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Essays on Empirical Macroeconomics and Finance

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Princeton, NJ : Princeton University

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Essays on Empirical Macroeconomics and Finance

Xiaochen Feng

A dissertation presented to the faculty of Princeton University
in candidacy for the degree of Doctor of Philosophy

Recommended for acceptance by the Department of Economics
Advisor: Atif Mian

May 2016

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Abstract

The first chapter investigates the risk-shifting agency problem for banks when faced with high competition. Protected by limited liabilities and insured deposits, banks faced with high competition may have the incentive to overly invest in risky assets. This chapter tests the risk-shifting hypothesis of competition by exploiting an exogenous variation in house price volatility. Using loan-application level data for the U.S. mortgage market from 2000 to 2005, I find that banks in high competitive county-level mortgage markets lowered lending standards (e.g., loan-to-income ratio, denial rate) by twice as much as those in less competitive markets in response to volatility in the local house price. Such competition-risk taking pattern was associated with worse economic outcomes after the crisis, including higher foreclosure rate, higher bank failure rate and higher unemployment rate in the non-financial sector.

The second chapter studies whether the increase in inter-state capital flows in the U.S. has substituted labor mobility in explaining the puzzling secular decline in inter-state labor mobility over the past three decades. The identification strategy is to use inter-state bank branching deregulation since the late 1970s and early 1980s as the exogenous shocks to inter-state capital mobility. Furthermore, using staggered bilateral bank branching deregulation between U.S. states, the exact substitution effect can be tested by looking at how labor between states moved before and after. Empirical results found in this chapter suggest that financial market integration and greater capital mobility can explain a significant fraction of the decline in inter-state

labor mobility.

The third chapter examines the fire-sales activities in the U.S. corporate bond market by insurance companies after a severe climate shock, Hurricane Katrina. The chapter tests whether property and casualty insurance companies unexposed to the shock also participated in the fire sales due to mark-to-market accounting rules. Empirical results are found to support this hypothesis and suggest that there was a negative price impact associated.

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Chapter 1

Bank Competition, Risk Taking and Their Consequences

1.1 Introduction

[1]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.

[1]I am grateful to Atif Mian, Markus Brunnermeier, David Sraer and Wei Xiong for their invaluable advice and guidance. I have also benefited from discussions with Gabriel Chodorow-Reich, Stijn Claessens, Charles Goodhart, Hyun Shin, Shang-jin Wei and seminar participants at University of Minnesota (Carlson School of Management), Federal Reserve Bank of Boston, National University of Singapore, Chinese University of Hong Kong, CUNY Baruch College, Brookings Institute, International Monetary Fund, ECB Forum on Central Banking (Sintra), Hong Kong Monetary Authority, City University of Hong Kong, Citivas Foundation Finance Seminar (Princeton University), and Princeton University Macroeconomics and Finance workshops. Financial support from Hong Kong Institute for Monetary Research (HKIMR) is gratefully acknowledged.

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[2]. Notably on the U.S. savings and loans 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[3]. 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 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

[2] 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)).

[3] "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.

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 borne 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[4]. 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 volatility of any asset. The feature of the U.S. housing market makes the identification possible due to the natural cross-

[4]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.

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[5]. 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

[5] 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.

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 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.

1.1.1 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 equity holders 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)[6]), 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))[7].

[6]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.

[7]

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.[8]. 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[9].

The second related strand of literature focuses on the effect of financial disruptions on real 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[10]. 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[11]. 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[12]. My paper also complements

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)).

[8]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.

[9]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.

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

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

[12]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.

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))[13], while this paper uses a cross-section empirical design.

1.2 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.

1.2.1 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 $f = 1$.

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

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

defaults by borrowers should the house price eventually fall. The decision problems of the borrowers and banks are described below in more details.

1.2.1.1. 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 down payment 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[14]. 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.,

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

1.2.1.2. 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

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

$\pi(l;\epsilon) = \alpha M \max\{1 + l - \epsilon, 0\}$. Note that this function π is 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, the house price is assumed riskless and stays at its initial value, i.e., $V_t = f = 1$ for $t \geq 1$.

Following Hellmann, Murdock and Stiglitz (2000), 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 $r'(h) < 0,\ r(\infty) = 0,\ r(0) > \frac{1-\delta}{\delta}\frac{\alpha(p-(1-\bar{e}))}{1-p}$. This assumption corresponds to the competitive equilibrium where banks simultaneously make interest rate offers to investors or depositors subject to a common demand curve whose slope is determined by bank competition, as in Hellmann et. al. (2000)[15]. Bank competition h here essentially determines the 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.

[15] 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 $h \to \infty$.

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.

1.2.2. 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 $h = \underline{h}$.

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.

1.2.3. 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 experienced by banks could affect local unemployment especially for smaller-sized firms through the tightening of local credit conditions, e.g., Chodorow-Reich (2014). Based on this literature and 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.

1.3 Mortgage Market and Data

1.3.1. 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[16]. 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[17]. 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 the pass-through of monetary policy. Various other

[16]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).

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

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[18]. 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.

1.3.2. 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[19].

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

[19] 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.

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. 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).

1.3.3. 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 1.1.

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.

1.4.1. Identification Strategy

1.4.1.1. 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[20]. 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.

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[21]. 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

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

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

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.

1.4.1.2. 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 uncorrelated with various measures

of economic fundamentals. Panel B in Table 1.2 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 1.3 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 Appendix of this chapter.

The joint distribution of the housing supply elasticity measure and the bank concentration measure is summarized in Panel A of Table 1.2. 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.

1.4.2. 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 grown 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].

[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]

Result of the first-stage regression is presented in Table 1.3 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 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.

1.4.3. 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.

1.4.3.1. 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.

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

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.

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 and the 2000 acceptance rates for that county. The loan-to-income ratio follows more closely with the theoretical model as it measures 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

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

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 $1\{\text{National Bank}\}$ 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 look at the evolution of the share of national banks at the county level by computing 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 the Riegle-Neal Act of 1994. 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.

1.4.3.2. Main Regression Results

Results on the loan-to-income ratio are reported in Table 1.4. 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

[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.

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 $1\{\text{National Bank}\}$. 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 $\times\, 1\{\text{National Bank}\}$) 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 for national banks the estimate of β_2 (-6.32) is reduced 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 1.5 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 laxer 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 $\times$ 1{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.

1.4.3.3. 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 1.6 reports the regression results. In columns (1)-(3) of Table 1.6, 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.

1.4.4. 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.

1.4.4.1. 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 1.7 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.

1.4.4.2. 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

(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 1.8 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 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.

[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.

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. More details are included in the Robustness section.

[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.

1.5 Robustness and Discussion

1.5.1. 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 1.9 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 $(\text{HPVol} \times \text{HHI} \times 1\{\text{National Bank}\})$ is positive.

For regression (1d), Table 1.10 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 $(\text{HPVol} \times \text{HHI} \times 1\{\text{National Bank}\})$ (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 1.11. In columns (1)-(4), the left-hand-side variable is the share of mortgage loans that have high spread in the interest rate

[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.

($> 3\%$ 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 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 to their bank concentration levels.

1.5.2. 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 1.12. 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 1.12 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 1{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$1{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.

1.5.3. 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 1.13. 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$\times$Concentration) is negative. More importantly, the estimate for the coefficient β_3 on (HPVol$\times$Concentration$\times$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.

1.5.4. Discussion

1.5.4.1. 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 1.14. 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 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

[32] 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.

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].

1.5.4.2. 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

[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.

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 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 1.3). To more formally address this issue, I use the realized house price volatility instead of the predicted value. In Table 1.12, 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.

1.6 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.

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 $h = \underline{h}$. □

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 $\frac{\partial l_0}{\partial \epsilon} \geq 0$. □

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, $\hat{h}'(\epsilon) \leq 0$. □

Figure 1.1. 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.

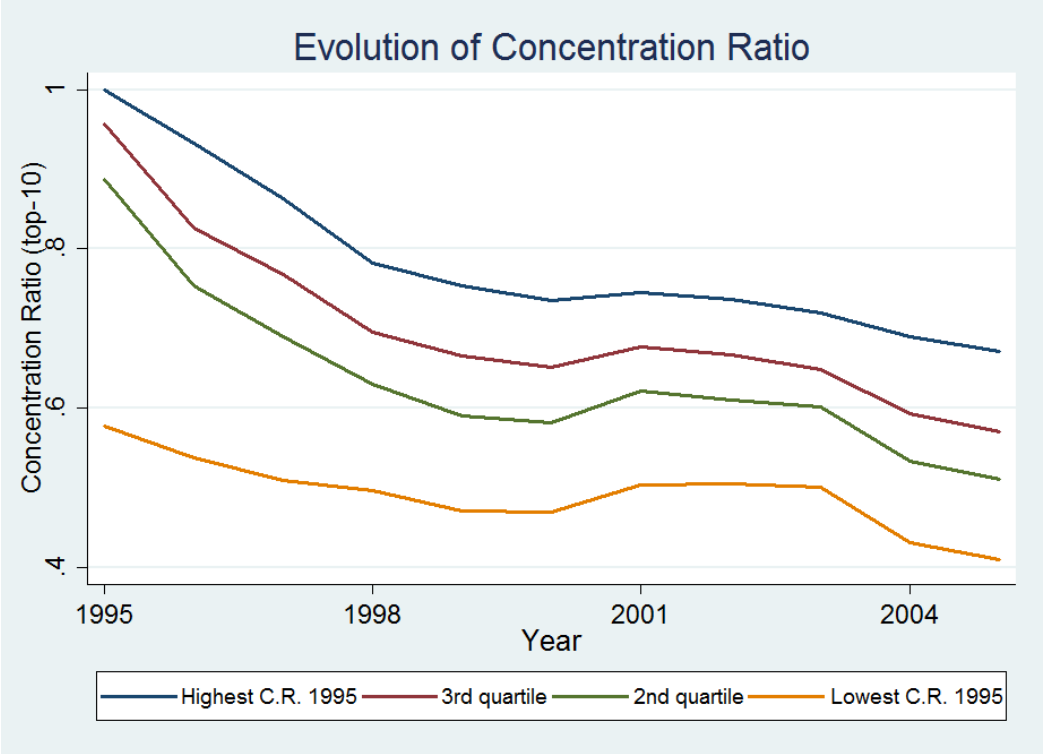


Figure 1.2. Historical House Price Volatility: 1982-1996

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).

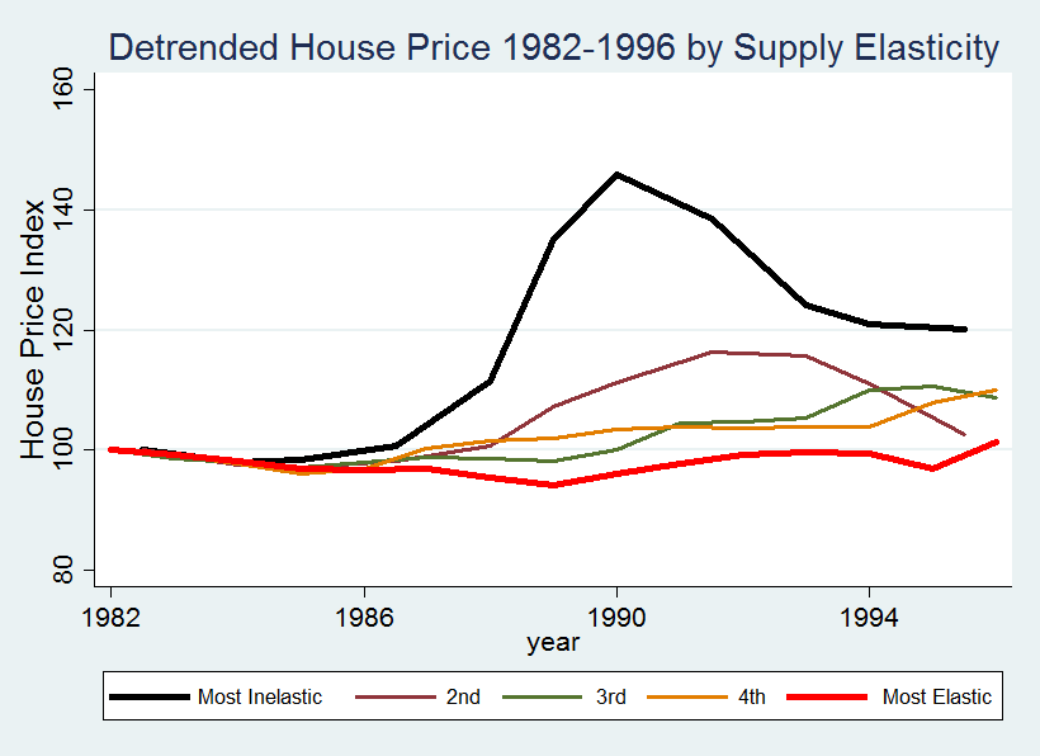
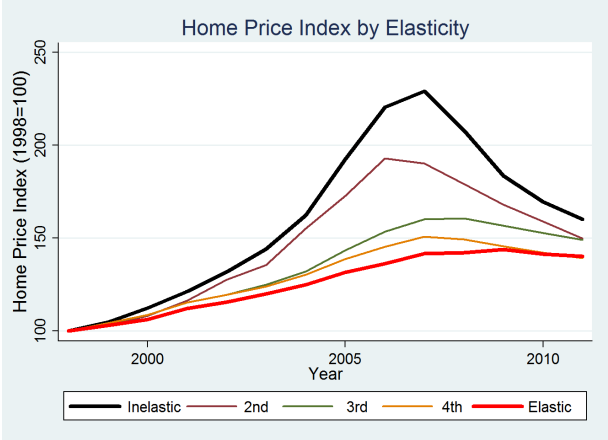


Figure 1.3

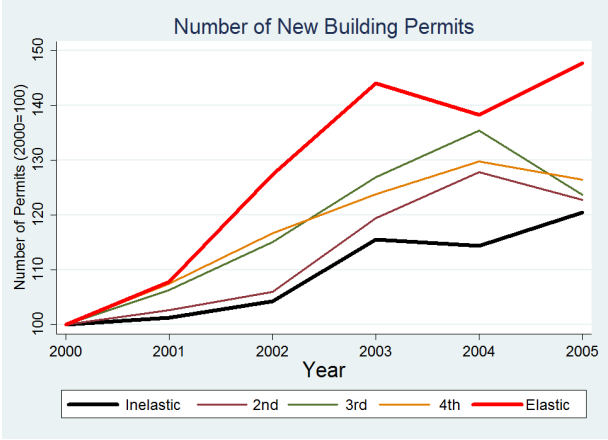
House Price Volatility Over the Recent Cycle and Exclusion Restriction

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

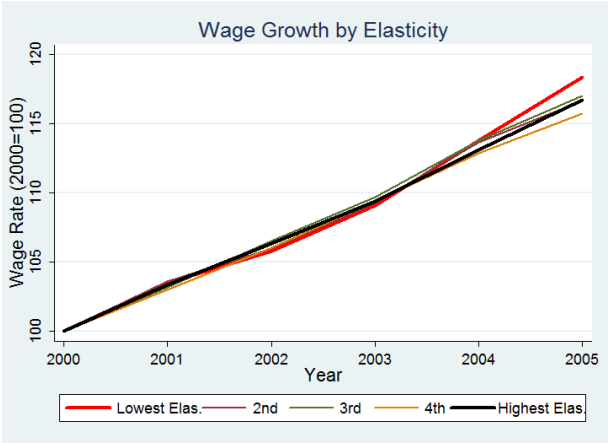
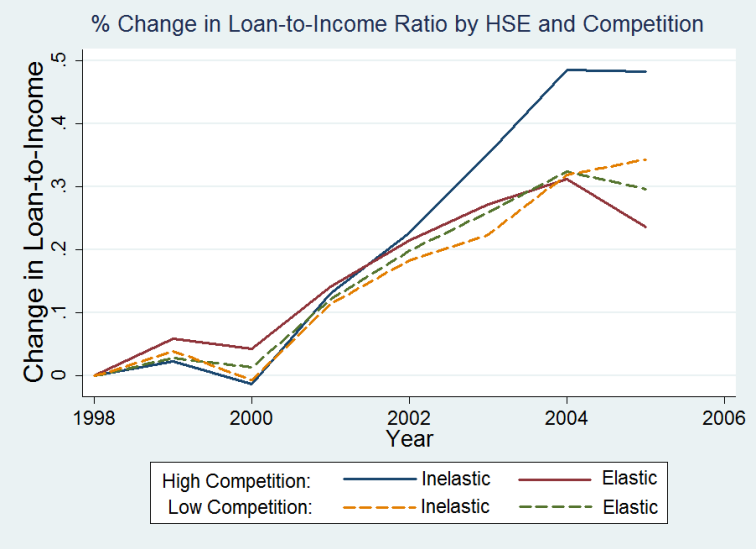

Wage Growth by Elasticity
Wage Rate (2000=100)
100
105
110
115
120
2000
2001
2002
2003
2004
2005
Year
Lowest Elas.
2nd
3rd
4th
Highest Elas.

