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

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Abstract

Bank competition can induce excessive risk taking due to risk shifting. With a competitive banking sector and insured deposits, banks may have the incentive to overly invest in risky assets. In this paper, I test this hypothesis using micro-level data in the U.S. mortgage market over the past housing cycle by studying how banks made mortgage lending decisions when subject to uncertainties in the local house price. Using geography-based housing supply elasticity (Saiz (2010)) as an instrument for local house price volatility, I find that, prior to the crisis from 2000 to 2005, banks in U.S. counties with a competitive mortgage market substantially lowered lending standards in response to high volatility in the house price, by twice as much as those in concentrated markets. Moreover, the effect of local competition was particularly strong for lending decisions made by small and regional banks, but was insignificant for national banks. Such risk taking pattern implied real economic consequences after the crisis. In counties where mortgage market was competitive, volatility in house price in the past housing cycle became more damaging: one standard-deviation increase in local house price volatility was associated with 1% higher foreclosure rate and 1.5% higher real-sector unemployment rate after the crisis; none for concentrated mortgage markets. The findings in this study suggest that competition among banks in the mortgage market was strongly associated with both the buildup of house price risk in the banking sector prior to the crisis and the adverse real economic impact after the crisis.

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1. Introduction

Can bank competition induce excessive risk taking and financial instability? This question has been a focus of policy discussions over the past decades, especially after the recent financial crisis. However, direct empirical evidence on this competition-instability view is still limited, and quantifying its impact on the real economy remains an uncompleted task. In this paper, I investigate this relationship empirically by examining the cross-sectional differences in the lending behavior before the recent crisis of U.S. mortgage-issuing banks facing house price uncertainties in relation to mortgage market competition. I also quantify the real economic consequences of this competition-risk-taking relationship by looking at the post-crisis outcomes in the real economy. Empirical findings in this paper suggest that competition in the mortgage market was strongly associated with both the buildup of house price risk in the banking system prior to the recent crisis and the negative economic impact after the crisis.

Competition among banks can encourage risk taking due to the risk-shifting agency problem. Guaranteed by limited liability and deposit insurance, banks have an option-like payoff function that rewards high volatility in the asset return (Jensen and Meckling (1976)). Bank competition, which undermines the franchise value of the bank, makes return volatility even more attractive. This is because only by investing in risky projects could banks in highly competitive environment make potential positive profits when the projects succeed, while the FDIC absorbs all the losses if they fail. Studies have shown that this competition-instability relationship was an important factor explaining the past economic crises[1]. Notably on the U.S. savings and loan crisis in the 1980s and 1990s, Keeley (1990) shows that the rise in U.S. bank risk in the 1980s was associated with the increased bank competition during the banking deregulation period of the 1970s and 1980s. On the recent financial crisis, however, less empirical evidence is known so far, despite that scholars including Bernanke (2007) suggested that much mortgage risk could have also been associated with the competitive lending environment[2]. Do we see that bank competition in the mortgage market contributed to more bank risk taking during the recent economic cycle? How would mortgage lending decisions be different between competitive and concentrated mortgage markets when facing future house price uncertainties? In this paper, I attempt to provide an answer to these questions by studying the U.S. mortgage market in the run-up to the recent crisis. I use the cross-sectional differences in local mortgage-market competition and in local house price volatility in the U.S. to test if stronger response of lending behaviors to house price volatility was associated with greater mortgage market competition. Below I describe the setup of my analysis

[1] On the international scope, there also seems to be a correlation between banking concentration and financial stability (e.g., Beck, Demirgüç-Kunt, and Levine (2004), Jiménez, Lopez, and Saurina (2010)).

[2] "Some misalignment of incentives, together with a highly competitive lending environment, ... likely compromised the quality of underwriting." – Chairman Ben S. Bernanke's speech on May 17, 2007, at the Federal Reserve Bank of Chicago's 43rd Annual Conference on Bank Structure and Competition, Chicago, Illinois.

in more details.

I begin with the observation that the local house-price volatility can significantly affect the performance of mortgage loans, where I define local house price volatility as the magnitude of the boom-bust fluctuation during a housing cycle. It especially affects the number of borrowers being underwater - owing more than the house value. Given a fixed loan amount during a housing cycle, a greater house price volatility simply implies positive capital gains and likely a low default rate if the initial housing boom persists, but it also implies more underwater mortgage borrowers and likely a high default rate if the price reverts. The volatility in the house price is shown to be empirically important in determining mortgage loan performance. For instance, studying the last housing cycle, Palmer (2014) finds that much of the subprime defaults during the crisis was exactly due to the sharp decline in the house price. Therefore, facing a higher house price volatility, the bank calculates the tradeoff when making lending decisions on the loan amount issued to borrowers: the bank may want to increase the loan amount to attract liquidity-constrained borrowers in anticipation of continued house price growth, but raising the loan amount could incur significant losses if a reversal happens. In the extreme case where the equity of the bank is wiped out due to a housing reversal, the bank would have to cease to operate and the FDIC would absorb all the losses.

A highly competitive mortgage market can encourage the willingness to take such risk, as banks facing high competition are more likely to regard the housing boom as an opportunity to raise the potential profit, by essentially betting on the housing boom to persist, while potential large losses due to a reversal would be born by the FDIC. This "risk-shifting" incentive predicts a stronger response of lending behaviors to the volatility in the house price for competitive mortgage markets than for concentrated mortgage markets. In this paper, I map this framework into the U.S. mortgage market, exploiting the cross-sectional variations in house price volatility and in local mortgage-market competition. In particular, I test whether the change in various lending standards from 2000 to 2005 was responsive to volatility of the local house price in this housing cycle, and most importantly, if the responsiveness was significantly different between competitive local mortgage markets and concentrated markets. Moreover, I also test if the competition effect was stronger for banks that are more vulnerable to local conditions, i.e., small and local banks, as opposed to national banks.

The focus of my empirical design is the relationship between changes in lending standards and the "interaction" term of house price volatility and bank competition. Using loan-level data, I follow the literature to construct various measures for local bank competition and changes in lending standards at the U.S. county-level[3]. The empirical challenge is on the identification of the volatility of local house price. In fact, it is generally difficult to identify the future price

[3] I measure local bank competition by the countylevel Concentration Ratio or the Herndahl index as of 2000, and the changes in lending standards (e.g., the loan-to-income ratio, the denial rate) from 2000 to 2005 at the county level.

volatility of any asset. The feature of the U.S. housing market makes the identification possible due to the natural cross-sectional variation in house price volatility by local geography. In the U.S. historically, the long-run housing volatility exhibited similar patterns over the past housing cycles. Glaeser, Gyourko and Saiz (2008) find that the housing supply elasticity, a land-availability measure constructed by Saiz (2010) using satellite data, was a key determinant for local house price volatility for the past housing cycles[4]. In my empirical analysis, I use this housing supply elasticity measure to instrument for historical local house price volatility (from 1982 to 1996) which naturally formed the prior for banks entering the 2000-2011 housing cycle, and then verify that the 2000-2011 housing cycle indeed followed the pattern as predicted. I also show that empirical results are robust to treating the realized house price volatility as exogenous.

In this paper, I find strong supporting evidence for the risk-shifting hypothesis. I find that, prior to the crisis from 2000 to 2005, banks in competitive local mortgage markets lowered lending standards in response to local house price volatility by at least twice as much as those in concentrated mortgage markets. These changes in lending standards include raising the loan-to-income ratio and reducing the denial rate. Similar results are obtained if lending standards are measured using the loan-to-value ratio and the fraction of high rate-spread mortgage loans (which are typically riskier and involve subprime borrowers). Moreover, the effect of local competition was significant mainly for decisions made by local and regional banks which were more vulnerable to local-market conditions, but was much less significant for national banks. This confirms that the risk taking mechanism worked through the banks' balance sheet, a prediction from the risk-shifting hypothesis.

These risk taking behaviors were associated with real costs, as more pre-crisis bank risk eventually implied worse post-crisis realizations. Especially, the real sector also suffered as the financial distress was transmitted to the real economy. I find that, after the crisis, volatility in the house price was much more damaging for competitive mortgage markets than for concentrated markets, in terms of local foreclosure and the unemployment in the real sector. One standard-deviation increase in the house price volatility implied a 1% higher foreclosure rate during 2007-2008 and a 1.5% higher unemployment rate during 2007-2009 for U.S. counties with a competitive mortgage market. The effect on unemployment was particularly strong for small-sized firms, suggesting that the real effect was indeed through the worsening of financial conditions. For counties with a concentrated mortgage market, these effects were insignificant.

The main academic contribution of this paper is two-fold. First, this paper is the first study

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Glaeser, Gyourko, and Saiz (2008) find that, in areas where land was extremely limited and housing supply was inelastic (e.g., San Francisco and Seattle), the local house price experienced large movements in both the booms and busts during the past housing cycles. On the contrary, areas where land was abundant and housing supply was elastic (e.g., Houston and Atlanta) had rather flat house price growth throughout. The reason for this pattern is any upward pressure during the boom was quickly absorbed by the building of new houses in elastic-supply areas, but was instantaneously reflected in the local house price for inelastic-supply areas.

that uses the cross-sectional variation in asset risk, i.e., house price risk, to examine the relationship between bank competition and risk taking. It attempts to help understand how the risk taking pattern was associated with the competitive lending environment for the past economic cycle. Empirical evidence is found supporting the competition-instability view of bank competition. Second, this paper highlights the macro-finance linkage through the risk taking channel of banks. It provides additional empirical evidence on the macro-finance linkage through banks' risk taking and particularly on the causes of the high unemployment rate after the recent financial crisis.

1.1. Related Literature

This paper is related to multiple strands of literature. First, it is related to the bank-competition-instability relationship due to agency problems. Jensen and Meckling (1976) identify the risk shifting agency problem between equityholders and debtholders of a firm, which can be especially severe for banks as bank liabilities are often explicitly or implicitly guaranteed by the government. Keeley (1990) points out that the risk taking incentive of a bank is associated with its charter value which is the expected future profits that accrue to the bank's owner, as higher charter value deters banks from investing in risky projects. In his framework, greater market power generates higher profits and charter value, reducing risk taking by the bank. Allen and Gale (2004) and Hellman, Murdock and Stiglitz (2000) consider a setting where competition among banks lowers the return on the safe asset and therefore it encourages risk taking. Competition in the asset market has drawn particular attention in recent decades (e.g., Boyd and De Nicoló (2005)[5]), as changes in funding costs in recent years no longer predict bank lending behaviors due to the nation-wide decline in funding costs (e.g., Loutskina and Strahan (2009))[6].

On empirical evidence, Keeley (1990) finds that the rise in bank risk in the 1980s (which later resulted in the S&L crisis) was associated with the increased bank competition during bank deregulation period in the 1970s and 1980s.[7]. On evidence of the risk-shifting agency problem of banks, using quasi-natural experiments, Landier, Sraer and Thesmar (2011) and Gan (2004) find that exogenous declines in the franchise value of banks can encourage risk taking behaviors. On the international scope, using panel data over 1980-1997 on 70 countries, Beck, Demirgüç-Kunt, and Levine (2004) find that a negative correlation between the frequency of banking crises and banking sector concentration, although they also show that fewer regulatory restrictions on banks, which could result in a more competitive banking sector, also improves banking stability[8].

The second related strand of literature focuses on the effect of financial disruptions on real

[5] Boyd and De Nicoló (2005) argue that bank competition in the asset market and deposit market can have different effects if corporate borrowers face the same risk shifting agency problem as banks. In the context of the U.S. mortgage market studied in this paper, such agency problems on the borrower side are not present.

[6] There is also a recent literature on competition for the liability side of financial institutions due to the performance-flow relationship for mutual funds or pre-committed returns for insurance companies (e.g., Becker and Ivashina (2013)).

[7] In Keeley (1990), the charter value of a bank is measured by Tobin's Q, which is the ratio of bank's market value to its replacement costs.

[8] See also Petersen and Rajan (1995), Claessens and Laeven (2004), Claessens, Demirgüç-Kunt and Huizinga (2001), Berger and Hannan (1989), Berger, Demsetz, and Strahan (1999), Jiménez, Lopez, and Saurina (2010) for more discussions on competition among banks.

economic activities. Kiyotaki and Moore (1997) point out that financial shocks can be amplified and greatly affect the real economy when firms have financial constraints[9]. This mechanism is further examined in Brunnermeier and Sannikov (2014) where they study endogenous leverage of banks due to endogenous volatility in asset prices. There are also recent studies looking at how financial factors can affect employment especially after the recent crisis. Chodorow-Reich (2014) finds that adverse financial shocks to banks implied worse employment outcomes for firms borrowing from the troubled banks. Mian and Sufi (2014) highlight the importance of household balance sheet in explaining the dramatic rise in unemployment after the crisis.

This paper is linked to the literature examining mortgage lending in the years preceding the recent crisis and the subsequent defaults during the crisis[10]. One closely related study is Palmer (2014) who shows that most defaults of recently issued subprime mortgages during the crisis were driven by dramatic fluctuations in the house price, as opposed to the decline in borrower quality. My study complements Palmer (2014) by studying bank credit supply factors due to competitive pressure that drove the risk taking behavior against house price volatility[11]. My paper also complements the literature explaining the aggregate risk taking behaviors by banks in the time series. There are studies from the time-series perspective that emphasize the agency problems (e.g., Allen and Gale (2004)) and other studies that bring in behavioral components which encourage optimism (e.g., Cheng, Raina, and Xiong (2013))[12], while this paper uses a cross-section empirical design.

2. Theoretical Framework

In this section, I set up a simple model to show how bank competition in the asset market and risk taking are associated when there is an aggregate shock in the economy. I also list the testable implications for the U.S. housing mortgage market according to this theoretical framework.

2.1. Environment

Consider a local mortgage market where banks compete for mortgage loans. Time is $t = 0, 1, 2, ..., \infty$. In period 0, the local house price experienced an initial boom from its initial value $f = 1$ to $V_{0-} = 1 + \epsilon$, which may later persist or revert with given probabilities p and $1 - p$, respectively. If the boom persists, the local house price at the end of period 0 would become $V_{0+} = 1 + 2\epsilon$; if the boom reverts, we have $V_{0+} = 1$. Parameter $\epsilon \in (0, \bar{\epsilon})$ measures the volatility of the local house price in this housing cycle. In all future periods, for simplicity, the house price is constant at its initial value $f = 1$.

[9] See also Peek and Rosengren (1997, 2000), Gan (2007), Gertler and Gilchrist (1994), Khwaja and Mian (2008).

[10] See Mian and Sufi (2009a, 2009b, 2010), Dagher and Fu (2011), Keys, Mukherjee, Seru, and Vig (2009), Demyanyk, and Van Hemert (2011), Purnanandam (2011).

[11] In both this paper and Palmer (2014), house price volatility is either instrumented or extrapolated using historical house price patterns. In this paper, I especially use a geography-based housing supply elasticity (Saiz (2010)) to instrument for the house price volatility anticipated by banks. See Glaeser, Gyourko and Saiz (2010) for additional discussions.

[12] See also Benabou (2012), Brunnermeier and Julliard (2008), Gennaioli, Shleifer and Vishny (2012). See Shiller (2007), Himmelberg, Mayer, and Sinai (2005) for empirical discussions.

There are two types of participants in the market, a continuum of potential home buyers of mass M and a continuum of banks. Home buyers face liquidity constraints and need to borrow loans from banks. After the initial house price, banks make decisions on the loan amount $1 + l \in [1,1+\epsilon]$ they want to issue to borrowers. Once the loan is issued to the borrower, the borrowers make repayment/default decisions on their loans at the end of the period after observing the eventual house price. The regulatory agency will inspect the balance sheet of each bank and banks with negative net equity will be seized and cease to operate. When making lending decisions after seeing the initial house price boom, banks would take into account the potential defaults by borrowers should the house price eventually fall. The decision problems of the borrowers and banks are described below in more details.

2.1.1. Borrower's Decisions

Borrowers have idiosyncratic liquidity constraints where each borrower's liquidity a is uniformly distributed over the unit interval $a \sim U[0,1]$. Therefore, after observing the house price $V_{0-} = 1 + \epsilon$, the fraction of borrowers that could afford the downpayment and purchase the house is $m(\epsilon, l) = 1 + l - \epsilon$. Borrowers would like to pay an interest $\alpha > 0$ on their loans. This setup implicitly assumes that the demand for mortgage loans is relatively inelastic in the housing boom period. This assumption is reasonable given that there is potential capital gain in the house for borrowers.

After observing the eventual house price V_{0+}, borrowers make their repayment decision, either to repay in full amount or default entirely on their loan[13]. The default decision depends on the borrower's equity in the house. If the borrower at the end of the period is underwater, i.e., the loan owed exceeds the value of the house, then default is more likely to happen. To capture this relationship, I assume that the repay probability θ of each borrower is simply an increasing function of the equity $V_{0+} - l$ that the borrower has in the house. For the purpose of simplicity, I assume that borrowers always repay if equity is non-negative and will always default if equity becomes negative, i.e.,

$$\theta(x) = \begin{cases} 1 & \text{if } x \geq 0 \\ 0 & \text{if } x < 0 \end{cases}$$

2.1.2. Banker's Problem and Bank Competition

Each bank maximizes a life-time profit function $E_0 \sum_{t=0}^{\infty} \delta^t \pi_t^i$ where π_t^i is the period-t profit for bank i and $\delta < 1$ is the discount rate. I analyze the bank's problem in the first period. If the bank chooses $l \leq 0$, i.e., refraining from raising the loan amount, the fraction of borrowers that have enough liquidity is $\max\{1 + l - \epsilon, 0\}$ and all loans will repay since the loan amount is for sure below the house value, yielding a total profit $\pi(l; \epsilon) = \alpha M \max\{1 + l - \epsilon, 0\}$. Note that this function π is

[13] I exclude the possibility of loan renegotiation for illustrative purpose. The qualitative results would go through with possible loan renegotiation and partial defaults.

increasing in l, therefore banks will choose $l^* = 0$. Alternatively, banks can take risk and raise the loan amount by $0 < l \leq \epsilon$. If the future house price continue to grow $V_{0+} = 1 + 2\epsilon$, all loans will repay yielding a profit of $\alpha M(1 + l - \epsilon)$; however, if eventually reversal happens $V_{0+} = 1$, then all loans default and the bank will incur a large loss $-\beta M(1 + l - \epsilon)$ where $\beta > 0$ is a large constant number.

