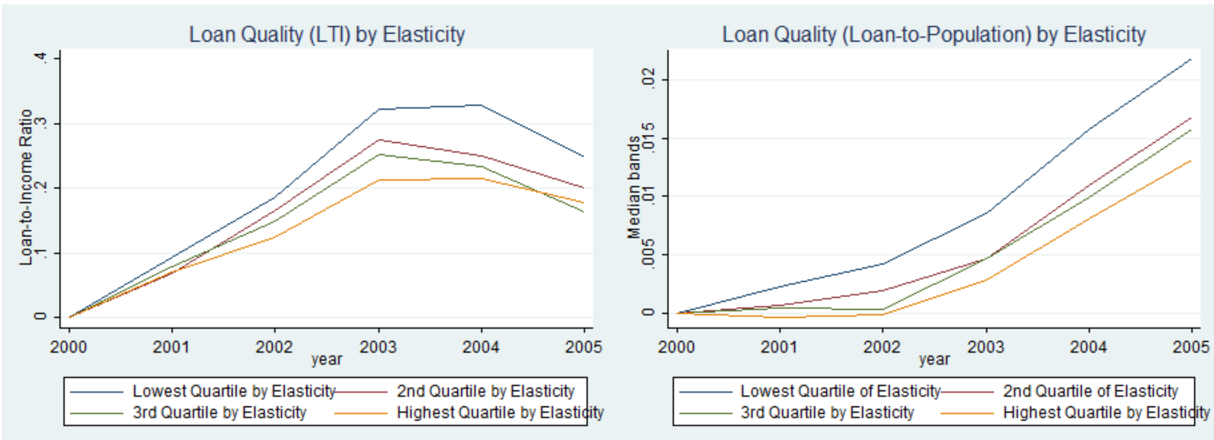


Figure 5

This figure plots the county-average riskiness of loans (loan-to-income ratio) from 2000 to 2005 for U.S. counties by elasticity and level of bank competition. The solid lines are the loan-to-income ratios for inelastic and elastic counties with a high level of bank competition ($HHI^{01} < 0.035$). The dashed lines are the loan-to-income ratios for inelastic and elastic counties with a low level of bank competition ($HHI^{01} > 0.035$).

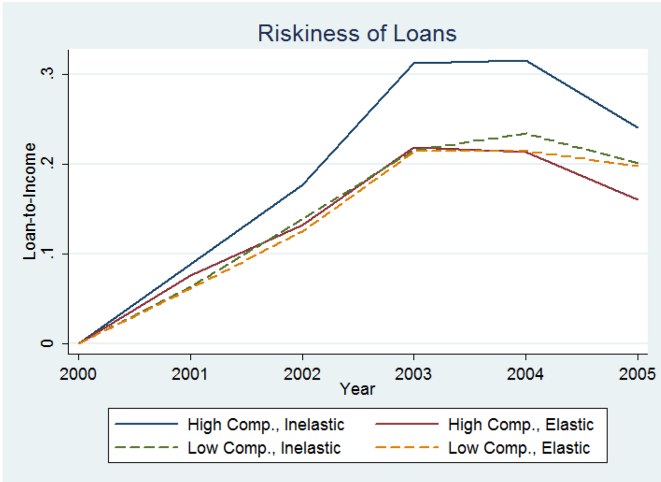


Figure 6

This figure plots the county-average riskiness of loans (loan-to-population ratio) from 2000 to 2005 for U.S. counties by elasticity and level of bank competition. The solid lines are the loan-to-population ratios for inelastic and elastic counties with a high level of bank competition ($HHI^{01} < 0.035$). The dashed lines are the loan-to-population ratios for inelastic and elastic counties with a low level of bank competition ($HHI^{01} > 0.035$).

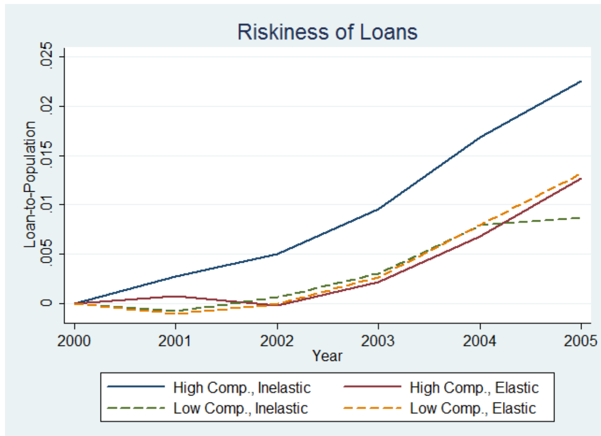


Figure 7

This figure plots the 2001-2005 change in average housing supply elasticity for banks' business against the 2001 average Herfindahl index for the bank.

