Nonbank Growth and Local Housing Prices*

Hyun-Soo Choi† Yongheng Deng‡ Heejin Yoon§

May 2024

Abstract

We study the effect of the uneven expansion of nonbank mortgage origination on the localized housing boom and bust cycles. Conforming eligibility is important for nonbank mortgage lending, and nonbanks have been expanded in the low-price neighborhoods as a positive supply shock. Exploiting the within-county variation in the conforming eligibility, we find that the expansion of nonbank lending induces relatively higher home price appreciation in low-price neighborhoods, resulting in a housing price convergence in the counties despite the differences in fundamentals. We find that the nonbank originations have been exposed to higher default risk, but the default is only realized after 2021 as the bullish housing market ends.

*We appreciate helpful comments from Robert Avery, Daniel Broxterman (Discussant), Jan Brueckner, Scott Frame, Lu Han, Timothy Riddiough, Changcheng Song, Christopher Timmins, Dayin Zhang, and Tingyu Zhou as well as seminar and conference participants at NUS, KAIST, the University of Wisconsin-Madison, 2024 TFA-KFA Joint Conference, and 2024 FSU-UF Critical Issues in Real Estate Symposium.

†Korea Advanced Institute of Science and Technology (e-mail: hschoi19@kaist.ac.kr)

‡University of Wisconsin-Madison (e-mail: yongheng.deng@wisc.edu)

§University of Wisconsin-Madison (e-mail: heejin.yoon@wisc.edu)

1. Introduction

Recoveries from the Global Financial Crisis have dramatically changed the landscape of the U.S. mortgage market. Once obsoleted during the financial crisis, nonbank mortgage originations returned, reaching 68% of all mortgage originations in the U.S. in 2020, as banks withdrew from the market due to the tightened regulation on them (Wall Street Journal, 2021). While the rapid rise of nonbank mortgage lending has been highlighted in the literature (Kim et al., 2022), the effect of the nonbank growth on creating differential housing dynamics in the local housing market is not yet clear.

Nonbanks are well-known for their core business practices of mortgage origination, relying on the originate-to-distribute (OTD) model by selling loans to the government-sponsored enterprises (GSEs)—Freddie Mac and Fannie Mae—and Ginnie Mae. As the GSEs are purchasing conforming mortgages, mainly defined by the upper limit of loan amounts, nonbanks are naturally more into the areas where the home prices are relatively low. This uneven expansion of nonbank would work as a positive credit shock to some neighborhoods within a county. In this paper, we study the role of uneven nonbank expansion as a credit shock to explain the heterogeneity in the local housing market dynamics and their consequences.

We use loan-level application data from the Home Mortgage Disclosure Act (HMDA) from 2013 to 2021. First, the data allows us to identify the mortgage originator for defining nonbank lenders if the lenders are non-depository mortgage originators that are not regulated by any federal regulators, as in Demyanyk and Loutskina (2016) and Gete and Reher (2021). Next, for the conforming eligibility of a mortgage application, we use the conforming loan limits (CLLs) set by the Federal Housing Finance Agency (FHFA), annually adjusting the county-level CLL to accommodate mortgage supply under the rising housing prices. While the year's national CLL applies to most of the counties in the U.S., some exceptions of a higher CLL are allowed in high-cost counties from the year 2008 to enhance housing affordability in high-cost areas.

Using the loan-level application data, we start to examine the loan approval process of the conforming loans especially when the mortgage originator is a nonbank lender. As conforming loans can be easily sold to the GSEs, originating conforming loans has been simple and straightforward for all lenders, which sometimes even creates an issue of lax lending standards (Dell'ariccia et al., 2012; Demyanyk and Van Hemert, 2011; Kim et al., 2022; Mian and Sufi, 2009). However, because of the institutional funding structure, nonbanks are more reliant on the OTD business model and their likelihood of loan origination heavily depends on the conforming eligibility of the mortgage than the bank lenders. Recently, the relatively weaker regulatory burden compared to traditional banks from the after-crisis recovery (Buchak et al., 2018; Gete and Reher, 2018; Irani et al., 2021; Roberts et al., 2018) and the advanced technological adoption in the origination and securitization through the FinTech development (Buchak et al., 2018; Fuster et al., 2019) have made nonbanks more aggressive on expanding their lending based on the conforming eligibility of the loan. As a result, we expect that lenders, in general, disproportionately approve more loan applications below the CLL, and the effect would be stronger for nonbank lenders.

Indeed, we find that all lenders are more likely to approve conforming mortgages by 4.58 percentage points after controlling the risk profile of borrowers and loan characteristics. However, when it comes to nonbanks, the approval rate is even higher by 3.71 percentage points. The results are robust to the inclusion of census tract×year fixed effects that absorb all the variations by the census tract and year, indicating that our results are not driven by any unobservable local demand shocks in the census tracts. The results align well with those of Bosshardt et al. (2023), who find that (i) lenders employ their own screening mechanisms rather than passively following the GSE underwriting standard, and (ii) nonbanks take even more risks due to lower expected loss given default.

While the GSEs would purchase both the *Jumbo Conforming*, a conforming loan that exceeds the national CLL, and *Non-Jumbo Conforming*, a conforming loan that is below the national CLL, as they are all conforming loans, the practices in the agency mortgage-backed securities (MBS) market would make nonbank lenders prefer *Non-Jumbo Conforming*. We find that the nonbanks' approval rate of *Non-Jumbo Conforming* is significantly higher than the approval rate of *Jumbo Conforming*, highlighting the nonbanks' preference for non-jumbo conforming market, even within the conforming loans, due to the securitizability of the loans.

