Lender Experiences and Mortgage Costs

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Abstract

This paper examines how lenders' past experiences with house price changes influence the mortgage rates they charge, focusing on the role of lender expectations. I hypothesize that lenders extrapolate from past house price changes to balance profit margins with default risk, offering lower rates when they anticipate future price increases. Consistent with this hypothesis, I show that lenders exposed to greater house price growth tend to charge lower mortgage rates. I rule out alternative explanations, such as differential local growth opportunities or the potential of banks to influence local prices, using placebo tests and geographic variation in lending patterns. Specifically, I find that moving from the 25th to the 75th percentile of price growth exposure is associated with a 4.5 percentage point reduction in loan rate spreads.

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1 Introduction

The U.S. residential mortgage market is the largest consumer finance market globally, with annual originations reaching trillions of dollars to finance both home purchases and the refinancing of existing mortgages. Mortgages represent the largest financial liability for most households and are integral to the financing of their most significant asset: housing. Given the scale of this market, even modest fluctuations in mortgage pricing can have far-reaching consequences, influencing lending volumes, homeownership rates, and overall financial stability. This raises important questions about the factors that determine mortgage costs: What role do mortgage lenders play in shaping access to credit and influencing the costs of borrowing? To what extent do lender experiences and expectations impact mortgage pricing decisions? How do these lender behaviors affect housing market cycles?

While much of the existing literature has focused on borrower characteristics—such as credit scores, income, and loan-to-value ratios—there is growing recognition that lenders' experiences and expectations play a critical role in shaping mortgage outcomes. Lenders adjust their pricing and lending decisions based on their beliefs about future house prices, risks, and broader economic conditions. Prior research has shown that past experiences with economic shocks or defaults can influence lenders' risk tolerance and lead to changes in credit availability (Malmendier and Nagel 2011, Greenwood and Hanson 2013). For instance, lenders who have experienced periods of higher defaults may price loans more conservatively, while those anticipating future price increases may loosen credit standards. These behaviors can amplify housing market cycles: optimism among lenders during periods of rising prices can fuel further increases, while pessimism during downturns can restrict credit and deepen recessions. This cyclical feedback loop aligns with the "financial accelerator" framework outlined by Bernanke, Gertler and Gilchrist (1999), but applied specifically to the housing market. Understanding how lenders form expectations and adjust their behavior in response to changing market conditions is therefore essential for explaining housing market volatility and its macroeconomic implications.

I argue that house price movements are partly driven by lenders' tendency to extrapolate from past price growth, leading them to overestimate (or underestimate) collateral values. When house prices rise, lenders may loosen credit standards and lower rates, fueling further price increases. Conversely, during downturns, pessimistic beliefs may tighten credit, exacerbating price declines. This feedback loop between lenders' beliefs and the housing cycle highlights the role of expectations in amplifying housing market volatility. Over time, however, lenders adjust their expectations based on new information, gradually correcting any irrationality until their beliefs align with realized prices. Figure 1 outlines this feedback loop between lenders' beliefs and the housing cycle.

I begin by developing a static model that, while simple, captures the key dynamics of how lenders' prior beliefs affect mortgage pricing and housing cycles. This model demonstrates that lenders' initial optimism or pessimism can have lasting effects on first-period outcomes, while second-period adjustments depend on whether realized prices diverge from initial expectations. When agents update their expectations quickly, the gap between realized and expected prices narrows, underscoring the self-correcting nature of this learning process.

Incorporating deviations from rationality into economic models is challenging, as it requires considering numerous variables—such as prices of nondurable goods, wages, interest rates, and inflation—and the processes through which agents form their beliefs. My objective is not to comprehensively explore all expectation formation processes, but rather to demonstrate that even a slight deviation from rationality on one key variable (house prices) can significantly impact the real economy. In this model, agents form beliefs through a learning process, updating their expectations based on new information about house prices, which in turn influences mortgage rates and lending behavior. Despite inaccuracies in their beliefs, agents behave optimally given their expectations. This model generates predictions on how past price exposure influences mortgage rates, which I test empirically.

To support the theoretical framework, I present empirical evidence showing the impact of lenders' beliefs on mortgage pricing. Using data from the Home Mortgage Disclosure Act (HMDA), I demonstrate that financial institutions tend to charge lower rate spreads on conventional, non-GSE loans in regions where house prices have increased at a slower pace. This analysis controls for borrower characteristics and local economic conditions, showing that lenders' extrapolation of past price trends can directly influence borrowing costs. Since housing demand is highly sensitive to mortgage rates, this finding suggests that irrational beliefs can have significant consequences for house price dynamics.

To further establish the relationship between house price growth and mortgage rates, I employ an empirical strategy focusing on regions with high housing supply elasticity, as measured by Saiz (2010). By leveraging variations in house price growth across regions, I argue that the observed relationship between growth rates and mortgage rate spreads is plausibly driven by lenders' expectations. The results indicate that moving from the 25th to the 75th percentile of house price growth results in mortgage rates that are, on average, more than 4

The rest of the paper proceeds as follows. Section 2 outlines a three-period model and presents key relationships with respect to model variables on lender beliefs. Section 3 discusses the data and the empirical approach. Section 4 presents the summary statistics and empirical results. I conclude in section 5.

Literature This paper relates to the literature studying how credit conditions and optimism contribute to the housing boom and bust. Mian and Sufi (2011) documents empirically that there was a causal effect of the rise in house prices on the increase in home equity-based borrowing, which then led to higher default rate starting in 2006.[1] Subsequent applied theory papers emphasize the role of credit conditions and beliefs through various modeling frameworks but have yet reached a consensus. For example, Iacoviello and Pavan (2013), Corbae and Quintin (2015), Landvoigt (2017), Favilukis, Ludvigson and Van Nieuwerburgh (2017), Greenwald (2018), Liu, Wang and Zha (2019) show that change in credit condition could induce a housing boom and bust. On the other hand, Gelain and Lansing (2014), Burnside, Eichenbaum and Rebelo (2016), Glaeser and Nathanson (2017), Nathanson and Zwick (2018), Kaplan, Mitman and Violante (2020), and Kindermann et al. (2020) emphasize irrational beliefs as the main driver for housing price movements. Greenwald and Guren (2019) reconciles the divergence by contending that whether credit condition can move housing price depends on the degree of segmentation in the housing market. This paper argues that the two competing causes–loose credit conditions and inaccurate beliefs–may not be separate. Instead, relaxation of the credit constraint can be a direct result of optimism.[2] If this is the case, then changes in credit conditions resulting from optimism could lead to shifts in housing prices even when the housing stock for homeowners remains unchanged. This is in the opposite direction to Jacobson et al. (2019), which also links credit conditions with optimism through adaptive learning, but assumes that credit condition fluctuations trigger changes in households beliefs. The literature has looked into various constraints and their corresponding role in generating a housing boom. It is typically assumed that borrowers face the loan-to-value (LTV) constraint and the payment-to-income (PTI) constraint.[3] Greenwald (2018) shows that how much an increase in home prices loosens the borrowing constraint depends on

[1]Other relevant empirical studies include Glaeser, Gottlieb and Gyourko (2013), Favara and Imbs (2015), Huo and Ríos-Rull (2016), Di Maggio and Kermani (2017), Adelino, Schoar and Severino (2018), and Gete and Reher (2018).

[2]This is consistent with the conclusion in Adelino, Schoar and Severino (2018) and Foote, Gerardi and Willen (2012), showing that optimism *causes* shifts in credit conditions.

[3]PTI constraint requires that the monthly mortgage payment is below a certain fraction of the borrowers' income.

the fraction of borrowers that are LTV-contrained. When house price rises and other variables remain unchanged, LTV-constrained households can borrow more given increasing value of housing collateral but PTI-constrained households cannot. Justiniano, Primiceri and Tambalotti (2019) finds instead that a lending constraint moderating the degree to which lenders can be extending total credit supply is more responsible for house price movements than collateral constraints on the borrowers' side. To allow for more straightforward demonstration of the model mechanism, this paper assumes only a loan-to-value constraint for borrowing and no lending constraint. Despite not having an explicit lending constraint, I interpret the change in LTV constraint over time as a *credit supply* shock since it is set by the lenders of credit.

In addition, this paper is also related to the literature on expectation formation and learning. Timmermann (1996) raises the idea that agents' learning of the true, exogenously determined data generating process of stock returns could yield excess volatility and self-referential learning yield additional volatility. Since then, there has been a growing literature that embeds learning into canonical macroeconomic models to study how learning matters for macroeconomic outcomes such as stock price (Adam, Marcet and Beutel (2017)) and business cycle fluctuations (Eusepi and Preston (2011))[4]. Previous studies (Glaeser and Nathanson (2017), Pancrazi and Pietrunti (2019), Pintus and Suda (2019), Kindermann et al. (2020), and Chodorow-Reich, Guren and McQuade (2021)) have also looked at learning and the housing market. Unlike my paper, most existing literature focuses on learning of exogenous fundamentals as opposed to endogenous objects such as prices, and do not feature the feedback loop between prices and beliefs. Belief process in this paper follows the notion of "internal rationality" raised by Adam and Marcet (2011). More specifically, lenders may possess irrational beliefs but optimize conditional on their subjective belief. I would like to show that this slight deviation from rationality[5] could generate abundant movements in house prices since the feedback loop serves as an amplifier of a shock to the real economy. Contrary to the existing literature that assumes an identical belief process for both the lenders and the borrowers of credit, my paper allows lender to extrapolate but holds beliefs of borrowers to be rational. I show that learning by lenders alone could induce house price dynamics that resemble the observations in data.

Finally, this paper also relates to the litarature gauges household belief through survey or other

[4]Evans and Honkapohja (2012) provides a summary of learning and its application to macroeconomics.

[5]I plan to show that this deviation from rationality is small by calculating how much the irrational agent would pay to become fully rational in the model.

methods. Coibion and Gorodnichenko (2012) documents the predictability of agents' ex-post mean forecast errors via their ex-ante mean forecast revisions, which contradicts the class of full-information, rational expectation models. Some works have looked at survey elicited beliefs on house prices. Case, Quigley and Shiller (2003) finds that expected house price remains to be high after long booms. Soo (2018) develops a housing sentiment index and shows that the index reaches its peak before house prices do during the housing boom, thereby concluding that beliefs predict prices. Piazzesi and Schneider (2009) finds higher degree of optimism among home buyers. Kuchler and Zafar (2019) shows that house price forecasts depend on personal experiences, and Armona, Fuster and Zafar (2019) demonstrates that participants revise their house price expectations in a way consistent with short-term momentum when presented with past prices in an information experiment. Kindermann et al. (2020) shows in German survey data that renters make more accurate forecasts of housing prices given that they have better access to the housing cash flow when they pay for housing services. The existing literature on house price beliefs are consistent with the scenario where individuals do not possess fixed expectations but instead revise based on noisy signals.

2 Conceptual Framework

I introduce a simple conceptual framework that links local house price fluctuations with lender expectations and mortgage rates. This framework guides the empirical approach to investigate the correlation between lenders' past experiences of price growth and the rates they offer in areas where housing and mortgage demand remain relatively unaffected by changes in house prices.

The economy consists of one representative borrower residing in each of the regions indexed by $k \in \{1, \cdots, K\}$. In each period, a borrower secures a one-period mortgage loan, which they may opt to repay or default on in the subsequent period. In case of default, lenders can reclaim a certain fraction of the house's market value. Lenders have the flexibility to offer mortgage loans to borrowers in any region by setting region-specific rates. Further elaboration on the model is provided below.