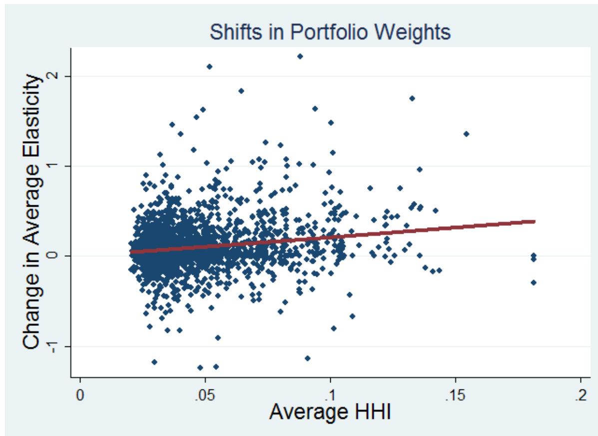


Figure 8

This figure plots the time evolution of loan riskiness (loan-to-income ratio) for loans issued by different types of banks in various areas with inelastic housing supply. The solid lines are for small and large banks in high-competition counties. The dashed lines are for small and large banks in low-competition areas. Small banks are defined as banks issuing fewer than 2,000 mortgages in 2001 and having a market share more than 10% in the county. Large banks are defined as banks issuing more than 20,000 mortgages in 2001 and having a market share less than 5% in the county.

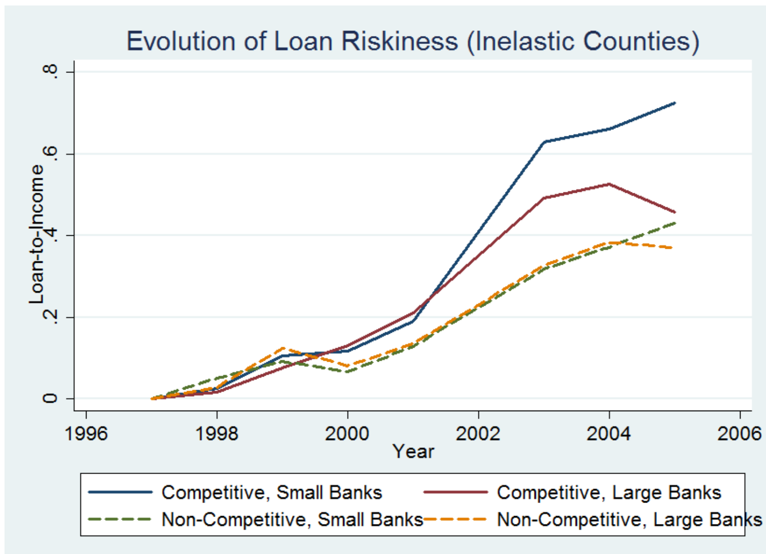


Figure 9

This figure plots the time evolution of loan riskiness (loan-to-income ratio) for loans issued by different types of banks in various areas with elastic housing supply. The solid lines are for small and large banks in high-competition counties. The dashed lines are for small and large banks in low-competition areas. Small banks are defined as banks issuing fewer than 2,000 mortgages in 2001 and having a market share more than 10% in the county. Large banks are defined as banks issuing more than 20,000 mortgages in 2001 and having a market share less than 5% in the county.

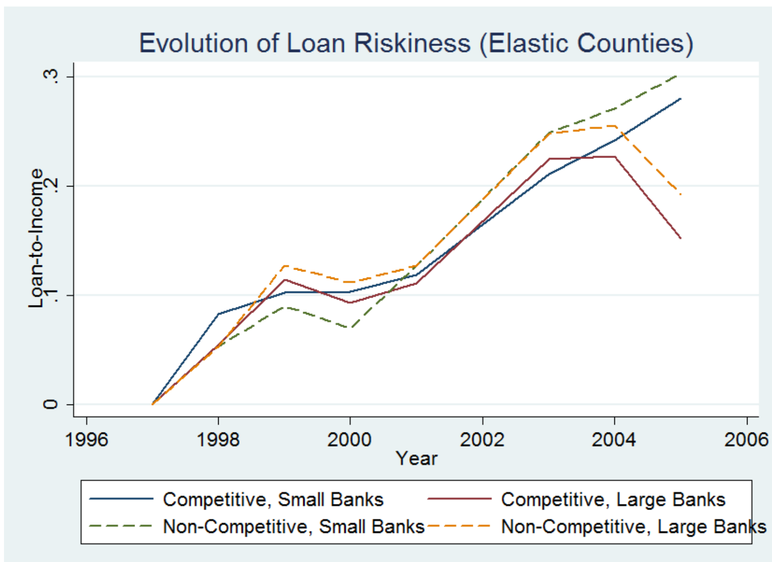


Figure 10

This figure plots the 2007Q1-2008Q2 foreclosure rate against housing supply elasticity. The left panel plots counties with a high level of bank competition . The right panel plots counties with a low level of bank competition.