Assumption 1. $p\alpha - (1 - p)\beta < 0$.

Assumption 1 ensures that increasing the loan amount does not generate a positive expected profit for the bank. This assumption indicates that it is only rational for the bank to choose $l > 0$ if it risks the possibility of bank failure. For all future periods where the house price is riskless and stays at its initial value, i.e., $V_t = f = 1$ for $t \geq 1$, I assume that the profit each bank i can earn at the end of the period is given by $r(h_i)M$ where h_i is the level of bank competition the bank faces and $r'(h) < 0,\ r(\infty) = 0,\ r(0) > \frac{1-\delta}{\delta}\frac{\alpha(p-(1-\bar{\epsilon}))}{1-p}$. Equivalently, one can endogenized the bank's interest rate offers by assuming that banks offer interest rate simultaneously subject to a common demand curve as in Hellman, Murdock and Stiglitz (2000)[14]. Note that in this model, bank competition h is defined as the determinant for bank profit investing in the safe asset.

In summary, plugging in the decisions described above, the profit the bank receives in period 0 is given by

$$\pi_0(l; \epsilon, h) = \begin{cases} \alpha(1 + l - \epsilon)M & \text{if boom persists} \\ -\beta(1 + l - \epsilon)M \cdot \mathbf{1}\{l > 0\} + \alpha(1 - \epsilon)M \cdot \mathbf{1}\{l = 0\} & \text{if reversal happens} \end{cases}$$

Regarding parameter values, I also make the following additional assumption.

Assumption 2. $p > (1 - \bar{\epsilon})$.

Assumption 2 ensures that the chance that the probability of a persistent housing boom is not too low. This assumption ensures that there exist some banks that are willing to take risk by lowering lending standards.

2.2. Theoretical Results

The following theoretical results can be obtained from the model considering only symmetric equilibrium.

Proposition 1. Assume the parameter values mentioned above and consider the period-0 decision l_0. There exists some $\epsilon_M > 0$ such that, for each fixed $\epsilon > \epsilon_M$, there are always $0 < \underline{h} < \bar{h}$ where banks choose $l_0 = \epsilon$ for $h = \bar{h}$ and $l_0 = 0$ for $h = \underline{h}$.

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Equivalently, one can endogenize the profit function as $r_i L(r_i, r_{-i})M$ where r_i is the terms (e.g., interest rate) bank i offers and r_{-i} the terms other banks offer. Banks simultaneously make offers on the terms and the total demand for loans is always M. The amount of loan business L satisfies $L_1 < 0$, $L_2 > 0$. Moreover, I denote $h \equiv \frac{\partial L}{\partial r}\frac{r}{L}$ as the level of bank competition in the lending market where h is the elasticity of substitution between the lending banks. When h goes to infinity, the lending market is perfectly competitive; when h approaches zero, the lending market is perfectly concentrated. In the symmetric equilibrium which is my focus, the profit function $\pi(h)$ is a decreasing function in h and $\pi(h) \to 0$ as $h \to \infty$.

The proof for this proposition is in the Appendix. This proposition essentially indicates that, when the lending market becomes extremely competitive, i.e., $h \to \infty$, the bank will choose l greater than 0 and to "gamble" that the housing price continues to grow. In this case, if the housing price reverts to its initial value at the end of period 0, the bank will declare bankruptcy and cease to operate. On the other hand, when the lending market is extremely concentrated, i.e., $h \to 0$, the bank will refrain from raising l in the bubbly period 0. This result is very intuitive: when $h \to \infty$, the franchise value of the bank diminishes so the bank has less to lose by gambling; when $h \to 0$, the franchise value of the bank is so large that it is not worth it to risk losing the charter in the case of housing market collapse.

Proposition 2. Given a fixed level of bank competition h, the period-0 decision l_0 is weakly increasing in ϵ, i.e., $\frac{\partial l_0}{\partial \epsilon} \geq 0$. Moreover, the relationship is stronger for competitive markets as bank competition h increases, i.e., $\frac{\partial^2 l_0}{\partial \epsilon \partial h} \geq 0$.

See proof in the Appendix.

Proposition 3. Given a fixed ϵ, define the threshold $\hat{h}(\epsilon) = \inf \{h : \ l(\epsilon; h) > 0\}$ to be level of bank competition above which banks would take housing risk. Then $\hat{h}'(\epsilon) \leq 0$.

See proof in the Appendix.

2.3. Empirical Predictions

In this paper, I formally test the risk shifting theory described above using cross sectional data. The theoretical model implies the following testable predictions.

Prediction 1. Banks increase the loan-to-income ratio of their mortgage loans in response to higher housing volatility. This response diminishes as local market concentration increases.

Prediction 2. Moreover, as the effect of bank competition on lending decisions works through the bank's balance sheet, local competition should mainly affect the lending decisions made by small and local banks as opposed to national banks.

Prediction 3a. After the crisis, higher volatility in the house price implies greater mortgage losses (i.e., foreclosures) in competitive mortgage markets; this relationship again diminishes as market concentration increases.

Prediction 3b. After the crisis, unemployment in the local economy would be worse for higher housing volatility. This relationship diminishes as the mortgage market becomes more concentrated.

Prediction 1 corresponds to Proposition 2, which states that the loan-to-income ratio increases with housing volatility but this relationship diminishes as the local mortgage market becomes more concentrated. Intuitively, this is because banks in competitive environment would be more willing to raise the loan-to-income ratio so that their loan performance is volatile and correlated with future house price movements. Prediction 2 extends Proposition 2 by emphasizing the fact that the local competition effect on lending decisions works through the bank's balance sheet, which yields a sharp prediction on the differential between banks that were vulnerable to local competition and those that were not. In particular, I compare lending decisions made by local and small banks with those made by large national banks. Prediction 2 derived from the risk shifting hypothesis suggests small and local banks would adjust their lending decisions based on local bank competition much more than national banks which usually hold a large and diversified portfolio of mortgages all over the country.

Predictions 3a and 3b relate the pre-crisis risk taking pattern to post-crisis outcomes. Prediction 3a essentially indicates that mortgage repayment after the crisis was more sensitive to volatility in the house price for competitive-lending markets than for concentrated-lending markets. This result is straightforward given that the response of lending standards to house price volatility was much stronger in competitive mortgage markets. Prediction 3b further looks at economic outcomes in the real sector. Since banks in competitive markets incurred severe financial distress after the housing price collapse, local real economic activities could also be disrupted. In particular, adverse financial conditions could affect local unemployment through the tightening of local credit conditions, e.g., Chodorow-Reich (2014). To capture the effect of negative credit-supply shocks, I look at local unemployment after the crisis by firm sizes and by industries. Details are included in later sections.

3. Mortgage Market and Data

3.1. Mortgage Market and Competition

In this paper, mortgage market is assumed to be local. Specifically, I assume that competition among banks in the local mortgage market is closely linked to the market power that affects lending decisions, and that the county-level measures of bank competition are good proxies for the competition that local banks are faced with[15]. This is largely accurate for the mortgage market in the U.S., even given the fact that the recent development of online platforms such as LendingTree.com has improved home buyers' ability to compare prices and search for better rates[16]. In fact, substantial evidence has been found suggesting that most borrowers only shop locally in the U.S. and that bank competition in the local mortgage market significantly affects mortgage lending. Using data from the Survey of Consumer Finances, Amel, Kennickell and Moore (2008) find that over 50% of households obtained mortgage loans from an institution that was less than 25 miles away from home. They find that the median household lived within just four miles of their primary financial institution and that 25% of households obtained mortgages just from this primary institution. Scharfstein and Sunderam (2014) show that measures of county-level mortgage market competition indeed capture the market power for banks. They find that these measures of bank competition strongly determine the markup in the loan term banks charge customers and predict

[15] Throughout this paper, I call all mortgage-issuing financial institutions "banks", while in the regressions, I control for the fraction of thrift institutions and commercial banks in the local mortgage market. For more discussions on different types of financial institutions, see Dagher and Fu (2011).

[16] Dinerstein, Einav, Levin and Sundaresan (2014) show that there is still heterogeneity in pricing for identical goods sold on the internet.

the pass-through of monetary policy. Various other studies have also shown that the average borrower only considered two loans while shopping for mortgages (Lacko and Pappalardo (2010)) and that local advertising affects the borrowing decisions of consumers (e.g., Gurun, Matvos and Seru (2013)). All the evidence listed above indicates that local bank competition in the mortgage market indeed determines the market power and profit margin for banks in the market. At the same time, metrics at the county level are reasonably accurate measuring the degree of local competition.

I follow the literature to measure local bank competition by the county-level Concentration Ratio (top-10 lenders) and the Herfindahl index as of 2000 (e.g., Scharfstein and Sunderam (2014)). The Concentration Ratio (C.R.) is the total market share of the top ten lenders in the county and the Herfindahl index (HHI) is defined as the sum of market share squared for all lenders in the county. A higher value in the Concentration Ratio and the Herfindahl index indicates greater bank concentration and less bank competition. To illustrate characteristics of bank competition in both the cross section and the time series, I plot in Figure 1 the evolution of the Concentration Ratio (top-10) at the U.S. county level from 1995 to 2005. The four lines in the figure are the quartiles of a total of 3185 counties according to their Concentration Ratio as of 1995[17]. One can see that over time, local mortgage markets have become more competitive, but the relative ranking of the Concentration Ratio has remained the same, suggesting that there is likely some friction in the background such as entry barriers. In this paper, I do not intend to address what drives the evolution of bank competition over time but only focus on the cross-section aspect of the discussion.

3.2. Mortgage Data

Mortgage loans were an asset commonly invested by financial institutions. According to data from the Call Report for commercial banks as of May 2006, real estate loans totaled 3.04 trillion U.S. dollars, which accounted for more than half of total loans and leases issued by banks. For the U.S. housing mortgage data used in this paper, I mainly rely on the Home Mortgage Disclosure Act (HMDA) database that records almost all mortgage loan applications[18].

For each loan application in a given year, the HMDA data contain information on whether the loan application was eventually approved, the type of the mortgage loan (e.g., home purchase or refinance), the loan amount, and the interest rate spread (available for HMDA after 2004). The data also has information on the lender of each loan application, including a lender identifier, the type of institution (e.g., commercial bank or thrift), and whether the loan was later securitized. On the information of the borrower, it reports the county, income and other personal information.

I use the HMDA data to construct measures capturing lending decisions by financial institutions.

[17] There are 3185 counties with data coverage in the Home Mortgage Disclosure Act (HMDA) database during the 1995-2005 period.

[18] The Home Mortgage Disclosure Act (HMDA) of 1975 require lenders that are above a certain size threshold to report detailed information for each loan application. This dataset is especially comprehensive in the recent decade which is the time period this paper focuses on.

I mainly rely on the loan-to-income ratio and the acceptance rate as my measures. I also distinguish lending decisions made by small/regional banks from those made by large national banks, using the lender identifier. To capture interest rate data, I construct the share of mortgage loans that have a high rate spread to measure the lending standards in the county. The HMDA data requires the report of loans with interest rate spread above the "prevailing rates at the time of application" by a certain threshold (e.g., 3% as in 2005) where the prevailing rates generally refer to the prime offer rate. These loans are usually riskier and they often involve subprime borrowers.

Using the HMDA data, I also construct county-level characteristics including the share of investment homes, share of thrift institutions, share of loans securitized, share of refinancing loans and etc.. To complement the riskiness measures of loans, I also construct the loan-to-value (LTV) ratio at the county level using survey data from Monthly Interest Rate Survey (MIRS).

3.3. Other Economic Data

For data on the house price, I use the S&P/Case-Shiller Home Price Index and the House Price Index provided by Zillow. The available data traces back to 1980. Using these data, I construct two measures related to the house price: house price volatility and house price cyclicality. I define local house price volatility as the percentage growth of the house price during the boom minus the percentage of house price change during the bust. Alternatively, I also use the measure for price cyclicality as in Palmer (2014) defined as $\sigma_i = \left(\frac{1}{T-1}\sum_{t=1}^{T}(\Delta HP_{it} - \Delta \bar{H}P_i)^2\right)^{1/2}$ for CBSA i between 1982 and 1996, constructed using quarterly house price data from 1982 to 1996. The housing supply elasticity measure is from Saiz (2010) which ranges from 0 to 5. I also construct the housing supply inelasticity measure, defined as $(5 - elasticity)/5$ so that the inelasticity measure ranges from 0 to 1. A higher inelasticity is associated with larger house-price fluctuations.

For employment data, I use county-industry-level data from Country Business Patterns (CBP) published by the Census Bureau. Employment changes from 2007 to 2009 can be calculated for different industries and for different establishment sizes. For bank failures, I use the list of failed banks published by the FDIC and hand-match the location of the banks' headquarter to the county code in my sample. For foreclosure data after the crisis, I rely on data from the U.S. Department of Housing and Urban Development (HUD). To construct county-level controls, I also use county-level population estimates and the wage rate from Quarterly Census of Employment and Wages from the U.S. Census Bureau. Complete summary statistics are reported in Table 1.

4. Empirical Analysis

The empirical analysis of this paper follows closely the theoretical predictions listed above. In the benchmark regression model, the dependent variable is various measures of the change in loan riskiness and the independent variables include the expected house price volatility and its interaction with local bank concentration. I especially focus on the boom period 2000-2005 in my analysis. The regression model is then given by

$$\textbf{(1)} \quad \Delta LoanRisk_i^{00-05} = \beta_0 + \beta_1 \text{HPVol}_i + \beta_2 \text{HPVol}_i \times \text{Concentration}_i + \beta_3 \text{Concentration}_i + \beta_4 X_i + \epsilon_i$$

where $\Delta LoanRisk_i^{00-05}$ measures the 2000-2005 change in loan riskiness for county i, HPVol_i is the expected house price volatility in the 2000-2011 housing cycle for county i, Concentration_i is the measure of bank concentration for county i and X_i includes a list of controls. For the analysis on post-crisis outcomes, I replace the left-hand-side variable with post-crisis economic outcomes, including the local foreclosure rate and unemployment rate.

A key empirical challenge is the identification of the expected house price volatility. In the next subsections, I discuss the identification strategy for my empirical analysis and address other related endogeneity concerns.

4.1. Identification Strategy

4.1.1. Identifying Volatility in the Local House Price

Features of the U.S. housing market make the identification possible, which is the key to this paper. Below I explain the identification in more details.

The local housing markets experienced multiple boom-bust cycles over the past decades, among which the 1982-1996 and the 2000-2011 cycles were the most notable ones. During the 1982-1989 housing boom, many U.S. metropolitan areas experienced real house price appreciation of over 15%, while more than half of these areas suffered real price declines in the 1989-1996 housing bust[19]. Similarly for the 2000-2011 housing cycle. Importantly, the house price in both episodes featured a very similar pattern of the cross-sectional heterogeneity. Glaeser, Gyourko and Saiz (2008) find that a key determinant of volatility in the local house price over these past housing cycles was local geography. In areas where land is limited for the building of new houses, e.g., San Francisco and Seattle, the house price in the booms rose sharply, since shocks were instantaneously reflected in the price, but experienced sharp drop later. On the contrary, in areas where much land was available for new buildings, e.g., Houston and Atlanta, any upward pressure on the house price was quickly absorbed by the building of new houses, so the house price remained flat throughout the cycles. They show that bubbles were much more likely to occur in areas with inelastic housing supply than elastic-supply areas for both housing episodes. That is to say, the housing supply elasticity differentiates the long-run volatility in the house price across U.S. geographic locations during both the 1982-1996 and the 2000-2011 housing cycles. In this paper, I use housing supply elasticity, constructed by Saiz (2010) using satellite data, to instrument for the long-run volatility in the house price using historical data which naturally formed a prior for the local house price volatility going forward. I also confirm that the 2000-2011 followed exactly the same pattern.

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See Glaeser, Gyourko and Saiz (2008) for further discussions.

To show this pattern graphically, Figure 2 plots the detrended house price index from 1982 to 1996 of quintiles in my sample according to their housing supply elasticity[20]. One can see that, consistent with the findings in Glaeser et. al. (2008), areas with inelastic housing supply (black and rose-red lines) experienced much more volatile house price movements than elastic-supply areas (red, orange and green lines). In inelastic-supply areas, the (detrended) local house price had a substantial increase before 1989 but later the price reverted dramatically. For elastic-supply areas, the growth rate of local house price was roughly the same as the local CPI rate. The 2000-2011 housing cycle followed exactly this long-run pattern of house price. Figure 3 plots the home price index for this housing cycle where we can see the very similar pattern that inelastic-supply areas had much more dramatic boom-bust cycles than elastic-supply areas.