2.1 Agents

Borrowers A household in region s inelastically consumes 1 unit of housing and takes out a mortgage loan of size m_t in period t. The size of the loan is determined by a binding loan-to-value (LTV) constraint:

$$m_t^s = \theta^{LTV} p_t^s \tag{1}$$

Mortgage sizes are equalized for all individuals in the same region, but could vary across regions as price p_t^s differs for each s. In each period t, the borrower in a region has the option to default on their house. The probability of default in region s offered by lender i is increasing in the mortgage rate spread q_t^{is} and decreasing in the expected next-period house price in period-$t+1$. Higher mortgage rates increase the borrower's repayment burden and raises the likelihood of default. In contrast higher expected house prices enhance the collateral value of housing, allowing borrowers to obtain more equity.[6] As home equity rises, borrowers have a stronger financial incentive to continue making mortgage payments to avoid losing their home and the potential gain from selling it at a higher price in the future. Additionally, if the borrower faces financial difficulty, they may be more likely to sell their home at a profit rather than defaulting, which further reduces the likelihood of default, so the default probability decreases with expected prices. We make the following assumption on the functional form of the default probability function:

Assumption 1. *We assume that the default probability for the borrower in k that receives a loan from lender j is given by:*

$$\iota_{t+1}(q_t^{is}) = \frac{Aq_t^{is}}{(p_{t+1}^s)^\beta}$$

The expected default probability for lender k will be:

$$\mathbb{E}[\iota_{t+1}(q_t^{is})] = \frac{Aq_t^{is}}{(\mathbb{E}[p_{t+1}^s])^\beta} \tag{2}$$

where A is a positive constant denoting the importance of mortgage rates in one's default decisions. We assume $\beta < 1$, meaning that the denominator does not increase as fast as the numerator. This implies that payment burden, or current obligations has a more immediate and stronger impact on default risk than expectations of future house price gains. Borrowers are often more concerned with their ability to meet today's financial obligations than with potential gains from house price appreciation tomorrow.

[6] For example, they could take out a home equity loan or home equity line of credit.

Lenders Lender i chooses its mortgage rate separately for each area $\{q_t^{i1}, \cdots, q_t^{iS}\}$ for loans originated in period t to maximize its expected profit in the following period:

$$\max_{\{q_t^{is}\}} \sum_{s=1}^{S} \mathbb{E}_t^i \left[\left(1 - \frac{Aq_t^{is}}{(\mathbb{E}[p_{t+1}^s])^\beta}\right)\theta^{LTV} p_t^s q_t^{is} + \frac{Aq_t^{is}}{(\mathbb{E}[p_{t+1}^s])^\beta}\delta \mathbb{E}[p_{t+1}^s]\right)\right] \tag{3}$$

In the event of a foreclosure in period $t+1$, lenders recover a fraction δ of the house's value at that time. Otherwise, lenders receive the mortgage payment agreed upon in period t. Given their fixed expectations regarding future house prices, lenders face a tradeoff when setting the mortgage rate q_t. A lower mortgage rate can reduce the incentive for some borrowers to default, as the outstanding debt becomes less burdensome compared to the cost of purchasing a new house.

How expected house prices matter for this tradeoff becomes evident in lenders' expected profit function. In equation (3), when the expected house price is higher at time $t+1$, lenders will anticipate obtaining a higher value from foreclosed houses, which may then reduce their optimal mortgage rates. Additionally, since the expected period-$(t+1)$ default fraction is a function of the lender's expectation of house price, p_{t+1}^s, lenders expect fewer households to default when their expected house price for region s is higher. This is because the expected opportunity cost of defaulting is now higher.

I now specify lenders' belief processes regarding house prices and the default fraction to further evaluate the effect of extrapolative expectations on house prices with respect to the mortgage rate they charge.

Assumption 2. *Lenders believe that house price change is an AR1 process with unobservable drift. They use past price changes to form beliefs on the current price. Specifically, denote the change in logged house price in region k from period $t-1$ to t by $\Delta \log p_t^k$, then:*

$$\mathbb{E}_t^i[\Delta \log p_{t+1}^s] = \widehat{\log p_{t+1}^{is}} - \log p_t^s = \Delta \log p_t^s + \underbrace{\sum_s (\alpha_{t-1}^{is} \Delta \log p_t^s - \alpha_{t-2}^{is} \Delta \log p_{t-1}^s)}_{exposure_{ist}}$$

The expectation of house price $\widehat{\log p_{t+1}^{is}}$ denotes lender i's belief of logged house price in area s at time $t+1$. $\alpha_t^{is} = \frac{\mu_t^{is} m_t^s}{\sum_n \mu_t^{in} m_t^n}$ is the share of loans extended in area s out of all the loans lender i extended in period t.

The belief formation process suggests that lenders base their expectations on the speed of house price changes in an area, drawing from their own experience of past price dynamics in regions where they have extended loans. Moreover, they assign greater importance to areas that account for a larger proportion of the total loans they have extended. This could be justified by that lenders' outlook on the housing market will be dependent on different signals of the fundamentals, which are affected by their observed local economic conditions reflected through local prices. When two mortgage lenders are forming expectations regarding house prices in the same region k, the lender who previously extended more loans in areas characterized by significant price growth anticipates higher prices in region k.

Mortgage rates and lender experiences The conceptual framework implies that the optimal mortgage rate charged by lender j in region k is higher when the expected next-period house price by lender j is higher.[7] This is because the expected value in case of default exceeds the effect from the increase in the default probability. Moreover, since lenders' expected price is assumed to be increasing with their exposure to the area where past prices have been growing faster, such lenders are predicted to optimally charge a lower rate in the same region. We can therefore examine this hypothesis using the equation:

$$q_t^{is} = \alpha_t + \beta_0 p_t^s + \beta_1 \Delta \log p_t^s + \beta_2 exposure_{ist} + \Gamma X_{ist} + v_{ist} \tag{4}$$

where we include the year fixed effects α_t and a list of controls X_{ist} that vary with loan-level characteristics. We expect $\beta_2 < 0$ since higher *exposure* implies high expected prices, which in turn leads to lower rate spread. However, even under a rational expectations null hypothesis, it might be the case that $\beta_2 < 0$ because areas that experience higher price growth tend to feature stronger fundamentals, which allows lenders to charge a lower rate given the reduced level of default risks. Iother words, the speed at which house price change takes place may reflect differences in local demand conditions for the lender and not just their expectations. This implies that lender-level cross-sectional regressions cannot disentangle the our hypothesis on lender forming expectation through their personal experiences from the rational expectations null hypothesis. We therefore develop a strategy that uses the leave-one-out measure for $exposure_{ist}$, while focusing on regions where prices do not vary much with fundamentals.

[7] See Appendix B for details.

3 Data and Empirical Approach

3.1 Data Source and Variables Construction

Mortgage Lending: The main data source is the mortgage-level application and characteristics data collected under the Home mortgage Disclosure Act (HMDA), covering the near universe of all U.S. mortgage applications. The HMDA data contains information on loan type, loan purpose, purchaser type, application outcome, census tract of loan application, rate spread, loan amount, as well as identifiers for the lending institution for each year. Starting from 2018, the dataset includes more variables, including the fees and points, loan-to-value ratio, debt-to-income ratio, and mortgage features (reverse mortgages, mortgages with open-end line of credit, and etc.) that can be studied in combination with the information on rate spread and loan amount.

In my main analysis, I focus on originated mortgages that are conventional, first-lien, and non government-insured from 2004 to 2020. I then restrict the sample to be non-GSE loans and loans for the purpose of home purchase alone. Government sponsored enterprises (GSEs) set interest rates on their securitized loans, and research such Hurst et al. (2016) as have shown that their mortgage rates charged do not vary spatially with predictable local default risks. Since the empirical strategy of this paper relies crucially on comparing the rates of loans made in the same MSA by different mortgage lenders who have plausibly heterogeneous perceived price changes and default risks and there is little room for GSE securitized loan rates to change with respect to local economic conditions or mortgage lender perceptions, I exclude them in my main analysis.[8] Moreover, since more variables start to become available in 2018, I further exclude loans that have a loan term other than 360 months as well as those that are reverse mortgages, mortgages with open-end lines of credit, interest-only mortgages, mortgages with prepayment penalties, intro-rate period, balloon payments, negative amortization, or other non-amortizing features for years 2018 to 2020. The analysis is at the MSA level. so I calculate average rate spread weighted by the loan amount for each loan generated by a borrower institution in each MSA. I trim the data by including only the 1st and the 99th percentile of rate spread for each year. In my robustness checks, I extend the sample to include GSE loans and loans for the purpose of refinancing.

[8] The national interest rate policy of GSE loans, however, does not imply that the rates of GSE loans remain unchanged with respect to aggregate economic trends. Therefore, the relationship hypothesized among house price changes, perceived default risks, and mortgage rates charged is like to still hold in the time series when accounting for the GSE loans. Excluding GSE loans in the baseline analysis therefore does not deny their roles in contributing to a housing boom and bust cycle.

House price and Fundamentals: I use the Freddie Mac House Price Index (FMHPI), aggregated to the yearly average level for each Metropolitan Statistical Area (MSA), and deflated by the national Consumer Price Index (CPI) for that year. The FMHPI calculates house price inflation based on transactions purchased by Freddie Mac and Fannie Mae. I merge this house price data with the measure of housing supply elasticity by MSA, as provided by Saiz (2010). From this, I construct two key variables.

First, I create indicators for MSAs experiencing minimal house price shocks by identifying MSAs where the change in house prices from year $t-2$ to $t-1$ falls within the middle 50% of price changes across all MSAs. Since the mean of house price changes is centered around zero, this approach captures regions where house prices have not significantly increased or decreased. I use this measure to define one of the samples analyzed in section 4.4.3.

Second, I measure each lending institution's exposure to house price growth or decline. For each institution i, I calculate the weighted average change in house prices across all MSAs in which the institution operates, weighting the house price index by the loan volume extended in each MSA over two consecutive years. To address potential endogeneity concerns, I employ a leave-one-out approach. Specifically, when calculating an institution's exposure in a particular MSA, I exclude the price change from that MSA to avoid bias in the exposure measure.

$$exposure_{ist} = \frac{\sum_{n \neq s} loan\_amount_{i,n,t-1} \times [\log(hpi)_{n,t} - \log(hpi)_{n,t-1}]}{\sum_{n \neq s} loan\_amount_{i,n,t-1}} \tag{5}$$

where i and t are indexes for a lending institution and a year respectively. s or n denotes the MSA. I also use county-level house prices and derive indicators for counties experiencing prices shocks and institution-level house price exposures at the county-level for my robustness checks.

Bank Balance Sheet: I obtain the Uniform Bank Performance Report (UBPR) collected by the Federal Financial Institution Examination Council (FFIEC). The UBPR contains information on bank performance measures and balance sheet composition for banks that file the quarterly Call Report. I use the UBPR to gather the ratio of deposits to assets, insured deposits to total deposits, loans to assets, real estate loans to assets, loans that are 90+ days past due to gross loans, tier one capital and net losses to average total loans, for each bank available. I match these variables to HMDA data using the RSSD ID assigned to financial institutions by the Federal Reserve.

Labor Force: I obtain data on MSA- and county- level labor force and unemployment rate for the U.S. Bureau of Labor Statistics. I then match the data to the HMDA data using the FIPS code.

3.2 Empirical Approach

To establish a causal relationship between lender-level house price shocks and the rates or fees charged on originated mortgages, I use an empirical design inspired by the literature on the impact of experience on expectations (e.g. Malmendier (2021), Bord, Ivashina and Taliaferro (2021), Chen (2017)). In particular, I leverage the differential price changes experienced by mortgage lending institutions given where they historically extended lending activities. The main identification challenge is that cross-sectional differences in house price movements may capture actual differences in local demand or other unobserved factors that are also able to influence local mortgage rates. To get around this endogeneity issue and pinpoint the supply channel, I consider the impact of lenders being exposed to geographies that underwent high degrees of decline in house prices on the rates or fees they charged in areas with low price changes in a given year. By restricting to areas where an institution carries out lending activities but the house price change is low, this strategy can plausibly exclude the impact of house price changes on credit demand within the same area since supply would not change much given a relatively stable price level. However, if lenders extrapolate from past price growth rates based on their experience across all geographies in which they are extending loans, then they will adjust the rates and fees accordingly even in such areas where change in demand can be absorbed by change in housing supply.