Figure 1.4

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

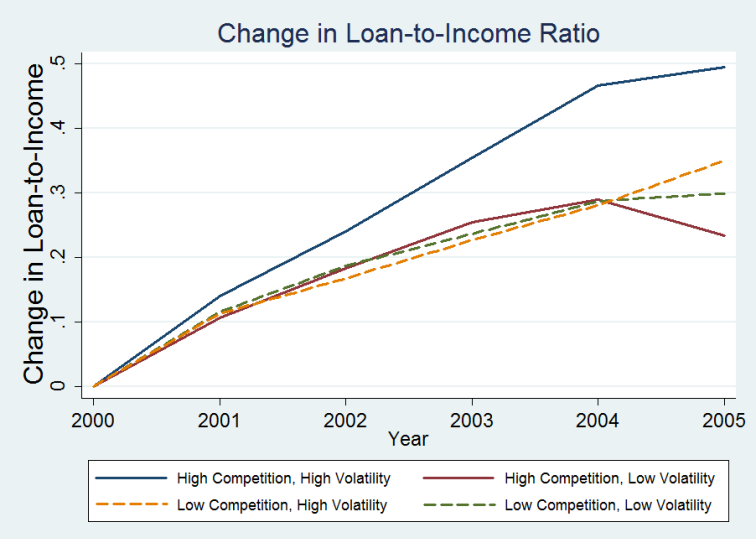
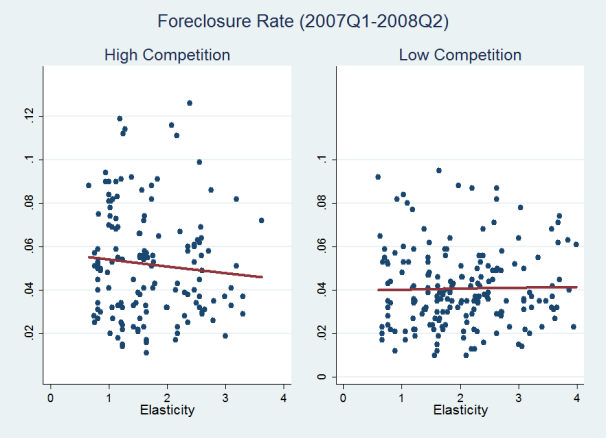


Figure 1.5

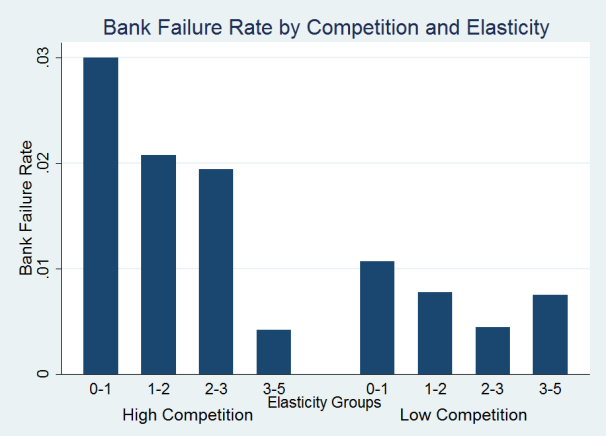
Bank Competition, House Price Volatility and Post-Crisis Outcomes

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.

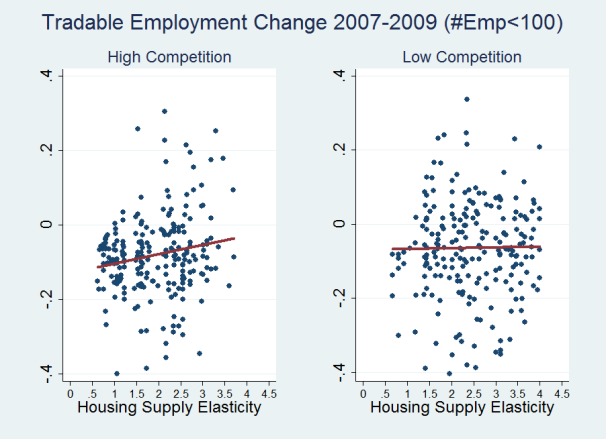
Panel A



Panel B



Panel C


Tradable Employment Change 2007-2009 (#Emp<100)
High Competition
Low Competition
.4
.2
0
-.2
-.4
0 .5 1 1.5 2 2.5 3 3.5 4 4.5
Housing Supply Elasticity

Appendix: Controlling for County Fixed Effects

Empirical analysis in the paper shows that, in counties where the lending market was competitive, the response of average loan-to-income ratio to housing risk was strong after controlling for many county characteristics such as wage growth, subprime and securitization percentage and etc. However, one might still be concerned that high- and low-competition counties are different in an unobservable way. Ideally, one would need to include county fixed effects to exclude all possible confounding factors about the specific county. In this section, I control for county fixed effects by comparing banks lending in the same county and show that competition affected lending decisions at the bank level.

I look into more details how two banks in the same county behaved differently. Consider two similar multiple-branch banks A and B lending mortgage loans in a county C. Suppose that bank A mainly operates in competitive mortgage markets and bank B has business in concentrated markets. According to the risk shifting hypothesis derived above, from 2000 to 2005, bank A would raise the loan-to-income ratio more than bank B in county C. Moreover, if county C has inelastic housing supply (i.e., high house price volatility), the difference between the lending behaviors of banks A and B would be the largest. To test this effect, I perform the following analysis.

(OA1) $\Delta LTI_{b,c}^{00-05} = \alpha_c + \beta_1 wHHI_b + \beta_2 wHHI_b \times Elas_c + \beta_3 X_b + \epsilon_{b,c}$

where $\Delta LTI_{b,c}^{00-05}$ is the 2000-2005 percentage change in average loan-to-income ratio of loans issued by bank b in county c, α_c is county fixed effect, $wHHI_b$ is the weighted average of Herfindahl indexes for bank b as of 2000, $Elas_c$ is the housing supply elasticity of county c, and X_b is a list of bank controls including the size, type, and loan amounts of the bank[34].

If the risk shifting mechanism is present, one would expect that a higher degree of market competition for the bank (i.e., lower $wHHI_b$) is associated with greater $\Delta LTI_{b,c}^{00-05}$, meaning that $\beta_1 < 0$. Moreover, the difference should be the largest in counties where house price is

[34] I restrict my sample to bank-county pairs where the county represents at least 3% and at most 50% of the bank's total mortgage portfolio as these banks would have similar lending strategies with respect to this county.

Table 1.1. 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 1.2. 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) %ΔWage 01-05	(2) %ΔEmployment 01-05	(3) %ΔFinance/RE Employment, 01-05	(4) 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 1.3. 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 1.4. 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 1.5. 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 1.6. 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 1.7. 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 $\times$ 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 1.8. Change in Employment in Local County

This table presents regressions of the change in tradable and non-tradable 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. $\times$ 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 1.9. 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 1.10. 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 1.11. 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 1.12. 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 1.13. 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 1.14. 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.

most volatile (i.e., lower elasticity), suggesting that $\beta_2 > 0$. Table OA1 shows the empirical estimates. In column (1), I regress the change in LTI for the bank on its weighted average of HHI alone. We can see a slightly negative correlation but it is statistically insignificant. In columns (2) and (3), I interact the weighted average HHI with the housing supply elasticity of the county. In column (2), we have $\beta_1 < 0$ and $\beta_2 > 0$ and both estimates are statistically significant. The interpretation of this result is that, for counties with very inelastic housing supply, a higher competition level (i.e., lower HHI) for the bank implies a larger increase in LTI from 2000 to 2005; for elastic-supply counties, this difference was much weaker. Columns (3) reports similar results for the same exercise by adding bank controls (e.g., bank size, bank type, headquarter state fixed effects) in the regressions. In columns (4)-(6), I repeat the same exercise but measure bank competition in a county by concentration ratio instead of the Herfindahl index. One can see that very similar estimates are obtained.

In sum, in this section, I include county fixed effects by comparing banks facing different levels of competition and lending in the same county. I show that banks that face higher competition lent more aggressively than other banks from 2000 and 2005, and this difference was the most significant for areas where house price grew the fastest.

Appendix: Bank-Level Analysis

Raising the loan-to-income ratio is one dimension that banks could increase their load on housing risk. Another dimension is that multi-branch banks might adjust their loan issuance through their branches. Increasing loan issuance aggressively in inelastic areas increases the correlation of the return of their mortgage portfolio with the aggregate housing shock. Banks mainly operating in competitive mortgage markets would be more willing to issue loans to inelastic areas through branches as to increase the correlation of loan performance to the house price shock.

For each bank, I compute the following measures. First, I compute the weighted average of the Herfindahl index (or concentration ratio) of counties for this bank as of 2000, denoted as $wHHI_b$. For 2001 and 2005 separately, I also compute the weighted average of elasticities of counties in which the bank had mortgage lending activities in, where the weights are the county's share in the bank's mortgage portfolio. I define this 2001-2005 difference

as $\Delta Elas_b^{01-05}$ for each bank b. The change in average elasticity consists of two parts: some mechanical change caused by natural loan growth in some areas and the intentional part that banks adjusted. The mechanical change takes into account the situation that some counties in the bank's portfolio experienced growth in population and total loan issuance which results in the change in the bank's average elasticity. To correct for this difference, I compute the measure $AverageChange_b^{01-05}$ defined as what the change in average elasticity would have been if the bank maintained the same market shares in all counties as its market shares in 2001. Subtracting it from the change in elasticity, i.e., $\Delta Elas_b^{01-05} - AverageChange_b^{01-05}$, would then measure the *intentional* change in bank b's portfolio choice across counties.

Specifically, the empirical model to test this prediction is shown below.

(OA2) $\Delta Elas_b^{01-05} - AverageChange_b^{01-05} = \beta_0 + \beta_1 wHHI_b + \beta_2 X_b + \epsilon_b$

where $\Delta Elas_b^{01-05}$ is the change in the weighted average elasticity of mortgage issuance across counties for bank b, $AverageChange_b$ is the average change in elasticity fixing the bank's market shares in all counties as of 2001, $wHHI_b$ is the weighted average Herfindahl indexes of counties in which bank b lent mortgages in 2000, and X_b is a list of bank controls including bank size, total mortgage issuance, and type of the bank.

As the housing supply elasticity measure is not available for all counties, I only focus on banks for which the measure covers at least 70% of their loan portfolio as of 2001 [35]. Table OA2 reports the regression results. Column (1) reports the regression result of the change in elasticity in relation to average Herfindahl for the bank. The coefficient is positive and significant, suggesting that banks faced with low concentration HHI (i.e., high competition) intentionally increased loan issuance in inelastic counties. In column (2), I only retain banks that had elasticity measure covering over 99% of their portfolio and find similar a similar estimate. Column (3) repeat the exercise by including bank controls, e.g., bank size, securitized share, and bank type[36]. In columns (4)-(5), I also include fixed effects for the headquarter state of the bank.

[35] I also require that each bank at least issued 100 mortgage loans as of 2005 and winsorize the change in elasticity ($\Delta Elas_b - AverageChange_b$) by 2.5% at each tail of its distribution. These steps essentially allow me to reduce the noise caused by very small banks in my sample.

[36] Bank type is defined as the type of regulatory agency that oversees the bank. The regulatory agency can be Office of the Comptroller of the Currency (OCC), Federal Reserve System (FRS), Federal Deposit Insurance Corporation

The coefficient on the weighted average HHI of the bank remains positive and statistically significant, especially when I only look at states that have a large number (> 150) of banks so the headquarter state fixed effects would not take out too much information. In columns (6)-(7), I use weighted average concentration ratio instead of Herfindahl index for each bank as of 2000. One can see that higher bank-level competition predicted greater shifts towards inelastic areas.

In sum, in this section, I show that banks competing more strongly in the mortgage market increased the weight of inelastic-county loans in their portfolio. The return of their portfolio was made more correlated with the house price shock. This is consistent with Prediction 2 that higher competition encourages banks to take on the housing risk through the extensive margin by issuing more loans in higher-risk areas.

Appendix: Other Robustness Checks

In this section, I perform robustness checks on the main regression (1). Specifically, I consider the following three categories of concerns. First, to address the concern that securitized loans did not remain on banks' balance sheet, I exclude all securitized loans from the sample and check if the non-securitized sub-sample yields similar estimates. I also include the quadratic form of house price volatility as controls. Second, I alternatively drop all refinancing loans. This is to address the question that characteristics of refinancing loans may contain different information than those for home purchase loans. Third, I also distinguish different types of financial institutions according to their regulatory agency. Performing this exercise is to address the concern that the capital structure and/or other items on the balance sheet may also affect banks lending decisions. The HMDA database identifies the regulatory agency of the financial institution for each mortgage loan. I specifically drop all thrift institutions and keep commercial banks only.

Regression results are reported in Table OA3. In Columns (1)-(3), I drop all loans in the sample that were securitized either by government-sponsored enterprises (GSEs) or private institutions. In column (1), we see that the coefficient on the interaction term between house price

(FDIC), Office of Thrift Supervision (OTS), National Credit Union Administration (NCUA), Department of Housing and Urban Development (HUD), and Consumer Financial Protection Bureau (CFPB). This information is obtained from the HMDA data.

volatility and bank concentration is strongly significant. The coefficient remains significant after controlling for the quadratic term of house price volatility, as shown in Column (2), or controlling for other county-level variables, as shown in Column (3). For Columns (4)-(5) and Columns (6)-(7) I keep only home-purchase loans and owner-occupied loans, respectively. One can see that the coefficients on the interaction term remains statistically significant with and without various controls.

In Columns (6)-(7), I only keep mortgage loans issued by commercial banks in the sample. Moreover, I also distinguish lending decisions made by national banks (i.e., operating in more than 15 states as of 2000) from those made by regional banks (i.e., operating in fewer than 15 states as of 2000). One can see that the coefficient on the interaction term between house price volatility and bank concentration is negative and statistically significant. Moreover, being issued by national banks offsets this relationship significantly. This result is consistent with the main specification in this paper and shows that the findings here were not driven by capital structure or changes to other (unobserved) items on the balance sheet.

In sum, in this section, I present robustness checks by dropping securitized loans, refinancing loans and loans issued by thrift institutions. Empirical results are robust to these alternative settings.

Table 1.15

Banks Competing in the Same County

This table presents regressions of bank-level average loan-to-income change from 2001 to 2005 in a given county on the average Herfindahl index for the bank. Bank-level Herfindahl index (wHHI), representing bank concentration, is the weighted average HHI of counties in which the bank had mortgage lending activities in 2001. To ensure that banks in each county are comparable, I require that each bank must have at least 3% and at most 50% of its total mortgage loans in the county and that each county must have at least 15 banks for the inclusion of county fixed effects. Standard errors are clustered at the county level.

	(1)	(2)	(3)	(4)	(5)	(6)
	Percentage change in loan-to-income, 2001-2005					
Bank Average Concentration	-0.31	-3.19^{**}	-3.44^{**}	-0.17	-0.75^{**}	-1.07^{***}
	(1.01)	(1.30)	(2.36)	(0.21)	(1.30)	(0.33)
Bank Average Concentration $\times$ Elasticity		1.50^{***}	1.68^{***}		0.35^{***}	0.42^{***}
		(0.56)	(0.57)		(0.13)	(0.13)
Share of Loans Securitized			-0.03			0.05^{*}
			(0.02)			(0.03)
Concentration Measure	HHI	HHI	HHI	C.R.	C.R.	C.R.
Bank Size and Type Controls	N	N	Y	N	N	Y
Bank Headquarter State F.E.	N	N	Y	N	N	Y
N	2159	2159	2159	2159	2159	2159
R^2	0.06	0.07	0.08	0.06	0.07	0.10

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

Table 1.16

Bank Portfolio Shift and Bank Competition

This table reports regressions of the 2001-2005 change in the intentional changes in weighted average elasticity of counties in which the bank had mortgage lending activities. This intentional change is measured by the actual change in weighted average elasticity for the bank minus what the average elasticity would have been if the bank maintained constant market shares in each county from 2001 to 2005. Bank-level Herfindahl index (wHHI), representing bank concentration, is the weighted average HHI of counties in which the bank had mortgage lending activities in 2001. Since the elasticity measure of some counties is missing, I require that at least the elasticity measure should cover at least 70% of the mortgage portfolio of the bank. To ensure that my results are not driven by extreme cases, I require that each bank issued at least 100 mortgage loans as of 2001 and winsorize the change in average elasticity at 2.5% at each tail of its distribution. Standard errors are robust.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Change in average elasticity						
Weighted Average HHI	2.71***	3.24**	2.78***	0.96	1.65***		
	(0.77)	(1.47)	(0.79)	(0.64)	(0.71)		
Weighted Average Concentration Ratio						0.78***	0.39***
						(0.10)	(0.12)
# of Mortgage Loans			0.97***		0.62***		0.62***
			(0.25)		(0.23)		(0.24)
# of States			0.001		0.002*		0.002*
			(0.001)		(0.001)		(0.001)
# of Counties			−0.08*		−0.04		−0.02
			(0.04)		(0.04)		(0.04)
Share of Loans Securitized			0.03		−0.02		−0.00
			(0.03)		(0.02)		(0.02)
Elasticity Measure Coverage Rate	> 70%	> 99%	> 70%	> 70%	> 70%	> 70%	> 70%
# of Banks in the State	All	All	All	All	> 150	All	All
Bank Type F.E.	N	N	Y	N	Y	N	Y
Bank Headquarter State F.E.	N	N	N	Y	Y	N	Y
N	2203	613	2203	2203	1782	2203	2203
R^2	0.01	0.013	0.03	0.42	0.42	0.03	0.43