To further illustrate that the effect of housing supply elasticity on local house price was through the quantity constraints of new houses, I plot the number of new building permits issued between 2000 and 2005 at the CBSA level in Figure 3. Comparing this figure with the one for home price, one can see that the order of these five lines has flipped: in elastic areas where housing price was flat, the number of new building permits grew substantially faster than in inelastic areas. This evidence further confirms that housing supply inelasticity measures the limitation on house quantity that was reflected in the local house price. I also plot the evolution of local real wage rates at the county level in Figure 3 Panel C where there is hardly any difference among these groups, suggesting that economic fundamentals over this time period did not differ significantly with respect to housing supply elasticity. For my analysis, even if there were potential differences between inelastic-supply and elastic-supply areas over the past housing cycle, it would not bias my estimates for the coefficient β_2 in regression (1), which is the focus of my empirical analysis, as long as those differences are present across bank competition levels. Time-series confounding factors, such as the this-time-is-different syndrome (Reinhart and Rogoff (2011)), would only make the estimate on coefficient β_1 harder to interpret, but would not affect the estimate or interpretation of the coefficient β_2.

In the rest of paper, I also transform the supply elasticity of housing that ranges from 0 to 5 into the inelasticity measure defined as $inelasticity = (5 - elasticity)/5$. This housing supply inelasticity measure now ranges from 0 to 1 and a higher value of inelasticity indicates a greater house price volatility.

4.1.2. Addressing the Endogeneity of Bank Competition

Another concern is that bank competition can be endogenous as well. First, for most of dependent variables that I study, I use the percentage change or the long difference between 2000 and 2005. Doing so would take out the "level" effect of bank competition. For the change in economic variables over this time period, I show that bank competition in the mortgage market, measured by the Herfindahl index and concentration ratio as of 2000 in the county, is in fact un-

[20] As inflation was high during that period, a national trend is subtracted for all groups.

correlated with various measures of economic fundamentals. Panel B in Table 2 shows the results of regressing the 2000-2005 change of various variables on Concentration Ratio. We can see that insignificant correlations are found for these variables. I also show in Table 3 Column (3) that bank concentration also did not predict house price volatility after controlling for local geography. In addition, the relative ranking of bank concentration has stayed the same over time (Figure 1) which suggests that the cross-sectional difference in competition was unlikely driven by factors specific to the recent housing cycle. For robustness, I also use concentration measures as of 1995.

To formally eliminate the concern of omitted variables, I show robustness checks including county fixed effects. Specifically, I look at how two otherwise similar banks have behaved differently in the *same* county in relation to the competition they face. More details are included in the Online Appendix of this paper[21].

The joint distribution of the housing supply elasticity measure and the bank concentration measure is summarized in Panel A of Table 2. We can see that the inelasticity has a similar distribution and range for the greater and lower halves of the Concentration Ratio, meaning that the interaction term in the regression is meaningful.

4.2. First Stage: Historical House Price Volatility and Housing Supply Inelasticity

The first-stage model regresses historical house price volatility on local housing supply inelasticity constructed by Saiz (2010). The cross-sectional variation in historical house price volatility forms the prior about future house price volatility going forward. To measure historical house price volatility, I focus on the 1982-1996 housing cycle and look at in particular how the local house price had grew from 1982 to its peak in 1989 and later declined from 1989 to 1996, as in Glaeser, Gyourko and Saiz (2008). For each county i, I construct a measure $HPVol_i$ that captures how volatile the local house price was during this boom-bust cycle, defined as the price growth during the boom minus the price change during the bust. For the 1982-1996 housing cycle, I define $HPVol_i = \ln(HPI_{i,1989}/HPI_{i,1982}) - \ln(HPI_{i,1996}/HPI_{i,1989})$ where HPI_y is the house price index in year y[22]. A higher value of $HPVol$ is associated with a greater growth of the house price from 1982 to 1989 and a greater decline in house price from 1989 to 1996, indicating a more dramatic boom-bust cycle. This measure captures both the potential upside and the downside that banks would need to take into account in making mortgage lending decisions[23].

Result of the first-stage regression is presented in Table 3 Column (1). I also repeat the same exercise by replacing the house price volatility from 1982 to 1996 with the house price volatility from 2000 to 2011. Results in columns (1)-(3) show that, consistent with Glaeser, Gyourko and

[21] To access the online appendix, visit http://www.princeton.edu/%257Exf/files/JMPOA-FENG.pdf

[22] For counties where the house price in the early 1980s was missing, I extrapolate the house price pattern based on the change from the first available year to 1989 assuming a linear trend.

[23] Note that by construction, this measure $HPVol$ can be negative when the growth in house price from 1996 to 1989 exceeds the growth from 1982 to 1989. Such low values of $HPVol$ indicate exactly the case where the house price had low volatility in the national housing cycle and there was no apparent housing bubble in those areas.

Saiz (2008), the inelasticity of housing supply predicted strongly the volatility of the local house price both for the 1982-1996 and the 2000-2011 housing cycles. In column (4), I regress the wage growth from 2000 to 2005 on housing supply inelasticity where the correlation is very weak and statistically insignificant. This means that it is unlikely that the economic fundamentals were significantly different for counties with different housing supply inelasticities. These relationship were further illustrated in Figures 2 and 3. In Figure 2 and Panel A of Figure 3, I plot the detrended house price from 1982 to 1996 and the house price index from 1988 to 2011 of quintiles of CBSA areas by housing supply elasticities.

Alternatively for robustness, I also construct the house price cyclicality measure following Palmer (2014), which is defined as $\sigma_i = \left(\frac{1}{T-1}\sum_{t=1}^{T}(\Delta HP_{it} - \Delta \bar{H}P_i)^2\right)^{1/2}$ for CBSA i and time ranges from 1982 to 1996 at the quarterly frequency. This measure captures how house price moves in the local area relative to its long-run trend. Robustness checks treating this measure as exogenous are also presented in later sections.

4.3. Lending Standards, House Price Volatility and Bank Competition

In this section, I present the main empirical analysis using the predicted house price volatility obtained from the previous first-stage regressions.

4.3.1. Empirical Model

According to the theoretical model, banks have the incentive to lower lending standards (e.g., raising the loan-to-income ratio) when faced with volatility in the local house price. Moreover, this incentive would be the strongest in markets where bank competition is high. A higher concentration of the local mortgage market would be associated with less risk taking behaviors in response to volatility in the house price. To formally test this hypothesis, one would perform the following regression.

$$\textbf{(1)}\quad \Delta LoanRisk_i^{2000-2005} = \beta_0 + \beta_1 HPVol_i + \beta_2 HPVol_i \times Concentration_i + \beta_3 Concentration_i + \beta_4 X_i + \epsilon_i$$

where $\Delta LoanRisk_i^{2000-2005}$ is the change in loan riskiness measure in county i from 2000 to 2005, $HPVol_i$ is the house price volatility predicted from the first stage regression, $Concentration_i$ is the county-level mortgage market concentration and X_i is a list of county controls. Regressions are all weighted by county population as of 2000 and standard errors are clustered at the CBSA level. For the depend variable, I mainly use two measures at the county level constructed using loan-level data: the loan-to-income ratio and the acceptance rate. The 2000-2005 change in the loan-to-income ratio is the change in natural log from 2000 to 2005 for each county's average loan-to-income ratio[24]. To compute the acceptance rate (i.e., one minus the denial rate) in a given year for a county, I divide the total number of loans approved in that county by the total number applications in that county for that year. The 2000-2005 is just the difference between the 2005

[24]Change in the loan-to-income ratio itself instead of ln(LTI) can be used and results are similar.

and the 2000 acceptance rates for that county. The loan-to-income ratio follows more closely with the theoretical model as it measures the the exposure to future house price volatility more directly. For the measure of bank concentration, I use the top-10 Concentration Ratio and leave the results using the Herfindahl index to the robustness section. Alternative, I also measure loan riskiness by the loan-to-value (LTV) ratio and the fraction of high-rate-spread loans, and measure bank concentration using the Herfindahl index (HHI). Results of these alternative measures are included in the robustness section as well.

(1a) $\Delta \ln LTI_i^{2000-2005} = \beta_0 + \beta_1 HPVol_i + \beta_2 HPVol_i \times Concentration_i + \beta_3 Concentration_i + \beta_4 X_i + \epsilon_i$

(1b) $\Delta AccRate_i^{2000-2005} = \beta_0 + \beta_1 HPVol_i + \beta_2 HPVol_i \times Concentration_i + \beta_3 Concentration_i + \beta_4 X_i + \epsilon_i$

The theoretical model has direct predictions on the signs of coefficients β_1 and β_2. The coefficient β_1 on the level term of house price volatility would be positive, indicating that lending standards would be lowered if house price volatility increases. The key coefficient of interest is β_2 on the interaction term between house price volatility and bank concentration. The theoretical prediction implies a negative β_2, meaning that the tendency to lower lending standards in response to house price volatility would decrease as the mortgage market becomes more concentrated (i.e., less competition).

The theoretical risk-shifting framework has even sharper implications. Since the competition effect on risk taking behavior goes through banks' balance sheet, we would see also see different estimates of β_1 and β_2 for banks that are affected by local competition differently. In particular, the effect of local competition would be particularly strong for lending decisions made by small and regional banks, but should be much less significant for national banks that had a large portfolio across many states. That is to say, we would see a much stronger estimate for β_2 for small and local banks than for national banks. To formally test this, I construct separately the change in lending standards of loans issued by local/regional banks and those issued by national banks, where I define national banks as those that had mortgage lending activities in more than fifteen states as of 2000 and local/regional banks as the rest[25]. I then run the above regression separately for local and regional banks and for national banks separately. The difference in coefficients is also tested by the inclusion of an indicator variable $\mathbf{1}\{\text{National Bank}\}$ representing the observation is the change in lending standards by national banks and its interaction with other variables. To rule out the possibility that there has been compositional changes between mortgages issued by small banks and by large banks, I plot in Figure OA1 in the Online Appendix the evolution of the share of national banks at the county level. The four lines in the figure are the quartiles of a total of 3185 counties according to their Concentration Ratio as of 1995. The share of national banks increased after the 1995 for all groups of counties, partly due to the wave of bank mergers after

[25] I define banks that issued mortgage loans in more than fifteen states and the total number of loans exceeded 10,000 reported in HMDA database as of 2000. The rest of the banks and new entrants are defined as local and regional banks. Results are robust to defining national banks as issuing in more than ten or twenty states.

the Riegle-Neal Act of 1994. We can see that after 2000, the share of national banks remained stable and exhibited similar patterns across the four quartiles of counties by bank competition, suggesting that the differential in coefficients would not be a result of the different compositional change in customers between local/regional banks and national banks.

4.3.2. Main Regression Results

Results on the loan-to-income ratio are reported in Table 4. In columns (1)-(3), the dependent variable is the 2000-2005 (natural-log) change in the loan-to-income ratio for mortgage loans issued by *local* and *regional* banks. One can see that the estimate of β_1 on local house price volatility is positive and the estimate of β_2 is significantly negative. This suggests that local and regional banks responded to volatility in the house price by lowering lending standards (i.e., increasing the loan-to-income ratio), and such response was very strong in competitive mortgage markets but weak in concentrated markets. For the most concentrated mortgage markets where the concentration ratio is above 0.8, the correlation between house price volatility and the change in lending standards is close to zero. In these regressions, I also control for real economic factors (e.g., the change in wages and employment) and mortgage market variables (e.g., the share of securitization and thrift institutions). We can see that the regression results are robust to the control of various factors.

In columns (4)-(6), I repeat the same exercise but replace the dependent variable with the 2000-2005 (natural-log) change in the loan-to-income ratio for mortgages issued by *national* banks. We see that the coefficient β_2 becomes much weaker in statistical significance. In column (6) where I control for various factors, we see that the estimate on β_2 becomes insignificant, indicating that the change in lending standards by national banks is not significantly affected by local competition. To formally test the differential in the estimates of β_2 between local/regional banks and national banks, I include both observations for local banks and those for national banks and interact these coefficients of interest with an indicator variable $\mathbf{1}\{\text{National Bank}\}$. In column (7), we see that the coefficient on the interaction term (HPVol $\times$ Concentration) has an estimate of -8.36 and is highly significant statistically. Moreover, the coefficient on the term (HPVol $\times$ Concentration $\times$ $\mathbf{1}\{\text{National Bank}\}$) has an estimate of 4.48 and is also statistically significant, suggesting that for national banks the coefficient β_2 is reduced by more than half. In column (8) where I also include various controls, we can see that national banks reduces the estimate of β_2 (-6.32) by more than two thirds (4.48). This exercise confirms that the differential in estimates of β_2 for national banks versus local banks is highly significant, both statistically and economically.

Table 5 reports the regression results on the change in the acceptance rate. In columns (1)-(3), the dependent variable is the 2000-2005 change in acceptance rate for loan applications of local and regional banks. A higher acceptance rate indicates more lax lending standards. One can see that the coefficient β_1 on house price volatility is positive and the coefficient β_2 on the interaction term (HPVol $\times$ Concentration) is negative and statistically significant. This implies that higher bank concentration reduces the incentive of local banks to respond to local house price volatility, a prediction from the theoretical model. In terms of magnitude, when bank concentration reaches 0.8 (i.e., the highest quintile), the response to house price volatility is close to zero, a result almost identical to the analysis above using the loan-to-income ratio as the measure for loan riskiness. In columns (4)-(6), I replace the dependent variable with the 2000-2005 change in the acceptance rate for mortgage applications by national banks. In this exercise, the coefficients β_1 and β_2 both become statistically insignificant, meaning that the loan approval decisions made by national banks were minimally affected by either local house price volatility or local bank competition. In columns (7)-(8), I formally test the differential in these coefficients. The coefficient on (HPVol $\times$ Concentration $\times$ $\mathbf{1}\{\text{National Bank}\}$) is 1.81 which wipes out most of the effect of β_2 on the term (HPVol $\times$ Concentration) (-2.79 or -2.20).

In sum, this section presents regression results on the relationship among the change in lending standards, house price volatility and local mortgage market competition, where the change in lending standards is measured by the natural-log change in loan-to-income ratio from 2000 to 2005 or the change in acceptance rate. The findings in this analysis show that lending standards were substantially lowered in response to volatility in the local house price for high-competition markets. More importantly, this competition effect only mattered for the lending decisions made by local and regional banks, but was insignificant for national banks. These results are very consistent with the theoretical predictions.

4.3.3. Combining National and Local Banks

Given the strong differential in the effect of local bank competition between national banks and local banks , I also check if the overall effect of bank competition is still significant. To formally show this, I combine national and local banks together for each county and perform regressions (1a) and (1b).

Table 6 reports the regression results. In columns (1)-(3) of Table 6, I use the 2000-2005 *percentage* change in the loan-to-income ratio for the county as the dependent variable. One can see that the coefficient β_1 on house price volatility is positive and the coefficient β_2 on the interaction term between house price volatility and bank concentration is strongly negative. This means that the relationship between the relax of lending standards and house price volatility diminishes as the market becomes concentrated. This competition effect is robust to the inclusion of various controls. In columns (4)-(6), I repeat the same exercise but replace the dependent variable with the change in *value* of the loan-to-income ratio, instead of the percentage change. We can see that very similar patterns can be obtained where $\beta_1 > 0$ and $\beta_2 < 0$. For the change in acceptance rate, columns (7)-(8) report the regression results. One can see again that a high bank concentration can reduce the response of the acceptance rate to house price volatility entirely.

The results for the regressions combining both national and local banks suggest that in the aggregate, we also see strong effects of bank competition in inducing stronger response to house price volatility. One standard-deviation increase in the predicted house price volatility ($s.d. \approx 0.05$) is associated with at least a 10% or 0.20 increase in the loan-to-income ratio and a 1.5% increase in the acceptance rate for the most competitive counties (i.e., lowest quintile by Concentration Ratio 0.45). For the most concentrated mortgage markets (i.e., highest quintile by Concentration Ratio 0.65), the relationship between the change in lending standards and house price volatility is reduced by more than half.

Results for the loan-to income ratio are illustrated graphically in Figure 4. The upper graph plots the percentage change in the loan-to-income ratio over time. Panel A plots the evolution of the percentage change of LTI from 1998 to 2005. The blue and red solid lines are inelastic-supply and elastic-supply areas with a competitive mortgage market, respectively, while the orange and green dashed lines are inelastic-supply and elastic-supply areas with a concentrated mortgage market. We can see a much larger difference between the two solid lines than between the two dashed line, suggesting that the response of LTI to house price volatility was much stronger in competitive markets than in concentrated markets. Panel B plots the same graph with the absolute change in the loan-to-income ratio in the 789 U.S. counties in the sample from 2000 to 2005 where similar conclusions can be drawn.

4.4. Post-Crisis Economic Outcome

In this section, I examine whether the risk taken by banks before the crisis had direct consequences after the crisis. In particular, I look at whether the pre-crisis lowering of lending standards resulted in worse economic outcomes including home foreclosures and bank failures. I also investigate whether the real economy especially real-sector employment suffered more in markets where the bank took more risk before the crisis.

4.4.1. Foreclosure Rate and Bank Failure Rate: Some Stylized Facts

Given that banks in competitive mortgage markets lowered lending standards in response to house price volatility, one would expect that the foreclosure rate should be more strongly associated with the house price change for competitive markets and less so for concentrated markets. To formally show this result, I perform a regression similar to the ones for pre-crisis lending standards but replace the dependent variable with the foreclosure rate in each county. The regression is given by

(2a) $$ForeclosureRate_i = \beta_0 + \beta_1 HPVol_i + \beta_2 HPVol_i \times Concentration_i + \beta_3 Concentration_i + \beta_4 X_i + \epsilon_i$$

where the foreclosure rate is the number of foreclosed homes per 100 population from 2007-2008, $HPVol_i$ is the house price volatility, $Concentration_i$ is the concentration ratio of county i as of 2000, and X_i county controls. To measure house price volatility, I use either the realized housing volatility $HPVol = \ln(HP_{06}/HP_{00}) - \ln(HP_{11}/HP_{06})$ (treating it as exogenous) or the predicted house price volatility from the first-stage regression on historical house prices. The regression is weighted by county population as of 2000 and standard errors are clustered at the CBSA level. Naturally, one would expect that the coefficient β_1 is positive meaning that higher house price volatility should be associated with higher foreclosure rate and that β_2 is negative suggesting that higher bank concentration reduces the sensitivity of home foreclosures to house price volatility.