To illustrate the empirical approach using a concrete example, consider two regions: the Kokomo, Indiana Metropolitan Area and the Miami-Fort Lauderdale-West Palm Beach, Florida Metropolitan Area. Even though house price kept declining across the entire United States from years 2006 to 2008, the rate at which it was declining remained heterogeneous for different regions. For Kokomo, price dropped around 2% from 2005 to 2006, and around 12% from 2006 to 2007; for Miami-Fort Lauderdale-West Palm Beach, price dropped around 60% from 2005 to 2006 and around around 31% from 2006 to 2007. If lenders somewhat "anchor" their expectation of how much price will change in this year compared to the amount it did last year, then those that were overwhelmingly extending lending activities in Kokomo would see that price drop exceeded their anticipation and others lending in Miami would conclude that price drop were below their anticipation. My empirical strategy leverages the variation in the differential changes in house price growth over two consecutive years, and hypothesize that lenders who historically conducted lending activities primarily in areas where house price growth rate will lower their current rate even in areas where the house price change between two consecutive years is small in magnitude, after controlling for other relevant factors.

With loan-level data from HMDA, I estimate the following baseline specification:

$$r_{list} = \alpha_t + \beta \Delta exposure_{it} + \Gamma X_{list} + \epsilon_{list} \tag{6}$$

where r_{ist} is the rate spread associated with a loan l originated by institution i in MSA s at year t. $\Delta exposure_{it}$ is the change in the exposure to the house price shock from period $t-2$ to period $t-1$ experienced by institution i as defined above. X_{it} is a series of loan-level, lender-level and MSA-level controls, including the price difference within region s between year t and $t-1$, that will be discussed in details in section 4.2.[9] The baseline regression includes year fixed effect α_t, and I include MSA-fixed effects in some specifications to make sure I am identifying the impact of changes in house price exposure on rate spread within each MSA. Standard errors for all regressions are clustered at the MSA level.[10]

3.3 Identifying Assumption and Alternative Explanations

The identifying assumption to specification (6) is that changes in lenders' exposure to the house price shock overall is orthogonal to other variables causing differences in the rates they charge at locations with high supply elasticity. In other words, banks with differential exposure to house price changes are required to be extending mortgage loans to similar borrowers under similar economics conditions after controlling for some borrower and regional characteristics. This then assumes that since lenders who extend mortgages in the same MSAs are making loans in similar fashion, the interest rates they charge can then be directly comparable. Tying back to the concrete example outlined above, lenders who in year 2005-2007 predominantly extended loans in Kokomo, Indiana Metropolitan Area would charge a lower rate for loans in year 2007 to borrowers in another MSA compared to other lenders who extend loans in the same MSA but predominantly lent in Miami-Fort-Lauderdale-West Palm Beach, after controlling for some borrower characteristics, bank strategies and performances, current price, and lagged price change. To ensure the specification is picking up the variation in rate spreads

[9] In particular, I include controls of logged CPI-adjusted house price $\log(hpi)_{st}$ and house price growth $\Delta\log(hpi)_{st}$, measuring changes between year t and year $t-1$.

[10] Clustering at the lender or the MSA level does not affect much the significant or implication of any of the results.

of lenders extending loan in the same MSA and the same year, I add MSA-by-year fixed effects in my analysis. I now outline some potential reasons why this identifying assumption may be violated as well as some alternative explanations.

First, idiosyncratic shocks to large banks may lead them to change the rates charged for all the mortgages they extend, which then subsequently affects house prices in some regions if mortgage applicants mostly borrow locally and these banks are a primary source of borrowing, raising the concern of reverse causality. Second, bank-wide opportunities or performance may be moved by another omitted variable that is only correlated with whether they locate branches or extend lending activities in areas undergoing severe house price shocks. When such omitted variable affects bank opportunity, then it could also affect the rate spread. Third, the measure of house price exposure may not fully take into account the existence of subprime loans. If institutions with higher exposure to real estate price shocks also tend to originate loans that are on average to borrowers with great credits in CBSAs that are not so heavily shocked by house price changes, then we could observe rates being lower for the loans generated by these lenders. Fourth, $\beta < 0$ may be caused by characteristics of institutions with different extents of exposure such as their sizes, which could be representative of banks' lending capacity as opposed to the extent of their price extrapolation. I discuss the first two threats to identification in section 4.3, and deal with the last two alternative explanations by adding controls of MSA-level denial rate and institution-level controls for characteristics in the baseline analysis in section 4.2.

4 Summary Statistics and Empirical Results

Having described the data, the empirical strategy, and the identifying assumption, I present the summary statistics and the empirical results in this section.

4.1 Summary Statistics

Table 1 presents summary statistics at the loan-year level, the MSA-year level, and the lender-year level. For loan-level and MSA-level statistics, I divide the sample based on the MSA-level price change for each given year, with those belonging to the middle 50% of price change denoted as "low-price-change" areas, [11] and reports separately for the two subsamples. From Panel (A), the average

[11] MSAs with price changes that exceed the 75th percentile of the price change distribution or fall below the 25th percentile across all MSAs in a given year are categorized as a high-price-change region in that year.

loan amount and rate spread for mortgages in high-price-change MSAs are $245,370 and 2.99, respectively. The loans originated in low-price-change MSAs have a slightly lower amount of $237,710 and a slightly lower spread of 2.76 on average. Applicants from high-price-change MSAs have a slightly lower mean income of $121,850 when compared to the mean income of $134,040 of applicants in low-price-change MSAs. The high-price-change and low-price-change subsamples are comparable in terms of mean fees-to-loan-amount ratio (1.06% for both), mean debt-to-income ratio (35.46% vs. 35.24%). The loan-to-value ratio, however, is higher for low-price-change MSAs (123.71%) than for high-price-change MSAs (84.28%). [12]

Panel (B) includes summary statistics for MSA-year pairs. The high-price-change MSAs are slightly larger in general. They have a higher average number of lenders (41.68 vs. 36/79), higher average population (862,680 vs. 788,860), larger size of the overall labor force (379,170 vs. 341,840), higher GSE and non-GSE lending. Despite the difference in size, high- and low-price-change MSAs are comparable on the average, in terms of the percent of minority population (25.51% and 23.36%), mortgage denial rate (17.01% and 17.04%), unemployment rate (6.34% and 6.01%, and the Herfindahl-Hirschman index (0.05 for both). Finally, panel (C) reports institution-year level statistics.[13] The average asset for an institution in the sample is $\$12,628,740$, with much variation indicated by a standard deviation of $\$132,750,870$. An institution originates $9,530$ loans on average in the sample, although this statistics also has a high standard deviation of $62,120$. There is also sizeable variation in the balance sheet compositions across lenders.

I now turn to the key independent variable of interest for my analysis, house price changes and institution-level price exposure as defined in equation (5). Figure 1 shows the variation in house price changes across time and geographies. Panel (A) shows house price change between two consecutive years on the aggregate. Price keeps dropping from 2006, but starts to increase since 2012. Panel (B) plots the second-difference in house price change, representing how much price change in a year surpasses or falls below the extent of price change between the two years prior. Panel (C) and (D) show that there is considerable variation in the second difference of price change both during both the housing bust and the rebound phase. MSAs in California and Florida experience the largest drop in price in 2006, and largest increase in 2012. Overall, areas undergoing larger drops in housing price

[12] Data on mortgage fees, loan-to-value ratio and debt-to-income ratio are only available from 2018-2020 HMDA dataset. The number of observations for each one of these three years, however, is higher than that for previous years.

[13] The institution-year statistics no longer distinguishes high-elasticity vs. low-elasticity MSAs as lending institutions tend to operate in multiple regions.

at the onset of the bust also tend to experience high price increase during rebound. Panel (A) of Figure 2 shows a histogram of raw values of price exposures experienced by lending institutions across all years in the sample and Panel (C) shows a histogram of raw values in the difference of price exposures. Although the histogram of raw values displays substantial variation in price change as well as second-difference in price change experienced by institutions, such variation across institution-year pairs could partly be attributed to time trend or institution performances and balance sheet compositions.[14] Thus, I residualize the measures for price exposure and differences in price exposure by partialling out influences of as well as the year fixed effects for each lending institution l in year t:

$$\begin{aligned} exposure_{lt} &= \beta X_l + \delta_t + \epsilon_{it} \\ \Delta exposure_{lt} &= \beta X_l + \delta_t + \epsilon_{it} \end{aligned} \tag{7}$$

where X_l is a vector of institution-level controls, including logged total assets, deposit-to-asset ratio, insured-deposit-to-deposit ratio, loan-to-asset ratio, and real-estate-asset-to-asset ratio. I further include year fixed effects δ_t. Panel (B) of Figure 2 plots the histogram for residualized institution price exposure and Panel (D) plots the histogram for residualized difference in institution price exposure. Both figures show that there are still variations after controlling for the influence of some institutional features and time trend.

Apart from the independent variable, I present some aggregate fact regarding the dependent variable of interest–mortgage rate spreads. The bottom two panels of Figure 2 plots the variation of raw and residualzed rate spreads charged for each originated loan. Rate spreads are residualized according to the equation:

$$rate\_spread_{ist} = \beta X_i + \delta_s + \delta_t + \epsilon_{ist} \tag{8}$$

where i, s, t denote loan, MSA, and year respectively. X_i is a vector of loan-level controls including the logged loan amount, preapproval status, HOEPA status, and type of purchaser. δ_s are MSA fixed effects, and δ_t are year fixed effects. This residualization removes the variation in rate spreads across originated loans that can be explained by differences in geographical or yearly factors or some other loan-level characteristics. Panel (B) demonstrates that there is substantial dispersion in mortgage rates even when the differences resulting from differential risks associated with lending are removed.

[14] For instance, a bank with stronger balance sheets may be more likely to establish additional branches and then extend lending activities in areas with higher price growth.

4.2 Baseline Results

I present results from estimating equation (6) of the impact of differential changes in house price exposure on the rates charged for non-GSE mortgages, originated in areas with high housing supply elasticity. Column (1) of Table 2 presents the results with loan-level controls, including logged loan amount, purchaser type, HOEPA status, preapproval status, and logged applicant income, as well as MSA-by-year fixed effects and lender fixed effects. From the first row of Column (1), the coefficient of interest is -1.606. To interpret in terms of magnitude, a lending institution will see a decline in rate spread of 4.5% if it is located at the 75th percentile of change in house price exposure compared to when it is located at the 25th percentile of change in house price exposure.

Column (2) adds in institution-level controls for logged assets, deposit-to-asset ratio, insured-deposit-to-deposit ratio, loan-to-asset ratio, real-estate-loan-to-asset ratio, past-due loan ratio, tier-one capital ratio, total-loss-to-loan ratio, and institution HHI[15] measuring the geographical presence of an institution's lending activity. Since the rate spread an institution charge may be driven in part by its strategy or balance sheet composition, including these controls could to some extents the preclude the influence of institutions' financial health or exposure to the real estate or other markets on rate spread. From column (2), institutions with a higher asset, lower loan-to-asset ratio, higher real-estate-loan-to-asset ratio, and higher geographical dispersion when extending loans tend to charge a lower rate spread. Column (3) includes loan-level and institution-level controls, and additionally controls for MSA attributes, including logged population, logged size of the labor force, mortgage denial rate, and logged total lending amount by the GSE. Logged population, The coefficients of interest are -1.338 and -1.084, respectively, for specifications in columns (2) and (3), so we see that adding controls for local demand and does reduce the magnitude of the coefficient estimate of interest.

While columns (1) - (3) already include year fixed effects, column (4) controls additionally for MSA fixed effect and column (5) add MSA-by-year fixed effects. This ensures that I am comparing across institutions that are extending lending activities in the same MSA and the same year. As mentioned in section 3.3, this specification assumes that lenders are comparable if they are extending loans in the same areas at the same time. The coefficients under these two specifications become -0.541 and

[15] The institution HHI is calculated according the formula: $HHI_{it} = \sum_{s \in L(l,t)} m_{lst}^2$ for an institution i in year t. $L(l,t)$ is the set of MSAs in which lender l extends some loans in year t. m_{lst} is the share of loan lender l extends in MSA s in year t among all the loans (across all MSAs) this lender extends in this year. This statistics could represent how concentrated an institution is in terms of its mortgage lending activities.

-0.754 and for the specification with MSA-by-year fixed effect, the coefficient is still statistically significant. The result from this specification is also presented in the binned scatter plot in Panel (A) of Figure 3. Assuming that the effect is roughly linear, which can be roughly supported by the binned scatter plot, then the magnitude of this effect can be quantified in a simple way: moving from the 25th percentile to the 75th percentile of the change in price exposure measure will result in 2% change in the rate spread on a mortgage while holding other loan and lender features constant.