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

Table 1.17

Robustness: Non-Securitized, Home-Purchase, and Commercial-Bank-Issued Loans

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 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)	(7)	(8)	(9)
	Percentage change in LTI, 00-05								
	Non-Securitized			Home-Purchase		Owner-Occupied		Commercial-Bank-Issued	
House Price Vol.	3.60^{***}	3.17^{***}	1.71^{**}	1.64^{***}	1.09^{***}	3.53^{***}	1.61^{***}	6.21^{***}	3.63^{*}
	(0.84)	(0.86)	(0.72)	(0.48)	(0.40)	(0.66)	(0.50)	(1.79)	(1.94)
HP Vol. × Bank Concentration	-5.25^{***}	-4.59^{***}	-2.62^{***}	-1.90^{**}	-1.63^{**}	-4.39^{***}	-2.17^{***}	-9.12^{***}	-6.35^{**}
	(1.52)	(1.49)	(1.27)	(0.92)	(0.70)	(1.16)	(0.84)	(3.04)	(3.23)
HP Vol. × Concentration × {National Bank}								5.68^{*}	5.68^{*}
								(3.38)	(3.40)
Bank Concentration (C.R.), 1995	0.15^{+}	0.12	0.11	0.52^{***}	0.21^{***}	0.38^{***}	0.21^{***}	0.48^{**}	0.44^{**}
	(0.10)	(0.11)	(0.09)	(0.08)	(0.06)	(0.08)	(0.06)	(0.20)	(0.19)
HP Vol. × {National Bank}								−2.70	−2.70
								(1.93)	(1.94)
Concentration × {National Bank}								−0.04	−0.04
								(0.18)	(0.18)
{National Bank}								0.07	0.07
								(0.10)	(0.10)
$(\text{HP Vol.})^2$		0.12							
		(0.11)							
%ΔWage			0.33^{***}		0.38^{***}		0.54^{***}		0.42^{*}
			(0.12)		(0.10)		(0.10)		(0.22)
log(Population)			−0.008		-0.015^{***}		-0.009^{*}		−0.002
			(0.006)		(0.004)		(0.005)		(0.009)
%ΔPopulation			−0.04		−0.12		−0.13		−0.01
			(0.13)		(0.08)		(0.11)		(0.21)
%ΔEmployment			0.23^{***}		0.17^{***}		0.19^{***}		0.12
			(0.07)		(0.05)		(0.06)		(0.11)
%ΔFinance/RE Employment			−0.02		−0.01		−0.02		−0.01
			(0.02)		(0.02)		(0.02)		(0.03)
Share of Subprime, 2005			−0.09		-0.16^{**}		0.00		−0.06
			(0.07)		(0.07)		(0.07)		(0.12)
Share of Thrifts, 2005			0.38^{**}		0.51^{***}		0.61^{***}		0.73^{***}
			(0.18)		(0.10)		(0.14)		(0.28)
Share of Refinancing, 2005			2.13^{***}		-1.63^{**}		1.77^{**}		4.16^{***}
			(0.74)		(0.72)		(0.77)		(1.38)
Share of Securitized, 2005			1.02^{***}		-0.19^{**}		0.35^{***}		0.86^{***}
			(0.18)		(0.09)		(0.11)		(0.21)
Share of Investment Homes, 2005			1.55^{***}		0.63^{***}		0.98^{***}		1.05^{***}
			(0.26)		(0.18)		(0.19)		(0.33)
Share of Non-Single Family Homes, 2005			-0.78^{***}		-0.44^{**}		-1.00^{***}		-1.19^{***}
			(0.24)		(0.17)		(0.22)		(0.30)
Constant	0.25^{***}	0.26^{***}	-0.35^{**}	-0.21^{***}	0.16	−0.02	-0.16^{*}	−0.10	-0.67^{***}
	(0.06)	(0.06)	(0.14)	(0.04)	(0.11)	(0.05)	(0.10)	(0.12)	(0.18)
N	789	789	789	789	789	789	789	1578	1578
R^2	0.21	0.22	0.47	0.24	0.58	0.39	0.64	0.21	0.34

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

Chapter 2

Does Capital Make Labor Stay in Town?

2.1 Introduction

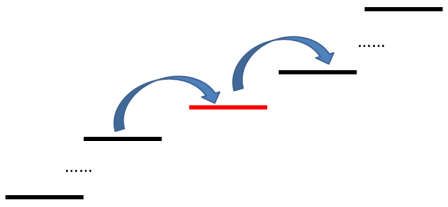
[1]One puzzling phenomenon in the recent macroeconomic literature is that interstate labor mobility across U.S. states has dramatically declined since the 1980s, which has drawn much attention among economists and policymakers. The magnitude of the decline is large: the fraction of people who have moved across state borders in a year has dropped from over 3% in 1982 to around 1.5% in 2010 (Figure 1). Mostly using survey data, studies in this literature have found that the decline in labor mobility was present across many characteristics (e.g., age, education, etc.) of households and workers (e.g., Kaplan and Schulhofer-Wohl (2013)). Various macroeconomic models with search frictions in the labor market have been introduced to explain this phenomenon, but the discussion is still far from conclusive. In this paper, I study how one particular economic force, the increasing mobility of capital across U.S. states, has contributed to the decline in labor mobility. Specifically, I test the substitution effect between mobilities of capital and labor using U.S. states banking deregulation in the 1980s and 1990s as the exogenous shocks to cross-state capital mobility. The findings in this paper suggest that a significant fraction of the

[1]I especially thank David Sraer for providing the data. I thank Atif Mian, Oleg Itskhoki, Greg Kaplan, Steve Redding and David Sraer for very helpful comments and suggestions. All remaining errors are mine.

recent decline in interstate labor mobility in the U.S. was associated with the integration of financial systems across states.

The intuition for the substitution between capital and labor mobilities is straightforward. Consider a world economy where states begin with different endowments of capital and labor which are the only two inputs in production[2] . Capital-abundant states have relatively high capital-labor ratios and capital-scarce states have low capital-labor ratios. First suppose in the base case that capital is not allowed to move across borders but labor can move subject to some convex costs. In this setup, there would be labor flows from capital-scarce states to capital abundant states, as capital-abundant (i.e, high capital-labor ratio) states would have a higher wage rate and a lower rental rate of capital than capital-scarce states (i.e., low capital-labor ratio). This is because each worker in the capital-abundant state has a higher amount of capital to work with and hence is more productive. The differential in wage rates between states gives rise to the incentive for workers to move, from lower-wage states to higher-wage states. One can illustrate this equilibrium with multiple states as a series of ladders where top ladders represent capital-abundant states and bottom ladders represent capital-scarce states (see Figure 2 Panel A below). Under the restriction on capital movements, we would expect that states on each ladder sends labor to the ones above and receives labor from the ones below. A more disperse distribution of these ladders would simply imply greater gross labor flows across states, as the gaps in labor returns that incentivize workers to move would be greater.

Panel A. Labor Flows Between Ladders Before Financial Liberalization

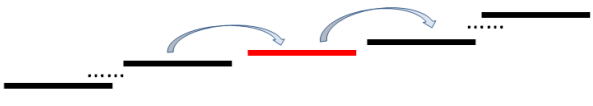


2

I follow MacDougall (1960) and Kemp (1964) and assume that there is one good, perfect competition, full employment and the same constant-returns-to-scale production technology in each state.

Now suppose that restrictions on capital movements are lifted and capital can flow freely across state borders. We examine how this change in capital mobility would result in changes in labor flows. After the increase in mobility, capital would then flow from capital-abundant states to capital-scarce states which potentially have higher returns to capital. The flow of capital tends to equalize the degree of capital abundance (i.e., capital-labor ratio) across states, and as a result, returns to labor tend to be equalized as well. Consequently, this diminishing differential in labor returns across states would result in lower interstate flows of labor. In the extreme case where capital-labor ratios are completely equalized, no labor has the incentive to migrate. In other words, capital mobility across states would *substitute* labor flows. Again, I illustrate this equilibrium as ladders of states by their capital abundance in Panel B of Figure 2 below. The increase in capital mobility simply brings the ladders (i.e., capital-to-labor ratios) to the same level, narrowing the gap between labor returns across states. Compared to the previous case where capital is not allowed to move, each state (except the very top and bottom ones) now sends fewer labor to ladders above and receives fewer labor from ladders below. In the aggregate, we would see a decline in the *gross* interstate flows of labor after capital account liberalization. In this paper, I examine the effects of financial liberalization on labor mobility and labor returns from 1982 to 2005 across U.S. states. To identify the changes in cross-state capital mobility, I also use bilateral interstate banking deregulation in the 1980s and 1990s as the exogenous shocks. Below I explain the details of my empirical analysis and describe the deregulation of the banking system of U.S. states which serves as the exogenous shocks to capital mobility in the analysis.

Panel B. Labor Flows Between Ladders After Financial Liberalization



U.S. states gradually deregulated their banking systems starting in late 1970s and allowed interstate branching. Before the deregulation, each state in the U.S. had an isolated banking system. The deregulation allowed banks from other states to set up branches and acquire local banks across state borders so capital flows have become mobile across states. Since then, the U.S. financial sector experienced a surge in growth of large bank holding companies. It is also since then that individual banking systems in each state have gradually integrated into one national banking system. The deregulation of interstate banking was implemented in the form of bilateral and multilateral agreements between two or more states. The agreements especially allowed bank holding companies (BHCs) to acquire commercial banks across state lines making cross-state capital flows more mobile. Various studies have used the deregulation of interstate banking in the U.S. as the change in banking capital allocation (e.g., Michalski and Ors (2012)[50], Landier, Sraer, Thesmar (2013)[42]). In my empirical analysis, I use data on both first-time deregulation of a state and detailed data on bilateral agreements between states as the exogenous change to cross-state capital mobility. I especially focus on how this change in capital mobility has affected the flows of labor across states lines.

The key findings in this paper are very consistent with the empirical implications mentioned above. Using Internal Revenue Service (IRS) and Current Population Survey (CPS) data on interstate migration, I find that, after a state deregulated its banking system with other states for the first time, it experienced a significant fall in total outflow of labor to other states, as predicted by the theoretical framework. This finding is robust to controlling the growth of trade in the state. The deregulation alone can account for a quarter of the total fall in labor outflow from 1982 to 2000 and the effect was mainly for states with a low bank loans per capita. To further pin down the substitution between capital and labor, I use detailed data on bilateral banking deregulation between U.S. states during this deregulation process. I find that bilateral banking deregulation lowered bilateral labor flows, and the main effect was again on the reduction of labor outflows from the state with a lower bank loans per capita, i.e., the relatively capital-scarce state. These findings confirm the theoretical predictions and suggest that the increase in capital mobility indeed substituted the flow of labor during the course of financial integration of U.S. states. It further indicates that the increasing capital mobility across U.S. states has contributed significantly to the decline in interstate labor moves observed in the data over this time period.

I also investigate whether the increase in capital mobility has indeed altered factor prices across states. In line with the theoretical predictions, I find that the growth rate of real wages increased significantly after banking deregulation, and this effect was the strongest for states with a low bank loan per capita as of 1980. In the most capital-scarce states (i.e., lowest quintile by bank-loan-to-population ratio), the deregulation of the banking sector increased the annual growth rate of real wages by 1.2%, while insignificant estimates are found for capital-abundant states (i.e., highest quintile by bank-loan-to-population ratio). I also look into the differential in wage growth across industries according to their reliance on banking and external finance as defined by Rajan and Zingales (1998)[3]. I find that banking deregulation had the strongest effect on real wage growth for industries that heavily depended on external financing. This confirms that the effect of banking deregulation on labor returns was through the increased abundance of banking capital, an important source of external finance. These additional findings on wage rates all suggest that the increased capital mobility due to banking deregulation has narrowed the gap between labor returns between capital-abundant and capital-scarce states, a prediction of the substitution effect between capital and labor.

This paper contributes to the literature in the following ways. First, it explores an important channel, i.e., the substitution of capital and labor, in explaining the puzzling decline in interstate migration in the U.S.. While U.S. states have become financially integrated since the interstate banking deregulation period in the 1980s and 1990s, studies on the impact of financial integration on interstate labor mobility is largely missing in the literature. This paper attempts to fill this gap and quantify the effect. Moreover, this paper also brings new elements and evidence to the literature of international factor mobility and the finance-growth nexus. Various studies have found similar patterns of increasing capital mobility and decreasing interstate labor mobility across states or provinces within Canada, Australia and some European countries as well (e.g., Beine, Bourgeon and Bricongne (2013)[8], Kaplan and Schulhofer-Wohl (2013)). This paper proposes a new research agenda in studying this long-run trend common to many countries.

[3] To measure reliance on external finance of industries, I use Dependence on External Finance (DEF) defined by Rajan and Zingales (1998) and hand-match 154 3-digit SIC industries in the Quarterly Census of Employment and Wages (QCEW) to the ISIC industries in their paper.

2.1.1. Related Literature

This paper is related to a few strands of literature. First, it is linked to the macro-labor literature explaining the decline in U.S. interstate migration. One closely related study is Kaplan and Schulhofer-Wohl (2012)[36] who provide extensive analysis on the hypotheses that explain the decline and conclude that the decline in geographic specificity is the key to understand the decrease in labor mobility. They also place emphasis on the decline of *gross* migration, which is also a phenomenon this study attempts to address. Ganong and Shoag (2013)[26] focus on the relationship between income convergence and housing regulation. Bayer and Juessen (2012) consider a two-location model where persistence in the income process could affect migration. For a more complete review of the literature, Molloy, Smith, and Mozniak (2011)[51] document the patterns in the decline in interstate migration and find that cyclical components including housing market dynamics cannot explain the puzzling decline.

The second strand of literature looks at the flow of factors in international trade. MacDougall (1960)[45] and Kemp (1964)[37] set up the model with two countries, two factors and one good. This setup is the easiest for the study of the mobility of one factor (i.e., labor) after the mobility of the other factor (i.e., capital) changes. Ruffin (1984)[60] provides a comprehensive review of the literature on international factor movements. On the substitution between trade and factor movements, the Heckscher-Ohlin framework predicts that they are substitutes, while Antras and Caballero (2007)[4] point out that, with the presence of financial friction, trade and factor movements can be complements.

This paper is also related to the literature that looks at how banking deregulation can affect real economic activities. Jayaratne and Strahan (1996)[34] discuss the relationship between economic growth and financial development. Morgan, Rime and Strahan (2004) use U.S. banking deregulation across U.S. states as exogenous shocks to show that real economic activities were synchronized after financial integration. Moreover, they show that economic volatility tended to decline after deregulation. On labor returns after financial liberalization, the literature mainly focuses on the distribution of income and empirical evidence is often mixed. Using U.S. data, Beck, Levine, and Levkov (2010)[6] find that financial liberalization tightened income distribution by increasing the wage of unskilled workers. Larrain (2013)[43] finds the opposite that financial liberalization encourages the wage growth of skilled workers due to the

complementarity between skill and capital. In this paper, I focus more on the different effects of financial liberalization on labor returns according to the relative capital abundance of states. I also use the Rajan and Zingales (1998)[58] definition of Dependence on External Finance (DEF) to study the different effects of financial liberalization on labor returns in different industries. The bilateral deregulation data have been used in various studies for other topics. Michalski and Ors (2012)[50] use this measure to study how economic integration especially trade followed financial integration. Using these data, Goetz and Gozzi (2013)[30] find that financial integration increased the co-movement of real economic activities, including wages, while Landier, Sraer, and Thesmar (2013)[42] find that house price co-movement also increased after banking integration. The outcome variables in their study, e.g., trade and co-movement of wages, are included as my control variables for the study of labor moves.

2.2 Theoretical Framework

In this section, I present a simple two-country two-factor model, similar to MacDougall (1960) and Kemp (1964). The setup is the simplest possible, which includes two countries, two factors (namely labor and capital), one good, perfect competition, full employment and same production technologies with constant returns to scale. In this setup, countries trade factors with each other. I use this simple model with the MacDougall-Kemp setup to show how the change in the mobility of capital would affect the degree of labor flows.

2.2.1. Environment

Let K be the amount of capital that the home state owns and L the size of the labor force. For the foreign state, amount of capital is K^* and size of labor force is L^*. Assume that the home state has relatively scarce capital compared to the foreign state. In this setting, the home country imports capital and exports labor with the foreign country: the home country sends M migrants to the foreign country while receiving Z units of investment in capital from the foreign country. Negative $M < 0$ and $Z < 0$ mean that factors flow in the opposite direction. In this model, I mainly consider the case where M and Z are non-negative.

Suppose that the ratio of labor force between the two states is $\eta = L/L^*$. Furthermore, I define quantities before factor movements in per capita terms,

where $k = K/L$, $m = M/L$, $z = Z/L$, $k^* = K^*/L^*$. After factors moves, I also define variables after factor movements in per capita terms, where $c = (K + Z)/(L-M) = (k+z)/(1-m)$ and $c^* = (K^*-Z)/(L^*+M) = (k^*-\eta z)/(1+m)$. Note that the variables k and k^* are the per capita capital endowment before factor movements take place, while c and c^* are the per capita capital after factor movements. The production functions take the form $F(C, L-M) = f(c)(L-M)$ and $G(C^*, L^* + M) = g(c^*)(L^* + M)$ for Home and Foreign, respectively. We make the following standard assumptions on functions f and g.

$f', g' > 0$, $f'', g'' < 0$, $f(0) = g(0) = 0$.

In the markets for both labor and capital, perfect competition is assumed. Let w and w^* denote the wage rates and let r and r^* denote the rental rate for capital in Home and Foreign, respectively. With a competitive market and full employment, the wage and rental rates are determined as

$w = f(c) - cf'(c)$, $w^* = g(c^*) - c^*f'(c^*)$, $r = f'(c)$ and $r^* = g'(c^*)$

For simplicity, I assume $f = g$ in later sections[4].

2.2.1.1. Capital Flow Restrictions

Suppose that capital initially is not perfectly mobile. I model restrictions on capital flow as a tax τ that the Home state can charge capital inflows. In the context of the U.S. banking system, one can think of the tax τ being the fees that a bank from other states would have to pay to acquire the permission to set up a branch in the state. For each unit of capital in the Foreign state, it earns a return of r^* if being invested in the Foreign state, but would earn $r(1-\tau)$ if invested in the Home state. Therefore, in the market for capital, capital will move from Foreign to Home if and only if $r(1-\tau) > r^*$. In equilibrium, we then must have $r(1-\tau) \leq r^*$, i.e., $f'(c)(1-\tau) \leq g'(c^*)$.