Figure 11

This figure plots the 2007-2009 change in tradable employment against housing supply elasticity. The left panel plots counties with a high level of bank competition . The right panel plots counties with a low level of bank competition.

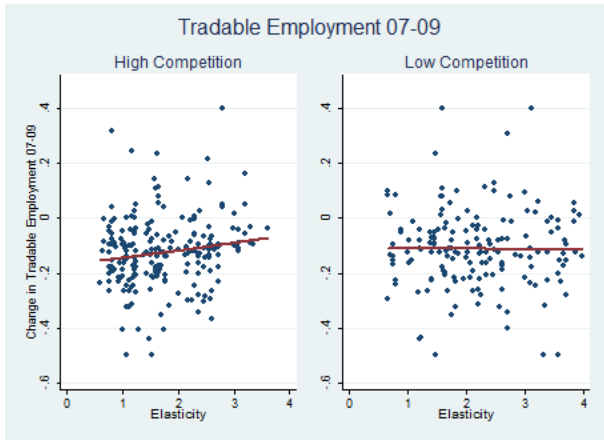


Figure 12

This figure plots U.S. home price by elasticity and level of competition. The solid lines are for inelastic counties (<2.6), and the dashed lines are for elastic counties (>2.6). Both groups are split by level of bank competition at 0.045 for HHI.

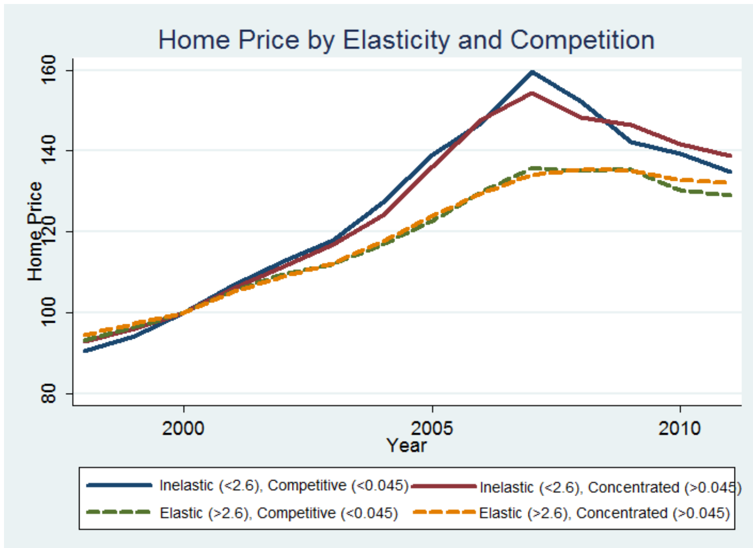


Table 1

Summary Statistics

	N	Mean	Median	SD
Housing Supply Elasticity, Saiz	818	2.45	2.34	1.24
Herfindahl-Hirschman Index (HHI)	2226	0.05	0.04	0.02
Debt-to-Income Ratio, 2006	2215	1.57	1.45	0.58
% Change in Home Price 2000-2006	1097	0.33	0.25	0.18
% Change in Home Price 2006-2011	1097	-0.09	-0.06	0.17
Commercial Bank Share, 2005	2215	0.56	0.56	0.12
% Change in Wages, 2001-2005	3138	0.14	0.13	0.19
Securitization Share, 2001	3253	0.56	0.57	0.13
Employment Share in tradables, 2005	2215	0.16	0.14	0.11
Employment Share in non-tradables, 2005	2215	0.24	0.24	0.06
Number of Households, thousands	2215	50.9	17.4	130.0

Table 2

This table presents coefficients of Large-LTI Fraction on the measure of housing volatility shock and the interaction term with the Herfindal index 2001.