4.3 Threats to Identification

In this section, I examine two threats two identification, reverse causality and omitted variables. First, if borrowers tend to form relationships with local lenders, then institution-specific shocks may lead banks to lower their mortgage rate, which then increases demand for housing and pushes up housing price growth in the region where they are primarily located. This could be particularly concerning if some large banks are geographically concentrated and could have disproportionate impacts on the areas where they are located. I address this concern of reverse causality using two approaches. First, I calculate the institution HHI according to the description in section 4.2, and I include only institutions in the bottom half of the HHI distribution for each year, so that these lenders are substantially dispersed geographically and would not be considered as local; it is then unlikely that they the price exposure measure for them would represent overwhelmingly their influence on the house prices in one region. Results are shown in columns (1) - (5) of Table 3. The coefficient estimates of interest are still of similar magnitude and significant in most specifications. Second, I assume that an institution could directly contribute to the local house price, price change, and change in its own price exposure. I hence partial out the effect of lending institutions and years on the measure of change in house price exposure, and use the residuals as the independent variable in estimating the main regression.[16] Result is shown in column (5) of Table 3. Again, the coefficient of change in price exposure on rate spread is significant, albeit slightly economically smaller than the baseline result.

Another potential threat to identification is omitted variable bias. For instance, if MSAs with higher degrees of changes in price exposures also tend to have differential opportunities for bank business or growth, then this could lead to banks predominantly located in such areas to adjust their rates but for reasons not related to their expectations given prior exposure to speed of house price change. However, this hypothesis implies that Δexposure would to some degrees predict variables

[16] I regress Δ exposure on indicators for years and institutions and obtain the residuals.

representing banks' performance and overall condition. Table 4 presents results from testing whether variables indicating banks' overall health can be predicted by the change in price exposure measure outlined above. I test the relationship between banks' deposit-to-asset ratio, loss-to-loan ratio, logged asset level and the change in price exposure, and show that such variables are not significantly affected by price exposure change after controlling for year, MSA fixed effects, and other loan level controls.

4.4 Robustness Checks

This section presents and discusses a number of robustness checks for my main results, including considerations of GSE loans, loans for the purpose of refinancing, alternative definitions of regions with minimal house price shocks, alternative time periods, alternative geographical classification, and costs other than the interest rates in generating mortgages.

4.4.1 GSE Lending

In my main analysis I restrict the sample to non-GSE loans because GSE mortgage rates are set by the agencies and would not vary with prices experienced by lending institutions generating these loans in the past. To see if rate spreads for GSE securitized loan are indeed not responsive to the change in institutions' price exposure and confirm that my baseline results are not picking up other alternative channels, I conduct a placebo test using GSE loans. Table A1 displays the results from estimating the baseline regression using GSE loans only. According to columns (4) - (5), the coefficient of change in the price exposure measure on rate spread is no longer statistically significant, after controlling for institution characteristics and MSA fixed effect. The magnitude of the coefficient estimate is small, meaning that rates of GSE mortgages would not move so far in the opposite direction that counteracts the effect of change in price exposure on rate spread for non-GSE loans, so that overall mortgage rate remains stable regardless of fluctuations in price exposure.

4.4.2 Refinancing

In my baseline analysis I include only loans for the purpose of home purchase. Nevertheless, if it is true that lenders revise their future house price expectations and subsequently charge a different mortgage rate based on growth rates of house prices that they were exposed to in the past, then this reasoning should be similarly applicable to refinancing loans, and we would expect to see similar results for such loans. Therefore, I estimate the same regression outlined in equation (6) using loans that are for the purpose of refinancing but with otherwise exactly the same features as those used for my main analysis, and present results in Table A2. According to column (5) that includes loan-level and institution-level controls, and both year and MSA fixed effects, the coefficient estimate of changes in price exposure on rate spread is still negative and significant. The coefficient estimate is at a slightly larger magnitude of -1.007 compared to the -0.754 in the baseline analysis for home purchase mortgages.

4.4.3 Alternative Sample

In this subsection I use an alternative sample for estimating equation 6. For the baseline analysis, I include MSAs with low price change in my sample since it is unlikely that supply changes in these areas, and in so doing teases out the influence of demand on rates charged. An alternative approach to selecting sample would be to use MSAs with high housing supply elasticity. By restricting to areas where the housing supply elasticity is in the upper half of the distribution, I assume that supply in these regions could adjust quickly enough to accommodate for the change in housing demand, and to some degrees partial out the effect of change in supply on house prices. Results from using this sample of MSAs with minimal degrees of price change could be found in Table A4. Coefficient estimates from this alternative sample are qualitatively similar to the baseline result.

In addition, I also examine 6 in the whole sample. The coefficient estimates are also similar to the ones estimated from the baseline specification, as shown in Table A3.

4.4.4 Alternative Time Periods

One natural question to ask is whether the results were driven by the housing and mortgage markets operating differently because of the Great Financial Crisis. I conduct another robustness test by excluding years for both the period of housing bust (2006 - 2009) and the years prior (2004-2006). I show the results for this alternative time period, using only observations from 2010 to 2020, in Table A5. The coefficient of interest is still significant and of similar magnitude as seen in column (5), indicating that results from the main analysis applies to recent years.

4.4.5 County-Level Analysis

The main analysis is conducted at the MSA level, which may be relatively coarse and omits areas with lower population density. I repeat the exercise at the county level using data on county-level house prices to see if the result is robust to alternative unit of analysis. Construction of the house price exposure measure is parallel to that at the MSA level. Regional controls, including size of labor force, mortgage denial rate, and GSE lending, in column (3) are defined at the county level. Since the price difference is defined at the MSA level, I use the sample selection method same as the one for the baseline specification but on the county level, by including counties with minimal degrees of price changes between two consecutive years. The results could be found in Table A6. All coefficient estimates are both quantitatively and qualitatively similar to the main MSA-level analysis.

4.4.6 Fees and Points

Apart from interest rates, the fees and points associated with a mortgage also constitute a non-negligible part of the costs associated with mortgage origination. Recent work such as Buchak and Jørring (2021) has shown that upfront fees of mortgages could respond to local conditions when the mortgage rates do not. It is thus important to examine how fees and points change. In particular, suppose that the mortgage fees become significantly higher when interest rates decrease, then the overall cost of originating one loan could remain unchanged in response to changes in price exposure or lenders' expectation. I estimate the following regression to study the changes in fees associated with mortgage origination:

$$\mathrm{f}_{list} = \alpha_t + r_{list} + \beta \Delta exposure_{it} + \Gamma X_{list} + \epsilon_{list} \tag{9}$$

where f represents the total fees (the sum of origination charges, discount points, and lender credits) over loan amount. One limitation, however, is that information on fees and points is only available in the HMDA dataset since year 2018. Table A7 shows the result. The coefficient on change of price exposure is not statistically significant in most specifications and the coefficient estimates are close to zero. For the specification that includes lender fixed effects, the coefficient estimate is statistically significant. However, the sign is small in magnitude and negative, which goes against the hypothesis that fees will adjust to counterbalance the change in rate spread when house price exposure shifts, meaning that the change in fees and points will only reinforce the decline in rate spread and reduce the overall cost of obtaining mortgages.

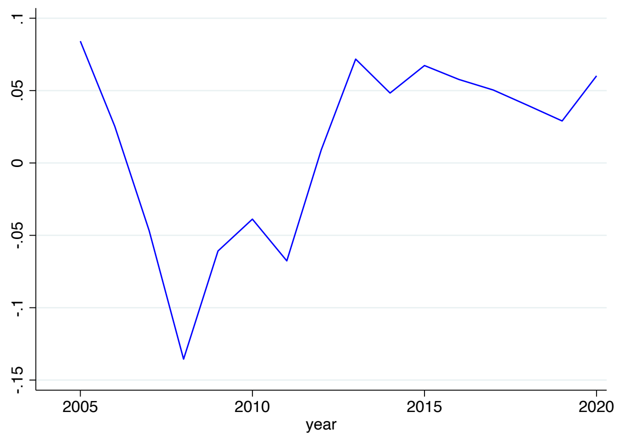
5 Conclusion

In this paper, I explore the connection among lender extrapolation, mortgage costs, and the housing cycle. I introduce a tractable conceptual framework where borrowers' access to credit depends on the size of the house, and lenders learn from past prices to form expectations of future prices. Expectations depend on past prices due to learning and affect future prices because of the binding borrowing constraint, which is a function of the house price. The model suggests that lenders with different past exposures to house price changes may form different beliefs and therefore charge different rates for mortgage origination. I then show, using HMDA data, that lenders experiencing faster price growth in areas where they historically extended lending activities tend to charge lower rates on loans that are otherwise comparable. This effect persists even in areas with minimal price changes or high supply elasticity, suggesting that supply-side effects are small. The magnitude of this effect is significant, and the results remain robust after including various controls. This evidence supports the notion that lenders' expectations can affect house prices through changes in mortgage costs.

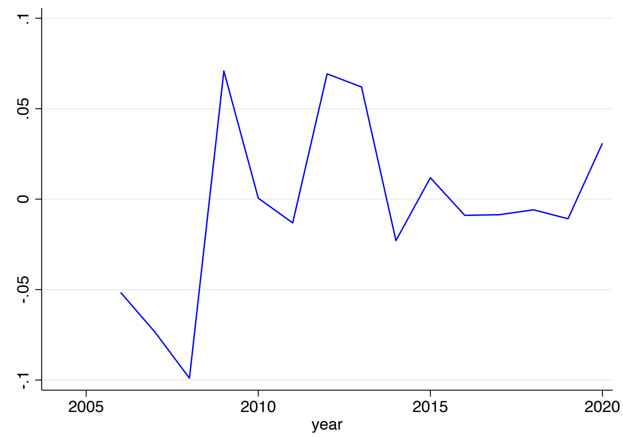
Even though this paper presents empirical evidence that lenders' expectations could matter for mortgage costs and, eventually, house prices, the size of the impact remains unexamined. Future research could involve constructing and calibrating a dynamic general-equilibrium model to quantify how much of the variation in house price movements can be explained by lenders' extrapolative beliefs. Furthermore, it would be interesting to study borrower and lender heterogeneity. Since consumers are credit-constrained to varying degrees, lenders' extrapolation could have differential effects on borrowers facing different levels of credit constraints, with implications for inequality. Additionally, identifying which lenders extrapolate from prices could be crucial for effective policymaking. These open questions are left for future research.

Figure 1: House Price Change in the U.S.