Throughout the paper, I assume that τ is initially a large positive number and that, in equilibrium, we have $r > r^*$ but $r(1-\tau) \leq r^*$. In other words, the return on capital in the Home state is higher than that of the Foreign state,

[4]The assumption $f = g$ is important to the results derived in later parts of this paper. However, similar conclusions can be drawn by relaxing this assumption, as long as capital earns a higher return and labor earns a lower return in the capital-scarce state than in the capital-abundant state.

but the restriction on capital flow, i.e., the tax τ, prevents additional capital from flowing into the Home state. In later sections, I consider how financial deregulation that lowers τ would affect other outcomes in the setup.

2.2.1.2. Labor Market Mobility

In the labor market, workers can either receive the wage rate w in the Home country or migrate to the Foreign country receiving w^*, subject to a moving cost ξw. One can think of the variable ξ_i for individual i as how much wage foregone the person has to incur if she migrates. The moving cost in the economy follows a distribution $H(\xi)$. Therefore, given the wage rates w and w^* in Home and Foreign, respectively, the worker with ξ_i will migrate if and only if $w \leq w^* - \xi w$, i.e., $\xi \leq \frac{w^*}{w} - 1$. I assume that workers with the lowest moving costs migrate first. Therefore, the fraction of workers that has migrated m is given by $H(\frac{w^*}{w} - 1)$.

This setup on labor mobility essentially links the wage rates and migration. The fraction of emigrants from Home to Foreign is an increasing function of the wage gap between these two states. A higher Foreign wage relative to the Home wage implies a higher likelihood that workers move.

2.2.2. Financial Liberalization and Labor Moves

Now consider that the Home state lowers the tax τ on capital inflows and allows capital to flow more freely. In this case, more capital will flow from the Foreign state to the Home state, raising the per capita capital level for the Home state and potentially lowering capital per capita in the Foreign state. This further implies that the wage rates of the two states should converge. To see this, recall that the wage rate for Home and Foreign are $w = f(c) - cf'(c)$ and $w^* = g(c^*) - c^*g'(c^*)$, respectively. A higher c and a lower c^* implies a higher wage w and a lower w^*. Therefore, in equilibrium, we would expect to see fewer emigrants from the Home state to the Foreign state. The following proposition summarizes this result.

Proposition 1. Define $\tilde{\tau} = -\tau$ as capital mobility. Consider a policy change in capital restriction that lowers τ, i.e., increases $\tilde{\tau}$. Then it implies that fewer emigrants would move from Home to Foreign, i.e., $\frac{\partial m}{\partial \tilde{\tau}} \leq 0$. Moreover, the decline in capital restrictions would imply converging wage rates, i.e., $\frac{\partial w}{\partial \tilde{\tau}} \geq \frac{\partial w^*}{\partial \tilde{\tau}}$.

Proof. See Appendix.

2.2.2.1. Empirical Predictions

The Proposition presented above has sharp empirical predictions on labor flows and wage rate growth after states liberalize their capital account. In this paper, I look at a particular economic episode from the 1980s to the 2000s in which U.S. states removed interstate banking restrictions. A state that removed its banking system allowed bank holding companies (BHCs) to acquire commercial banks in the state. This process happened gradually over time between states. In some cases, two states signed an agreement on interstate branching deregulation, while in some other cases, a regional deregulation agreement was signed among multiple states. In this context, the following empirical predictions can be tested.

1. After a state deregulated its banking system for the first time, the outflow of labor should fall.
2. After two states signed a bilateral branching deregulation agreement, the bilateral labor flow should drop and the effect should be mainly on the outflow of labor from the state with a lower bank loan per capita.
3. After a state deregulated its banking system, the growth rate of real wages should rise, especially for states with a lower initial bank loan per capita.

In addition, the following implication can be tested.

4. Moreover, across industries, the increase in the growth of real wages should mainly take place for industries that depend heavily on banking and external finance, as defined in Rajan and Zingales (1998).

In later sections, I test these implication using interstate migration data and interstate banking deregulation data in the U.S. from 1982 to 2005. Below, I describe the data sources and detailed information on the banking deregulation data.

2.3 Data

2.3.1. Migration Data

To measure migration, I rely on two sources. The first one is the state-to-state and county-to-county migration data provided by Internal Revenue Service (IRS). The IRS data is computed at the annual frequency based on tax filings of individuals for each tax year. Data is available starting in 1978 but there are a few missing years at the beginning of the report. The IRS data identifies migrant by comparing the street address, state information and ZIP code of each individual from the previous year. If the person changes her state/county information from the previous tax year, then she is regarded as having moved across states/counties. The IRS data contains less noise and allows me compute the state-to-state migration at the annual frequency.

The IRS data however also has its limitations. One issue, well recognized by others as well in the literature, is that the IRS data only cover people with high incomes that need to file taxes and that they only tract mailing addresses which can be misleading in some cases (Internal Revenue Service, 2008). For example, the mailing address can be that of the financial institution that the taxpayer uses, and a change in the financial institution can result in a record of moving. The IRS data generally report a lower migration rate than other survey sources and a smaller declining trend (e.g., Kaplan and Schulhofer-Wohl (2013)). For my purpose, I mainly focus on the occupation-related migration decisions, so the IRS data are a reasonably accurate enough source for me to measure state-to-state labor flows. Another limitation of the IRS data is that there seems to have been a change in computation methods from 1990 onwards. Therefore, when computing the outflow of labor as percentage of population, I use IRS migration data after 1989, and when computing the growth rate of labor flows, I use IRS migration data in all available years except for 1990.

The second source for migration data is based on Current Population Survey (CPS) conducted by the Bureau of Census. I use the March CPS data on migration starting in 1982. In the CPS survey, each respondent is asked whether he/she lives in the same home one year ago, and if not, where she lived. The CPS then records the state code for the respondent's current resident state and the state he/she lived one year ago. I dropped all observations where respondents lived abroad in the previous year. I then construct, for each state, the

estimated number of emigrants to other states in each year. Since the data is collected based on surveys, estimates on state-to-state flows may be less reliable than the total outflow of people. Therefore, in this paper, I use CPS data only to construct the outflow of people in each year. Another limitation of the CPS data is that it does not follow respondents, therefore it is generally difficult to control for other factors such as the earnings history that potentially affect the moving decisions of the individual. This can be a concern for studies that look at labor market frictions in a macroeconomic setting and would not be a key issue for this paper which mainly focus on the aggregate migration.

2.3.2. Banking Data

For bilateral banking deregulation data, I use the same data as in Landier, Sraer and Thesmar (2013) and Michalski and Ors (2012). This data contains information on the year in which two states opened up their banking systems to each other. During the deregulation period starting in late 1970s until late 1990s, U.S. states joined bilateral and regional agreements allowing bank holding companies (BHCs) to acquire commercial banks across states. It is only after the deregulation did bank holding companies experience a significant expansion into national bank holding companies. Moreover, these agreements were signed between states in a time-staggered fashion. The data on the year that each state pair signed the banking deregulation agreement has been used by authors to answer different questions. Michalski and Ors (2012) show that the integration of real economy also followed financial integration. Landier, Sraer and Thesmar (2013) use the data to show that financial integration increases the co-movement of house prices across states. Goetz and Gozzi (2014) also show that business cycles across states have become more synchronized after states deregulated their banking system. Departing from their studies that focus on the aggregate economic consequence of financial liberalization, I focus on how the exogenous change in the market for one factor (i.e., capital) has affected the market for another factor (i.e., labor).

In order to measure the degree of financial integration of two states, I need to obtain information about the geographic distribution of a BHC's assets. I calculate each BHC's holdings of assets across states using the Call Report starting in 1980. For each commercial bank that is included in the Call Report and identified by its identification number (RSSD9001), I obtain information about its total assets (RCFD2170), total commercial and industrial loans

(RCFD1600), its state of location (RSSD9200), and the BHC that it is affiliated with (RSSD9348). I implicitly assume that all of a commercial bank's asset holdings and commercial loans were within the state of its location. The state information for each commercial bank is relatively accurate in capturing where the bank's loans were issued, especially prior to 2000. It was only after the Riegle-Neal Act of 1994 that commercial banks started setting up branches significantly across states (Morgan et al. (2004)).

To measure the level of capital abundance for each state, I first collapse the total commercial and industrial loans for each commercial bank at the annual frequency and then compute how much loan was issued in each year within each state. I focus on the year of 1980, before the deregulation episode, and construct the per capita bank loans for each state as of 1980, denoted as kpp^{1980}. I define (banking) capital abundance by this kpp^{1980} measure. A higher kpp^{1980} indicates a higher degree of capital abundance for the state. The kpp^{1980} measure ranges from 2.34 (South Carolina) to 34.53 (New York) in 1980. In most of the analysis below, I also split states into two halves by the kpp^{1980} measure. I call states with $kpp^{1980} < 5$ capital-scarce and those with $kpp^{1980} \geq 5$ capital-abundant.

To measure how the banking sectors of two states are integrated, for each commercial bank, I look for and track the BHC that owns it. Then, for each state pair, I compute (1) the total assets of commercial banks that are owned by a common BHC across these two states in each year, and (2) the total assets of all commercial banks in these two states in each year. I define the degree of banking integration as ratio of the total assets owned by some common BHCs to the total assets in these two states. This measure serves as a proxy for how easier BHCs can move capital across the state borders and is used in Goetz et al. (2014).

2.3.3. Wage Data and Other Controls

Data on wages is based on Quarterly Census of Employment and Wages (QCEW) published by the Bureau of Labor Statistics (BLS) at the quarterly frequency. It provides county-industry level data on employment and wages by ownership (e.g., public or private). I dropped data on public sectors and only focus on establishments that are private. To perform analysis together with bank deregulation of states, I aggregate data to state-industry level at the annual frequency.

A nice feature of the QCEW data is that it is comprehensive and is available at the 3-digit SIC industry level prior to 2000 and at the 6-digit NAICS industry level after 2000. To show the effect of bank deregulation on different industries by the degree of Dependence on External Finance (DEF), I use state-industry wages at the 3-digit SIC industry level. Moreover, I hand-match the 3-digit SIC industry codes to the ISIC codes used by Rajan and Zingales (1998) according to the verbal description of industries. I am able to match 154 3-digit SIC industries to those included in Rajan and Zingales (1998). The measures for Dependence on External Finance range from 0 to 0.7 for these 154 industries. In the empirical analysis on wage growth, I split the industries into four quartiles by the DEF measure. More details are included in later sections.

In the empirical analysis, I also control for the increase in trade and finance sectors for the deregulated states. To do that, I use the growth of employment shares in these industries for each state at the annual frequency. The data source is from County Business Patterns (CBP) database where state-industry-level data is available at the annual frequency since 1974. Two-digit SIC codes are used to identify which industries are categorized as tradable industries, financial industries, and mining industries. Employment shares for those industries out of total state population are included as controls.

2.4 Empirical Analysis

In this section, I describe the empirical models used to test the predictions mentioned above. I first test how the deregulation of a state affected the labor outflow of a state. I also use bilateral agreements between state on branching deregulation and show how bilateral labor flows were affected. Lastly, I confirm the capital-labor substitution effect by studying the growth of real wages for each state after banking deregulation.

2.4.1. Banking Deregulation and Labor Moves

As suggested in the theoretical framework, the deregulation of a state's banking system would encourage capital inflows which can substitute the labor outflow from this state. To formally test this mechanism, I use the following regression model

(1) $\frac{EM_{it}}{P_{it}} = \alpha_i + \delta_t + \beta DEREG_{it} + \gamma X_{it} + \epsilon_{it}$

where EM_{it} is the number of emigrants from state i in year t, P_{it-1} is the population of state i in year $t-1$, $DEREG_{it}$ is the indicator whether state i has deregulated its banking system in year t for the first time, α_i the state fixed effect, δ_t the year fixed effect, X_{it} includes a list of state controls. This regression investigates the relationship between outflow ratio and banking deregulation for state i. Regression is weighted by state population as of 1980 and standard errors are clustered at the state level. According to the theoretical results presented above, bank deregulation would invite capital inflows which substitute labor outflows. This means that after banking deregulation of state i, labor outflow should drop, which means $\beta < 0$ in the regression. In this regression, I focus on state that liberalized their banking system in or after 1989[5] Note that the inclusion of state fixed effects takes out the difference in outflow ratio between states at the beginning of the sample. The inclusion of year fixed effects allows me to control for year-specific changes to all states. In the regression, I need to control for trade activities for each state. This is because, if trade volume increased dramatically at the same time as bank deregulation, then the increased trade can make the returns to factors converge according to the Heckscher-Olin framework. To proxy for trade activities, I include the share of employment for the wholesale trade sectors (two-digit SIC code 50) for each state in each year. I also control for employment shares for financial/insurance sectors (two-digit SIC code 60) and for mining industries (two-digit SIC code 10).

Tables 2 (IRS data) and 3 (CPS data) report the regression results. In columns (1)-(5) of Table 2, I report the regression results where the regressions are weighted by state population as of 1980. In column (1), I include year fixed effects whereas both year and state fixed effects are included in columns (2)-(5). One can see that the coefficient on the deregulation variable DEREG is significantly negative, robust to the state controls. In terms of magnitude, the DEREG indicator corresponds to 0.08% drop in the outflow ratio, while in the aggregate, the outflow ratio dropped from 1.5% to 1.3% from 1990 to 2000. This suggests that over this time period, the deregulation of the state's banking sector corresponds to one third of the drop in outflow ratio. Columns (6)-(10) of Table 2 repeat the same exercise by using OLS regressions. One can see that very similar estimates can be obtained. Table 3 performs a similar exercise using CPS data. We see consistent estimates of the coefficient β in

[5]There is an apparent change in statistical methods computing migration in the IRS data from 1990. Therefore, in this paper, I use data after 1989 for the fraction of emigrants out of population (outflow ratio). For the change of outflow ratio, I use all available years except for 1990.

columns (1)-(2). When splitting states into two halves by their bank loans per capita as of 1980, we see that the coefficient is larger for capital-scarce states (Column (3)) than for capital-abundant states (Column (4)). Ordinary least squares regressions give similar estimates as shown in Columns (5)-(6). In the CPS data, from 1982 to 2000, the mean outflow of labor for states dropped from 3.4% to 2.7%. Therefore, the estimate -0.25 of β (Column (2) of Table 3) shows that the $DEREG$ indicator corresponds to about 30% of the drop in labor flows, consistent with the estimates using IRS data.

In the regression model, the inclusion of state fixed effects can take out the difference in levels, but what if states were on different trajectories and had different growth rates in outflow ratio in the first place? To address this concern, I look at the percentage change in emigrants from a state and regress it on the deregulation indicator with the inclusion of state fixed effects. Specifically, I use

(2) $\Delta \ln \frac{EM_{it}}{P_{it}} = \alpha_i + \delta_t + \beta_1 DEREG_{it} + \beta_2 DEREG_{it} \times \text{I}\{\text{Capital Scarce}\}_i + \gamma X_{it} + \epsilon_{it}$

where X_{it} includes the change in variables from the previous years and the other variables were the same as above. The variable $\text{I}\{\text{Capital Scarce}\}_i$ is the indicator variable whether the 1980 capital abundance measure for state i is among the lower half. The inclusion of state fixed effects in this case allows for different initial growth path of the outflow ratio, whereas the inclusion of year fixed effects allows for year-specific changes to the growth rate of the outflow ratio for all states. The capital-labor substitution effect implies that banking deregulation should lower the growth of outflow ratio, but the effect should be mainly for relatively capital-scarce states. In other words, β_2 should be negative.

Table 4 reports the regression results. Columns (1)-(3) show the estimates using weighted least squares where weights are state populations as of 1980. We can see that the coefficient β_2 on the interaction term was strongly negative, meaning that the effect of banking deregulation on the drop in outflow ratio was mainly for capital-scarce states. For capital-scarce states, deregulation accounts for 13% drop in annual growth of the ratio of emigrants to population.

Columns (4)-(6) repeat the same exercise using OLS regressions. Again, one can see that β_2 is significantly negative and is of the same magnitude.

In sum, in this section, I show that the deregulation of a state's banking system led to significant falls in labor outflow and this effect was the strongest for relatively capital-scarce states. This corresponds to the empirical prediction described above and suggests that capital mobility substituted labor flows in this process.

2.4.2. Bilateral Deregulation Agreements and Bilateral Labor Flows

So far, I only considered the effect of first-time banking deregulation on the outflow of labors. A limitation of the previous analysis is that the number of data points is limited, since only a fraction of states had their banking sector deregulated after 1989 which the migration data covers. In this section, I perform similar exercise on bilateral banking deregulation and bilateral labor flows.

Banking deregulation gradually happened between states in terms of bilateral or regional agreements. After two states signed bilateral agreement on branching deregulation, bank holding companies were allowed to acquire commercial banks in both states. Previous studies have shown that after bilateral agreements were signed, the fraction of assets in the two states held by common bank holding companies dramatically increased (e.g., Landier, Sraer and Thesmar (2013)). I treat the bilateral deregulation as the exogenous shock to capital mobility and study how bilateral labor flows were affected. From the theory presented above, one would expect that bilateral deregulation would especially lower the labor from the relatively capital-scarce state to the capital-abundant state.