Table 7 reports the regression results. In columns (1)-(3), I use the predicted house price volatility from the first stage. One can see that the coefficient β_1 on HPVol is positive and that β_2 is negative and highly significant. This suggests that, for U.S. counties with a concentrated mortgage market, the vulnerability of home foreclosures to house price volatility is close to zero. Moreover, this regression result is robust to the inclusion of state fixed effects as shown in column (3). In columns (4)-(6), I repeat similar exercises using the realized house price volatility over the 2000-2011 housing cycle where house price volatility is defined as $HPVol = \ln(HP_{06}/HP_{00}) - \ln(HP_{11}/HP_{06})$. One can see a similar pattern that the coefficient β_1 is positive and β_2 is negative. The units between these two exercises are different, but they show a consistent magnitude in terms of how concentration in the mortgage market reduces the sensitivity of local foreclosures to house price volatility. For areas where the mortgage market was highly competitive (i.e., the concentration ratio is 0.45 at the lowest quintile), the coefficient β_1 on house price volatility is 0.03, meaning that one standard deviation increase in the realized house price volatility ($s.d. \approx 0.34$) implies a 1% higher foreclosure rate during 2007-2008. Panel A in this Figure 5 plots this relationship. The left graph in Panel A plots foreclosure rate (2007Q1-2008Q2) against housing supply elasticity for U.S. counties with a competitive mortgage market and the right graph plots counties with a concentrated mortgage market. One can see that this relationship in competitive mortgage markets is stronger than in concentrated markets.

The next question is whether we see bank failures followed the same pattern. To answer this question, I show some stylized facts on the bank failure rate after the crisis. From 2008Q1 through 2014Q3, there were nearly 500 failures of U.S. banks reported by the FDIC. Most of these banks were later acquired by other banks that assumed the deposit liabilities. As banks have failed for many reasons beyond poor mortgage loan performance, it is impossible to pin down the exact channel that caused these bank failures, without investigating more into banks' balance sheet. Therefore, the relationship shown here is somewhat stylized.

To show the interaction between house price volatility and bank competitive more clearly, I group all counties in my sample by competition {high, low} and house supply elasticity $\{0 - 1, 1 - 2, 2 - 3, 3 - 5\}$, where a lower value for supply elasticity is associated with higher house price volatility. For each group of counties, I calculate (1) the number of failed banks where the headquarter falls into that group as reported by FDIC and (2) the total number of banks that had mortgage lending activities in that group of counties as of 2005 as reported by HMDA. Then I compute the bank failure rate for each group of counties by dividing the number of failed banks by the total number of banks that had lending activities. Figure 5 Panel B plots the bank failure rate for each group of counties.

On the left graph of Figure 5 Panel B are counties with high mortgage competition. We can see that the bank failure rate is strong associated with housing supply inelasticity, a proxy for housing price volatility. In the most inelastic-supply areas (i.e., elasticity between 0-1), 3% of the banks that lent in those areas failed after the crisis. This number gradually drops as elasticity rises (i.e., house price volatility falls) and is well below 1% for the lowest group by house price volatility. On the right graph of this figure are counties with low mortgage competition. One can see that across different groups of supply elasticity, the bank failure rate remains around or below 1%. This means that higher volatility in the house price did not strongly imply a higher bank failure rate, unlike for mortgage markets with high bank competition.

4.4.2. Unemployment in the Real Sector

In the previous section, we see that areas where banks lowered lending standards also experienced greater foreclosure rates and bank failures. Given the special role that banks play in the real economy, these adverse financial shocks could be felt by other sectors in the economy as well. In particular, did areas that had lowering of lending standards also experience worse employment in the real sector? The answer to this question is especially important for the understanding of the causes of the severe decline in employment in the Great Recession. In this section, I study this question by looking at the change in employment in the real sector after the crisis.

For each county, I look at the employment change from 2007 to 2009 in sectors not related to finance, real estate and construction. The regression model is given by

$$\textbf{(2b)}\ \ \Delta \ln Emp_i^{07-09} = \beta_0 + \beta_1 HPVol_i + \beta_2 HPVol_i \times Concentration_i + \beta_3 Concentration_i + \beta_4 X_i + \epsilon_i$$

where $\Delta \ln Emp_i^{07-09}$ is the percentage change in employment from 2007 to 2009 in county i, $HPVol_i$ is the house price volatility predicted from the first stage, $Concentration_i$ is the HHI measure for bank concentration for county i, and X_i includes county controls. This specification is the same as the regressions above and just replaces the dependent variable with the change in employment. The coefficients of interest are β_1 and β_2. If a higher house price volatility is associated with worse employment outcomes, then β_1 should be negative. Moreover, if bank concentration reduces this relationship, we would then have $\beta_2 > 0$. A negative β_1 and a positive β_2 imply that the worsening of financial conditions was transmitted to the real economy and that the effect was the most significant in areas with a competitive mortgage market. For the top 5% of counties with bank concentration $HHI > 0.1$, the share of employment in the industries of interest as a percentage total population experienced large fluctuations from 2007 to 2009[26]. Therefore, in my analysis, I also show results after dropping the top 5% of counties where $HHI > 0.1$, reducing the number of counties from 789 to 751 in my sample.

Table 8 reports the regression results. Columns (1)-(2) report the regression results using all counties and columns (3)-(9) drop the top 5% of the sample where bank concentration HHI exceeds 0.1 so less noise is introduced in the employment data. In columns (1)-(3), one can see

[26]This is partially due to measurement errors in employment data indicated by the noise flag in the County Business Patterns (CBP) dataset. Counties with extremely high bank concentration (HHI>0.1) tend to have smaller population and fewer number of enterprises. The CBP dataset is required to mask entries where the number of enterprises is too low for confidential reasons.

that the coefficient β_1 on house price volatility is negatively while β_2 is strongly positive, a pattern predicted above. According to the estimates in column (3), for the most competitive counties, a standard deviation increase in the predicted house price volatility ($s.d. \approx 0.05$) implies the drop in employment by 1.5%, whereas for the most concentrated counties, the effect of house price volatility on employment diminishes to zero. In column (4), I include the debt-to-income ratio 2006 as a control. Doing so is to take into account the fact that some of the drop in employment, especially for non-tradable sectors such as restaurants and grocery stores, was due to the balance sheet of local households (Mian and Sufi (2014)). The inclusion of the debt-to-income ratio does not alter the result on the coefficient β_2, meaning that bank concentration still reduces significantly the sensitivity of the drop in employment to local house price volatility. Column (5) includes other controls at the county level such as the shares of finance and non-tradable industries. Similar estimates are obtained.

To further confirm that the effect of worsening financial conditions in competitive markets when house price volatility is high, I also look at the change in employment by establishment sizes[27]. In columns (6) to (9), I separately look at firms with number of employees below 20, between 20 and 50, between 50 and 100, and above 100[28]. One can see in columns (6)-(7) that, for smaller-sized establishments, the coefficients β_1 and β_2 are significant, meaning that a higher house price volatility incurs a greater loss in employment for these establishments and that higher bank concentration reduces such relationship. For firms of larger sizes (columns 8 and 9), the estimates on β_1 and β_2 are overall statistically insignificant, suggesting that larger-sized firms are less subject to the worsening of financial conditions[29]. This differential between small and large firms is consistent with the fact that smaller-sized firms are the most vulnerable to adverse financial shocks.

One potential concern with this analysis is that local demand might have also played a role on local employment. The volatility in house price could importantly alter the balance sheet of local households. For example, there is potential concern that competition in the mortgage market might induce more defaults during the crisis and could either lower or raise employment[30]. To address this concern, I divide industries into tradable and non-tradable as in Mian and Sufi (2014). Figure 5 Panel C summarizes the result for this robustness check analysis where I plot the change in tradable employment for establishments fewer than 100 employees. The left panel displays the relationship between the change in tradable employment from 2007 to 2009 with housing supply elasticity for counties with a competitive mortgage market while the right panel of this figure plots this relationship but for concentrated markets. One can see that the relationship between the change in employment and housing supply elasticity vanishes as the market becomes more concentrated, a result consistent with the predictions and other findings described above.

[27] A limitation of this approach is that the CBP dataset does not track firms.

[28] Firms of size above 500 did not exist in many of the counties in my sample. Therefore, I restrict my attention to firms below size 500.

[29] The differential between small and large firms is also statistically significant (unreported).

[30] Competition in the mortgage markets might induce more home foreclosures that had negative externalities on the real economy, so it might lower employment. Alternatively, the option to default for those households might help more households from indebtedness which might instead raise employment.

More details are included in the Robustness section.

5. Robustness and Discussion

5.1. Alternative Measures for Bank Competition and Riskiness of Loans

In the previous sections for the analysis on bank risk taking, I measure local bank concentration using the top-10 Concentration Ratio which is the total market share of the top-10 lenders. In this section, I show results using the Herfindahl index (HHI) at the county level as of 2000 for robustness. I also use alternative measures for the riskiness of loans, namely the share of high-interest mortgages and the loan-to-value (LTV) ratio.

The Herfindahl index is computed as the sum of squares of market shares for all financial institutions that have lending activities in a county. A higher value of HHI indicates more bank concentration and less competition. The regression models using the HHI are given by

(1c) $\Delta \ln LTI_i^{2000-2005} = \beta_0 + \beta_1 HPVol_i + \beta_2 HPVol_i \times HHI_i + \beta_3 HHI_i + \beta_4 X_i + \epsilon_i$

(1d) $\Delta AccRate_i^{2000-2005} = \beta_0 + \beta_1 HPVol_i + \beta_2 HPVol_i \times HHI_i + \beta_3 HHI_i + \beta_4 X_i + \epsilon_i$

where the dependent variables are the percentage change in the loan-to-income ratio ($\Delta \ln LTI$) from 2000 to 2005 in county i and the change in the acceptance rate ($\Delta AccRate$), $HPVol_i$ is the house price volatility of county i predicted in the first stage, HHI_i is the Herfindahl index in county i as of 2000, and X_i includes a list of county controls. Similar to the regressions using the Concentration Ratio as the measure for bank concentration, we would expect to see a positive estimate for β_1 and a negative coefficient β_2.

Table 9 reports the regression results for regression (1c). In columns (1)-(3), the change in lending standards for local and regional banks is used as the dependent variable. One can see that the estimate for β_1 is positive and significant while the coefficient β_2 is strongly negative. This indicates that lending standards were lowered in response to volatility in the house price, but a higher bank concentration level reduces this lowering of standards. Columns (4)-(6) repeat the same exercise but use the change in loan-to-income for national banks as the dependent variable. One can see that the coefficient on the interaction term β_2 is much less significant statistically, suggesting that the local competition effect on risk taking was insignificant for national banks. In column (7)-(8), I test the difference in estimates for β_2 between local and national banks. One can see that the coefficient on the term (HPVol $\times$ HHI $\times$ $\mathbf{1}\{$National Bank$\}$) is positive.

For regression (1d), Table 10 reports the results. Again, columns (1)-(3) use the change in the acceptance rate for local and regional banks while columns (4)-(6) use that for national banks. One can see a similar pattern that the coefficient β_2 is much more significant for local/regional banks than for national banks. Columns (7)-(8) include the indicator variable for national banks and we can see that the coefficient on the term (HPVol $\times$ HHI $\times$ $\mathbf{1}\{$National Bank$\}$) (around 14.4) wipes out most of the effect of β_2 (between -16.29 and -13.26). These results are very consistent with the regression results obtained by using the Concentration Ratio.

I also use two alternative measures for lending decisions: (1) the share of loans with high spread in the interest rate and (2) the percentage change in the loan-to-value (LTV) ratio. Starting in 2004, the Home Mortgage Disclosure Act (HMDA) requires all mortgage-issuing financial institutions to report the interest rate of each mortgage if the rate spread is 3% above the prime offer rates. These loans are generally riskier and likely involve subprime borrowers. For each county, I construct the share of mortgages that have high spread in the interest rate as of 2005 to measure the riskiness of loans. I am not able to construct the 2000-2005 change in the share for each county due to data limitation. However, I argue that this measure is relatively accurate to measure the change in lending standards. This is because the share of subprime mortgages out of total mortgage origination was very low nationally in 2001 (between 2.5%-7.5% depending on methods of estimation), but only rocketed after 2002-2003 reaching 25% in 2005-2006. Therefore, the 2005 share of high-interest mortgages itself captures mainly the change from 2000 to 2005. For the loan-to-value ratio, I construct the average change from survey data between 2001 and 2005[31]. Note that there is a strong negative correlation between the 2000-2005 change in LTV and the house price volatility, as the house price term mechanically enters the LTV ratio. Therefore, the focus of the analysis is on the interaction term β_2 between house price volatility and bank concentration, while the coefficient β_1 on the house price volatility is more difficult to interpret.

The regression results are reported in Table 11. In columns (1)-(4), the left-hand-side variable is the share of mortgage loans that have high spread in the interest rate ($>$ 3% relative to the prime offer rate). One can see in column (1) that the estimate on β_1 is positive, meaning that a higher house price volatility generally implies a greater fraction of high-risk borrowers. The coefficient β_2 on the interaction between house price volatility and bank concentration is strongly negative, suggesting that the relationship between share of high-risk borrowers and house price volatility diminishes as the mortgage market becomes concentrated. In columns (2)-(4), I included various controls and the results remain similar. Columns (5)-(7) use the 2000-2005 percentage change in the average loan-to-value ratio for each county as the dependent variable. In column (5) where I look at the relationship between the change in LTV with house price volatility, there is a mechanical negative relationship. This is because the house price mechanically enters as the denominator in the LTV metric. However, we can still see in columns (6)-(7) that we consistently have negative β_2 estimates.

In sum, this section uses alternative measures for bank concentration (e.g., the HHI) and for loan riskiness (e.g., high-spread mortgage share, LTV). Regression results are robust. In the Online Appendix, I also show additional robustness results including dropping loans issued by thrift institutions, securitized or refinancing loans and splitting the sample into groups according

[31] The data source for loan-to-value ratio is the Monthly Interest Rate Survey (MIRS). The data is available at the zip-code level. I construct the county-level data by properly weighting zip-code observations by the population.

to their bank concentration levels.

5.2. Treating House Price Volatility as Exogenous

In most of the analysis above, I use housing supply elasticity to instrument for the long-run volatility in the house price. In this section, for robustness checks, I treat the house price volatility as exogenous and observable at the time of making loan decisions. I repeat regressions similar to the ones above but simply replace the predicted house price volatility with the actual ones. I present the regression results in Table 12. To measure the realized house price dynamics, I use four measures: the realized house price volatility from 1982 to 1996 (columns 1 and 2), the realized house price cyclicality from 1982 to 1996 (columns 3 and 4), the house price growth from 2000 to 2005 (columns 5 and 6), and the realized house price volatility during 2000-2011 (columns 7 through 10). The reason to include the house price growth from 2000 to 2005 is that this measure is observable at the time of bank making lending decisions. The focus of the regression analysis is still the coefficient β_2 in regression (1).

One can see in Table 12 that regressions of all specifications yield similar results. The coefficient β_1 on house price volatility/cyclicality is positive and the coefficient on the interaction term β_2 is negative. This suggests that bank concentration reduces the response of lending standards to house price volatility. For columns (9) and (10), I include the indicator $\mathbf{1}\{\text{National Bank}\}$ and its interaction with other terms. The regression results in these two columns show that β_2 on (HPVol$\times$ Bank Concentration) is negative, while the coefficient β_3 on HPVol$\times$Bank Concentration$\times\mathbf{1}\{\text{NationalBank}\}$ is strongly positive. This is consistent with the results shown previously, suggesting that only lending decisions by local banks are subject to local competition.

In sum, the findings in this subsection treating the 2000-2011 house price volatility as exogenous show consistent results as using an instrument for the long-run house price volatility. These consistent results show that instrumenting for the long-run volatility yields an accurate enough estimate for the house price volatility that actually happened in the 2000-2011 housing cycle. In addition, the empirical results are shown to be robust to various specifications and measures.

5.3. Bank Competition Measures as of 1995

As discussed above, one way to address the endogeneity of bank competition is to construct competition measures before the housing cycle. Doing so would rule out the possibility that factors specific about the 2000-2011 housing cycle changed how banks compete in certain locations. The measure I use for this analysis is the county-level Concentration Ratio as of 1995.

Regression results are reported in Table 13. In columns (1)-(2), the dependent variable is the 2000-2005 percentage change in the loan-to-income ratio at the county level. We can see that the coefficient β_1 on house price volatility is positive while the coefficient β_2 on the interaction term between house price volatility and bank concentration is strongly negative. This is consistent with all regressions presented above that bank concentration reduces the response of lending standards to house price volatility. In columns (3)-(6), I look at the change in lending standards for local banks and national banks separately. Columns (3)-(4) look at the change in acceptance rate from 2000 to 2005 where the indicator for national banks is included. Again, we can see that β_1 on house price volatility is positive and β_2 on (HPVol×Concentration) is negative. More importantly, the estimate for the coefficient β_3 on (HPVol×Concentration×$\mathbf{1}${National Bank}) is positive, meaning that the magnitude of β_2 is almost entirely offset for national banks. This result is consistent with the findings in the previous sections. Columns (5)-(6) report the same exercise but look at the percentage change in the loan-to-income ratio. While the estimates on β_3 are less statistically significant, we see similar signs of coefficients as previous exercises.