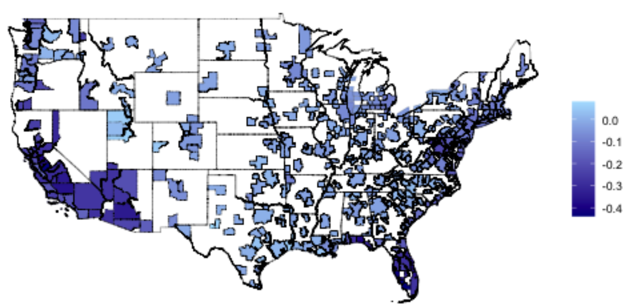
(A) Price change over time



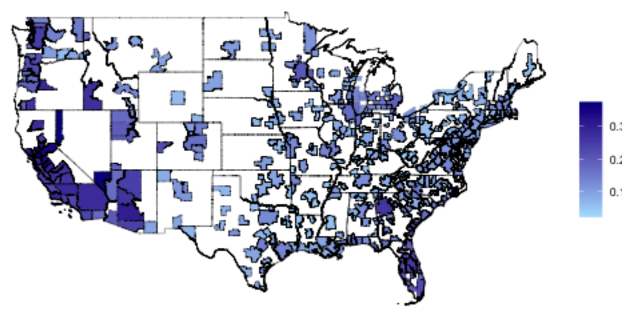
(B) Difference in Price change over time



(C) Nationwide difference in price change between 2005 and 2006, and between 2004 and 2005

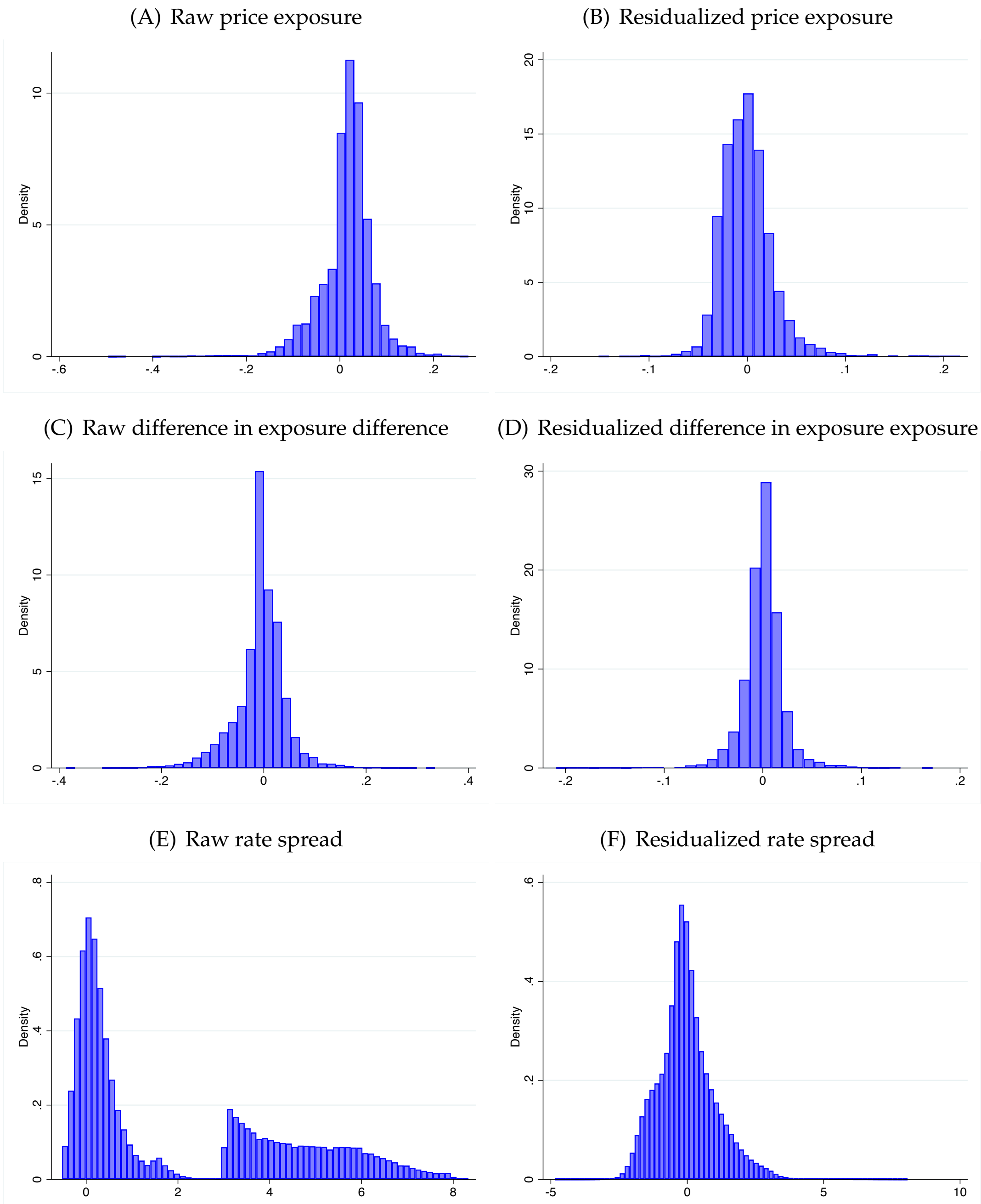


(D) Nationwide difference in price change between 2010 and 2011, and between 2011 and 2012



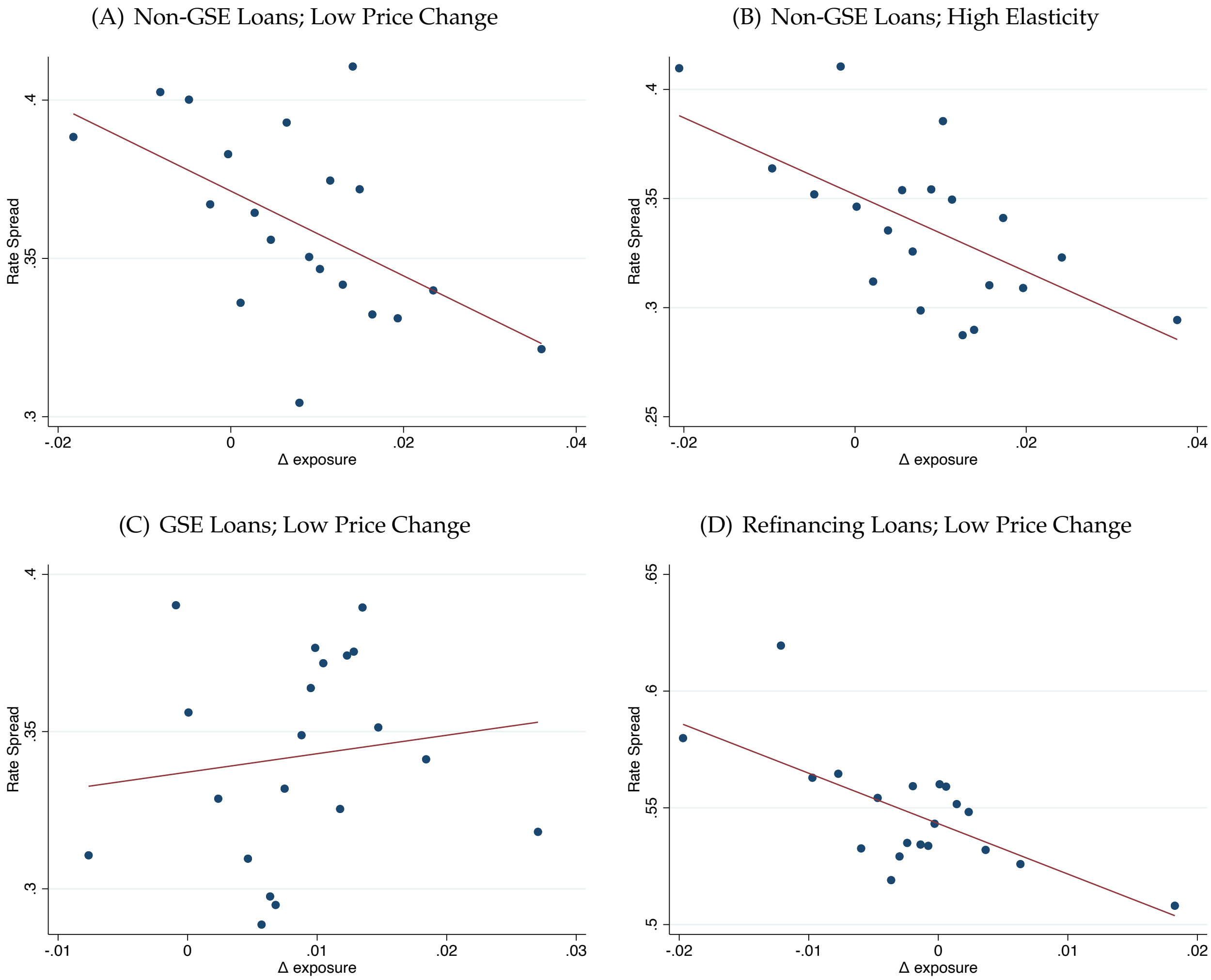
Note: Figure plots the distribution of house price exposure across time and space. The data source is the 2004-2020 HMDA dataset. Panel (A) plots the mean price change between a year and the previous year over time across all MSAs. Panel (B) plots the mean of second difference in price change over time across all MSAs. Panel (C) plots the distribution of MSA-level difference in house price change between years 2005 and 2006, and house price change between years 2004 and 2005, with darker shades representing higher price drops. Panel (D) plots the distribution of MSA-level difference in house price change between years 2011 and 2012, and hosue price change between years 2010 and 2011, with darker shades representing higher price increases.

Figure 2: Distribution of Rate Spreads and Price Exposures



Note: Figure shows the distributions of mortgage rate spreads at the loan level and house price exposure at the lender level. The data source is the 2004-2020 HMDA dataset. Only conventional, first-lien, non-GSE, and originated loans are included. Data is trimmed at the 1st and the 99th percentiles pf rate spread. Panel (A) plots the distribution of raw house price exposure defined in equation (5). Panel (B) plots the distribution of house price exposure residualized according to (7). Panel (C) plots the distribution of raw difference in price exposure between two consecutive years. Price (D) plots the distribution of residualized differences, controlling for the same variables as for Panel (B). Panel (E) plots the distribution of raw interest rates. Panel (F) plots the distribution of rate spread residualized according to (8). I control for loan characteristics, including logged loan amount, HOEPA status, preapproval status, and CBSA and year fixed effects for rate spread residualization, and institution characteristics, including total assets, deposits over assets, insured deposits over deposits, loans over assets, and real estate assets among assets.

Figure 3: Impact of change in house price exposure on rate spread: binscatter plot



Note: Figure displays results from running the regression specified in equation (6) using the HMDA 2004-2020 dataset, including non-GSE securitized loans for home purchase in areas with high. Panel (A) plots for non-GSE loans for home purchase in MSAs with little house price change. Panel (B) plots for non-GSE loans for home purchase in MSAs with high Saiz supply elasticity. Panel (C) plots for GSE loans for home purchase in MSAs with little house price change. Panel (D) plots for non-GSE loans for refinancing in MSAs with little price change. All regressions include loan-level controls, institution-level controls, and year and MSA fixed effects.

Table 1: Summary Statistics

	High Pirce Change			Low Price Change		
	Count	Mean	Std.Dev.	Count	Mean	Std.Dev.
Panel (A): Loan-year summary statistics						
Loan amount ($ 000s)	2,426,254	245.37	247.78	1,937,883	237.71	165.90
Rate spread	2,426,254	2.99	2.31	1,937,885	2.76	2.43
Applicant income ($ 000s)	2,343,912	121.85	2,088.47	1,887,549	134.04	2,424.85
Fees over loan amount (%)	937,151	1.06	1.28	901,220	1.06	1.69
Loan-to-value ratio (%)	931,629	84.28	13.56	898,873	123.71	37,123.22
Debt-to-income ratio (%)	936,633	35.46	9.86	905,464	35.24	9.87
Panel (B): MSA-year statistics						
Mortgage Lenders	3,077	41.68	56.08	3,104	36.79	51.18
Population (000s)	2,191	862.68	1,322.17	2,330	788.86	1,318.24
Minority population (%)	2,506	25.51	22.80	2,525	23.36	22.80
Denial rate (%)	3,077	17.01	4.70	3,104	17.04	4.60
HHI	3,077	0.05	0.03	3,104	0.05	0.03
Unemployment rate (%)	2,996	6.34	2.91	2,941	6.01	2.54
Labor force (000s)	2,996	379.17	822.97	2,941	341.84	849.14
GSE Lending Amount (000 000s)	3,077	160.06	933.67	3,104	147.94	816.37
Non-GSE Lending Amount (000 000s)	3,077	193.48	818.44	3,104	148.41	758.19
Panel (C): Institution-year statistics						
Assets ($ 000s)	20,297	12,628.74	132750.87			
Deposits/Assets (%)	5,401	80.92	7.85			
Loans/Assets (%)	5,401	69.83	11.89			
Real estate assets/Assets (%)	5,401	53.10	14.94			
Insured deposits/Deposits (%)	5,401	4.38	8.19			
Loan count (000s)	15,960	9.53	62.12			

Note: Table shows the number of observations, the mean, and the standard deviation for variables. Panel (A) reports loan-level statistics using the HMDA data for conventional, first-lien, non-GSE originated loans for the purpose of home purchase, where loan amount, rate spread, and applicant income are available from years 2004-2020, and Fees, LTV, and DTI are available from years 2018 - 2020. Panel (B) reports MSA-level statistics, where unemployment and labor force are obtained from BLS, and other statistics are calculated from the 2004-2020 HMDA dataset. Panel (c) reports institution-level statistics, where assets and loan counts are obtained from the 2004-2020 HMDA data, and other variables are obtained from the UBPR report. Low- and high- elasticity regions are defined in section 3.2.