Specifically, the regression for the bilateral analysis is given by

$$\textbf{(3)}\ \frac{M_{ijt}}{N_{it}} = \alpha_{ij} + \delta_{it} + \theta_{jt} + \beta_1 DEREG_{ijt} + \beta_2 DEREG_{ijt} \times \text{I}\{\text{Capital Scarce}\}_{ij} + \gamma X_{ijt} + \epsilon_{ijt}$$

where M_{ijt} is the number of emigrants from state i to state j in year t, N_{it} is the population of state i in year t, $DEREG_{ijt}$ is the indicator whether states i and j

have entered bilateral agreements on banking deregulation, I$\{$Capital Scarce$\}_{ij}$ is the indicator that state i has lower bank loan per capita than state j as of 1980, α_{ij} the fixed effects for (State 1 $\times$ State 2), δ_{it} and θ_{jt} are state-year fixed effects, and X_{ijt} is control variables. The inclusion of state-pair fixed effects takes out the different levels of outflow ratio in both directions of a state pair. The inclusion of state-year fixed effects accommodates any state-specific shocks in any given year. Therefore, the deregulation measure captures purely the change to their pair after deregulation took place. In this regression, I also control for the three-year-forward wage correlation between two states in each year. This correlation between the two states is computed using quarterly wages from the current year to the following two years. The inclusion of wage correlation as a control variable takes into account the change in risk-sharing motives between states. In all regressions, standard errors are clustered at the state-pair level. In this framework, one would expect that the coefficient β_2 should be strongly negative, indicating that in each pair of states, deregulation between the two states should significantly lower the labor flow from the relatively capital-scarce state to the capital-abundant state.

Table 5 reports the regression results. In columns (1)-(5), regressions are weighted by state population as of 1980. In columns (1) and (2), only year fixed effects are included, whereas state-year fixed effects are included in columns (3)-(5). One can see that estimates of coefficient β_2 on the interaction term are strongly negative for all regressions, robust to the inclusion of various controls. This suggests that the deregulation between two states did imply lower labor flows and the effect was mainly on the outflow of labor from the relatively capital-scarce state. Columns (6)-(9) report the results of the OLS regression. One can see that similar estimates, both qualitatively and quantitatively, are obtained. Robustness is checked using Generalized Least Squares (GLS) estimator allowing for heteroskedasticity and autocorrelation.

To further confirm that the deregulation indicator used above represents the change in financial integration of the two states, I use an alternative measure of bank integration $Integration_{ijt}$ which measures the fraction of assets in the two states i and j that were jointly held by a common bank holding company in year t. This measure is also used by Goetz et. al (2014) for the study of financial integration. I repeat the exercise using $Integration_{ijt}$ in place of $DEREG_{ijt}$. Results are discussed in the section for robustness.

Another important note is that the estimates on β_1 is slightly positive in these regressions. This suggests that the inflow of labor might go up after the capital-scarce state opened up its banking sector. However, the magnitude of β_1 is much smaller than β_2 and is statistically insignificant. In the OLS specification, the estimates for β_1 even turn negative. These results suggest that bank deregulation raised the inflow of labor only marginally, if any at all. Therefore, the net effect of banking deregulation on gross labor flows remains significant.

The analysis in this section suggests that financial integration contributed strongly to the decline in labor flows. The U.S. banking system was once disintegrated and capital mobility is restricted. After financial deregulation between states, the increased mobility reduced the need for labor to move. In the next sections, I provide supporting evidence showing that the return to labor was affected after deregulation.

2.4.3. Labor Returns for Capital-Scarce States After Banking Deregulation

The increased mobility in capital across states would mean that returns to labor would tend to converge. To study the equalization of labor returns, I look at the growth rate of wages after deregulation. One would expect that after deregulation, the growth rate of real wages should be higher and moreover, the effect should be the strongest for relatively capital-scarce states. To formally show this result, I consider

(4) $\Delta \ln w_{ikt} = \alpha_{ik} + \delta_{kt} + \beta DEREG_{it} + \epsilon_{ikt}$

where $\Delta \ln w_{ikt}$ is the percentage change in the real wages of industry k in state i for year t, $DEREG_{it}$ is the indicator whether state i has deregulated its banking sector in year t, and α_{ik} and δ_{kt} fixed effects. I run this regression by quintiles of states according to bank loan per capita as of 1980 (denoted as kpp^{1980}). The measure kpp^{1980} proxies for the capital abundance of the state. A higher (lower) kpp^{1980} indicates that the state is relatively capital abundant (scarce). In the theoretical framework, we see that the increased mobility of capital should raise the return to labor for capital-scarce states, meaning that

$\beta > 0$. To formally show this result, I split the sample into quintiles by the measure of bank loan per capita kpp^{1980} and perform the regression on each subsample individually. In all regressions, I include state-industry fixed effects. Table 6 presents the regression results.

In columns (1)-(2), all data is included. Column (1) includes year fixed effects where column (2) includes industry-year fixed effects. We see that the coefficient β is strongly positive when all data points are included. The estimate is around 0.45, meaning that the annual growth rate of real wages would be raised by 0.45% a year after banking deregulation. In columns (3)-(7), I repeat the same regression with industry-year fixed effects on each quintile of states by the measure of bank loan per capita as of 1980, i.e., kpp^{1980}. In columns (3)-(7), the measure of kpp^{1980} rises from left to right. We can see that for states with a low kpp^{1980} value, the estimates of β is statistically more significant and quantitatively larger than the estimates for state with a high kpp^{1980}. For states whose kpp^{1980} belongs to the lowest quintile (i.e., the most capital-scarce states), banking deregulation raises the annual growth rate of real wages by 1.2% (column (3)). On the contrary, for states whose kpp^{1980} is among the highest quintile (i.e., the most capital-abundant states), banking deregulation had little effect (0.03% and insignificant) on the growth rate of real wages (column (7)). This analysis suggests that capital mobility forces returns to labor converge, implying factor substitution between capital and labor. In the next subsection, I also look at the different impact on wages for different industries.

2.4.4. Labor Returns for External-Finance-Dependent Industries After Deregulation

To further confirm the effect of banking deregulation on labor returns, I also look at different industries that may be affected by banking deregulation differently. To do that, I rely on the Dependence on External Finance (DEF) measure constructed by (Rajan and Zingales (1998)). This DEF measure indicates how the growth of firms in each industry relied on external financing. A higher DEF value means the industry relies more strongly on external financing. Since banking deregulation essentially changed the availability of banking finance to local firms, the DEF measure naturally captures the differential in impact of banking deregulation on real wage growth across these industries. I hand-matched three-digit SIC codes in my sample to the ISIC code in their paper

and split the sample into four quartiles of industries by the DEF measure. For each subsample, I repeat the regression

(5) $\Delta \ln w_{ikt} = \alpha_{ik} + \delta_t + \beta DEREG_{it} + \epsilon_{ikt}$

Table 7 presents the regression results. Column (1) repeat the first column of Table 6 where all industries are included. Columns (2)-(5) report, from left to right, the regression results for subsamples from the lowest Dependence on External Finance (DEF) to the highest DEF. A higher DEF indicates the industry is more reliant on external finance. Therefore, the deregulation of the banking system would imply that real wage growth should be the highest for these industries. We see that, indeed, the estimates for β rise from 0.16 to 0.92 from column (2) to column (5). For industries with the highest dependence on external finance, the deregulation of the banking sector significantly raised the annual real wage growth by more than 0.9%; the effect was insignificant for industries that rely less on external finance. This evidence suggests that the effect of banking deregulation indeed alters the relative returns to labor across states, which further induced the change in labor flows.

2.5 Robustness and General Equilibrium

In this section, I check for the robustness of the empirical findings above and discuss general equilibrium effects. The robustness checks mainly include two aspects: alternative measures for bank integration and additional controls for the results on labor returns.

2.5.1. Alternative Measures for Banking Integration

To ensure that the $DEREG$ indicator used in previous regressions precisely captures the degree of financial integration between two state, I measure financial integration more directly. As the deregulation of the banking sector was mainly through the acquisition of commercial banks in the deregulated states by bank holding companies (BHCs). I measure the integration of the banking systems of two states by the fraction of loans in these two states that were held by bank holding companies that operate across these two states, as in Goetz

et. al. (2014), where I denote as $IntPerc_{ij}$ for states i and j. Various studies (e.g., Landier, Sraer, and Thesmar (2013)[42]) have shown that, after interstate banking deregulation, an increasingly larger fraction of assets is held by BHCs that operate businesses across states. Therefore, the measure $IntPerc_{ij}$ captures the degree of banking integration between states reasonably well. To construct the measure, I use Call Report on commercial banks and trace their ultimate BHC parent by item RSSD9348. I assume that the loans issued by a commercial banks were entirely in the state where the commercial bank was located, which is a reasonable assumption before 2000.

The regression is given by

$$\textbf{(6)}\ \frac{M_{ijt}}{N_{it}} = \alpha_{ij} + \delta_{it} + \theta_{jt} + \beta_1 IntPerc_{ijt} + \beta_2 IntPerc_{ijt} \times \text{I}\{\text{Capital Scarce}\}_{ij} + \gamma X_{ijt} + \epsilon_{ijt}$$

where $\frac{M_{ijt}}{N_{it}}$ is the outflow ratio for state i in year t, $IntPerc_{ijt}$ is the fraction of bank loans in states i and j that were held by common BHCs in year t, $\text{I}\{\text{Capital Scarce}\}_{ij}$ is the indicator that state i has a lower loan per capita than state j as of 1980, $\alpha_{ij}, \delta_{it}, \theta_{jt}$ are fixed effects, and X_{ijt} include controls. Similar as the analysis above, we would expect that $\beta_2 < 0$.

Table 8 shows the regression results. We see that the estimates for β_2 are consistently negative under different model specifications. Comparing the estimates with the ones obtained using the $DEREG$ indicator, one can see that the magnitudes are very similar. Again, the purpose of this robustness check is to ensure that the deregulation between two states indeed represents how financially integrated the two states are. The regression results show that, if we use alternative measures that directly capture the degree of financial integration, we obtain similar estimates and conclusions.

2.5.2. Robustness for Labor Returns

Previously, I show that labor returns in industries that depend on external financing experienced the greatest growth. To check for the robustness of this result, I also include industry-year fixed effects in this section. The inclusion of industry-year fixed effects allows one to capture the potential shocks to the

industries in each year. Specifically, I run the following regression for groups of industries by their measures of Dependence on External Finance (DEF).

(7) $\Delta \ln w_{ikt} = \alpha_{ik} + \delta_{kt} + \beta DEREG_{it} + \epsilon_{ikt}$

where $\Delta \ln w_{ikt}$ is the percentage growth of real wages for industry k in state i in year t, $DEREG_{it}$ is the indicator of banking deregulation, α_{ik} is the state-industry fixed effect, and δ_{kt} is the newly added industry-year fixed effect.

Regression results are presented in Table 9. Columns (1)-(4) show the estimates of β for industries with the lowest DEF measure to the highest DEF value (from left to right). One can see that, for industries that heavily depend on external financing, the annual growth rate of real wages was raised by 0.9% after banking deregulation, whereas the effect was only 0.16% and insignificant for industries that least depend on external financing. These estimates are very similar to the ones obtained without the industry-year fixed effects.

2.5.3. General Equilibrium: Labor Inflows After Deregulation

In the analysis above, I focus mainly on the effect of banking deregulation on labor outflows. A closely related question is whether labor inflows significant increased after a capital-scarce state liberalizes its banking sector. In this section, I look at the growth rate of labor inflows after banking deregulation.

(8) $\Delta \ln IM_{it} = \alpha_i + \delta_t + \beta DEREG_{it} + \epsilon_{it}$

where $\Delta \ln IM_{it}$ is the percentage change of labor inflows to state i in year t, $DEREG_{it}$ is the indicator whether state i has opened up its banking sector in year t, α_i the state fixed effects, and δ_t the year fixed effects. If banking deregulation significantly induce more labor inflows, one would expect that β to be strongly positive. Regression results are presented in Table 10.

In columns (1)-(2) of Table 10, we see that estimates of coefficient β on $DEREG$ are not significant. In columns (3)-(4), I split the sample into capital-scarce

states versus capital-abundant states according to the loan per capita as of 1980 (i.e., kpp^{1980}), and perform the regression separately. One can see that, for capital-scarce states ($kpp^{1980} < 5$), the coefficient is slightly positive, but statistically insignificant (column (3)). Moreover, the estimates are much smaller than the impact on labor outflows. However, for capital-abundant states, the coefficient is negative and statistically significant (column (4)). This pattern suggests that the effect of deregulation of the banking sector between a capital-abundant state and a capital-scarce state was mainly the reduction of the labor flow from the capital-scarce state to the capital abundant state. In the aggregate, we observe a drop in the labor outflows of the capital-scarce states (which is equivalent as a drop in labor inflows for capital-abundant states), but not significant amount of labor inflows to capital-scarce states, which is consistent with the results we previously obtained using bilateral labor flows. This pattern is further confirmed in Columns (7)-(9) where CPS data is used instead of IRS data.

This section presents the impact of banking deregulation on labor inflows where I find that labor inflows did not significantly increase after a capital-scarce state deregulated its banking system but dropped after a capital-abundant state did so. This evidence suggests that, if one measures labor mobility as the gross rate of migration, banking deregulation between states unambiguously lowered labor mobility. Furthermore, the findings in this exercise also suggest that the change in labor returns in a state can have a different effect on the willingness to migrate for workers out of the state than for the state's current residents. This can be a result of non-labor preferences playing an important role in the decision of migration. People may either enjoy better the amenity-related goods better in the home state or simply have more information about amenity of the home state and acquiring additional information about other states involves a cost. Therefore, 10% increase in the wage rate of the Home state may significantly reduce the amount of emigrants from the Home state, but it may not have an equal impact on the willingness of workers in other states to immigrate. This can be due to either a convex cost of migration for other states, or simply people discount the improvements in other states. A general equilibrium model can be built to quantify the effect of each channel, but it is beyond the scope of this paper at this stage.

2.6 Conclusion

This paper attempts to examine the impact of financial integration across U.S. states on the interstate labor market. It especially studies the substitution effect between capital and labor mobilities after financial liberalization and quantifies this mechanism in reducing interstate migration in the U.S.. Discussions on the impact of financial integration on labor mobility, especially in explaining the long-run decline in U.S. interstate migration, are largely missing. This paper finds that the effect of this channel can be significant economically.

One additional note is that the study in this paper is by no means restricted to the U.S.. Various studies have found similar patterns of increasing capital mobility and decreasing interstate labor mobility across states or provinces within Canada, Australia and some European countries as well (e.g., Beine, Bourgeon and Bricongne (2013)[8], Kaplan and Schulhofer-Wohl (2013)). This paper can also help us understand this long-run trend common to many countries.

Appendix: Proofs for Propositions

Proof for Proposition 1

Proof. Suppose that the Home state is relatively capital-scarce and the Foreign state is relatively capital-abundant. With a tax on capital flow τ, interest rates r (Home) and r^* (Foreign) should satisfy $r > r^*$ and $r(1-\tau) \leq r^*$ in equilibrium. If the second inequality initially binds, i.e., $r(1-\tau) = r^*$, then a fall in the value of τ will make it more binding. If the second inequality does not bind initially, the fall in τ can either make it binding or still relaxed.

First consider the case that the fall in τ does not make the inequality bind. In this case, the original level of capital still satisfies the two inequalities. Therefore, the new equilibrium is the same as the old one and capital does not change. In this case, we have $\frac{\partial m}{\partial \tau} = \frac{\partial w}{\partial \tau} = \frac{\partial w^*}{\partial \tau} = 0$.

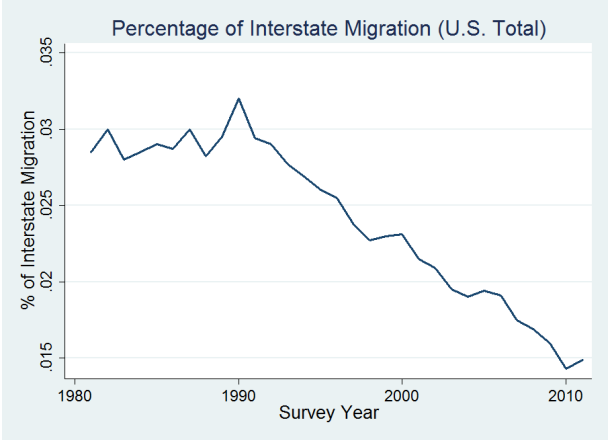
Now consider that the fall in τ either makes the originally binding inequality more binding or the originally relaxed inequality now binding. In these situations, the ratio $\frac{r^*}{r}$ unambiguously increase as a result. Recall that $\frac{r^*}{r} = \frac{f'(c^*)}{f'(c)}$ and that $c + c^* = k + k^*$ which is the resource constraint. Then we must have c increase and c^* decrease, i.e., capital flows from Foreign to Home. Note that $w = f(c) - cf'(c)$ and $w^* = f(c^*) - c^* f'(c^*)$ are increasing in their respective capital available to utilize. Therefore, we have $\frac{w^*}{w}$ decrease, suggesting that the fraction of emigrants from Home to Foreign $m = H(\frac{w^*}{w} - 1)$ decrease as well. That means $\frac{\partial m}{\partial \tau} > 0$ and that $\frac{\partial w}{\partial \tau} < \frac{\partial w^*}{\partial \tau}$.

Combining the above cases, we have $\frac{\partial m}{\partial \tilde{\tau}} \leq 0$ and $\frac{\partial w}{\partial \tilde{\tau}} \geq \frac{\partial w^*}{\partial \tilde{\tau}}$, where $\tilde{\tau} = -\tau$ measures capital mobility. □

Figure 2.1

This figure plots the evolution of interstate migration in the U.S. from 1982 to 2010. Migration data is based on Current Population Survey (CPS). Panel A of this figure plots the percentage of interstate migration relative to the U.S. total population. It measures the percentage of people that migrated across state borders from the previous year. Panel B of this figure plots the median percentage of outflow of labor at the state level. The two panels show similar patterns and magnitudes.