5.4. Discussion

5.4.1. Discussion: Local Demand and Supply Shocks for Employment

As mentioned above, when analyzing the adverse impact of house price volatility on local employment through the bank balance sheet, one potential concern is local demand which could either offset or amplify the effect[32]. In this section, I address this concern by differentiating tradable sectors from non-tradable sector and focusing on tradable employment from 2007 to 2009.

Non-tradable sectors include local restaurants, grocery stores and the sales of various products which heavily depend on local demand. Tradable sectors which include the manufacturing of machinery, apparel and electronics, on the contrary, produce goods that are demanded nationally. Mian and Sufi (2014) show that the decline in local demand due to the housing market collapse had strong effects for non-tradable employment from 2007 to 2009 but had little effect on tradable employment. As tradable sectors are minimally subject to local demand shocks, I focus on tradable sector employment alone to make sure that the estimates capture the effect of local supply shocks. To ensure that counties are relatively comparable, I drop 61 counties that had tradable employment share out of total population below 3%, resulting in 728 counties in the sample.

I repeat the regression (6) but replace the dependent variable with the employment change in tradable sectors from 2007 to 2009 as follows.

(2c) $$\Delta \ln TradEmp_i^{07-09} = \beta_0 + \beta_1 HPVol_i + \beta_2 HPVol_i \times Concentration_i + \beta_3 Concentration_i + \beta_4 X_i + \epsilon_i$$

Regression results are reported in Table 14. Column (1) shows that on average, higher house price volatility is associated with a greater decline in tradable employment from 2007 to 2009. The estimates for coefficient β_2 in columns (2)-(4) are positive and statistically significant, suggesting

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One possibility is that bank competition encouraged lending to lower-quality borrowers (e.g., lower income), making them severely underwater after the collapse of the housing market. Then we might see weaker local demand associated with higher bank competition which would result in lower employment. Another possibility is that, if only borrowers that were severely underwater chose to default on their mortgage loans, we might see stronger local demand associated with bank competition since default on the mortgage loans protect these borrowers from suffering balance sheet shocks.

that higher bank concentration reduces this relationship. Various controls are included and the results remain similar. In particular, I include the debt-to-income ratio of the county as of 2006 in columns (3) and (4) as a control. We can see that the coefficient on the debt-to-income ratio is insignificant, confirming the findings in Mian and Sufi (2014) that tradable employment was not affected by local demand between 2007 and 2009. To show further that the decline in employment was only specific to the post-crisis period, I replace the left-hand-side variable with the 2003-2007 change in tradable employment which can be regarded as a placebo regression (Columns 5-6). We can see clearly that neither β_1 nor β_2 is statistically significant. This suggests that the decline in tradable employment and its relationship with bank competition is only a phenomenon after the crisis[33].

5.4.2. Discussion: Demand for Mortgage Loans and House Price Amplification of Credit Supply

So far, we have discussed the change in lending standards by banks as the change in mortgage loan supply. Naturally, we could also have demand factors changing in the background. How would changes in mortgage loan demand play a role in this process? Would the change in demand explain the results we have found?

In particular, the demand for loans could increase if the local county experienced high volatility in the house price as households see potential capital gains in buying a house. This can be especially profitable if households have the option to default in case of housing market collapse. Eventually, the mortgage issuers would have to absorb all the losses. Or alternatively, demand factors could have amplified the housing cycle, as investors based on extrapolation may have the incentive to invest in homes whose price has been growing fast, pushing up the house price even further. Could the demand factor be the main driving force for the empirical patterns we have shown, in particular the interaction term β_2?

First of all, the option to default would lower mortgage returns for banks, which is exactly the type of risk banks would need to consider. In fact, if such incentive is prevalent enough, banks would even consider tighten their lending standards. Second, if extrapolative demand amplifies the housing cycle, such demand factors could yield an amplified first-stage regression, but would not change the second-stage results. Third, in the regression analysis presented above, I control for demand factors including the growth rate of population, wage growth and employment growth. Moreover, I also control for the share of investment homes in the mortgage market. From the regression results, we can see that controlling these factors does not alter the main results we have found that lending standards dropped for high-volatility markets and bank concentration reduced this relationship. It indicates that the empirical results were not primarily driven by shifts in

[33] One interesting note is that the coefficient on population growth from 2003 to 2007 is highly significant and close to 1 (column (6)), meaning that the growth in employment from 2003 to 2007 and population almost tracked each other one to one while the local house price and bank competition had little effect.

demand.

Furthermore, the shift in demand would not explain the differential in estimates of β_2 between local banks and national banks. If the greater demand in markets with high house price volatility was the significant driving force in the background, we would see national banks that had greater resources to mobilize respond more strongly to higher local demand in competitive markets. The abundance of deposits and wholesale funding for national banks would have allowed them to take full advantage of the stronger demand in competitive markets. However, in the regressions, we see exactly the opposite that β_2 is much less significant for decisions made by national banks than for local banks. This evidence indicates that the effect of local competition on bank lending standards worked through the supply of mortgages.

In addition, credit supply factors can amplify house price risk. During the boom, stronger credit supply can make the house price growth stronger (e.g., Adelino, Schoar and Severino (2012), Favara and Giannetti (2014)), whereas in the bust, the pre-crisis "excessive" credit supply could also lead to larger decline in the house price (e.g., Mian and Sufi (2010)). To address this concern, I first show that the actual house price volatility has a statistically insignificant correlation with bank concentration after controlling for local geography, i.e., housing supply inelasticity (Table 3). To more formally address this issue, I use the realized house price volatility instead of the predicted value. In Table 12, I define house price volatility in four different ways and obtain estimates of similar magnitude on the coefficient β_2 of the interaction term between house price volatility and bank concentration. This suggests that the amplification effect of credit supply on house price volatility is not driving the results found in this paper.

6. Conclusion

Whether a competitive banking sector can induce financial instability has been an important question for both academic research and policy debates. With explicit or implicit government guarantees, a highly competitive banking sector and the associated risk-shifting agency problem might incentivize banks to take advantage of these guarantees and take excessive risk. There are diverse views on this relationship that could suggest very different policy implications. While studies have shown that the U.S. savings and loan crisis in the 1980s was associated with competition in the U.S. banking system, less empirical evidence is known for the recent economic cycle.

Did bank competition contribute to bank risk over the past economic cycle? This paper attempts to provide an answer by exploiting the cross-sectional differences in local house price volatility and in local mortgage-market competition. Particularly, I instrument for the long-run house price volatility using the Saiz (2010) measure of housing supply elasticity. I find that, while U.S. banks overall increased the exposure to house price volatility before the crisis, banks in highly competitive mortgage markets doubled the magnitude relative to those in concentrated markets. The findings in this paper also suggest that this risk taking pattern implied worse economic outcomes including higher unemployment rate after the crisis. For U.S. counties with a competitive mortgage market, one standard deviation in the house price volatility implies a 1% higher foreclosure rate during 2007-2008 and a 1.5% higher unemployment rate from 2007 to 2009; for concentrated local mortgage markets, the effect of house price volatility was insignificant.

The results of this paper suggest that much of the house price risk in the banking sector prior to the crisis and the post-crisis economic outcomes were associated with competition in the mortgage market. It attempts to shed light on the general mechanism how competition among banks interacts with the long-run risk component over the business cycle. This paper exploits a nice exogenous cross-sectional variance in such risk ,i.e., the house price volatility, but the key mechanism discussed here can exist and be applied to many other settings as well.

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Appendix: Proofs for Propositions

Proof for Proposition 1

Proof : First note that the profit in period 0 if boom persists is given by $\pi_0(l;\epsilon) = \alpha M \max\{1 + l - \epsilon, 0\}$, which is increasing in l. Therefore, conditional on the bank raises l above zero, choosing $l = \epsilon$ dominates all other choices. In this case, the profit that the bank receives is αM. The bank is willing to raise l above zero if and only if $p[\alpha M + \frac{\delta}{1-\delta} r(h)M] > \alpha(1-\epsilon)M + \frac{\delta}{1-\delta} r(h)M$. Rearranging this inequality gives $\alpha p - \alpha(1-\epsilon) - (1-p)\frac{\delta}{1-\delta} r(h) > 0$.

Given that $p > 1 - \bar{\epsilon}$ (A2) and that $r(h) \to 0$ as $h \to \infty$, then for each $\epsilon > \epsilon^M \equiv 1 - p$, there exist $\bar{h}$ such that the above inequality holds. Also, since $r(0) > \frac{1-\delta}{\delta} \frac{\alpha(p-(1-\bar{\epsilon}))}{1-p}$, we have that $h = 0$ guarantees the above inequality does not hold. Therefore, there exists $0 < \underline{h} < \bar{h}$ such that banks choose $l_0 = \epsilon$ for $h = \bar{h}$ and $l_0 = 0$ for $h = \underline{h}$. $\square$

Proof for Proposition 2

Proof : Note that the bank chooses to raise l_0 above 0 if and only if $\alpha p - \alpha(1-\epsilon) - (1-p)\frac{\delta}{1-\delta} r(h) > 0$. For a given value of h that yields an optimal $l_0 > 0$, we know that $l_0 = \epsilon$ as the profit in period 0 if boom persists is given by $\pi_0(l;\epsilon) = \alpha M \max\{1 + l - \epsilon, 0\}$, which is increasing in l. In this case, we have $\frac{\partial l_0}{\partial \epsilon} > 0$. For a given value of h that yields an optimal $l_0 > 0$, increasing ϵ expands the range of parameters that makes the bank choose $l_0 = \epsilon > 0$. In this case, we have $\frac{\partial l_0}{\partial \epsilon} \geq 0$. Combining the two cases yields $\frac{\partial l_0}{\partial \epsilon} \geq 0$. $\square$

Proof for Proposition 3

Proof : Recall that the bank chooses to raise l_0 above 0 if and only if $\alpha p - \alpha(1-\epsilon) - (1-p)\frac{\delta}{1-\delta} r(h) > 0$. Therefore, the threshold $\hat{h}(\epsilon) = \inf\{h : l(\epsilon; h) > 0\}$ is implicitly defined as $\alpha p - \alpha(1-\epsilon) - (1-p)\frac{\delta}{1-\delta} r(h) = 0$. Since $r'(h) < 0$, raising ϵ requires h to fall. Therefore, $\hat{h}'(\epsilon) \leq 0$. $\square$

Figure 1. Evolution of Concentration Ratio (Top-10)

This figure plots the evolution of the Concentration Ratio (top-10) from 1995 to 2005 at the county level where the Concentration Ratio (top-10) is defined as the total market share of the top ten mortgage lenders in the county. The four lines represents the four quartiles of counties by their Concentration Ratio as of 1995. The Concentration Ratio measure has declined over time nationally, suggesting increasingly competitive local mortgage markets in the U.S.. However, the relative ranking of Concentration ratio across U.S. counties has remained the same over the years.

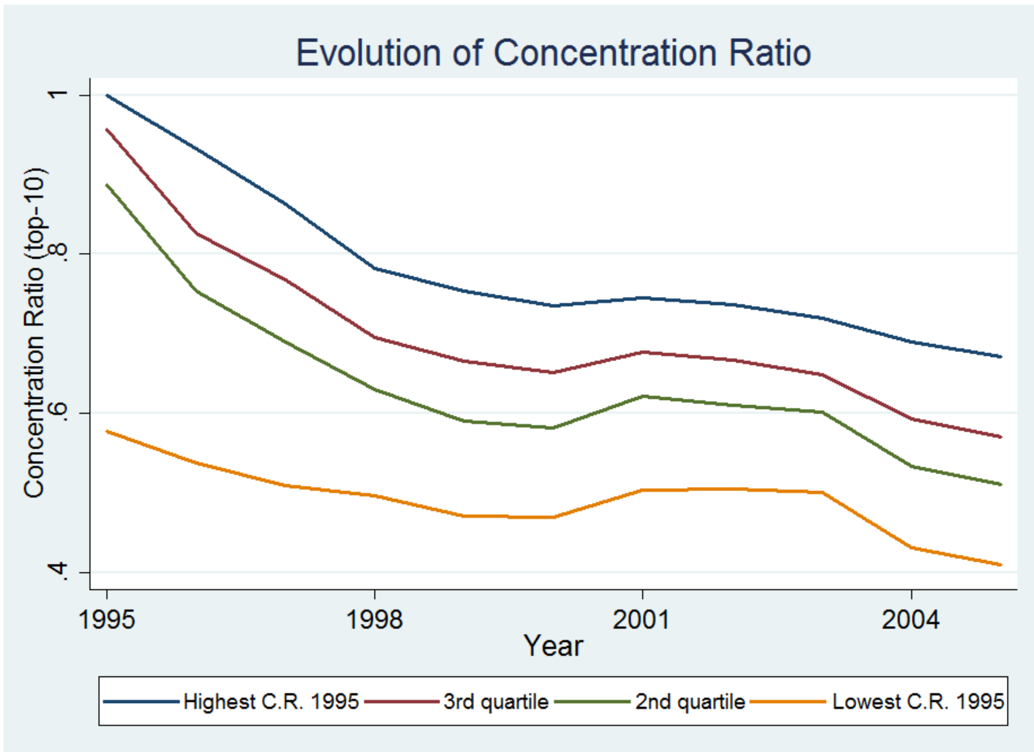


Figure 2. Historical House Price Volatility: 1982-1996

This figure plots the quintiles of the detrended S&P/Case-Shiller Home Price Index from 1982 to 1996 at the CBSA level according to the local house price elasticity (Saiz (2010)). Since inflation was high during this period, a national trend is subtracted for all groups. We can see that the most inelastic areas (the black and rose-red lines) experienced much larger house price volatility than the elastic areas (the red, orange and green lines), consistent with the findings in Glaeser, Gyourko and Saiz (2008).

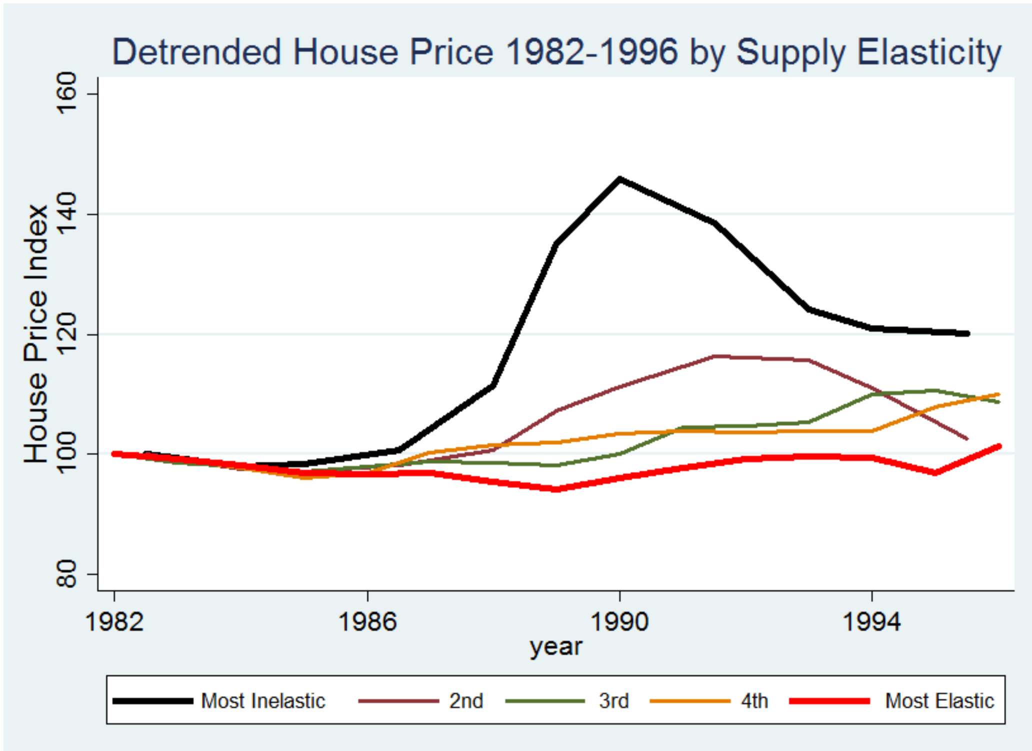
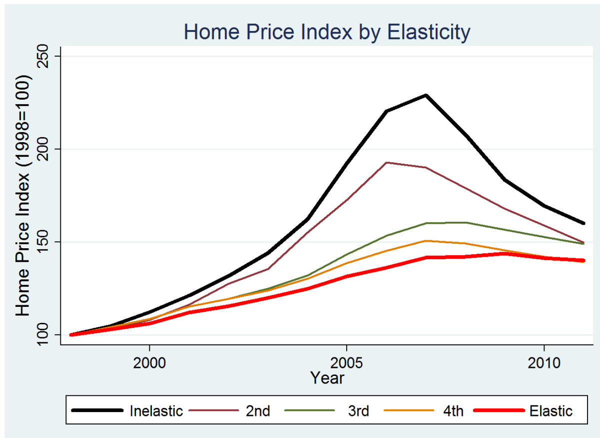


Figure 3

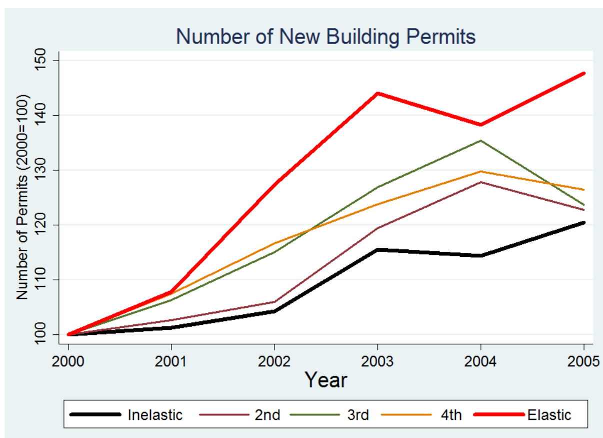
House Price Volatility Over the Recent Cycle and Exclusion Restriction

Panel A in this figure plots the S&P/Case-Shiller Home Price Index for quintiles of CBSA areas by their housing supply elasticity (Saiz (2010)). Panel B plots the number of new building permits from 2000 to 2005 for these quintiles by housing supply elasticity. Panel C plots the growth of real wages in these quintiles by housing supply elasticity.