Table 2: Impact of change in house price exposure on rate spread

	(1)	(2)	(3)	(4)	(5)
Δ exposure	-1.606***	-1.338***	-1.084**	-0.541	-0.754*
	(0.2463)	(0.4765)	(0.4319)	(0.3290)	(0.4488)
log(amount)	-0.197***	-0.233***	-0.254***	-0.244***	-0.249***
	(0.0104)	(0.0140)	(0.0119)	(0.0119)	(0.0118)
log(income)	-0.00659	-0.00711	-0.00496	-0.000819	0.00151
	(0.0055)	(0.0092)	(0.0096)	(0.0081)	(0.0078)
log(assets)	-0.0935***	-0.0142*	-0.0206**	-0.0160**	-0.0136*
	(0.0224)	(0.0081)	(0.0095)	(0.0066)	(0.0072)
institution HHI	-0.394***	-0.167***	-0.169***	-0.158***	-0.160***
	(0.1042)	(0.0389)	(0.0452)	(0.0353)	(0.0359)
deposit/asset		-0.171	-0.121	-0.185	-0.236*
		(0.1321)	(0.1306)	(0.1269)	(0.1283)
insured deposit/deposit		0.248**	0.211*	0.0567	0.0361
		(0.1192)	(0.1157)	(0.1480)	(0.1339)
loan/asset		0.470***	0.473***	0.397***	0.441***
		(0.0786)	(0.0798)	(0.0823)	(0.0779)
real estate loan/asset		-0.278**	-0.299**	-0.189*	-0.167*
		(0.1159)	(0.1282)	(0.1015)	(0.0887)
loan past due		0.000358	0.000741	0.00152	0.000759
		(0.0040)	(0.0035)	(0.0033)	(0.0034)
tier one capital		0.00940*	0.0121***	0.0113***	0.00997**
		(0.0049)	(0.0045)	(0.0039)	(0.0039)
loss/loan		-0.0105	-0.00128	-0.00548	-0.00726
		(0.0265)	(0.0230)	(0.0154)	(0.0190)
Year FE	Yes	Yes	Yes	Yes	Yes
Balance Sheet Controls	No	Yes	Yes	Yes	Yes
MSA Controls	No	No	Yes	No	No
MSA FE	Yes	No	No	Yes	Yes
MSA × Year FE	Yes	No	No	No	Yes
Lender FE	Yes	No	No	No	No
Adjusted R^2	0.920	0.374	0.381	0.416	0.422
Observations	210,164	113,808	100,144	113,790	113,584

Note: Table displays results from running the regression specified in equation (6) using the HMDA 2004-2020 dataset, including non-GSE securitized loans for home purchase in areas with little price change. Column (1) includes lender fixed effect and MSA-by-year fixed effect. Column (2) includes loan-level controls, including logged logged loan amount, logged applicant income, purchaser type (private vs. others), HOEPA status, and preapproval status, and controls for features of the institutions generating the loans, including logged asset, ratios of deposit to asset, insured deposit to deposit, loan to asset, real estate loan to asset, loans that are past due, tier one capital, loss to loan., and institution HHI measuring geographical divergence. Column (3) adds MSA-level controls, including logged population, logged labor force, mortgage denial rate, HHI, and logged total GSE lending. Column (4) adds MSA-fixed effects. Column (5) adds MSA-by-year fixed effects. Standard errors are clustered by MSA.

Table 3: Impact of change in house price exposure on rate spread (tests of reverse causality)

	(1)	(2)	(3)	(4)	(5)
Δ exposure	-1.692***	-1.190**	-1.093**	-0.465	-0.519
	(0.2993)	(0.4994)	(0.4687)	(0.3699)	(0.5096)
log(amount)	-0.199***	-0.236***	-0.252***	-0.249***	-0.253***
	(0.0112)	(0.0144)	(0.0135)	(0.0120)	(0.0118)
log(income)	-0.00861	-0.00716	-0.00546	0.000163	0.00212
	(0.0060)	(0.0094)	(0.0099)	(0.0083)	(0.0081)
log(assets)	-0.100***	-0.0130	-0.0193**	-0.0161***	-0.0143**
	(0.0243)	(0.0085)	(0.0095)	(0.0060)	(0.0064)
institution HHI	-0.441***	-0.214***	-0.185***	-0.166***	-0.165***
	(0.1486)	(0.0563)	(0.0647)	(0.0501)	(0.0507)
deposit/asset		-0.147	-0.127	-0.181	-0.204*
		(0.1462)	(0.1375)	(0.1238)	(0.1212)
insured deposit/deposit		0.156	0.115	-0.0182	-0.0366
		(0.1205)	(0.1046)	(0.1510)	(0.1280)
loan/asset		0.542***	0.521***	0.397***	0.435***
		(0.0966)	(0.0832)	(0.0728)	(0.0702)
real estate loan/asset		-0.254**	-0.257**	-0.150*	-0.123*
		(0.1161)	(0.1225)	(0.0862)	(0.0698)
loan past due		0.000643	0.000958	0.00185	0.00124
		(0.0042)	(0.0038)	(0.0032)	(0.0033)
tier one capital		0.00695	0.00854**	0.00832**	0.00723**
		(0.0042)	(0.0039)	(0.0033)	(0.0034)
loss/loan		0.00623	0.0187	0.0125	0.0220
		(0.0282)	(0.0252)	(0.0169)	(0.0209)
Year FE	Yes	Yes	Yes	Yes	Yes
Balance Sheet Controls	No	Yes	Yes	Yes	Yes
MSA Controls	No	No	Yes	No	No
MSA FE	Yes	No	No	Yes	Yes
MSA × Year FE	Yes	No	No	No	Yes
Lender FE	Yes	No	No	No	No
Adjusted R^2	0.919	0.372	0.379	0.415	0.421
Observations	188,730	99,558	88,201	99,540	99,335

Note: Table displays results from running the regression specified in equation (6) using the HMDA 2004-2020 dataset, including non-GSE securitized loans for home purchase in areas with little price change. Column (1) includes lender fixed effect and MSA-by-year fixed effect. Column (2) includes loan-level controls, including logged logged loan amount, logged applicant income, purchaser type (private vs. others), HOEPA status, and preapproval status, and controls for features of the institutions generating the loans, including logged asset, ratios of deposit to asset, insured deposit to deposit, loan to asset, real estate loan to asset, loans that are past due, tier one capital, loss to loan., and institution HHI measuring geographical divergence. Column (3) adds MSA-level controls, including logged population, logged labor force, mortgage denial rate, HHI, and logged total GSE lending. Column (4) adds MSA-fixed effects. Column (5) adds MSA-by-year fixed effects. Standard errors are clustered by MSA.

Table 4: Impact of change in house price exposure on rate spread (tests of reverse causality)

	(1)	(2)	(3)	(4)	(5)	(6)
Δ exposure	-0.0397	-0.132	0.357	-0.409	-2.418	-3.772
	(0.1255)	(0.1387)	(1.0598)	(1.1046)	(2.0491)	(2.9065)
Institution Controls	No	Yes	No	Yes	No	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
MSA Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.266	0.482	0.216	0.462	0.145	0.608
Observations	542	444	542	444	1,232	444

Note: Table displays results from regressing institution conditions on the change in lenders' price exposure, house price this year and the change between house price this and last year, as well as MSA and year fixed effects. The independent variables are banks' deposit-to-asset ratio (Columns 1 and 2), loss-to-loan ratio (Columns 3 and 4), and logged asset level (Columns 5 and 6). Controls for other bank-level characteristics are included in columns (2), (4), and (6). Standard errors are clustered by MSA.

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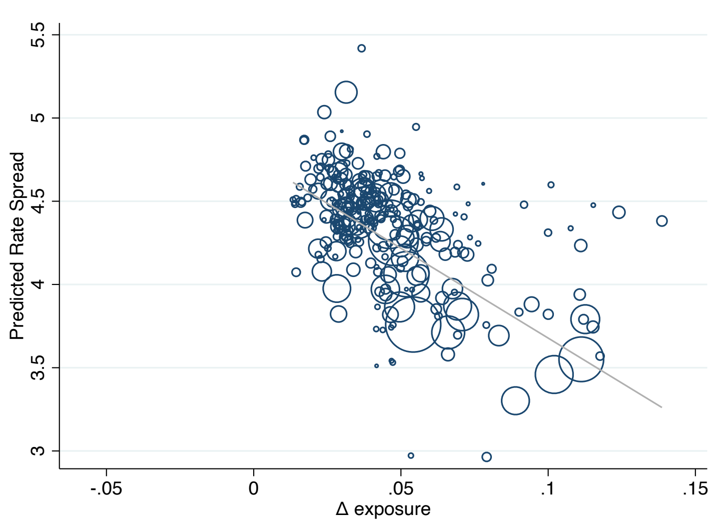
A Appendix

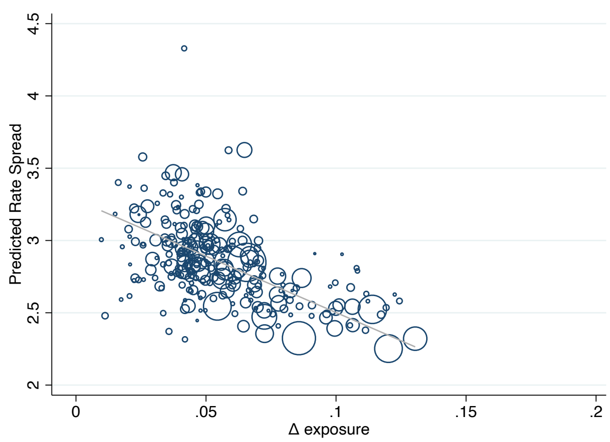
A Additional Figures and Tables

Figure A1: MSA-level rate spread vs. change in exposure

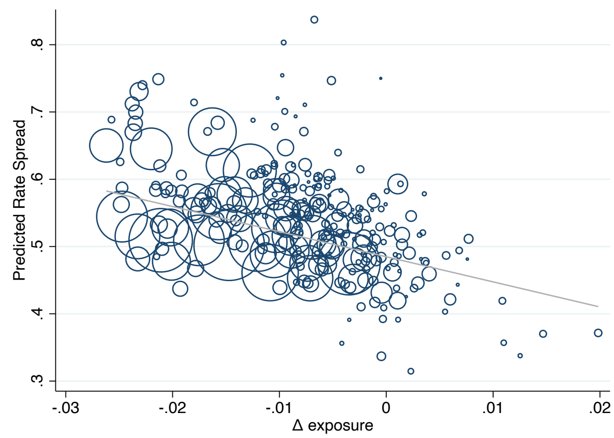
(A) 2009



(B) 2012



(C) 2019



Note: Figure shows scatter plot of mean rate spread for each MSA against Δ exposure in one year, where exposure is defined according to equation (5). The data source is the 2004-2020 HMDA dataset. Controls include MSA-level population, minority population, lender concentration as represented by HHI, mortgage denial rate, mean lenders' assets, Saiz supply elasticity, current-year house price and price change. Sizes of the circles represent average loan amount in a MSA. Panel (A) plots for year 2009. Panel (B) plots for year 2012. Panel (C) plots for year 2019.