	(1)	(2)	(3)	(4)	(5)
	Δ Large-LTI Fraction (2001-2005)				
Elasticity	-0.033^{***}	-0.037^{***}	-0.045^{***}	-0.032^{***}	-0.04^{***}
	(0.004)	(0.004)	(0.01)	(0.003)	(0.00)
HHI × Elasticity	0.28^{***}	0.33^{***}	0.18^{**}	0.27^{***}	0.19^{***}
	(0.06)	(0.06)	(0.05)	(0.05)	(0.04)
HHI	-0.77^{***}	-0.27	0.21	-0.82^{***}	0.23
	(0.20)	(0.29)	(0.31)	(0.15)	(0.35)
$(\text{HHI})^2$		-4.03^{**}	-3.74^{**}		
		(1.86)	(1.72)		
$(\text{Elasticity})^2$			0.003^{***}		0.002^{***}
			(0.001)		(0.001)
log(Population)			-0.000		-0.000
			(0.002)		(0.002)
Securitization Share			-0.10^{***}		-0.09^{***}
			(0.03)		(0.02)
$\%\Delta$Wage			0.07^{***}		0.06^{***}
			(0.02)		(0.02)
Commercial Bank Share			-0.08^{**}		-0.09^{***}
			(0.03)		(0.02)
Constant	0.17^{***}	0.19^{***}	0.25^{***}	0.15^{***}	0.23^{***}
	(0.01)	(0.03)	(0.04)	(0.01)	(0.03)
N	818	818	818	818	818
Adj. R^2	0.13	0.19	0.19	0.20	0.27
Large LTI Definition	> 3	> 3	> 3	> 3.5	> 3.5

***, **, * denote statistical significance at the 1%, 5% and 10% levels.

Table 3

This table presents coefficients of Loan-to-Population Ratio and Acceptance Rate on the measure of housing volatility shock and the interaction term with the Herfindal index 2001.

	(1)	(2)	(3)	(4)
	Δ Loan-to-Population (2001-2005)		ΔAcceptance Rate for Large LTI Loans (01-05)	
Elasticity	-0.003^{***}	-0.002^{*}	0.00	-0.01
	(0.001)	(0.001)	(0.01)	(0.01)
HHI × Elasticity	0.04^{**}	0.03^{**}		0.19
	(0.02)	(0.01)		(0.13)
HHI	-0.20^{***}	-0.10^{**}		-0.42
	(0.05)	(0.05)		(0.46)
$(\text{Elasticity})^2$		-0.00		0.001
		(0.00)		(0.001)
log(Population)		-0.002^{***}		-0.01^{***}
		(0.001)		(0.00)
Securitization Share		0.04^{***}		-0.19^{***}
		(0.01)		(0.07)
%ΔWage		0.06^{***}		0.00
		(0.02)		(0.05)
Commercial Bank Share		-0.05^{***}		0.16^{***}
		(0.01)		(0.05)
Constant	0.03^{***}	0.04^{***}	0.03^{***}	0.13
	(0.00)	(0.01)	(0.00)	(0.08)
N	818	818	818	818
Adj. R^2	0.04	0.31	0.00	0.09
Large LTI Definition	All	All	>3.5	>3.5

***, **, * denote statistical significance at the 1%, 5% and 10% levels.

Table 4

This table presents coefficients of the 2001-2005 change in the average elasticity of bank's mortgage portfolio on the 2001 average Herfindahl index for the bank.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Change in Average Elasticity 2001-2005							
HHI	2.12^{***}	2.15^{***}	1.75^{***}	1.80^{***}	1.77^{***}	1.77^{***}	1.77^{***}	1.80^{***}
	(0.34)	(0.34)	(0.42)	(0.42)	(0.42)	(0.42)	(0.43)	(0.60)
log(# of Loans)		0.009^{***}	0.012^{***}					0.018^{***}
		(0.004)	(0.003)					(0.0067)
Fraction Securitized 2001		-0.001	0.011	0.003	-0.01	-0.005		-0.000
		(0.001)	(0.019)	(0.019)	(0.02)	(0.019)		(0.000)
#of States				0.002^{**}				
				(0.001)				
# of Counties					-0.00			
					(0.00)			
N	2449	2449	2449	2449	2449	2449	1126	1126
Adj. R^2	0.03	0.04	0.08	0.075	0.08	0.074	0.03	0.11
Sub-sample of Banks	All	All	All	All	All	All	Single-State	Single-State
Controls up to nth order of Size	N	log	log	N	N	$n = 3$	N	log
Bank Head State F.E.	N	N	Y	Y	Y	Y	N	Y
Bank Type F.E.	N	N	Y	Y	Y	Y	N	Y

***, **, * denote statistical significance at the 1%, 5% and 10% levels.

Robust standard errors are shown in parentheses.