Panel A



Panel B



Panel C

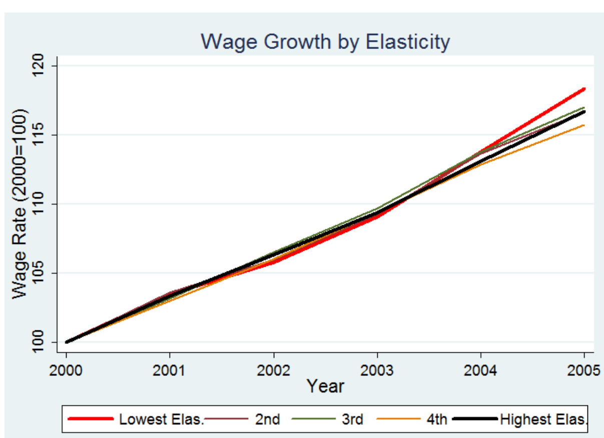
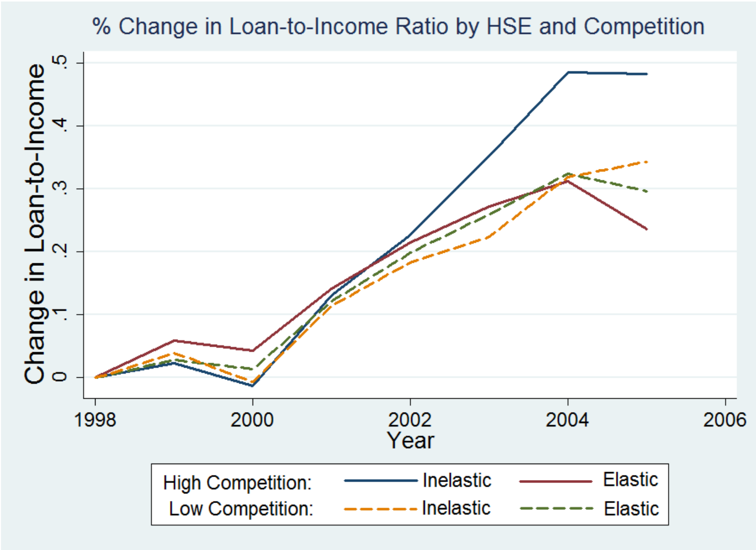


Figure 4

Loan-to-Income Ratio vs. House Price Volatility and Bank Competition

Panel A in this figure plots the evolution (percentage change) of the loan-to-income ratio in the 789 U.S. counties in the sample from 1998 to 2005. The blue and red solid lines are inelastic-supply and elastic-supply areas with a competitive mortgage market, respectively. The orange and green dashed lines are inelastic-supply and elastic-supply areas with a concentrated mortgage market. Panel B plots the same graph with the absolute change in the loan-to-income ratio in the 789 U.S. counties in the sample from 2000 to 2005.

Panel A



Panel B

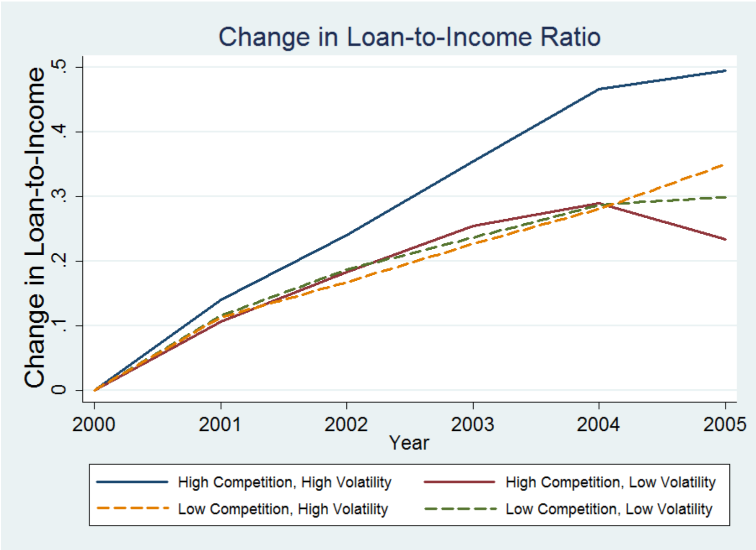
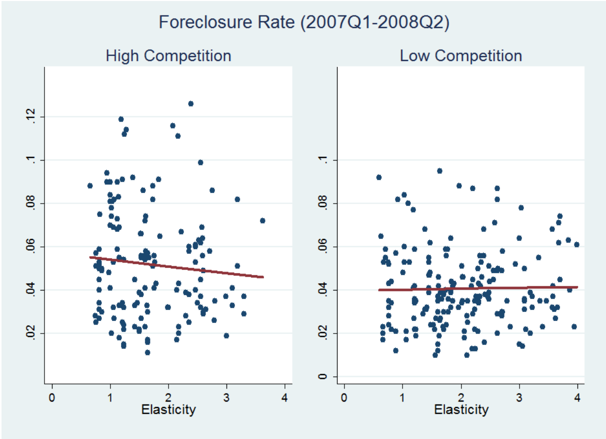


Figure 5

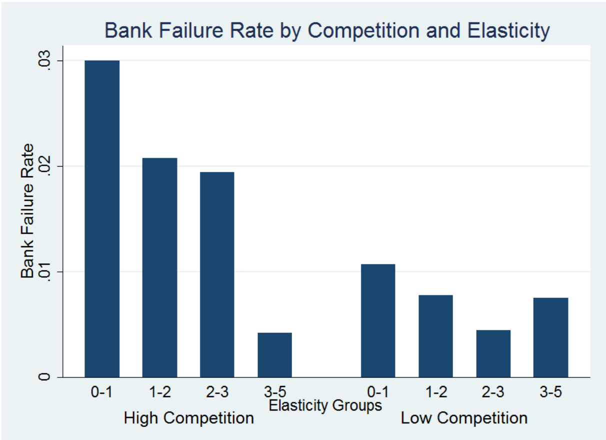
Bank Competition, House Price Volatility and Post-Crisis Outcomes

Panel A in this figure plots the foreclosure rate from 2007Q1 to 2008Q2 reported by the HUD against the Saiz housing supply elasticity. The left figure in Panel A plots this relationship for U.S. counties with a competitive mortgage market and the right figure in Panel A plots counties with a concentrated mortgage market. Panel B in this figure plots the rate of bank failures from 2008Q1 to 2014Q2 reported by the FDIC against groups of the Saiz housing supply elasticity.The bank failure rate is computed as the number of bank failures in each group of supply elasticity divided by the total number of banks that had lending activities in the group as of 2005. The left figure in Panel B plots the bank failure rate for areas with a competitive mortgage market and the right figure in Panel B plots the bank failure rate for areas with a concentrated mortgage market. Panel C of this figure plots the percentage change in tradable employment from 2007 to 2009 for establishments with size below 1000 against housing supply elasticity at the U.S. county level. The left panel plots this relationship for counties with a competitive mortgage market and the right panel plots this relationship for counties with a concentrated mortgage market.

Panel A



Panel B



Panel C

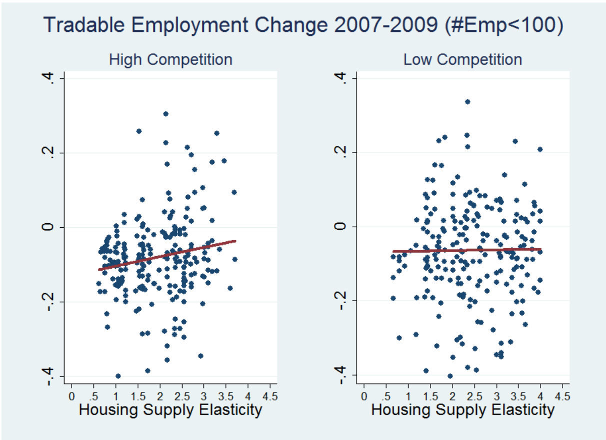


Table 1. Summary Statistics

This table presents summary statistics for the 789 U.S. counties covered in this sample where data is available. Total population in these counties account for 68% of total U.S. population as of 2000. The weighted mean and standard errors use population in the county as of 2000 as weights.

	N	Mean	SD	10th	90th	Weighted Mean	Weighted SD
Concentration Ratio (top-10), 2000	789	0.53	0.10	0.41	0.67	0.48	0.08
Concentration Ratio (top-10), 1995	789	0.62	0.18	0.40	0.90	0.48	0.13
Herfindahl Index, 2000	789	0.05	0.03	0.03	0.10	0.04	0.02
House price volatility measure, 1982-1996	789	0.02	0.30	-0.36	0.27	0.06	0.34
House price cyclicality measure, 1982-1996	789	0.018	0.009	0.010	0.029	0.018	0.008
House price volatility measure, 2001-2011	789	0.42	0.33	0.14	0.85	0.61	0.42
House price (Zillow) volatility measure, 2001-2011	482	0.55	0.42	0.14	1.18	0.75	0.46
Housing supply elasticity (Saiz)	789	2.32	1.00	1.02	3.66	1.74	0.94
Population, 2000 (thousands)	789	243.32	522.08	20.72	569.95	1362.08	2160.09
Percentage change in loan-to-income ratio, 2000-2005	789	0.20	0.10	0.07	0.35	0.22	0.12
Change in acceptance rate, 2000-2005	789	-0.06	0.05	-0.12	0.00	-0.07	0.04
Change in loan-to-value ratio, 2001-2005	789	-0.02	0.08	-0.10	0.07	-0.04	0.06
Share of high-spread mortgage loans, 2005	789	0.26	0.08	0.17	0.36	0.27	0.08
Employment growth (tradable + non-tradable), 2007-2009	789	-0.03	-0.08	-0.11	0.05	-0.03	0.05
Employment growth (tradable), 2007-2009	789	-0.12	-0.23	-0.32	0.07	-0.11	0.13
Employment growth (tradable), 2003-2007	789	-0.03	0.33	-0.30	0.29	-0.06	0.18
Population growth, 2001-2005	789	0.05	0.07	-0.01	0.17	0.04	0.07
Employment growth, 2001-2005	789	0.05	0.12	-0.07	0.18	0.02	0.09
Finance/real estate employment growth, 2001-2005	789	0.09	0.23	-0.13	0.34	0.07	0.17
Weekly wage growth, 2001-2005	789	0.12	0.05	0.08	0.17	0.12	0.03
Share of thrift institutions, 2005	789	0.13	0.05	0.07	0.20	0.16	0.05
Share of securitized loans, 2005	789	0.54	0.09	0.40	0.65	0.59	0.07
Share of refinancing loans, 2005	789	0.002	0.003	0.001	0.005	0.004	0.007
Share of investment homes, 2005	789	0.09	0.04	0.04	0.14	0.07	0.03
Share of non-single-family homes, 2005	789	0.05	0.05	0.01	0.10	0.04	0.04

Table 2. Joint Distribution of Concentration Ratio (top-10), Saiz Housing Supply Inelasticity and Other Variables

Panel A in this table presents the distribution of the Saiz housing supply inelasticity within the greater and lower halves of the sample by the Concentration Ratio (top-10). Concentration ratio (top-10) is defined as the total market share of the top-10 lenders in the county as of 2000. From the joint distribution listed in the table, we can see that the inelasticity has a similar distribution and range for the greater and lower halves of the Concentration Ratio. Panel B in this table presents the correlation between the change in economic variables between 2000 to 2005 with the Concentration Ratio at the county level. Regressions are weighted by county population as of 2000 and standard errors are clustered at the CBSA level. Constant terms are not reported in the table.

Panel A

Saiz housing supply inelasticity	5th Percentile	25th Percentile	Median	75th Percentile	95th Percentile	N
Greater half by Concentration Ratio ($C.R. \geq 0.515$)	0.13	0.32	0.51	0.66	0.80	394
Lower half by Concentration Ratio ($C.R. < 0.515$)	0.25	0.45	0.55	0.73	0.83	395

Panel B

	(1)	(2)	(3)	(4)
	%ΔWage 01-05	%ΔEmployment 01-05	%ΔFinance/RE Employment, 01-05	Finance/RE Share, 2005
Concentration Ratio	−0.03	−0.04	0.01	−0.04
	(0.03)	(0.07)	(0.11)	(0.03)
N	789	789	789	789

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

Table 3. First Stage Regression and Exclusion Restriction

Column (1) of this table presents the first stage regression of historical house price volatility on housing supply inelasticity. Columns (2)-(3) show validity of using the long-run volatility predicting house price volatility during the 2000-2011 housing cycle. Column (4) shows the wage rate growth from 2000 to 2005 in relation to housing supply inelasticity, where weak correlation is found. House price volatility is defined as the house price growth in the boom period minus the change in house price during the bust. For the 1982-1996 housing cycle, house price volatility is defined as $\ln(HP_{1989}/HP_{1982}) - \ln(HP_{1996}/HP_{1989})$; for the 2000-2011 housing cycle, house price volatility is defined as $\ln(HP_{2006}/HP_{2001}) - \ln(HP_{2011}/HP_{2006})$. Bank concentration is measured by the Concentration Ratio (top-10) as of 2000, i.e., the total market share of the top-10 lenders in the mortgage market. All variables are at the county level. All regressions are weighted by county population as of 2000 and standard errors are clustered at the CBSA level.

	(1)	(2)	(3)	(4)
	HP Volatility, 1982-1996	HP Volatility, 2000-2011		Wage Change, 2000-2005
Housing Supply Inelasticity	0.56^{***}	1.37^{***}	1.34^{***}	0.004
	(0.22)	(0.15)	(0.16)	(0.015)
Bank Concentration (C.R.)			-0.18	
			(0.32)	
Constant	-0.28^{**}	-0.28^{***}	-0.20	0.15^{***}
	(0.12)	(0.08)	(0.20)	(0.01)
N	789	789	789	789
R^2	0.10	0.37	0.37	0.00

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

Table 4. Loan-to-Income, National Banks versus Local Banks: Concentration Ratio

This table presents regressions of the change in loan-to-income ratio in a county on local house price volatility, instrumented by housing supply inelasticity (Saiz (2010)). The change in loan-to-income ratio is the percentage growth of the average loan-to-income ratio in a county from 2000 to 2005. Bank concentration is measured by the Concentration Ratio (i.e., total market share of top-10 lenders) in that county as of 2000. National banks are defined as lending mortgages in at least fifteen states as of 2000; local banks are defined as lending mortgages in less than fifteen states as of 2000. All regressions are weighted by the number of households in a county as of 2000. Standard errors are clustered at the CBSA level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Percentage change in loan-to-income ratio, 2000 to 2005							
	Local Banks			National Banks			All	
House Price Vol.	5.31***	4.66***	4.27***	2.74***	1.56**	1.30**	5.70***	3.87***
	(0.96)	(0.96)	(0.96)	(0.76)	(0.67)	(0.59)	(0.95)	(0.95)
HP Vol. × Bank Concentration	−7.51***	−7.63***	−6.81***	−2.63*	−1.98*	−1.35	−8.36***	−6.32***
	(1.66)	(1.63)	(1.63)	(1.38)	(1.16)	(1.02)	(1.66)	(1.61)
HP Vol. × Concentration × {National Bank}							4.48**	4.48**
							(2.00)	(2.01)
Bank Concentration (C.R.)	0.64***	0.59***	0.50***	0.34***	0.22***	0.17**	0.79***	0.54***
	(0.12)	(0.12)	(0.12)	(0.10)	(0.07)	(0.07)	(0.14)	(0.10)
HP Vol. × {National Bank}							−2.17*	−2.17*
							(1.15)	(1.15)
Concentration × {National Bank}							−0.42***	−0.42***
							(0.11)	(0.11)
{National Bank}							0.22***	0.22***
							(0.06)	(0.06)
%ΔWage	0.47**		0.47**	0.35**		0.39***		0.43***
	(0.21)		(0.18)	(0.16)		(0.10)		(0.12)
log(Population)	−0.011		−0.02	0.009		−0.012**		−0.015**
	(0.010)		(0.01)	(0.010)		(0.006)		(0.007)
%ΔPopulation	−0.62***		−0.44**	−0.46***		−0.20*		−0.32**
	(0.23)		(0.22)	(0.15)		(0.12)		(0.13)
%ΔEmployment	0.18		0.13	0.36***		0.22***		0.17**
	(0.14)		(0.12)	(0.09)		(0.06)		(0.08)
%ΔFinance/RE Employment	−0.02		−0.02	0.03		−0.01		−0.01
	(0.04)		(0.03)	(0.03)		(0.02)		(0.02)
Share of Subprime, 2005		−0.07	−0.04		−0.06	0.02		−0.01
		(0.15)	(0.14)		(0.09)	(0.07)		(0.09)
Share of Thrifts, 2005		0.41*	0.49**		0.69***	0.85***		0.67***
		(0.23)	(0.24)		(0.14)	(0.14)		(0.17)
Share of Refinancing, 2005		−0.28	0.22		1.91***	2.48***		1.35
		(1.35)	(1.28)		(0.70)	(0.83)		(0.85)
Share of Securitized, 2005		−0.15	−0.00		0.51***	0.51***		0.25
		(0.17)	(0.18)		(0.12)	(0.13)		(0.12)
Share of Investment Homes, 2005		0.64*	0.51		1.48***	1.37***		0.94***
		(0.36)	(0.32)		(0.25)	(0.24)		(0.20)
Share of Non-Single Family Homes, 2005		−0.95***	−1.00***		−1.11***	−1.06***		−1.03***
		(0.29)	(0.28)		(0.27)	(0.24)		(0.24)
Constant	−0.08	−0.10	0.03	−0.17	−0.38***	−0.28**	−0.26***	−0.23**
	(0.15)	(0.15)	(0.16)	(0.17)	(0.10)	(0.13)	(0.08)	(0.10)
N	789	789	789	789	789	789	1578	1578
R^2	0.36	0.42	0.45	0.45	0.63	0.67	0.35	0.52