Table A1: Impact of change in house price exposure on rate spread (GSE loans)

	(1)	(2)	(3)	(4)	(5)
Δ exposure	-0.0908	0.699*	0.835**	0.521	0.409
	(0.1962)	(0.4011)	(0.4037)	(0.3859)	(0.3918)
log(amount)	-0.220***	-0.272***	-0.275***	-0.277***	-0.279***
	(0.0087)	(0.0088)	(0.0103)	(0.0103)	(0.0103)
log(income)	0.0248***	0.0420***	0.0422***	0.0437***	0.0445***
	(0.0034)	(0.0034)	(0.0039)	(0.0036)	(0.0036)
log(assets)	-0.0169	-0.0158***	-0.0152***	-0.0143***	-0.0140***
	(0.0138)	(0.0031)	(0.0030)	(0.0029)	(0.0029)
institution HHI	-0.150	-0.295***	-0.272***	-0.303***	-0.312***
	(0.1031)	(0.0353)	(0.0315)	(0.0339)	(0.0328)
deposit/asset		0.0482	0.0939	0.172***	0.165***
		(0.0756)	(0.0588)	(0.0585)	(0.0594)
insured deposit/deposit		0.0848	0.126*	0.0553	0.0571
		(0.0593)	(0.0704)	(0.0560)	(0.0556)
loan/asset		0.154***	0.150***	0.210***	0.216***
		(0.0452)	(0.0517)	(0.0442)	(0.0459)
real estate loan/asset		0.0395	0.0906	0.0638	0.0735
		(0.0617)	(0.0691)	(0.0615)	(0.0646)
loan past due		-0.00341*	-0.00273	-0.00167	-0.00173
		(0.0018)	(0.0017)	(0.0014)	(0.0014)
tier one capital		-0.0124***	-0.0135***	-0.0105***	-0.0103***
		(0.0035)	(0.0038)	(0.0033)	(0.0032)
loss/loan		0.0178	0.0349*	0.0373**	0.0389**
		(0.0208)	(0.0204)	(0.0183)	(0.0184)
Year FE	Yes	Yes	Yes	Yes	Yes
Balance Sheet Controls	No	Yes	Yes	Yes	Yes
MSA Controls	No	No	Yes	No	No
MSA FE	Yes	No	No	Yes	Yes
MSA × Year FE	Yes	No	No	No	Yes
Lender FE	Yes	No	No	No	No
Adjusted R^2	0.880	0.392	0.397	0.405	0.405
Observations	525,215	400,041	361,694	400,029	399,789

Note: Table displays results from running the regression specified in equation (6) using the HMDA 2004-2020 dataset, including GSE securitized loans for refinancing in areas with high housing supply elasticity only. Column (1) includes only loan-level controls, including logged logged loan amount, logged applicant income, purchaser type (private vs. others), HOEPA status, and preapproval status. Column (2) adds controls for features of the institutions generating the loans, including logged asset, ratios of deposit to asset, insured deposit to deposit, loan to asset, real estate loan to asset, loans that are past due, tier one capital, loss to loan., and institution HHI measuring geographical divergence. Column (3) adds MSA-level controls, including logged population, logged labor force, mortgage denial rate, HHI, and logged total GSE lending. Column (4) adds MSA-fixed effects. Standard errors are clustered by MSA.

Table A2: Impact of change in house price exposure on rate spread (refinancing loans)

	(1)	(2)	(3)	(4)	(5)
Δ exposure	-1.832***	-0.541**	-0.645**	-0.492*	-1.007***
	(0.2674)	(0.2602)	(0.3013)	(0.2679)	(0.2976)
log(amount)	-0.216***	-0.113***	-0.127***	-0.120***	-0.123***
	(0.0131)	(0.0117)	(0.0125)	(0.0120)	(0.0114)
log(income)	0.0837***	0.0268***	0.0312***	0.0281***	0.0309***
	(0.0108)	(0.0065)	(0.0073)	(0.0061)	(0.0055)
log(assets)	0.0176	-0.0111**	-0.0132**	-0.0113**	-0.00943*
	(0.0310)	(0.0051)	(0.0061)	(0.0053)	(0.0050)
institution HHI	-0.398***	-0.0897***	-0.0818***	-0.0864***	-0.0859***
	(0.1449)	(0.0213)	(0.0259)	(0.0213)	(0.0215)
deposit/asset		-0.0718	0.000748	-0.0717	-0.152**
		(0.0717)	(0.0792)	(0.0665)	(0.0622)
insured deposit/deposit		0.0400	0.0323	0.00707	-0.00129
		(0.0617)	(0.0678)	(0.0644)	(0.0485)
loan/asset		0.229***	0.227***	0.155**	0.123**
		(0.0712)	(0.0838)	(0.0607)	(0.0564)
real estate loan/asset		-0.246***	-0.257***	-0.167***	-0.110**
		(0.0709)	(0.0831)	(0.0495)	(0.0483)
loan past due		-0.00178	-0.00102	-0.00120	-0.00109
		(0.0029)	(0.0035)	(0.0029)	(0.0022)
tier one capital		0.00145	0.00289	0.00162	-0.000404
		(0.0028)	(0.0031)	(0.0031)	(0.0031)
loss/loan		0.0142	0.0128	0.0154	0.0264*
		(0.0161)	(0.0172)	(0.0163)	(0.0152)
Year FE	Yes	Yes	Yes	Yes	Yes
Balance Sheet Controls	No	Yes	Yes	Yes	Yes
MSA Controls	No	No	Yes	No	No
MSA FE	Yes	No	No	Yes	Yes
MSA × Year FE	Yes	No	No	No	Yes
Lender FE	Yes	No	No	No	No
Adjusted R^2	0.847	0.627	0.638	0.638	0.640
Observations	177,850	42,874	37,086	42,848	42,637

Note: Table displays results from running the regression specified in equation (6) using the HMDA 2004-2020 dataset, including non-GSE securitized loans for refinancing in areas with high housing supply elasticity only. Column (1) includes only loan-level controls, including logged logged loan amount, logged applicant income, purchaser type (private vs. others), HOEPA status, and preapproval status. Column (2) adds controls for features of the institutions generating the loans, including logged asset, ratios of deposit to asset, insured deposit to deposit, loan to asset, real estate loan to asset, loans that are past due, tier one capital, loss to loan., and institution HHI measuring geographical divergence. Column (3) adds MSA-level controls, including logged population, logged labor force, mortgage denial rate, HHI, and logged total GSE lending. Column (4) adds MSA-fixed effects. Standard errors are clustered by MSA.

Table A3: Impact of change in house price exposure on rate spread (whole sample)

	(1)	(2)	(3)	(4)	(5)
Δ exposure	-0.906***	-1.490***	-1.405***	-0.592**	-0.689**
	(0.1629)	(0.4077)	(0.4050)	(0.2797)	(0.3372)
log(amount)	-0.193***	-0.229***	-0.252***	-0.250***	-0.253***
	(0.0098)	(0.0106)	(0.0111)	(0.0105)	(0.0095)
log(income)	-0.00200	-0.00328	-0.00340	0.00358	0.00555
	(0.0042)	(0.0069)	(0.0073)	(0.0060)	(0.0055)
log(assets)	-0.0777***	-0.00917*	-0.0161***	-0.0147***	-0.0119***
	(0.0177)	(0.0051)	(0.0057)	(0.0042)	(0.0044)
institution HHI	-0.220**	-0.187***	-0.191***	-0.169***	-0.183***
	(0.0945)	(0.0312)	(0.0341)	(0.0249)	(0.0251)
deposit/asset		-0.183*	-0.103	-0.147*	-0.188**
		(0.0999)	(0.0978)	(0.0820)	(0.0853)
insured deposit/deposit		0.186*	0.146	0.0402	0.00783
		(0.0968)	(0.0918)	(0.0796)	(0.0762)
loan/asset		0.466***	0.462***	0.377***	0.402***
		(0.0556)	(0.0562)	(0.0528)	(0.0506)
real estate loan/asset		-0.225***	-0.251***	-0.134**	-0.115**
		(0.0712)	(0.0739)	(0.0555)	(0.0506)
loan past due		0.00618	0.00424	0.00256	0.00343
		(0.0052)	(0.0042)	(0.0037)	(0.0036)
tier one capital		0.00567	0.00557	0.00655**	0.00575*
		(0.0044)	(0.0042)	(0.0032)	(0.0030)
loss/loan		0.0189	0.0159	0.0200	0.0188
		(0.0208)	(0.0198)	(0.0162)	(0.0184)
Year FE	Yes	Yes	Yes	Yes	Yes
Balance Sheet Controls	No	Yes	Yes	Yes	Yes
MSA Controls	No	No	Yes	No	No
MSA FE	Yes	No	No	Yes	Yes
MSA × Year FE	Yes	No	No	No	Yes
Lender FE	Yes	No	No	No	No
Adjusted R^2	0.915	0.387	0.396	0.426	0.430
Observations	521,177	224,410	197,645	224,409	243,216

Note: Table displays results from running the regression specified in equation (6) using the HMDA 2004-2020 dataset, including non-GSE securitized loans for home purchase. Column (1) includes lender fixed effect and MSA-by-year fixed effect. Column (2) includes loan-level controls, including logged logged loan amount, logged applicant income, purchaser type (private vs. others), HOEPA status, and preapproval status, and controls for features of the institutions generating the loans, including logged asset, ratios of deposit to asset, insured deposit to deposit, loan to asset, real estate loan to asset, loans that are past due, tier one capital, loss to loan., and institution HHI measuring geographical divergence. Column (3) adds MSA-level controls, including logged population, logged labor force, mortgage denial rate, HHI, and logged total GSE lending. Column (4) adds MSA-fixed effects. Column (5) adds MSA-by-year fixed effects. Standard errors are clustered by lending institutions.

Table A4: Impact of change in house price exposure on rate spread (alternative sample)

	(1)	(2)	(3)	(4)	(5)
Δ exposure	-1.452***	-1.644***	-1.368***	-0.625*	-0.586
	(0.3094)	(0.4927)	(0.5172)	(0.3396)	(0.4528)
log(amount)	-0.192***	-0.258***	-0.284***	-0.262***	-0.266***
	(0.0161)	(0.0149)	(0.0132)	(0.0091)	(0.0084)
log(income)	-0.00970	-0.000176	-0.000917	0.00959	0.0128
	(0.0063)	(0.0098)	(0.0113)	(0.0083)	(0.0081)
log(assets)	-0.0822***	-0.00885	-0.0191**	-0.0149**	-0.0140**
	(0.0275)	(0.0084)	(0.0090)	(0.0068)	(0.0070)
institution HHI	-0.367***	-0.165***	-0.145**	-0.135***	-0.156***
	(0.1000)	(0.0498)	(0.0564)	(0.0460)	(0.0498)
deposit/asset		-0.212	-0.288	-0.462***	-0.500***
		(0.1690)	(0.1858)	(0.1526)	(0.1657)
insured deposit/deposit		0.288	0.321	0.0499	0.0638
		(0.2287)	(0.2200)	(0.1623)	(0.1542)
loan/asset		0.218**	0.390***	0.312***	0.294***
		(0.0957)	(0.1158)	(0.0991)	(0.1011)
real estate loan/asset		-0.165	-0.369***	-0.222**	-0.154*
		(0.1315)	(0.1332)	(0.0927)	(0.0803)
loan past due		0.00382	0.00350	0.000422	-0.000192
		(0.0070)	(0.0067)	(0.0060)	(0.0061)
tier one capital		-0.00102	0.000910	0.00225	0.000129
		(0.0058)	(0.0066)	(0.0052)	(0.0049)
loss/loan		0.0361	0.0340	0.0345*	0.0572**
		(0.0291)	(0.0272)	(0.0190)	(0.0268)
Year FE	Yes	Yes	Yes	Yes	Yes
Balance Sheet Controls	No	Yes	Yes	Yes	Yes
MSA Controls	No	No	Yes	No	No
MSA FE	Yes	No	No	Yes	Yes
MSA × Year FE	Yes	No	No	No	Yes
Lender FE	Yes	No	No	No	No
Adjusted R^2	0.923	0.383	0.402	0.435	0.444
Observations	191,849	98,747	786,11	987,46	984,77

Note: Table displays results from running the regression specified in equation (6) using the HMDA 2004-2020 dataset, including non-GSE securitized loans for home purchase in areas with supply elasticity belonging to the top 50th percentile only. Column (1) includes lender fixed effect and MSA-by-year fixed effect. Column (2) includes loan-level controls, including logged logged loan amount, logged applicant income, purchaser type (private vs. others), HOEPA status, and preapproval status, and controls for features of the institutions generating the loans, including logged asset, ratios of deposit to asset, insured deposit to deposit, loan to asset, real estate loan to asset, loans that are past due, tier one capital, loss to loan., and institution HHI measuring geographical divergence. Column (3) adds MSA-level controls, including logged population, logged labor force, mortgage denial rate, HHI, and logged total GSE lending. Column (4) adds MSA-fixed effects. Column (5) adds MSA-by-year fixed effects. Standard errors are clustered by MSA.