Table 5

This table presents coefficients of the 2007Q1-2008Q2 county foreclosure rate on the measure of housing volatility shock and the interaction term with the Herfindahl index.

	(1)	(2)	(3)	(4)
	Foreclosure Rate (2007Q1-2008Q2)			
Elasticity	-0.003^{***} (0.001)	-0.010^{***} (0.002)	-0.005^{***} (0.002)	-0.006^{***} (0.002)
HHI		-0.98^{***} (0.11)	-0.75^{***} (0.11)	-0.95^{***} (1.22)
Elasticity $\times$ HHI		0.23^{***} (0.04)	0.17^{***} (0.04)	0.25^{***} (0.05)
$(\text{Elasticity})^2$				-0.00 (0.00)
$\log(Population)$				0.003^{***} (0.001)
Debt-to-Income 2006			0.011^{***} (0.001)	
Constant	0.055^{***} (0.002)	0.081^{***} (0.003)	0.048^{***} (0.005)	0.03^{***} (0.01)
N	818	818	818	818
Adj. R^2	0.02	0.12	0.18	0.14
Population	All	All	All	All
Model	WLS	WLS	WLS	WLS

***, **, * denote statistical significance at the 1%, 5% and 10% levels. WLS regressions use population as weights.

Table 6

This table presents coefficients of the 2007-2009 change in county tradable employment on the measure of housing volatility shock and the interaction term with the Herfindahl index. The placebo uses the 2005-2007 change in tradable employment.

	(1)	(2)	(3)	(4)	(5)	(6)
	Change in Tradable Employment (2007-2009)					
	All Counties		High Competition		Low Competition	
Elasticity	0.013^{**}	0.019^{**}	0.022^{**}	0.021^{*}	0.008	0.006
	(0.005)	(0.007)	(0.011)	(0.013)	(0.010)	(0.010)
HHI		0.07		0.51		1.07
		(0.51)		(2.55)		(1.12)
$\log(Population)$		0.004		0.00		
		(0.007)		(0.01)		
Tradable Share		-0.30^{**}		-0.39^{*}		
		(0.12)		(0.22)		
Debt-to-Income 2006		0.00		-0.02		
		(0.01)		(0.02)		
Constant	-0.15^{***}	-0.19^{*}	-0.17^{***}	-0.16	-0.15^{***}	-0.20^{***}
	(0.01)	(0.10)	(0.02)	(0.18)	(0.03)	(0.06)
N	746	746	236	236	272	272
Adj. R^2	0.01	0.03	0.02	0.03	0.00	0.00
Model	WLS	WLS	WLS	WLS	WLS	WLS

***, **, * denote statistical significance at the 1%, 5% and 10% levels. WLS regressions use population as weights.

	(7)	(8)	(9)
	Change in Tradable Employment (2005-2007)		
	All Counties	High Competition	Low Competition
Elasticity	0.003	0.00	-0.01
	(0.005)	(0.01)	(0.01)
Constant	-0.016	-0.00	0.015
	(0.012)	(0.02)	(0.024)
N	746	236	272
Adj. R^2	0.00	0.00	0.00
Model	WLS	WLS	WLS

***, **, * denote statistical significance at the 1%, 5% and 10% levels.
WLS regressions use population as weights.

Table 7

This table presents coefficients of the 2007-2009 change in county non-tradable employment on the measure of housing volatility shock.

	(1)	(2)	(3)	(4)	(5)	(6)
	Change in Non-Tradable Employment (2007-2009)					
	All Counties		High Competition		Low Competition	
Elasticity	0.011***	0.003	0.022***	0.014***	0.005*	0.002
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
HHI		0.19		−0.33		−0.30
		(0.14)		(0.78)		(0.25)
$\log(Population)$		−0.001		−0.004		0.002
		(0.002)		(0.004)		(0.004)
Non-Tradable Share		−0.01		0.05		0.03
		(0.05)		(0.08)		(0.09)
Debt-to-Income 2006		−0.028***		−0.021***		−0.034***
		(0.004)		(0.006)		(0.008)
Constant	−0.07***	0.01	−0.09***	0.004	−0.04***	0.01
	(0.003)	(0.04)	(0.01)	(0.063)	(0.01)	(0.06)
N	789	746	255	255	293	293
Adj. R^2	0.04	0.13	0.14	0.18	0.01	0.06
Model	WLS	WLS	WLS	WLS	WLS	WLS

***, **, * denote statistical significance at the 1%, 5% and 10% levels. WLS regressions use population as weights.