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

Table 5. Acceptance Rate, National Banks versus Local Banks: Concentration Ratio

This table presents regressions of the change in acceptance rate (i.e., 1−denial rate) in the county on local house price volatility, instrumented by housing supply inelasticity (Saiz (2010)). The change in acceptance rate is the fraction of accepted loans in 2005 minus the fraction of accepted loans in 2000. Bank concentration is measured by the Concentration Ratio (i.e., total market share of top-10 lenders) in that county as of 2000. National banks are defined as lending mortgages in at least fifteen states as of 2000; local banks are defined as lending mortgages in less than fifteen states as of 2000. All regressions are weighted by the number of households in a county as of 2000. Standard errors are clustered at the CBSA level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Change in acceptance rate, 2000 to 2005							
	Local Banks			National Banks			All	
House Price Vol.	2.09^{***}	1.84^{***}	1.40^{**}	0.50	0.49	0.51	2.09^{***}	1.75^{***}
	(0.66)	(0.69)	(0.59)	(0.39)	(0.33)	(0.35)	(0.66)	(0.60)
HP Vol. × Bank Concentration	-2.79^{**}	-2.73^{**}	-1.77^{*}	−0.98	−0.85	−0.81	-2.79^{**}	-2.20^{*}
	(1.32)	(1.36)	(1.06)	(0.70)	(0.60)	(0.63)	(1.32)	(1.15)
HP Vol. × Concentration × {National Bank}							1.81^{*}	1.81^{*}
							(1.03)	(1.03)
Bank Concentration (C.R.)	0.16^{*}	0.15^{*}	0.18^{**}	−0.02	−0.05	-0.06^{*}	0.16^{*}	0.15^{*}
	(0.09)	(0.09)	(0.08)	(0.03)	(0.03)	(0.03)	(0.09)	(0.08)
HP Vol. × {National Bank}							-1.59^{***}	-1.59^{***}
							(0.54)	(0.54)
Concentration × {National Bank}							-0.17^{**}	-0.17^{**}
							(0.08)	(0.08)
{National Bank}							0.04	0.04
							(0.04)	(0.04)
%ΔWage		0.46^{***}	0.44^{***}		0.07	0.07		0.25^{***}
		(0.21)	(0.14)		(0.06)	(0.06)		(0.08)
log(Population)		0.003	0.004		-0.006^{**}	-0.006^{*}		−0.001
		(0.006)	(0.008)		(0.002)	(0.003)		(0.005)
%ΔPopulation		−0.07	−0.23		−0.08	−0.08		−0.15
		(0.13)	(0.14)		(0.08)	(0.08)		(0.10)
%ΔEmployment		−0.05	−0.04		0.08^{**}	0.07^{**}		0.02
		(0.09)	(0.08)		(0.04)	(0.04)		(0.05)
%ΔFinance/RE Employment		−0.00	−0.01		−0.00	−0.00		−0.00
		(0.03)	(0.02)		(0.02)	(0.02)		(0.02)
Share of Thrifts, 2005			0.02			-0.13^{*}		−0.06
			(0.13)			(0.07)		(0.08)
Share of Refinancing, 2005			-3.17^{***}			1.00^{***}		-1.09^{**}
			(0.70)			(0.36)		(0.45)
Share of Securitized, 2005			0.16			−0.00		0.08
			(0.16)			(0.07)		(0.11)
Share of Investment Homes, 2005			0.09			−0.08		0.01
			(0.23)			(0.10)		(0.14)
Share of Non-Single Family Homes, 2005			-0.41^{***}			0.02		-0.19^{*}
			(0.15)			(0.08)		(0.10)
Constant	−0.08	−0.12	-0.21^{*}	0.01	0.09^{**}	0.12^{***}	−0.04	−0.06
	(0.15)	(0.11)	(0.13)	(0.02)	(0.04)	(0.04)	(0.05)	(0.08)
N	789	789	789	789	789	789	1578	1578
R^2	0.17	0.20	0.27	0.02	0.08	0.11	0.35	0.38

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

Table 6. Lending Standards: National and Local Banks Combined

This table presents regressions of the change in loan-to-income ratio (both in percentage and in absolute value) and the change in acceptance rate for all banks in the county on local house price volatility, instrumented by housing supply inelasticity (Saiz (2010)). Bank concentration is measured by the Concentration Ratio (i.e., total market share of top-10 lenders) in that county as of 2000. All variables are at the county level. All regressions are weighted by the number of households in a county as of 2000. Standard errors are clustered at the CBSA level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Δ lnLoan-to-Income, 2000-2005			ΔLoan-to-Income, 2000-2005			ΔAcceptance Rate, 2000-2005	
House Price Vol.	3.86***	3.19***	2.00***	8.44***	6.72***	4.14***	0.66**	0.54*
	(0.70)	(0.64)	(0.51)	(1.87)	(1.68)	(1.23)	(0.32)	(0.30)
HP Vol. × Bank Concentration	−4.92***	−3.78***	−3.08***	−9.26***	−6.77**	−6.05***	−0.96*	−0.81^{+}
	(1.32)	(1.14)	(0.88)	(3.28)	(3.13)	(2.11)	(0.54)	(0.53)
Bank Concentration (C.R.)	0.43***	0.39***	0.25***	0.82***	0.85***	0.57***	0.04	0.01
	(0.09)	(0.09)	(0.06)	(0.19)	(0.21)	(0.16)	(0.03)	(0.03)
%ΔWage		0.47***	0.48***		0.76**	0.82***		0.15**
		(0.14)	(0.10)		(0.35)	(0.26)		(0.06)
log(Population)		0.004	−0.017***		0.03	−0.04***		−0.004*
		(0.008)	(0.005)		(0.02)	(0.01)		(0.002)
%ΔPopulation		−0.41***	−0.22**		−0.72**	−0.56**		0.05
		(0.14)	(0.10)		(0.36)	(0.26)		(0.05)
%ΔEmployment		0.33***	0.23***		0.63**	0.46***		0.05**
		(0.09)	(0.06)		(0.25)	(0.14)		(0.02)
%ΔFinance/RE Employment		−0.00	−0.02		0.08	0.02		0.00
		(0.03)	(0.02)		(0.07)	(0.05)		(0.01)
Share of Subprime, 2005			−0.02			−0.18		0.09***
			(0.09)			(0.17)		(0.03)
Share of Thrifts, 2005			0.62***			1.52***		−0.05
			(0.13)			(0.31)		(0.04)
Share of Refinancing, 2005			3.31***			11.74***		2.82***
			(0.98)			(2.36)		(0.26)
Share of Securitized, 2005			0.35***			1.14***		−0.05
			(0.11)			(0.26)		(0.06)
Share of Investment Homes, 2005			1.18***			2.42***		0.30***
			(0.20)			(0.50)		(0.09)
Share of Non-Single Family Homes, 2005			−1.01***			−2.31***		0.08
			(0.22)			(0.52)		(0.06)
Share of National Banks, 2000			0.16***			0.67***		0.09***
			(0.05)			(0.14)		(0.03)
Constant	−0.06	−0.13	0.04	−0.14	−0.63*	−0.92***	−0.10***	−0.14***
	(0.05)	(0.13)	(0.17)	(0.11)	(0.36)	(0.26)	(0.01)	(0.04)
N	789	789	789	789	789	789	789	789
R^2	0.39	0.44	0.67	0.44	0.48	0.72	0.08	0.33

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

Table 7. Foreclosure Rate After the Crisis

This table presents regressions of the foreclosure rate in the county from 2007Q1 to 2008Q2 on local house price volatility, instrumented by housing supply inelasticity (Saiz (2010)). Bank concentration is measured by the Concentration Ratio (i.e., total market share of top-10 lenders) in that county as of 2000. All variables are at the county level. All regressions are weighted by the number of households in a county as of 2000. Standard errors are clustered at the CBSA level.

	(1)	(2)	(3)	(4)	(5)	(6)
	Foreclosure Rate (%)					
	Predicted HPVol			Realized HPVol		
HP Vol.	0.07**	0.43***	0.33***	0.03***	0.06**	−0.07***
	(0.03)	(0.13)	(0.10)	(0.003)	(0.03)	(0.01)
HP Vol × Concentration		−0.75***	−0.66***		−0.07	−0.06**
		(0.23)	(0.18)		(0.05)	(0.03)
Concentration		−0.03*	−0.02		−0.00	0.02
		(0.02)	(0.01)		(0.02)	(0.01)
log(*Population*)			0.002+			0.002
			(0.001)			(0.001)
Securitized Share, 2005			0.07***			0.06***
			(0.02)			(0.02)
Investment Home Share, 2005			0.22***			0.26***
			(0.05)			(0.03)
N	791	791	791	791	791	791
R^2	0.03	0.08	0.65	0.24	0.26	0.70
State F.E.	N	N	Y	N	N	Y

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

Table 8. Change in Employment in Local County

This table presents regressions of the change in tradable and nontradable employment combined from 2007 to 2009 in the county on local house price volatility, instrumented by housing supply inelasticity (Saiz (2010)). I particularly exclude finance/insurance, real estate and construction industries. Bank concentration is measured by the Concentration Ratio (i.e., total market share of top-10 lenders) in that county as of 2000. All regressions are weighted by the number of population in the county as of 2000. Standard errors are clustered at the CBSA level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Percentage Change in Employment, 2007-2009								
House Price Vol.	-0.08^{*}	-0.14	-0.30^{**}	-0.20^{+}	-0.16	-0.18^{**}	-0.35^{***}	-0.34^{*}	-0.04
	(0.04)	(0.10)	(0.13)	(0.13)	(0.12)	(0.08)	(0.13)	(0.19)	(0.24)
HP Vol. × Bank Concentration (HHI)		2.01	6.01^{**}	4.82^{**}	4.24^{*}	3.08^{**}	4.87^{*}	3.67	1.30
		(1.56)	(2.43)	(2.40)	(2.33)	(1.35)	(2.64)	(4.06)	(4.71)
Bank Concentration (HHI)		0.18	-0.04	-0.06	0.16	-0.01	-0.03	0.39	0.28
		(0.12)	(0.17)	(0.16)	(0.16)	(0.10)	(0.19)	(0.29)	(0.33)
Debt-to-income, 2006				-0.010^{**}					
				(0.004)					
log(Population), 2007					0.002				
					(0.003)				
%ΔPopulation, 2007-2009					0.86^{***}				
					(0.16)				
Finance/RE Employment Share, 2005					0.28^{***}				
					(0.09)				
Non-Tradable Employment Share, 2005					0.10				
					(0.06)				
Share of Subprime, 2005					0.03				
					(0.04)				
Share of Thrifts, 2005					0.03				
					(0.05)				
Share of Securitized, 2005					0.00				
					(0.05)				
Share of Investment Homes, 2005					0.34^{***}				
					(0.09)				
Constant	-0.030^{***}	-0.04^{***}	-0.03^{***}	-0.01	-0.16^{***}	-0.015^{**}	-0.01	-0.03^{*}	-0.07^{***}
	(0.003)	(0.01)	(0.01)	(0.01)	(0.05)	(0.006)	(0.01)	(0.02)	(0.02)
Firm Size	All	All	All	All	All	(0,20]	(20,50]	(50,100]	(100,500]
N	789	789	751	751	751	751	751	725	725
R^2	0.01	0.02	0.02	0.03	0.17	0.03	0.02	0.02	0.01

***, **, *, + denote statistical significance at the 1%, 5%, 10% and 15% levels.

Table 9. Loan-to-Income, National Banks versus Local Banks: Herfindahl Index

This table presents regressions of the change in loan-to-income ratio in the county on local house price volatility, instrumented by housing supply inelasticity (Saiz (2010)). The change in loan-to-income ratio is the percentage growth of the average loan-to-income ratio in a county from 2000 to 2005. Bank concentration is measured by the Herfindahl index (i.e., the sum of market share squared) in that county as of 2000. National banks are defined as lending mortgages in at least fifteen states as of 2000; local banks are defined as lending mortgages in less than fifteen states as of 2000. All regressions are weighted by the number of population in the county as of 2000. Standard errors are clustered at the CBSA level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Percentage change in loan-to-income ratio, 2000 to 2005							
	Local Banks			National Banks			All	
House Price Vol.	2.88^{***}	2.01^{***}	1.98^{***}	1.98^{***}	0.81^{**}	0.85^{***}	2.87^{***}	1.71^{***}
	(0.46)	(0.45)	(0.46)	(0.37)	(0.31)	(0.29)	(0.45)	(0.47)
HP Vol. × Bank Concentration	-28.01^{***}	-24.78^{***}	-23.80^{***}	-11.40^{*}	-5.40	-5.24	-28.32^{***}	-21.12^{***}
	(6.45)	(6.62)	(6.51)	(6.22)	(4.76)	(4.63)	(6.32)	(6.81)
HP Vol. × Concentration × {National Bank}							13.20^{+}	13.20^{+}
							(9.19)	(9.28)
Bank Concentration (C.R.)	2.43^{***}	2.49^{***}	2.06^{***}	1.06^{**}	0.77^{**}	0.48	3.13^{***}	2.21^{***}
	(0.44)	(0.49)	(0.44)	(0.41)	(0.34)	(0.33)	(0.56)	(0.40)
HP Vol. × {National Bank}							-0.60	-0.60
							(0.61)	(0.61)
Concentration × {National Bank}							-1.87^{***}	-1.87^{***}
							(0.47)	(0.48)
{National Bank}							0.10^{***}	0.10^{***}
							(0.03)	(0.03)
%ΔWage	0.44^{*}		0.43^{**}	0.33^{**}		0.37^{***}		0.40^{***}
	(0.22)		(0.19)	(0.16)		(0.10)		(0.13)
log(Population)	-0.014		-0.017	0.005		-0.014^{**}		-0.016^{**}
	(0.009)		(0.012)	(0.009)		(0.006)		(0.007)
%ΔPopulation	-0.71^{***}		-0.50^{**}	-0.52^{***}		-0.22^{*}		-0.36^{***}
	(0.24)		(0.22)	(0.14)		(0.12)		(0.13)
%ΔEmployment	0.22		0.17	0.37^{***}		0.22^{***}		0.19^{**}
	(0.15)		(0.12)	(0.10)		(0.07)		(0.08)
%ΔFinance/RE Employment	-0.02		-0.03	0.03		0.01		-0.01
	(0.04)		(0.03)	(0.03)		(0.02)		(0.02)
Share of Subprime, 2005		-0.02	-0.00		-0.06	0.01		0.01
		(0.15)	(0.14)		(0.09)	(0.07)		(0.08)
Share of Thrifts, 2005		0.39^{*}	0.46^{*}		0.68^{***}	0.84^{***}		0.65^{***}
		(0.23)	(0.24)		(0.14)	(0.15)		(0.17)
Share of Refinancing, 2005		-0.29	0.27		1.91^{***}	2.60^{***}		1.44^{+}
		(1.46)	(1.39)		(0.73)	(0.95)		(0.89)
Share of Securitized, 2005		-0.17	-0.02		0.50^{***}	0.49^{***}		0.23^{*}
		(0.18)	(0.18)		(0.12)	(0.13)		(0.12)
Share of Investment Homes, 2005		0.69^{*}	0.53		1.53^{***}	1.41^{***}		0.97^{***}
		(0.38)	(0.33)		(0.25)	(0.25)		(0.20)
Share of Non-Single Family Homes, 2005		-1.06^{***}	-1.09^{***}		-1.16^{***}	-1.09^{***}		-1.09^{***}
		(0.31)	(0.29)		(0.27)	(0.24)		(0.25)
Constant	0.17	0.09	0.21	-0.00	-0.30^{***}	-0.19^{*}	-0.02	-0.04
	(0.12)	(0.13)	(0.14)	(0.13)	(0.09)	(0.11)	(0.04)	(0.08)
N	789	789	789	789	789	789	1578	1578
R^2	0.35	0.42	0.45	0.44	0.62	0.67	0.34	0.52