Table A5: Impact of change in house price exposure on rate spread (recent years)

	(1)	(2)	(3)	(4)	(5)
Δ exposure	-0.0534	-1.338***	-1.084**	-0.541	-0.754*
	(0.3609)	(0.4765)	(0.4319)	(0.3290)	(0.4488)
log(amount)	-0.224***	-0.233***	-0.254***	-0.244***	-0.249***
	(0.0102)	(0.0140)	(0.0119)	(0.0119)	(0.0118)
log(income)	0.0152***	-0.00711	-0.00496	-0.000819	0.00151
	(0.0056)	(0.0092)	(0.0096)	(0.0081)	(0.0078)
log(assets)	0.0883**	-0.0142*	-0.0206**	-0.0160**	-0.0136*
	(0.0398)	(0.0081)	(0.0095)	(0.0066)	(0.0072)
institution HHI	0.0125	-0.167***	-0.169***	-0.158***	-0.160***
	(0.1185)	(0.0389)	(0.0452)	(0.0353)	(0.0359)
deposit/asset		-0.171	-0.121	-0.185	-0.236*
		(0.1321)	(0.1306)	(0.1269)	(0.1283)
insured deposit/deposit		0.248**	0.211*	0.0567	0.0361
		(0.1192)	(0.1157)	(0.1480)	(0.1339)
loan/asset		0.470***	0.473***	0.397***	0.441***
		(0.0786)	(0.0798)	(0.0823)	(0.0779)
real estate loan/asset		-0.278**	-0.299**	-0.189*	-0.167*
		(0.1159)	(0.1282)	(0.1015)	(0.0887)
loan past due		0.000358	0.000741	0.00152	0.000759
		(0.0040)	(0.0035)	(0.0033)	(0.0034)
tier one capital		0.00940*	0.0121***	0.0113***	0.00997**
		(0.0049)	(0.0045)	(0.0039)	(0.0039)
loss/loan		-0.0105	-0.00128	-0.00548	-0.00726
		(0.0265)	(0.0230)	(0.0154)	(0.0190)
Year FE	Yes	Yes	Yes	Yes	Yes
Balance Sheet Controls	No	Yes	Yes	Yes	Yes
MSA Controls	No	No	Yes	No	No
MSA FE	Yes	No	No	Yes	Yes
MSA $\times$ Year FE	Yes	No	No	No	Yes
Lender FE	Yes	No	No	No	No
Adjusted R^2	0.708	0.374	0.381	0.416	0.422
Observations	134,728	113,808	100,144	113,790	113,584

Note: Table displays results from running the regression specified in equation (6) using the HMDA 2010-2020 dataset, including non-GSE securitized loans for home purchase in areas with little price change. Column (1) includes lender fixed effect and MSA-by-year fixed effect. Column (2) includes loan-level controls, including logged logged loan amount, logged applicant income, purchaser type (private vs. others), HOEPA status, and preapproval status, and controls for features of the institutions generating the loans, including logged asset, ratios of deposit to asset, insured deposit to deposit, loan to asset, real estate loan to asset, loans that are past due, tier one capital, loss to loan., and institution HHI measuring geographical divergence. Column (3) adds MSA-level controls, including logged population, logged labor force, mortgage denial rate, HHI, and logged total GSE lending. Column (4) adds MSA-fixed effects. Column (5) adds MSA-by-year fixed effects. Standard errors are clustered by MSA.

Table A6: Impact of change in house price exposure on rate spread (county level)

	(1)	(2)	(3)	(4)	(5)
Δ exposure	-1.865***	-1.469***	-1.426***	-0.418*	-0.773**
	(0.2578)	(0.3309)	(0.3299)	(0.2284)	(0.3052)
log(amount)	-0.185***	-0.244***	-0.248***	-0.244***	-0.251***
	(0.0078)	(0.0107)	(0.0110)	(0.0087)	(0.0086)
log(income)	-0.00958**	0.00338	0.00282	0.0121**	0.0152***
	(0.0045)	(0.0057)	(0.0062)	(0.0048)	(0.0046)
log(assets)	-0.137***	-0.0156***	-0.0217***	-0.0201***	-0.0181***
	(0.0204)	(0.0039)	(0.0042)	(0.0030)	(0.0033)
institution HHI	-0.262***	-0.187***	-0.180***	-0.190***	-0.187***
	(0.0705)	(0.0240)	(0.0266)	(0.0221)	(0.0235)
deposit/asset		-0.205**	-0.130	-0.160**	-0.203***
		(0.0824)	(0.0833)	(0.0737)	(0.0761)
insured deposit/deposit		0.181**	0.140*	0.113*	0.0733
		(0.0904)	(0.0821)	(0.0622)	(0.0620)
loan/asset		0.384***	0.436***	0.315***	0.366***
		(0.0469)	(0.0525)	(0.0482)	(0.0493)
real estate loan/asset		-0.256***	-0.275***	-0.149***	-0.149***
		(0.0666)	(0.0684)	(0.0483)	(0.0484)
loan past due		0.00302	0.00206	0.00162	0.00194
		(0.0033)	(0.0029)	(0.0028)	(0.0028)
tier one capital		0.00537*	0.00702**	0.00710***	0.00710***
		(0.0032)	(0.0032)	(0.0025)	(0.0026)
loss/loan		0.00687	0.0135	0.0172	0.0152
		(0.0177)	(0.0175)	(0.0118)	(0.0145)
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes
Balance Sheet Controls	No	Yes	Yes	Yes	Yes
County Controls	No	No	Yes	No	No
County Fixed Effect	Yes	No	No	Yes	Yes
County $\times$ Year FE	Yes	No	No	No	Yes
Lender FE	Yes	No	No	No	No
Adjusted R^2	0.920	0.367	0.358	0.416	0.404
Observations	279,072	157,480	136,615	157,266	156,347

Note: Table displays results from running the regression specified in equation (6) using the HMDA 2004-2020 dataset, including non-GSE securitized loans for home purchase in counties with little price change. Column (1) includes lender fixed effect and county-by-year fixed effect. Column (2) includes loan-level controls, including logged logged loan amount, logged applicant income, purchaser type (private vs. others), HOEPA status, and preapproval status, and controls for features of the institutions generating the loans, including logged asset, ratios of deposit to asset, insured deposit to deposit, loan to asset, real estate loan to asset, loans that are past due, tier one capital, loss to loan., and institution HHI measuring geographical divergence. Column (3) adds county-level controls, including logged population, logged labor force, mortgage denial rate, HHI, and logged total GSE lending. Column (4) adds county-fixed effects. Column (5) adds county-by-year fixed effects. Standard errors are clustered by county.

Table A7: Impact of change in house price exposure on rate spread (fees and points)

	(1)	(2)	(3)	(4)	(5)
Δ exposure	-0.00458	-0.0103	-0.00852	-0.00863	-0.0196**
	(0.0057)	(0.0088)	(0.0086)	(0.0068)	(0.0095)
log(amount)	-0.00616***	-0.00511***	-0.00553***	-0.00629***	-0.00627***
	(0.0003)	(0.0003)	(0.0004)	(0.0003)	(0.0003)
log(income)	0.000410***	0.000155	0.000220	0.000297**	0.000280**
	(0.0001)	(0.0002)	(0.0002)	(0.0001)	(0.0001)
log(assets)	0.00132	0.0000920	-0.0000591	-0.000189*	-0.000208**
	(0.0008)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
institution HHI	0.00144	-0.00298***	-0.00345***	-0.00283***	-0.00300***
	(0.0028)	(0.0011)	(0.0012)	(0.0010)	(0.0009)
deposit/asset		-0.00434	-0.00293	-0.00632**	-0.00628*
		(0.0031)	(0.0030)	(0.0032)	(0.0033)
insured deposit/deposit		-0.00302	-0.00448**	-0.00172	-0.00167
		(0.0020)	(0.0021)	(0.0022)	(0.0025)
loan/asset		0.0123***	0.0107***	0.00770***	0.00746***
		(0.0027)	(0.0023)	(0.0019)	(0.0020)
real estate loan/asset		-0.00425**	-0.00379**	-0.00289**	-0.00261*
		(0.0021)	(0.0018)	(0.0013)	(0.0014)
loan past due		-0.0000719	-0.0000661	-0.000114	-0.0000932
		(0.0000)	(0.0000)	(0.0001)	(0.0001)
tier one capital		0.000157	0.000170*	0.000140**	0.000134**
		(0.0001)	(0.0001)	(0.0001)	(0.0001)
loss/loan		0.000747	0.00104	0.000585*	0.000729*
		(0.0007)	(0.0008)	(0.0003)	(0.0004)
Year FE	Yes	Yes	Yes	Yes	Yes
Balance Sheet Controls	No	Yes	Yes	Yes	Yes
MSA Controls	No	No	Yes	No	No
MSA FE	Yes	No	No	Yes	Yes
MSA $\times$ Year FE	Yes	No	No	No	Yes
Lender FE	Yes	No	No	No	No
Adjusted R^2	0.316	0.161	0.171	0.226	0.235
Observations	121,580	109,702	102,009	109,700	10,9689

Note: Table displays results from running the regression specified in equation (9), using the HMDA 2018-2020 dataset, including non-GSE securitized loans for refinancing in MSAs with low price change only. Column (1) includes lender fixed effect and MSA-by-year fixed effect. Column (2) includes loan-level controls, including logged logged loan amount, logged applicant income, purchaser type (private vs. others), HOEPA status, and preapproval status, and controls for features of the institutions generating the loans, including logged asset, ratios of deposit to asset, insured deposit to deposit, loan to asset, real estate loan to asset, loans that are past due, tier one capital, loss to loan., and institution HHI measuring geographical divergence. Column (3) adds MSA-level controls, including logged population, logged labor force, mortgage denial rate, HHI, and logged total GSE lending. Column (4) adds MSA-fixed effects. Column (5) adds MSA-by-year fixed effects. Standard errors are clustered by MSA.

B Conceptual Framework

B.1 Lender's Problem

The expected profit for a lender i in area s is given by:

$$
\begin{aligned}
\Pi(q_t^{is}) &= \Big(1 - \frac{A\theta^{LTV} p_t^s q_t^{is}}{(\mathbb{E}[p_{t+1}^s])^\beta}\Big)\theta^{LTV} p_t^s q_t^{is} + \big(\frac{A\theta^{LTV} p_t^s q_t^{is}}{(\mathbb{E}[p_{t+1}^s])^\beta}\big)\Big)\delta\mathbb{E}[p_{t+1}^s] \\
&= \theta^{LTV} p_t^s q_t^{is} - A\Big(\frac{(\theta^{LTV} p_t^s q_t^{is})^2}{(\mathbb{E}[p_{t+1}^s])^\beta}\Big) + A\delta\theta^{LTV} p_t^s q_t^{is}\big(\mathbb{E}[p_{t+1}^s]\big)^{1-\beta}
\end{aligned}
$$

Taking the first-order condition with respect to q_t^{kj} yields:

$$
\frac{2A\theta^{LTV} p_t^s q_t^{is}}{(\mathbb{E}[p_{t+1}^s])^\beta} = \theta^{LTV} p_t^s + \frac{A\delta}{(\mathbb{E}[p_{t+1}^s])^{\beta-1}}
$$

which implies that the optimal mortgage rate that lender j should set in region k can be written as:

$$
\begin{aligned}
q_t^{is*} &= \frac{\theta^{LTV} p_t^s (\mathbb{E}[p_{t+1}^s])^\beta + A\delta(\mathbb{E}[p_{t+1}^s])^{\beta-1}}{2A\theta^{LTV} p_t^s} \\
&= \frac{(\mathbb{E}[p_{t+1}^s])^{\beta-1}}{2\theta^{LTV} p_t^s} + \frac{\delta}{2\theta^{LTV} p_t^s}
\end{aligned}
$$

This indicates that the optimal rate decreases with expected next-period house price when $\beta < 1$.