Panel A. Percentage of Interstate Migration Relative to U.S. Total Population



Panel B. Percentage of Population Outflow at State Level

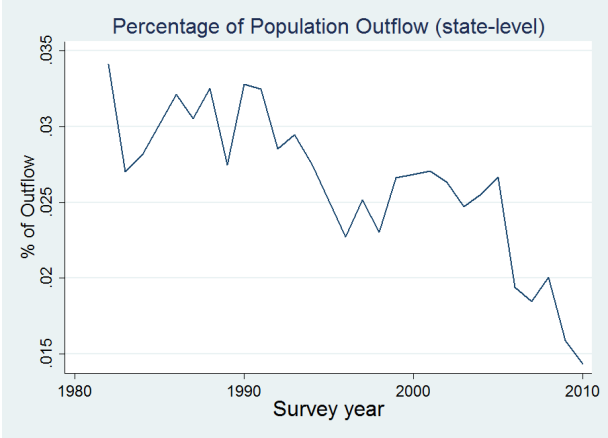
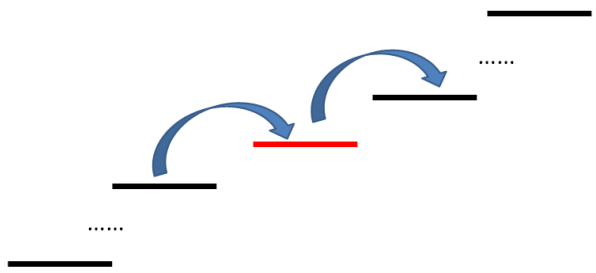


Figure 2.2

Labor Flows Between Ladders of States Before and After Financial Liberalization

This figure illustrates the flow of labor between ladders of states by the degree of capital abundance. A higher (lower) ladder represents a state with higher (lower) level of capital abundance which is measured by per capita bank loan of the state as of 1980 in this paper. Panel A shows the labor flows before states deregulate their banking system. Labor flows from the relatively capital-scarce states to capital-abundant states. The distribution of capital abundance is dispersed so the gross migration of workers is large. Panel B shows the labor flows after state deregulate their banking system allowing capital to flow freely. The distribution of capital abundance across states would collapse, equalizing the returns to labor across states. Each state sends less labor to ladders above and receives less labor from below, so gross migration declines.

Panel A. Labor Flows Between Ladders Before Financial Liberalization



Panel B. Labor Flows Between Ladders After Financial Liberalization



Table 2.1.

Summary Statistics

Summary statistics are presented in the table below. Weighted mean and weighted standard deviation are reported where weights are state populations as of 1980.

	N	Mean	SD	10th	90th	Weighted Mean	Weighted SD
Percentage of Labor Outflow (CPS), 1984-2000	1070	0.03	0.02	0.02	0.06	0.03	0.01
Percentage of Labor Outflow (IRS), 1990-2000	150	0.01	0.01	0.01	0.02	0.01	0.003
Percentage of Labor Inflow (CPS), 1984-2000	1070	0.04	0.02	0.02	0.05	0.03	0.01
Percentage of Labor Inflow (IRS), 1990-2000	150	0.02	0.30	-0.36	0.27	0.06	0.34
Population of State, 1980 (thousands)	51	4,442	4,700	652.7	10,817	9,316	6,797
Banking capital per capita, 1980 (thousands)	51	5.59	3.23	3.68	7.24	7.16	5.65
Year of first-time banking deregulation	51	1987	2.65	1984	1991	1987	2.01
Annual growth in share of mining industry employment	816	-0.02	0.38	-0.02	0.09	-0.04	0.34
Annual growth in share of wholesale trade employment	816	0.02	0.08	-0.01	0.09	0.01	0.06
Annual growth in share of finance employment	816	0.02	0.08	-0.01	0.09	0.01	0.06
Year of bilateral deregulation	28050	1992	3.24	1987	1995	1992	3.23
Percentage of bilateral labor outflow (%), IRS	28050	0.02	0.06	0.001	0.06	0.02	0.04
Percentage of bilateral banking integration	28050	0.05	0.11	0.00	0.19	0.06	0.12
Percentage of bilateral banking integration, 1990	2550	0.03	0.10	0.00	0.14	0.04	0.11
Percentage of bilateral banking integration, 2000	2550	0.05	0.11	0.00	0.19	0.06	0.12
Correlation of quarterly wages, 3-year forward	28050	0.94	0.07	0.86	0.99	0.93	0.07
Annual growth of real wages, all years	58527	0.003	0.06	-0.05	0.06	0.004	0.06
Annual growth of real wages, 1990-2000	27870	0.012	0.06	-0.04	0.07	0.012	0.06
Dependence on External Finance (DEF) measure	58527	0.36	0.32	0.08	0.77	0.36	0.32

Table 2.2.

Labor Outflow and Banking Deregulation: IRS Data

This table reports the regression results of the relationship between labor outflows and banking deregulation. Migration and population data use Internal Revenue Service (IRS) state-to-state migration data which is from 1990 to 2000. DEREG, the indicator of first-time banking deregulation, is based on the same data as in Landier, Sraer and Thesmar (2014). Employment shares of state population are based on County Business Patterns (CBP) data at the annual frequency. In columns (1)-(5), regressions are weighted by state population. In columns (6)-(10), OLS regressions are used. Standard errors are clustered at the state level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Ratio of Labor Outflow to Population $\frac{EM_{it}}{P_{it}}$									
	WLS					OLS				
$DEREG$	-0.58^{***}	-0.08^{**}	-0.07^{*}	-0.08^{*}	-0.08^{**}	-0.49^{***}	-0.10^{*}	-0.08	-0.09^{*}	-0.09^{*}
	(0.16)	(0.04)	(0.05)	(0.05)	(0.04)	(0.14)	(0.06)	(0.06)	(0.05)	(0.05)
Emp. share of wholesale trade			0.17					0.13		
			(0.13)					(0.12)		
Emp. share of finance				-0.18					-0.21^{*}	
				(0.12)					(0.11)	
Emp. share of mining					0.28					0.36^{*}
					(0.20)					(0.19)
N	150	150	150	150	150	150	150	150	150	150
R^2	0.26	0.93	0.96	0.96	0.96	0.23	0.93	0.93	0.94	0.94
Year F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
State F.E.	N	Y	Y	Y	Y	N	Y	Y	Y	Y

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

Table 2.3.

Labor Outflow and Banking Deregulation: CPS Data

This table reports the regression results of the relationship between labor outflows and banking deregulation. Migration and population data use Current Population Survey (CPS) data which is from 1982 to 2005. DEREG, the indicator of first-time banking deregulation, is based on the same data as in Landier, Sraer and Thesmar (2014). Capital-scarce (capital-abundant) states are defined as having a ratio of bank loans to population lower (higher) than 5 as of 1980. In columns (1)-(4), regressions are weighted by state population. In columns (5)-(6), OLS regressions are used. Standard errors are clustered at the state level.

	(1)	(2)	(3)	(4)	(5)	(6)
	Ratio of Labor Outflow to Population $\frac{EM_{it}}{P_{it}}$					
	WLS				OLS	
	All		Capital-Scarce	Capital-Abundant	All	
$DEREG$	-0.72^{***}	-0.25^{**}	-0.36^{**}	-0.16	-0.73	-0.43^{*}
	(0.22)	(0.12)	(0.17)	(0.13)	(0.50)	(0.25)
N	1071	1071	546	525	1071	1071
R^2	0.04	0.62	0.50	0.66	0.03	0.63
Year F.E.	Y	Y	Y	Y	Y	Y
State F.E.	N	Y	Y	Y	N	Y

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

Table 2.4.

Labor Outflow Growth and Banking Deregulation

This table reports the regression results of the relationship between labor outflow growth and banking deregulation. Migration and population data use Internal Revenue Service (IRS) data which is from 1984 to 2000. DEREG, the indicator of first-time banking deregulation, is based on the same data as in Landier, Sraer and Thesmar (2014). Capital-scarce (capital-abundant) states are defined as having a ratio of bank loans to population lower (higher) than 5 as of 1980. Employment shares of state population are based on County Business Patterns (CBP) data at the annual frequency. In columns (1)-(3), regressions are weighted by state population. In columns (4)-(6), OLS regressions are used. Standard errors are clustered at the state level.

	(1)	(2)	(3)	(4)	(5)	(6)
	Percentage change in labor outflow					
	WLS			OLS		
$DEREG$	-0.08	-0.03	-0.03	-0.02	0.02	0.02
	(0.07)	(0.05)	(0.05)	(0.03)	(0.03)	(0.03)
$DEREG \times \{\text{Capital Scarce}\}$		-0.13^{**}	-0.13^{**}		-0.08^{**}	-0.08^{**}
		(0.06)	(0.06)		(0.03)	(0.03)
Growth of wholesale trade			0.004			0.005
			(0.030)			(0.015)
Growth of finance			-0.01			-0.01
			(0.02)			(0.01)
Growth of mining			0.003			-0.004
			(0.004)			(0.004)
N	816	816	816	816	816	816
R^2	0.29	0.30	0.30	0.27	0.28	0.28
Year F.E.	Y	Y	Y	Y	Y	Y
State F.E.	Y	Y	Y	Y	Y	Y

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

Table 2.5.

Labor Flows and Bilateral Banking Deregulation

This table reports the regression results of the relationship between bilateral labor outflows and bilateral banking deregulation. Migration and population data use Internal Revenue Service (IRS) data which is from 1984 to 2000. DEREG, the deregulation indicator between two states, is based on the same data as in Landier, Sraer and Thesmar (2014). The relative capital scarcity indicates whether the origination state of the labor flow had a lower ratio of bank loans to population than the destination state as of 1980. Three-year forward income correlation is computed as the correlation between wages in the two states in the 12-quarter forward window, using state-level Quarterly Census on Employment and Wages (QCEW) data at quarterly frequency. In columns (1)-(5), regressions are weighted by state population. In columns (6)-(9), OLS regressions are used. Standard errors are clustered at the state-pair level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Outflow of labor ratio $\frac{M_{ijt}}{N_{it}}$								
	WLS					OLS			
$DEREG_{ijt}$	3.79	3.92	0.81	5.04^{*}	1.20	-2.56	-3.64	-0.08	-0.74
	(2.53)	(2.55)	(2.50)	(2.59)	(2.74)	(2.47)	(2.74)	(3.63)	(4.77)
$DEREG_{ijt} \times$ I{Capital Scarce}$_{ij}$	-6.85^{***}	-6.56^{***}	-3.01^{**}	-8.58^{***}	-3.97^{**}	-5.40^{***}	-4.68^{***}	-7.49^{**}	-7.15^{***}
	(1.55)	(1.53)	(1.48)	(1.76)	(1.71)	(2.23)	(1.70)	(3.03)	(2.49)
3-Year Forward Income Correlation		-0.35^{**}			-0.17				0.91^{**}
		(1.45)			(0.39)				(0.37)
N	28050	28050	28050	28050	28050	28050	28050	28050	28050
R^2	0.01	0.01	0.13	0.25	0.36	0.01	0.09	0.19	0.26
Year F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y
(Origin State $\times$ Destination State) F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y
(Origin State $\times$ Year) F.E.	N	N	Y	N	Y	N	Y	N	Y
(Destination State $\times$ Year) F.E.	N	N	N	Y	Y	N	N	Y	Y

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

Table 2.6.

Returns to Labor, Banking Deregulation and Capital Abundance

This table reports the regression results of the relationship between real wage growth and banking integration. DEREG, the first-time deregulation indicator, is based on the same data as in Landier, Sraer and Thesmar (2014). Level of (banking) capital abundance kpp^{1980} is defined as the ratio of bank loans to population as of 1980. Wage data is based on state-level Quarterly Census on Employment and Wages (QCEW) data at annual frequency. Regressions are weighted by state population and standard errors are clustered at the state level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Percentage of real wage growth $\Delta \ln w_{ikt}$ (Unit: %)						
	All States		Lowest kpp^{1980}	2nd Quintile	3rd Quintile	4th Quintile	Highest kpp^{1980}
$DEREG$	0.42^{***}	0.45^{***}	1.20^{***}	0.54^{**}	0.18	0.13	0.03
	(0.12)	(0.11)	(0.28)	(0.21)	(0.30)	(0.23)	(0.18)
N	58527	58527	10290	13902	10332	13860	10143
R^2	0.07	0.15	0.29	0.28	0.30	0.27	0.30
Year F.E.	Y	Y	Y	Y	Y	Y	Y
(State $\times$ Industry) F.E.	Y	Y	Y	Y	Y	Y	Y
(Industry $\times$ Year) F.E.	N	Y	Y	Y	Y	Y	Y

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

Table 2.7.

Returns to Labor, Banking Deregulation and Dependence on External Finance

This table reports the regression results of the relationship between real wage growth and banking integration. DEREG, the first-time deregulation indicator, is based on the same data as in Landier, Sraer and Thesmar (2014). The degree of Dependence on External Finance (DEF) for each 3-digit SIC industry is based on the matching to the ISIC industries as in Rajan and Zingales (1998). Wage data is based on state-level Quarterly Census on Employment and Wages (QCEW) data at annual frequency. Regressions are weighted by state population and standard errors are clustered at the state level.

	(1)	(2)	(3)	(4)	(5)
	Percentage of real wage growth $\Delta \ln w_{ikt}$				
	All Industries	Lowest DEF	2nd Quartile	3rd Quartile	Highest DEF
$DEREG$	0.42^{***}	0.16	0.50^{**}	0.68^{***}	0.92^{***}
	(0.12)	(0.35)	(0.21)	(0.24)	(0.30)
N	58527	7182	19824	12348	9030
R^2	0.07	0.08	0.07	0.09	0.08
Year F.E.	Y	Y	Y	Y	Y
(State $\times$ Industry) F.E.	Y	Y	Y	Y	Y

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

Table 2.8.

Alternative Measure for Financial Integration

This table reports the regression results of the relationship between bilateral labor outflows and bilateral banking integration. Migration and population data use Internal Revenue Service (IRS) data which is from 1984 to 2000. $IntPerc$ measures the ratio of bank assets in the two states held by some common bank holding company (BHC) to the total bank assets in the two states. The relative capital scarcity indicates whether the origination state of the labor flow had a lower ratio of bank loans to population than the destination state as of 1980. Three-year forward income correlation is computed as the correlation between wages in the two states in the 12-quarter forward window, using state-level Quarterly Census on Employment and Wages (QCEW) data at quarterly frequency. Regressions are weighted by origination-state population and standard errors are clustered at the state-pair level.

	(1)	(2)	(3)	(4)	(5)
	Outflow of labor ratio $\frac{M_{ijt}}{N_{it}}$				
$IntPerc_{ijt}$	3.62	3.61	2.42	3.42	2.51
	(2.59)	(2.57)	(2.30)	(2.25)	(2.66)
$IntPerc_{ijt} \times$ I{Capital Scarce}$_{ij}$	-6.64^{***}	-6.59^{***}	-3.73^{*}	-6.77^{***}	-5.69^{**}
	(2.30)	(1.53)	(2.09)	(2.06)	(2.58)
3-Year Forward Income Correlation		-0.36^{**}			
		(1.40)			
N	28050	28050	28050	28050	28050
R^2	0.01	0.02	0.13	0.26	0.36
Year F.E.	Y	Y	Y	Y	Y
(Origin State $\times$ Destination State) F.E.	Y	Y	Y	Y	Y
(Origin State $\times$ Year) F.E.	N	N	Y	N	Y
(Destination State $\times$ Year) F.E.	N	N	N	Y	Y

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

Table 2.9.

Labor Return Growth by Dependence on External Finance: Robustness

This table reports the regression results of the relationship between real wage growth and banking integration. DEREG, the first-time deregulation indicator, is based on the same data as in Landier, Sraer and Thesmar (2014). The degree of Dependence on External Finance (DEF) for each 3-digit SIC industry is based on the matching to the ISIC industries as in Rajan and Zingales (1998). Wage data is based on state-level Quarterly Census on Employment and Wages (QCEW) data at annual frequency. Regressions are weighted by state population and standard errors are clustered at the state level.

	(1)	(2)	(3)	(4)
	Percentage of real wage growth $\Delta \ln w_{ikt}$			
	Lowest DEF	2nd Quartile	3rd Quartile	Highest DEF
$DEREG$	0.16	0.57^{***}	0.67^{***}	0.90^{***}
	(0.34)	(0.20)	(0.23)	(0.29)
N	7182	19824	12348	9030
R^2	0.15	0.13	0.18	0.16
(Industry $\times$ Year) F.E.	Y	Y	Y	Y
(State $\times$ Industry) F.E.	Y	Y	Y	Y

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

Table 2.10.