***, **, *, + denote statistical significance at the 1%, 5%, 10% and 15% levels.

Table 10. Acceptance Rate, National Banks versus Local Banks: Herfindahl Index

This table presents regressions of the change in the acceptance rate (i.e., 1−denial rate) in the county on local house price volatility, instrumented by housing supply inelasticity (Saiz (2010)). The change in the acceptance rate ratio is the 2000-2005 change in the fraction of accepted mortgage loan applications. Bank concentration is measured by the Concentration Ratio (i.e., total market share of top-10 lenders) in that county as of 2000. National banks are defined as lending mortgages in at least fifteen states as of 2000; local banks are defined as lending mortgages in less than fifteen states as of 2000. All regressions are weighted by the number of households in a county as of 2000. Standard errors are clustered at the CBSA level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Change in acceptance rate, 2000 to 2005							
	Local Banks			National Banks			All	
House Price Vol.	1.38^{***}	1.28^{***}	0.94^{***}	0.08	0.14	0.23	1.38^{***}	1.25^{***}
	(0.29)	(0.33)	(0.30)	(0.15)	(0.13)	(0.16)	(0.29)	(0.30)
HP Vol. × Bank Concentration	-16.10^{**}	-14.73^{**}	-8.79^{*}	−1.69	−1.90	−2.79	-16.29^{**}	-13.26^{**}
	(6.61)	(6.99)	(5.20)	(2.39)	(2.06)	(2.52)	(6.76)	(5.82)
HP Vol. × Concentration × {National Bank}							14.41^{**}	14.46^{**}
							(6.05)	(6.05)
Bank Concentration (C.R.)	0.35	0.22	0.64^{**}	−0.12	-0.27^{**}	-0.31^{**}	0.09	0.11
	(0.42)	(0.42)	(0.31)	(0.17)	(0.14)	(0.15)	(0.07)	(0.06)
HP Vol. × {National Bank}							-1.30^{***}	-1.30^{***}
							(0.26)	(0.27)
Concentration × {National Bank}							-0.47^{*}	-0.49^{*}
							(0.27)	(0.30)
{National Bank}							−0.02	−0.02
							(0.02)	(0.02)
%ΔWage		0.42^{***}	0.39^{***}		0.08	0.07		0.24^{***}
		(0.13)	(0.13)		(0.06)	(0.06)		(0.08)
log(Population)		−0.001	−0.00		-0.006^{**}	-0.009^{**}		−0.004
		(0.006)	(0.01)		(0.003)	(0.003)		(0.005)
%ΔPopulation		−0.15	-0.25^{*}		−0.08	−0.08		−0.16
		(0.13)	(0.14)		(0.09)	(0.08)		(0.10)
%ΔEmployment		−0.03	−0.01		0.09^{**}	0.08^{**}		0.04
		(0.09)	(0.08)		(0.04)	(0.04)		(0.05)
%ΔFinance/RE Employment		−0.00	−0.00		−0.00	0.00		−0.00
		(0.03)	(0.02)		(0.02)	(0.02)		(0.02)
Share of Subprime, 2005			0.17^{**}			0.10^{**}		0.15^{***}
			(0.08)			(0.04)		(0.05)
Share of Thrifts, 2005			0.09			−0.11		−0.01
			(0.11)			(0.07)		(0.07)
Share of Refinancing, 2005			-2.96^{***}			1.24^{***}		−0.75
			(0.78)			(0.40)		(0.47)
Share of Securitized, 2005			0.11			−0.02		0.05
			(0.15)			(0.07)		(0.10)
Share of Investment Homes, 2005			0.08			−0.09		−0.01
			(0.23)			(0.09)		(0.14)
Share of Non-Single Family Homes, 2005			-0.43^{***}			0.02		-0.19^{*}
			(0.16)			(0.08)		(0.10)
Constant	0.02	−0.00	−0.11	0.00	0.07^{**}	0.12^{***}	−0.00	−0.03
	(0.02)	(0.09)	(0.11)	(0.01)	(0.03)	(0.04)	(0.04)	(0.08)
N	789	789	789	789	789	789	1578	1578
R^2	0.18	0.21	0.28	0.01	0.07	0.14	0.36	0.40

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

Table 11. Share of Loans with High Spread in Interest Rate

Columns (1)-(4) of this table presents regressions of the share of high-rate-spread mortgage loans in the county as of 2005 on local house price volatility, instrumented by housing supply inelasticity (Saiz (2010)). Columns (5)-(7) reports the regression of the percentage change in the loan-to-value (LTV) ratio from 2001 to 2005 in the county on the instrumented local house price volatility. The share of high-rate-spread loans is the fraction of loans that have a rate spread higher than the threshold that the Home Mortgage Disclosure Act requires to report after 2004. The loan-to-value ratio is computed using survey data from Monthly Interest Rate Survey (MIRS) at the zip-code level and weighting zip-code level data appropriately by population to construct the county level data. Bank concentration is measured by the Concentration Ratio (i.e., total market share of top-10 lenders) in that county as of 2000. All regressions are weighted by the number of population in the county as of 2000. Standard errors are clustered at the CBSA level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Share of loans with high spread in interest rate				Percentage change in loan-to-value		
House Price Vol.	1.03^{***}	0.84^{*}	0.84^{*}	1.34^{***}	-0.42^{***}	0.37	0.36
	(0.51)	(0.51)	(0.44)	(0.43)	(0.10)	(0.35)	(0.32)
HP Vol. × Bank Concentration	-2.57^{***}	-2.45^{**}	-2.00^{**}	-2.43^{***}		-0.88^{+}	-0.84^{+}
	(1.00)	(1.06)	(0.80)	(0.76)		(0.61)	(0.58)
Bank Concentration (C.R.)	-0.27^{***}	-0.22^{***}	-0.18^{***}	-0.21^{***}		0.08^{**}	0.07
	(0.03)	(0.06)	(0.06)	(0.06)		(0.04)	(0.04)
%ΔWage		0.09	0.06	−0.01			−0.09
		(0.10)	(0.10)	(0.09)			(0.06)
log(Population)		0.012^{***}	0.012^{**}	0.010^{**}			−0.005
		(0.004)	(0.005)	(0.005)			(0.004)
%ΔPopulation		0.05	−0.06	−0.02			-0.10^{+}
		(0.10)	(0.11)	(0.10)			(0.07)
%ΔEmployment		−0.03	−0.07	−0.05			−0.04
		(0.06)	(0.05)	(0.05)			(0.04)
%ΔFinance/RE Employment		−0.02	−0.02	-0.04^{**}			-0.02^{*}
		(0.03)	(0.02)	(0.02)			(0.01)
Share of Thrifts, 2005			-0.47^{***}	-0.66^{***}		−0.05	−0.07
			(0.10)	(0.10)		(0.08)	(0.08)
Share of Refinancing, 2005			0.19	1.20^{*}		−0.34	−0.23
			(0.69)	(0.70)		(0.67)	(0.67)
Share of Securitized, 2005			0.23^{**}	0.24^{**}		-0.16^{*}	−0.07
			(0.11)	(0.11)		(0.10)	(0.08)
Share of Investment Homes, 2005			0.10	0.71^{***}		−0.19	−0.17
			(0.22)	(0.20)		(0.18)	(0.17)
Share of Non-Single Family Homes, 2005			0.05	−0.15		0.56^{***}	0.50^{***}
			(0.11)	(0.12)		(0.10)	(0.10)
Constant	0.40^{***}	0.22^{***}	0.12^{*}	0.22^{**}	-0.016^{***}	0.02	0.06
	(0.03)	(0.07)	(0.07)	(0.10)	(0.004)	(0.07)	(0.10)
N	789	789	789	789	789	789	789
State Fixed Effects	N	N	N	Y	N	N	N
R^2	0.17	0.21	0.32	0.53	0.14	0.26	0.29

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

Table 12. Realized House Price Volatility

This table presents regressions of the change in loan-to-income ratio in a county on the realized house price volatility. There are four definitions of house price volatility: the realized 1982-1989 house price volatility (columns 1 and 2), the realized 1982-1996 house price cyclicality (columns 3 and 4), the realized 2000-2005 house price growth (columns 5 and 6) and the realized 2000-2011 house price volatility (columns 7-10). The change in loan-to-income ratio is the percentage growth of the average loan-to-income ratio in a county from 2000 to 2005. Bank concentration is measured by the Concentration Ratio (i.e., total market share of top-10 lenders) in that county as of 2000. National banks are defined as lending mortgages in at least fifteen states as of 2000; local banks are defined as lending mortgages in less than fifteen states as of 2000. All regressions are weighted by the number of population in a county as of 2000. Standard errors are clustered at the CBSA level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Percentage change in loan-to-income ratio, 2000 to 2005									
House Price Vol.	0.68^{***}	0.39^{***}	0.26^{*}	0.18^{***}	0.67^{***}	0.65^{***}	0.29^{***}	0.23^{***}	0.49^{**}	0.59^{***}
	(0.13)	(0.07)	(0.14)	(0.05)	(0.13)	(0.09)	(0.06)	(0.04)	(0.21)	(0.17)
HP Vol. × Bank ConcentrationMeasure	-1.00^{***}	-0.59^{***}	-0.40^{+}	-2.73^{**}	-0.43^{**}	-0.52^{***}	-0.23^{*}	-0.14^{+}	-0.62^{+}	-0.86^{***}
	(0.34)	(0.20)	(0.27)	(1.08)	(0.21)	(0.18)	(0.13)	(0.09)	(0.40)	(0.33)
HP Vol. × Concentration × {National Bank}									0.82^{*}	0.82^{*}
									(0.43)	(0.44)
Bank Concentration Measure	0.19	0.17	0.64	4.23^{**}	0.42^{***}	0.30^{***}	0.27^{***}	0.05	0.77	0.59^{***}
	(0.14)	(0.09)	(0.50)	(1.99)	(0.11)	(0.08)	(0.07)	(0.06)	(0.21)	(0.16)
HP Vol. × {National Bank}									-0.33^{+}	-0.33^{+}
									(0.22)	(0.22)
Concentration × {National Bank}									-0.61^{***}	-0.61^{***}
									(0.19)	(0.19)
{National Bank}									0.28^{***}	0.28^{***}
									(0.10)	(0.10)
%ΔWage		0.48^{***}				-0.00		0.04		-0.03
		(0.13)				(0.09)		(0.09)		(0.12)
log(Population)		-0.012^{**}				-0.016^{***}		-0.018^{***}		-0.019^{***}
		(0.004)				(0.003)		(0.003)		(0.004)
%ΔPopulation		-0.05				-0.42^{***}		-0.61^{***}		-0.74^{***}
		(0.13)				(0.07)		(0.07)		(0.11)
%ΔEmployment		0.12				0.07		0.14^{***}		0.09^{+}
		(0.09)				(0.05)		(0.05)		(0.06)
%ΔFinance/RE Employment		0.00				0.01		0.02		0.04^{*}
		(0.03)				(0.01)		(0.02)		(0.02)
Share of Subprime, 2005		0.01				0.03		-0.28^{***}		-0.12^{*}
		(0.08)				(0.05)		(0.05)		(0.07)
Share of Thrifts, 2005		0.47^{***}				0.37^{***}		0.47^{***}		0.36^{***}
		(0.17)				(0.08)		(0.07)		(0.13)
Share of Refinancing, 2005		7.31^{**}				0.55		2.38^{***}		1.90^{***}
		(3.18)				(0.59)		(0.50)		(0.55)
Share of Securitized, 2005		0.55^{***}				-0.01		0.12^{*}		-0.08
		(0.15)				(0.09)		(0.06)		(0.12)
Share of Investment Homes, 2005		1.19^{***}				0.26^{*}		0.77^{***}		0.56^{***}
		(0.31)				(0.14)		(0.11)		(0.20)
Share of Non-Single Family Homes, 2005		-1.39^{***}				-0.43^{***}		-0.59^{***}		-0.43^{***}
		(0.19)				(0.13)		(0.09)		(0.16)
Constant	0.09	-0.23^{*}	-0.21	-0.07	-0.18^{***}	0.06	-0.02	0.21^{***}	-0.28^{**}	0.11
	(0.07)	(0.12)	(0.25)	(0.09)	(0.06)	(0.07)	(0.04)	(0.06)	(0.12)	(0.13)
House Price Vol. Definition	HP Vol., 1982-1996		HP Cyclicality, 1982-1996		$\%\Delta HP^{00-05}$		Zillow HP Vol, 2001-2011		HP Vol, 2001-2011	
Bank Concentration Definition	C.R. (top-10)		C.R.	HHI	C.R. (top-10)		C.R. (top-10)		C.R. (top-10)	
N	789	789	789	789	789	789	481	481	1578	1578
R^2	0.35	0.70	0.13	0.15	0.73	0.82	0.42	0.78	0.43	0.61

***, **, *, + denote statistical significance at the 1%, 5%, 10% and 15% levels.

Table 13. Bank Competition Measure as of 1995 and Risk Taking

This table presents regressions of the change in loan-to-income ratio and in the acceptance rate in the county on local house price volatility, instrumented by housing supply inelasticity (Saiz (2010)). The change in loan-to-income ratio is the percentage growth of the average loan-to-income ratio in a county from 2000 to 2005. The change in the acceptance rate ratio is the 2000-2005 change in the fraction of accepted mortgage loan applications.Bank concentration is measured by the Concentration Ratio (i.e., total market share of top-10 lenders) in that county as of 2000. National banks are defined as lending mortgages in at least fifteen states as of 2000; local banks are defined as lending mortgages in less than fifteen states as of 2000. All regressions are weighted by the number of population in the county as of 2000. Standard errors are clustered at the CBSA level.

	(1)	(2)	(3)	(4)	(5)	(6)
	Percentage change in LTI, 00-05		Change in Acceptance Rate, 00-05		Percentage change in LTI, 00-05	
House Price Vol.	3.50***	1.84***	1.72***	1.49***	4.56***	2.95***
	(0.63)	(0.38)	(0.48)	(0.47)	(0.66)	(0.67)
HP Vol. × Bank Concentration	−4.17***	−2.62***	−2.07**	−1.59**	−5.92***	−4.38***
	(1.07)	(0.61)	(0.85)	(0.77)	(0.96)	(1.07)
HP Vol. × Concentration × {National Bank}			1.80***	1.80***	1.90	1.90
			(0.62)	(0.62)	(1.65)	(1.66)
Bank Concentration (C.R.), 1995	0.23***	0.13**	0.07	0.08	0.45***	0.45***
	(0.06)	(0.05)	(0.06)	(0.06)	(0.09)	(0.12)
HP Vol. × {National Bank}			−1.51***	−1.51	−0.95	−0.95
			(0.42)	(0.42)	(0.97)	(0.98)
Concentration × {National Bank}			−0.03	−0.03	−0.22***	−0.22***
			(0.05)	(0.05)	(0.06)	(0.06)
{National Bank}			−0.03	−0.03	0.13***	0.13***
			(0.03)	(0.03)	(0.04)	(0.04)
%ΔWage		0.51***		0.25***		0.45***
		(0.10)		(0.08)		(0.12)
log(Population)		−0.012**		−0.002		−0.014**
		(0.005)		(0.005)		(0.007)
%ΔPopulation		−0.18*		−0.15^{+}		−0.32**
		(0.10)		(0.09)		(0.13)
%ΔEmployment		0.20***		0.03		0.17**
		(0.06)		(0.05)		(0.07)
%ΔFinance/RE Employment		−0.02		−0.00		−0.01
		(0.02)		(0.02)		(0.02)
Share of Subprime, 2005		−0.06		0.12		−0.08
		(0.06)		(0.06)		(0.08)
Share of Thrifts, 2005		0.63***		−0.02		0.61***
		(0.13)		(0.08)		(0.16)
Share of Refinancing, 2005		2.23***		−1.11**		1.59*
		(0.77)		(0.43)		(0.82)
Share of Securitized, 2005		0.41***		0.07		0.31***
		(0.11)		(0.11)		(0.11)
Share of Investment Homes, 2005		1.16***		0.00		1.00***
		(0.20)		(0.14)		(0.18)
Share of Non-Single Family Homes, 2005		−1.06***		−0.20**		−1.03***
		(0.22)		(0.10)		(0.23)
Constant	−0.03	−0.16	0.00	−0.05	−0.02	−0.14
	(0.05)	(0.11)	(0.04)	(0.09)	(0.04)	(0.10)
N	789	789	1578	1578	1578	1578
R^2	0.39	0.67	0.35	0.39	0.35	0.52

***, **, *, + denote statistical significance at the 1%, 5%, 10% and 15% levels.

Table 14. Change in Tradable Employment in Local County

This table presents regressions of the percentage change in employment of tradable sectors in the county on local house price volatility, instrumented by housing supply inelasticity (Saiz (2010)). The change in tradable employment is the percentage change of total employment in the county from 2007 to 2009, where tradable industries are defined similarly as in Mian and Sufi (2014). Bank concentration is measured by the Concentration Ratio (i.e., total market share of top-10 lenders) in that county as of 2000. Columns (5)-(6) also report regression results using the 2003-2007 change as placebo tests. All regressions are weighted by the number of population in the county as of 2000. Standard errors are clustered at the CBSA level.

	(1)	(2)	(3)	(4)	(5)	(6)
	Percentage Change in Tradable Employment, 2007-2009				%Δ Tradable Employment, 03-07	
House Price Vol.	-0.20^{*}	-1.32^{**}	-1.38^{**}	-1.45^{*}	-0.69	0.35
	(0.12)	(0.56)	(0.54)	(0.79)	(1.10)	(0.95)
HP Vol. × Bank Concentration		2.25^{**}	2.23^{**}	2.41^{*}	0.80	-0.62
		(1.02)	(1.02)	(1.42)	(1.86)	(1.63)
Bank Concentration (C.R.)		-0.04	-0.05	-0.06	-0.03	0.10
		(0.08)	(0.08)	(0.10)	(0.11)	(0.10)
Debt-to-income, 2006			0.01	0.01		
			(0.02)	(0.03)		
%ΔPopulation, 2007-2009				0.03		
				(0.39)		
%ΔPopulation, 2003-2007						0.89^{***}
						(0.19)
log(Population), 2007				0.01		
				(0.01)		
Finance/RE Employment Share, 2005				-0.00		
				(0.01)		
Non-Tradable Employment Share, 2005				0.11		
				(0.18)		
Share of Subprime, 2005				-0.07		
				(0.11)		
Share of Thrifts, 2005				-0.14		
				(0.21)		
Share of Securitized, 2005				0.13		
				(0.16)		
Share of Investment Homes, 2005				0.22		
				(0.43)		
Constant	-0.10^{***}	-0.08^{*}	-0.10^{**}	-0.22	-0.02	-0.14^{**}
	(0.01)	(0.04)	(0.05)	(0.23)	(0.06)	(0.06)
N	728	728	728	728	728	728
State Fixed Effects	N	N	N	Y	N	N
R^2	0.01	0.02	0.02	0.11	0.01	0.10

***, **, *, + denote statistical significance at the 1%, 5%, 10% and 15% levels.