Labor Inflows After Banking Deregulation

This table reports the regression results of the relationship between labor inflows and banking deregulation. Migration and population data use Internal Revenue Service (IRS) data and Current Population Survey which are from 1984 to 2005. In columns (1)-(6), IRS data is used; in columns (7)-(9), CPS data is used. DEREG, the indicator of first-time banking deregulation, is based on the same data as in Landier, Sraer and Thesmar (2014). Capital-scarce (capital-abundant) states are defined as having a ratio of bank loans to population lower (higher) than 5 as of 1980. In columns (3)-(4), OLS regressions are used; in all other columns, regressions are weighted by state population. Standard errors are clustered at the state level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Percentage change in labor inflow								
	IRS						CPS		
	All				Capital-Scarce	Capital-Abundant	All		
$DEREG$	−0.04	0.003	−0.01	0.01	0.02	−0.05*	−0.03	−0.03	−0.03
	(0.03)	(0.03)	(0.02)	(0.02)	(0.05)	(0.02)	(0.04)	(0.07)	(0.04)
Model	WLS	WLS	OLS	OLS	WLS	WLS	WLS	WLS	WLS
N	663	663	663	663	338	325	1020	520	500
R^2	0.05	0.05	0.05	0.28	0.37	0.26	0.09	0.09	0.09
Year F.E.	N	Y	N	Y	Y	Y	Y	Y	Y
State F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y

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

Chapter 3

Climate Shocks and Fire Sales

3.1 Introduction

[1]Global climate change is a challenge created and faced by all mankind. It is associated with increasing temperature, change in composition of the atmosphere, and more frequent and severe natural disasters. It is generally believed that low-income and island countries are particularly subject to these climate events, as they typically lack the tools and technologies for adaptation and mitigation. For advanced countries, it is often believed that better adaptation is achieved by stronger infrastructure that protects against climate events and that better mitigation is achieved by high penetration of insurance products that protect against wealth losses. However, better mitigation through insurance is based on the presumption that insurance companies can perfectly diversify climate risks and this presumption is being increasingly challenged. First, climate shocks are becoming more frequent and more correlated, making diversification more difficult. Second, the intensity of climate events is on the rise, making insurance companies vulnerable to one-time shocks. This pa-

[1]I thank Wei Peng for very helpful comments and suggestions. All remaining errors are mine.

per looks in details the second perspective, and investigates whether a large one-time climate shock can have disturbances on the financial market.

Large shocks can generate significant price deviations from the fundamental value of an asset (Schleifer and Vishny, 1997[3]). There are a few alternative channels through which this can happen. For example, when the price of an asset is initially lower than its fundamental value, higher margin requirements can force investors to reduce positions, resulting in a downward spiral (Brunnermeier and Pedersen, 2008[14]). Another channel is to go through fair-value accounting where financial securities are evaluated at market prices (Barth, 2004[5]). The idea is that, faced with regulatory capital requirements, financial institutions during severe market downturns have the incentive to sell assets that are heavily discounted in market transactions in an attempt to avoid further tightening of capital requirements. These alternative channels are often argued to exacerbate fire-sales activities during crises. Establishing these casual links is challenging, however. During severe financial crises, it is often the case that almost all financial institutions are under tight capital constraints and asset prices fall across the board, making empirical analysis difficult to distinguish alternative channels. In fact, shocks that originate from the financial sector are endogenous by themselves.

This paper exploits one purely exogenous shock that hit the U.S. bond market, due to one of U.S.'s costliest natural disaster Hurricane Katrina in 2005. The shock hit a few southeastern U.S. states, claiming over 100 billion USD in property damages much of which was insured by property and casualty insurance companies. To meet huge amounts of claim payouts, property and casualty insurance companies that were exposed to these states had to liquidate their asset holdings much of which is fixed-income securities including corporate bonds. The shock can have significant impact on the bond market through the

trading activities by property and casualty insurance companies despite that the Hurricane only affected a few southeastern states. In particular, the downward pressure of bonds sold by insurance companies exposed to the Hurricane can induce unexposed insurance companies to sell these assets at the same time. This is because lower market prices of these securities would hurt the balance sheet of unexposed insurance companies through fair-value accounting. Moreover, this effect would be the strongest for insurance companies with tighter regulatory capital constraints.

This paper in particular focuses on the selling behavior of corporate bonds immediately by insurance companies after Hurricane Katrina. Insurance companies are the largest institutional investors of corporate bonds in the United States with total holdings larger than mutual funds and pension funds combined. As of 2005, the year of Hurricane Katrina, U.S. property and casualty insurers held roughly $185 billion in corporate bonds. The focus of the study is on how unexposed insurance companies participated in the fire-sales activities following the sell-offs by exposed insurance companies. Regulatory capital-constrained property and casualty insurance companies that were unexposed to the Hurricane might also sell these assets due to the downward price pressure on their balance sheet, or they have the incentive to liquidate these bonds quickly and avoid further tightening of regulatory capital constraints. I test this mechanism directly by looking at the relationship between the probability of selling the corporate bond and the degree of adequacy of regulatory capital. I also verify that the corporate bonds sold by severely affected insurance companies indeed experienced negative abnormal returns in the aftermath of the hurricane[2].

[2]Zhang and Massa (2011)[65] show that after Hurricane Katrina, corporate bonds sold by exposed property and casualty insurance companies overall experienced abnormal returns.

Empirical results in this paper show that capital adequacy ratio predicts the selling decision of property and casualty insurance companies that were unaffected by Hurricane Katrina. A lower capital adequacy ratio is associated with higher probability of bond selling conditioning on positive holdings before the hurricane. This is consistent with the hypothesis that temporary price decline had the largest effect on balance sheet of property and casualty insurance companies with tight capital constraints. To confirm that this channel is through the mark-to-market accounting rules, I conduct the same analysis on life insurance companies that do not use fair value accounting for fixed-income assets. On the contrary, the capital adequacy ratio for life insurance companies is uncorrelated with their selling decisions. Furthermore, corporate bonds that were sold aggressively by property and casualty insurance companies indeed experienced significant negative abnormal returns after the hurricane.

This paper is also broadly related to the impact of climate change on economic activities and financial stability. The impact of global climate change is tremendous. Carbon dioxide and other greenhouse gases emitted by human activities have trapped much heat in the atmosphere. Since 1880, the average temperature globally has risen 1.4 degrees Fahrenheit and has a continuously increasing trend. Nine of the 10 warmest years on record have occurred, bringing significant impact on economic and social activities, e.g., crop yields, disease transmission. Accompanied include also the melting of arctic and land ice, the rise of sea level, more intense heat waves, and more frequent and severe hurricanes and typhoons.

The natural disasters associated with global climate change can be extremely costly. Low-income and island countries are often more susceptible to extreme climate events. It is because generally these countries lack the tools and technologies for adaptation and mitigation. For example, Hurricane Ike in 2008,

one of the costliest hurricanes to the Caribbean, damaged 95% of the houses in Turks and Caicos Islands and made one million homeless in Hispaniola of Haiti. These damages often have significant long-term impact on economic activities due to the destruction of physical and human capital which is particularly crucial for the economic development of low-income countries. Moreover, these damages to infrastructure and associated burdens on government budget make the countries even more susceptible to future climate events.

For more advanced countries, it is generally believed that more adaptation and mitigation tools are available. Residential buildings are made with stronger material that can defend better strong weather events. Infrastructure is often built in areas that are prone to natural disasters. Moreover, it is generally believed also that advanced countries can recover from the impact of weather events more quickly. One important reason is the higher coverage of insurance policies that protect against adverse weather shocks. For example, property and casualty insurance companies provide insurance policies that protect against leakage of water in building roofs. In the U.S., federal government provides flood insurance policies which help protect against water damages from hurricanes. Life insurance companies also provide the source of finance when members of a household died in severe weather events. However, better adaptation and mitigation through insurance is based on the presumption that insurance companies can perfectly diversify risks and this presumption is being increasingly challenged. First, as mentioned above, global climate change has made extreme weather events more frequent and correlated across regions, making diversification of risks more difficult. There is a potential need for property and casualty companies to reprice their existing policies to reflect these increasing correlations. Second, the intensity of weather events is increasing, making insurance companies vulnerable to one-time extreme weather events. A severe one-time weather events would require insurance companies to liqui-

date their asset holdings to meet claim payouts. The development of catastrophe bonds (CAT bonds) aims at improve risk sharing between insurance companies and investors in response to the increasing likelihood of severe climate shocks.

This paper investigates this question above in details by conducting an event study around Hurricane Katrina of 2005 in the United States. I study how the shock from the extreme weather event was transmitted and amplified in the financial market through insurance companies' liquidation of assets to meet policy payouts. The exact channel is the mark-to-market accounting rules applied to property and casualty insurance companies. These rules imply that large climate events can be transmitted and amplified in financial markets.

This paper is organized as follows. Section 2 describes the insurance industry in the U.S. and the background information of Hurricane Katrina. Section 3 provides information on data. Section 4 presents the empirical model and results, followed by the concluding Section 5.

3.2 Insurance Industry and Hurricane Katrina

3.2.1. Insurance Companies as Institutional Investors

Insurance companies are important institutional investors in the U.S. financial markets. In terms of the size of the insurance industry, the total assets of insurance companies together account for between 40% to 50% of US GDP. Because of their liability structure and business models, insurance companies typically allocate a large fraction of their investments to fixed-income securities. Among their total asset holdings, 91% is in fixed-income securities which include corporate bonds, treasury bonds, municipal bonds and foreign bonds.

This makes insurance companies the largest institutional holder of U.S. corporate bonds with total holdings larger than mutual funds and pension funds combined. As of 2005, the year of Hurricane Katrina, U.S. P&C insurers held roughly $185 billion in corporate bonds.

The fact that insurance companies are the largest institutional investors of bonds makes their role in the financial market particularly important. Their acquisitions of corporate bond would make cheaper the external financing for companies in the real economy. It is shown that during the 2008-2009 financial crisis, many companies were able to issue corporate bonds to offset the negative impact of the credit crunch originated from banks, suggesting the importance of bond market investors in supporting the real economy. Moreover, the liability structure of insurance companies makes them uniquely a potentially shock absorber in the times of crises. Unlike banks, insurance companies, especially life insurers, typically have less liquid and longer-term liabilities which could enable insurance companies to behave as a long-term investor. In fact, this potential characteristic of the industry is an important consideration for regulators when making regulatory rules regarding their capital requirements, e.g., Solvency II. Their behaviors in the corporate bond market could, therefore, have large impact on corporate bond prices and the financing conditions of the issuers of these bonds.

3.2.2. Risk-Based Capital and Mark-to-Market Accounting for Insurance Companies

The insurance industry is highly regulated in the U.S.. While insurance companies are regulated by individual state's regulators and their liabilities are backed up by state guaranty funds, state regulators impose a consistent set of rules on their capital requirements. The National Association of Insurance Commissioners (NAIC) has adopted Risk-Based Capital (RBC) requirements on insurance companies since the 1990s. Risk-Based Capital is a method of

calculating the minimum amount of capital determined as appropriate for the insurance company's overall business, size and risk profile. Based on an RBC Formula, it requires a company with a higher degree of risk to hold more capital, and thus, it limits the amount of risk the company takes. The types of risks in the RBC framework include asset risk, underwriting risk, and other risk including interest rate risk that is specific to life insurance companies. Among these risk categories, asset risk accounts for the largest share of the required capital. Insurance companies are required to maintain at least 200% of the minimum required capital, also called Authorized Control Level (ACL) of capital. Failure to comply could result in regulatory interventions, including seizure of the company.

It is therefore important to evaluate assets and liabilities of insurance companies properly. Under the U.S. regulation, Property and Casualty insurance companies use Mark-to-Market (MtM) accounting rules for financial securities they hold on their asset side. This means that the value of their assets will fluctuate according to the market prices of these securities. Despite the benefits of mark-to-market accounting rules such as better reflection of the risk undertaken in general, MtM rules can generate procyclical trading behaviors in the event of large market shocks or during financial crises. A sharp price decline of an insurer's assets would tighten the capital constraint it is facing and encourage the insurer to sell these assets before the price continues declining. If many investors in the market are exposed to these assets, they would join force in selling these assets. Such selling behavior would impose further downward pressure on the market price and could lead to more selling of these assets. In this way, the selling activity of one company would impose a pecuniary externality on the rest of the market. Such amplification mechanism is central to the policy debate on financial stability and macro-prudential policies.

One exception to the MtM accounting rules is life insurance companies. Due to their long-term liabilities and business models, life insurance companies are natural buy-and-hold investors of fixed-income securities. To reflect such differences in their business models, fixed-income securities held by life insurers are valued using historical cost accounting. Any temporary fluctuations in the market prices for these bonds therefore would have no impact on the balance sheet of life insurance companies, except when the value of these assets is determined as significantly and permanently impaired.

It has been documented in the literature that MtM rules indeed induced stronger fire-sale activities during the recent financial crisis. For example, Ellul et. al. (2011)[22] document that the downgrading of certain corporate bonds during the global financial crisis led to the fire sales of these securities. On the other hand, there is some evidence that life insurance companies that do not use MtM rules seem to have served the role of stabilizer during crisis times. However, most of the existing studies focus on the trading behaviors during crises in which all asset prices decline significant together with the economic fundamentals, and an exogenous shock that is large enough to affect these investors and is unrelated to economic fundamentals would be desirable to study the effect of these fire-sale activities purely driven by MtM and capital regulation. This paper exploits one such exogenous shock of Hurricane Katrina in 2005. I study how insurance companies liquidate positions to meet insurance claims and how these liquidations had impact on other market participants.

3.2.3. Climate Shocks

The adverse impact of climate shocks on the financial market is traditionally viewed as limited. One important reason is that extreme weather events like hurricanes only happen rarely and to certain geographic areas, and insurance

companies are in general well diversified to ride through such climate shocks. Another reason is that even if the shock is large enough to bring down a few highly exposed insurance companies, there is very little impact on unaffected insurance companies.

These reasons, however, have been increasingly challenged in today's world. The gradual but significant process of climate change has made extreme weather events more likely, more intensive, and more correlated across geographic regions. All these factors have made insuring against extreme weather events more expensive than ever. At the same time, financial market mechanisms can amplify the shocks originated from these weather events. As it happened during the crisis, mechanisms including mark-to-market accounting rules in the financial market can significantly amplify shocks. In this paper, I focus on arguably the costliest natural disaster in history that happened in the U.S., Hurricane Katrina, and investigate the impact on the financial market, in particular the corporate bond market.

Hurricane Katrina was an Atlantic hurricane that affected multiple states in the U.S. between August 28 and September 1, 2005. The storm claimed over 1200 lives, making it the deadliest hurricane in the U.S. since the 1928 Okeechobee hurricane. Total property damage exceeded 100 billion (2005 USD). Among these damages of properties, it is estimated that $40 billion to $55 billion was privately insured, a higher amount than the 9/11 attach in 2001. To meet these payouts, insurance companies would have to liquidate their financial assets among which fixed-income assets account for the largest fraction. Louisiana, Alabama, and Mississippi are among the states that were affected the most and they in total had a direct damage of over $80 billion. Total losses for insurance companies were huge. For example, the total direct losses of insurance companies in 2005 for Louisiana alone reached $37.9 billion dollars,

over 900% of the year before and the year after. Insurance companies that had large exposure to the affected states also suffered large total direct losses. In Louisiana, the two largest property and casualty insurance companies, State Farm and AllState, had direct losses of $7.9 billion and $5.8 billion in 2005, respectively. These losses were more than ten times of the losses the year before. Property and casualty insurance companies affected by Hurricane Katrina incurred huge losses without having much higher premium income as the hurricane was very difficult to predict such events months before they happened.

Figure 3.1 below shows these total direct losses and direct premiums written in Louisiana between 2004 and 2007. The total direct losses of insurance companies in 2005 for Louisiana alone reached $37.9 billion dollars, over 900% of the year before and the year after. Direct premiums written did not change much over these years, reflecting the fact that extreme weather events are technically difficult to forecast months before they happen. Insurance companies that had large exposure to the affected states also suffered large total direct losses. In Louisiana, the two largest property and casualty insurance companies, State Farm and AllState, had direct losses of $7.9 billion and $5.8 billion in 2005, respectively. These losses were more than ten times of the losses the year before. Similar patterns can be found for other affected states and to other companies in these affected states. A concentrated group of insurance companies that had large exposure to these affected states were severely hit by the shock.

To meet such surges in claims on the insurance policies, affected property and casualty insurance companies would need to liquidate in a short period of time a large amount of their asset holdings, of which a large fraction is bonds. Consequently, there could be downward pressure on the price of the assets being sold. Moreover, the selling behavior of these affected companies can have impact on other investors too. Facing a declining price of the assets and with

mark-to-market accounting rules for the value of these assets, property and casualty insurance companies holding the same assets that were being sold would have more constrained balance sheet and have the incentive to unload these assets to maintain a certain degree of capital ratio. Moreover, the decision to sell these assets by unaffected insurance companies would depend on the amount of regulatory capital they had. Companies with higher capital surplus should be less incentivized to sell these undervalued assets. In this study, I test this sell herding effect by insurance companies unaffected by Hurricane Katrina on assets that were liquidated by companies that were affected. I particularly focus on corporate bonds as they accounted for a large fraction of insurance companies' assets. Moreover, I test if property and casualty insurance companies that had lower regulatory capital surplus were more likely to sell these bonds.

3.3 Data

3.3.1. Asset Purchases and Sales for Insurance Companies

Insurance companies are required to report their asset holdings and transactions to the National Association of Insurance Commissioners (NAIC) in Schedule D. The reporting of the holdings of financial securities is conducted annually, while the reporting of transactions of financial securities is conducted every quarter. Schedule D covers insurance companies' investment in corporate bonds, municipal bonds, common stocks, and preferred stocks. In particular, Schedule D contains the sales of each security by each insurance company with available information on the CUSIP code of the security, date of the transaction, and the total value of the transaction. In this paper, I use the CUSIP codes to identify the securities being sold and match these codes to the holdings by

each insurance company.

In this paper, I focus on the selling activities of corporate bonds. Insurance companies are important institutional investors of corporate bonds, and at the same time, corporate bonds account for a large fraction of insurance companies' holdings as well. In the dataset, during the three months after Hurricane Katrina, there are 160 non-financial corporate bonds being sold by affected property and casualty insurance companies in the secondary market. To study the cross-sectional differences in the selling behavior of insurance companies, I restrict the sample to the thirty-five bonds that at least ten unaffected insurance companies held as of 2005Q2. This restriction allows me to control for bond fixed effects and to study the cross sectional characteristics of insurance companies that held them. Price information on these bonds is from Bloomberg.

3.3.2. Balance Sheet Data for Insurance Companies

To study the mechanism of fire sales of securities, I investigate the relationship between insurance companies' selling decisions and firm characteristics. I mainly focus on the capital surplus relative to regulatory requirement as this variable measures how close the regulatory capital constraint is binding. There are a few ways to construct this variable, and I use different definitions to check for robustness of empirical results. The first definition is the normalized capital surplus, defined as the amount of total adjusted capital in excess of the Authorized Control Level (ACL) of capital, normalized by total assets. The ACL of capital is the amount of capital insurance companies are required to hold to avoid the seizure of the company by regulators. The second definition is the capital ratio, defined as the ratio of total adjusted capital to the ACL level of capital. Both definitions are normalized variables and measure how constrained the regulatory capital is for each insurance company.

Information of insurance companies are based on A.M. Best Global Statement File which contains both standard balance sheet data and data on regulatory capital designated by NAIC. For each property and casualty insurance company, I also measure the exposure to Hurricane Katrina using their balance sheet information. The dataset contains information on the Direct Premiums Written (DPW) and Total Claim Losses (TCL) in each U.S. state and territory at the annual frequency. I specifically look at the top ten insurance companies ranked by the total direct premiums written as of 2005 in states affected by Hurricane Katrina, namely, Louisiana, Alabama, and Mississippi.

3.4 Methodology

3.4.1. Empirical Strategy

I distinguish property and casualty insurance companies that were severely affected by Hurricane Katrina from those unaffected. I define the ten largest insurance companies in the affected U.S. states as affected insurance companies, ranked by net premiums written. Affected states here includes Louisiana, Alabama, and Mississippi. The selling activities by these ten largest companies would have large price impact on the assets being sold. I define unaffected insurance companies as having no insurance policies written in these three affected states as of 2005.

Hurricane Katrina mainly impacted the U.S. between August 28 and September 1, 2005. I study the trading behavior of insurance companies between September 1 and December 31, 2005, right after the hurricane. Robustness is checked extending the trading period by another quarter. I focus the corporate bonds that were sold by affected insurance companies during this time window. The reason why I focus on corporate bonds is that insurance companies are the largest institutional investors of corporate bonds. This makes their trading

decisions very important to the volatility in the market and to the financing conditions of firms in the real sectors.

In my analysis, for each bond being sold by affected insurance companies, I study whether unaffected insurance companies holding the bond prior to the shock tended to sell it as well in the time window. There would be incentive for unaffected insurance companies to sell these bonds if the mark-to-market rules tightened their capital constraints. Specifically, I test this mechanism by investigating whether unaffected insurance companies with lower regulatory capital surplus had greater incentive to sell these bonds. Capital surplus ratio is defined as the amount of regulatory capital the firm had as of 2004 as a percentage of the required amount of capital. A 200% minimum is required to avoid regulatory interventions. A higher capital surplus ratio indicates stronger resistance to undervalued assets on their balance sheet. A firm with capital surplus ratio close to 200% would be sensitive to the value of their assets. I restrict my sample to bonds that were held by more than fifteen insurance companies as of the second quarter of 2005.

In my regression, for each unaffected insurer j and each bond i being sold by affected insurance companies, I look at the selling decision by the insurer conditional on the fact that the insurer had positive holdings of the bond as of the second quarter of 2005. Specifically,

$$Pr(Sell = 1|PositiveHoldings)_{ij} = \alpha_i + \beta_1 \cdot CapSurplus_j + \epsilon_{ij}$$

where $CapSurplus$ is the regulatory capital surplus for insurance company j at year end of 2004. I measure capital surplus by the total regulatory capital surplus normalized by total assets and by the ratio of regulatory capital to minimum capital required. The coefficient of interest in this regression is β_1. A

negative β_1 indicates that insurers with lower capital surplus were more likely to sell the affected bond. In the analysis, I focus on selling behaviors between September 1 and December 31 of 2005. For robustness, one can extend the time window by another quarter. A negative coefficient β_1 would indicate that firms with lower capital surplus ratios were more likely to sell these bonds conditional on positive holdings before the shock hit.

3.4.3. Identifying the Fire-Sale Channel

To identify the fire-sales channel, one needs to compare the trading behavior of property and casualty insurance companies after Hurricane Katrina to that of other institutional investors that are not subject to the type of capital constraints as property and casualty insurance companies. Life insurance companies are naturally the ideal candidate. Life insurance companies in the U.S.. Life insurance companies are regulated by the National Association of Insurance Commissioners (NAIC), similarly to property and casualty insurance companies, and are subject to regulatory capital constraints imposed by the NAIC based on formulas that are specific to life insurers. Unlike property and casualty I study the behaviors of life insurers which do not use mark-to-market accounting for bond holdings, unless the bond is determined as "significantly and permanently impaired in value". The fact that life insurance companies use the historical cost rules for accounting reduces the need for them to unwind their positions when there are short-term fluctuations in asset prices. Instead, such regulation for life insurance companies is also to encourage them to purchase these securities when prices fall, encouraging their role as market stabilizers.

The regression analysis using life insurance companies is expected to yield a different result than that using property and casualty insurance companies.

In particular, the coefficient on capital surplus should be insignificant. Table 3.3 shows the regression results. One can see that capital surplus does not explain the selling behavior of life insurance companies for the affected corporate bonds. This is in contrast to the relationship between capital surplus and selling behavior for property and casualty insurance companies shown above, confirming that the mark-to-market accounting rules played an important role in relating the selling behavior with the regulatory capital surplus of the insurance company.

3.4.4. Verifying Price Impact

From the analysis above, I see that insurance companies with weaker regulatory capital tend to participate in the fire sales of corporate bonds after Hurricane Katrina hit. The contrast between behaviors of property and casualty insurance companies and life insurance companies highlights the importance of mark-to-market in encouraging procyclical trading behavior.

To further confirm that insurance companies sold these corporate bonds to avoid constraints of their balance sheet, one needs to verify that these bonds being sold indeed experienced downward price pressure. More specifically, bonds that had greater exposure to vulnerable insurance companies would have larger price decline after Hurricane Katrina. I define the exposure to vulnerable insurance companies for each bond as the share of value outstanding held by property and casualty insurance companies with low regulatory capital surplus. A higher share of value outstanding held by low-capital insurance companies means that any negative external price shock would likely be amplified by the fire-sales behavior of these low-capital insurers.

The price impact of each bond is defined as the abnormal return of the bond between August 22 and December 20 of 2005, a 120-day period, where the former date is the Monday of the week of Hurricane Katrina. Robustness is checked by changing the time window of the calculation of abnormal returns. I define the abnormal return of a bond as the return of the bond over the specified time window in excess of the yield of the treasury bond of similar maturity.

The sample of corporate bonds includes those being sold by affected property and casualty insurance companies. Among these 58 bonds, the average 120-day abnormal return is -1.35%. There is some degree of heterogeneity in the abnormal returns with the 25th percentile being -1.73% and the 75th percentile being -0.21%. The independent variable of interest is the exposure of the bond to low-capital insurance companies before the shock, measured by the share of value outstanding held by low-capital property and casualty insurance companies relative to the value held by all insurance companies.

Specifically, the regression is given below

$$AbnormalReturn_i = \alpha_i + \beta_1 ExposureToLowCap_i + \beta_2 \cdot X_i + \epsilon_i$$

where $AbnormalReturn$ is the 120-day abnormal return for each bond after Hurricane Katrina, $ExposureToLowCap$ is the measure of exposure of the bond to low-capital property and casualty insurance companies as of 2005Q2, and X includes a list of control variables. Control variables include the share of bond outstanding held by life insurance companies, the (logged) total value of bond outstanding held by all insurance companies, the number of property and casualty insurance companies that held the bond, the number of life insurance companies that held the bond, and information on the bond issuer.

One would expect that the coefficient β_1 to be negative, as higher exposure to low-capital insurance companies tend to be associated with greater fire-sales activities. Moreover, I repeat this empirical exercise but change the time window to be the 120-day abnormal return before Hurricane Katrina ending on August 22. This time frame is supposedly unrelated to Hurricane Katrina, and thus the abnormal returns should not be strongly correlated with the exposure to low-capital insurance companies.

Regression results are presented in Table 3.4. Columns (1)-(3) show the results of regressions where the dependent variable is the 120-day abnormal return since August 22. I can see that the coefficient on the share of bonds outstanding held by low-capital property and casualty insurance companies is significantly negative. This suggests that for a bond that is mostly held by properties and casualty insurance companies with low regulatory capital experienced more negative abnormal returns after Hurricane Katrina. In terms of the magnitude, the difference between the 25th and 75th percentiles of *Low-Cap Share* is associated with negative 1.9% abnormal returns in the 120-day period after Hurricane Katrina. This magnitude can explain an effect even larger than the average 120-day abnormal returns of the corporate bonds in the sample.

Columns (4)-(5) show the regression results using the 120-day abnormal return before Hurricane Katrina, i.e., from April 21 to August 19, 2005. One can see that the coefficient is no longer significantly negative. This result shows that the relationship between larger exposure to low-capital property and casualty insurance companies and greater negative abnormal returns is only present after Hurricane Katrina hit the affected areas but not before it, which is consistent with the hypothesis that mark-to-market accounting rules tend to amplify shocks originated from the climate event.

3.5 Discussion and Conclusion

The impact of climate events on financial stability is an important issue in assessing the social costs of carbon emissions, besides the physical damages these events can cause. This paper is among the first studies that look at historical climate events and investigate the transmission of these shocks to the financial market. In this paper, I focus on one of the most severe hurricanes in the U.S. history, Hurricane Katrina, and study how the shock from the hurricane was transmitted and amplified through property and casualty insurance companies that provided insurance coverage to properties losses in states affected by the hurricane. The channel through which the shock was transmitted is the mark-to-market rules that applied to property and casualty insurance companies.

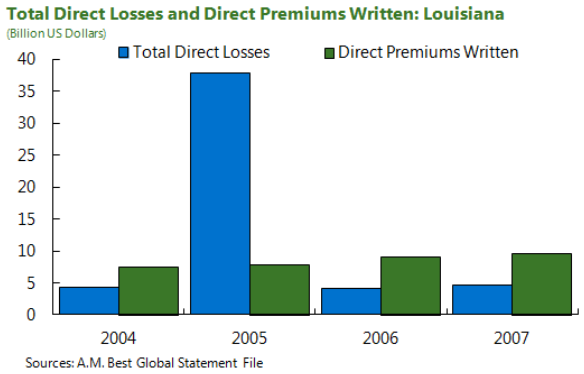
The empirical results in this paper suggest that a purely exogenous climate shock can generate much trading activity and price movements in financial markets if the magnitude of the shock is large enough. This indicates the ability of better mitigation is being increasingly challenged not only by more correlated extreme climate shocks but also by one-time severe shocks that can be transmitted and amplified in financial markets.

Figure 3.1

Total Direct Losses (TDL) and Direct Premiums Written (DPW) from 2004 to 2007: Louisiana

This figure illustrates the total direct losses (TDL) and direct premiums written (DPW) around the time Hurricane Katrina hit Louisiana. Panel A shows the total direct losses and direct premiums written in Louisiana from 2004 to 2007 for the property and casualty insurance industry. One can see that total direct losses surged in 2005 to almost $40 billion while direct premiums written had remained flat. Panel B plots the total direct losses and direct premiums written for the largest two property and casualty insurance companies in Louisiana (as of 2005) between 2004 and 2007. One can see that each company experienced total direct losses of over $5 billion in 2005 in Louisiana alone.

Panel A. Total Direct Losses and Direct Premiums Written: Louisiana



Panel B. Total Direct Losses in Louisiana for State Farm and AllState

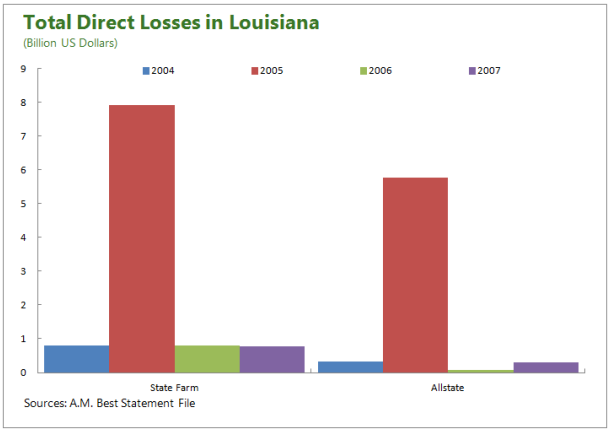


Table 3.1. Summary Statistics

Summary statistics are presented in the table below. Balance sheet items are for property and casualty insurance companies covered in the sample as of 2004. I define the abnormal return of a bond as the return of the bond over the specified time window in excess of the yield of the treasury bond of similar maturity.

	N	Mean	SD	10th	90th
Capital Ratio (Normalized by Total Assets)	1531	0.41	1.48	0.10	0.67
Capital adequacy Ratio	1531	6.92	4.61	2.93	13.45
Retention Ratio	1531	0.73	0.32	0.27	0.99
Combined Ratio	1531	1.00	0.29	0.81	1.19
Loss Ratio	1531	0.74	0.30	0.50	0.93
Net Leverage Ratio	1531	3.26	3.73	1.25	4.74
Current Liquidity Ratio	1531	1.51	0.97	0.96	2.09
Higher-Risk Asset Ratio	1531	0.11	0.10	0.01	0.23
Log(Total Assets)	1531	14.46	1.99	11.44	17.16
120-Day Abnormal Returns, Post Katrina	58	-0.013	0.033	-0.047	0.006
120-Day Abnormal Returns, Pre Katrina	58	0.007	0.015	-0.011	0.024

Table 3.2. Selling of Corporate Bonds After Hurricane Katrina by Property and Casualty Insurance Companies

This table presents results of the regression of selling the affected corporate bonds on firm characteristics of property and casualty insurance companies. Affected bonds are defined as bonds sold by property and casualty insurance companies affected by Hurricane Katrina. Columns (1)-(4) represent results of the OLS regression and columns (5)-(7) present results of the probit regression.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS				Probit		
Capital Surplus	-0.064^{***}	-0.029^{**}	-0.037^{**}	-0.033^{**}	-0.146^{***}	-0.039^{*}	-0.038^{*}
	(0.22)	(0.014)	(0.015)	(0.015)	(0.055)	(0.020)	(0.020)
Retention Ratio				0.017			0.012^{**}
				(0.011)			(0.005)
Combined Ratio				-0.001			-0.011
				(0.003)			(0.006)
Loss Ratio				-0.000			-0.002^{*}
				(0.004)			(0.001)
Current Liquidity Ratio				-0.008			-0.022
				(0.008)			(0.018)
Net Leverage Ratio				0.008^{*}			0.010
				(0.004)			(0.008)
Higher-Risk Asset Ratio				0.081			0.142^{*}
				(0.075)			(0.071)
Size				0.010^{*}			0.020^{*}
				(0.006)			(0.006)
N	1531	1531	1531	1531	1531	1531	1531
Bond Fixed Effects	N	N	Y	Y	N	N	N
R-squared	0.01	0.01	0.04	0.12	0.03	0.02	0.16
Capital Surplus	Normalized	Capital Ratio	Capital Ratio	Capital Ratio	Normalized	Capital Ratio	Capital Ratio

Note: ***, **, * represent statistical significance at 1%, 5%, and 10% levels, respectively.

Table 3.3. Selling of Corporate Bonds After Hurricane Katrina: Life Insurance Companies

This table presents results of the regression of selling the affected corporate bonds on firm characteristics of life insurance companies. Affected bonds are defined as bonds sold by property and casualty insurance companies affected by Hurricane Katrina. Columns (1)-(2) represent results of the OLS regression and columns (3)-(4) present results of the probit regression.

	(1)	(2)	(3)	(4)
	OLS		Probit	
Capital Surplus	−0.27	0.07	−0.24	0.68
	(0.47)	(0.39)	(0.25)	(1.19)
N	1036	1036	1036	1036
Bond Fixed Effects	N	Y	N	N
R-squared	0.00	0.32	0.00	0.03
Capital Surplus	Capital Ratio	Capital Ratio	Normalized	Capital Ratio

Note: ***, **, * represent statistical significance at 1%, 5%, and 10% levels, respectively.

Table 3.4. 120-Day Abnormal Returns Before and After Hurricane Katrina

This table presents results of the regression of 120-day abnormal returns in the cross section of the 58 corporate bonds being sold by affected insurance companies. Columns (1)-(3) show regression results where the dependent variable is the 120-day abnormal return after Hurricane Katrina. Columns (4)-(5) show regression results where the dependent variable is the 120-day abnormal return before the Hurricane.

	(1)	(2)	(3)	(4)	(5)
	Post -Katrina Period			Pre-Katrina Period	
Low-Cap Share	-0.19^{*}	-0.27^{**}	-0.33^{***}	0.029	0.023
	(0.11)	(0.12)	(0.12)	(0.021)	(0.021)
# of Low-Cap		0.0015	0.0017^{*}		0.0002
		(0.0011)	(0.0010)		(0.0002)
Life Share			0.046		
			(0.037)		
# of Life			−0.0002		
			(0.0002)		
log(Outstanding)			−0.003		
			(0.007)		
Constant	−0.007	−0.009	0.033	0.007^{*}	0.006
	(0.008)	(0.008)	(0.040)	(0.003)	(0.004)
N	58	58	58	58	58
R-squared	0.08	0.09	0.12	0.02	0.03

Note: ***, **, * represent statistical significance at 1%, 5%, and 10% levels, respectively.

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