When nonbank lenders are more inclined to originate mortgages under the CLL, we expect that the nonbank origination share would have grown more in areas where a larger proportion of loan applications are eligible for conforming mortgages. By aggregating the loan-level application data to the census tract-year panel dataset, we define *Nonbank Share* as the share of nonbank mortgage originations in a census tract, and construct tract-level home price appreciation and price-to-rent ratio using the Zillow Home Value Index (ZHVI) and the rent data from the American Community Survey (ACS).[1]

We find that the census tracts with higher conforming loan eligibility exhibit a significant increase in nonbank origination shares, resulting in an uneven expansion of nonbank shares within a county. With the battery of controls on the census tract characteristics and granular county×year fixed effects, we find that a 1 SD increase in *Conforming Eligibility* increases the share of nonbank origination by 6.9% within a county, which is about 30% of a 1 SD of nonbanks' origination share. As *Conforming Eligibility* is a function of a lower home price, our results indicate that nonbank expansion is more concentrated in the lower home-price neighborhoods.

Note that the expansion of nonbank origination in low-price neighborhoods also can be a result of nonbanks filling the gap due to the withdrawal of traditional banks from the mortgage market in the neighborhoods. However, we find that the aggregate mortgage lending actually increased in the census tracts with a larger expansion of nonbank lending. That is, we find that the uneven expansion of mortgage origination by nonbanks across neighborhoods is not driven by filling the gap of withdrawal of banks in the neighborhood.

[1] To identify the conforming-eligible census tracts, we define *Conforming Eligibility* with $CLL - (ZHVI \times 0.8)$, as 80 percent loan-to-value ratios (LTV) are the most common practice in mortgage origination in the U.S (Adelino et al., 2012; An and Yao, 2016; Lilley and Rinaldi, 2021). As $CLL - (ZHVI \times 0.8)$ measures the deviation of the home value in a census tract from its CLL, a large positive $CLL - (ZHVI \times 0.8)$ indicates that the price of an average house in a census tract is highly eligible for a conforming loan.

Using *Conforming Eligibility* as the instrumental variable, we examine the effect of uneven credit shock on local home prices. All else equal, additional credit supply can generate a price impact on the local housing market, which potentially leads to a localized bubble as we observed in the last global financial crisis (Chinco and Mayer, 2016; Choi et al., 2016; Gao et al., 2021). We find that the increase in nonbank origination share raises the home value of the census tract. A 1 SD increase in nonbank origination share increases the local home price appreciation of the census tract by 0.89%–1.81%. We find a similar result using the change in the price-to-rent ratio, where we control for the local rent prices as the fundamental cash flow of the home value.

When the low-price areas have price appreciation that is relatively higher than the high-price areas *within a county*, we expect that the heterogeneity in home prices within a county would decrease. By defining county-level measures of house price dispersion across census tracts within a county, we find that the county-level nonbank share instrumented by county-level conforming eligibility reduces the price dispersion within a county. That is, when comparing two counties within a state and year with different levels of nonbank share, a county with a higher nonbank share experiences a stronger price convergence within the county, as low-price census tracts in the county experience a higher price growth than the other census tracts in the county, narrowing the price heterogeneity within the county.

However, the price convergence within a county associated with the expansion of nonbank origination could be driven either by a demand-side story or due to a supply-side story. To distinguish the two compelling possibilities with the opposite conclusion, we examine the difference in delinquency rates across mortgage loans by the originators. If the extended loans in the low-price neighborhoods were to the low-quality borrowers by aggressive nonbank lenders as the supply-side story, we are likely to observe an increase in mortgage delinquency (Di Maggio and Kermani, 2017; Iacoviello, 2005; Kiyotaki and Moore, 1997).[2] Thus, we

[2]On the other hand, the demand-side story is that there exists a large underserved population living in low-price neighborhoods who were not able to be served by traditional banks, for example, because of the lack of enough credit history despite good creditworthiness. In this case, the expansion of nonbanks helps borrowers in low-price neighborhoods to finance themselves to purchase homes, fulfilling the underserved demands. Then,

examine the effects of the uneven nonbank expansion on mortgage delinquency through the panel regression at the loan–year-month level, by merging the HMDA data with the GSE monthly performance data from 2013 to 2022. For our analysis, we include detailed loan characteristics at the origination, such as FICO score, LTV ratio, loan amount, and mortgage rate, and include granular fixed effects for the time-invariant local conditions and unobserved time-varying market conditions that apply to all locations.

We first find that the mortgage loans originated by nonbanks are 0.3 percentage points more likely to be underwater in a given year-month than the loans originated by banks. We also find that the distance to underwater is shorter when the mortgages are originated by nonbanks. That is, the originations by nonbanks are on average closer to the underwater situation, which is a necessary condition for the default event. In addition, we find that mortgage originations by nonbanks are more likely to be 90+ days delinquent, the most widely used measure to define severe delinquency, than loans originated by traditional banks. As default decisions are known to be strongly affected by the incentive to default, we also control the incentive by the measures of in-the-moneyness of a loan for the prepayment and default option in the literature (Deng and Quigley, 2012; Deng et al., 2000) to find the similar result. Our results on the loan performance originated by nonbanks support the supply-side story of localized boom and bust.

Moreover, by interacting the nonbank indicator with the dummies of the reporting years, we find that nonbank originations have been more likely to be underwater regardless of the year in our sample period. That is, the risk of being delinquent has been always higher in mortgage loans originated by nonbanks than in mortgage loans by banks. However, the delinquency looks different: the mortgages originated by nonbanks show a lower delinquency rate during the pre-2020 period, but more delinquencies are realized after 2021, the year when the housing market began to slow down. The results suggest that the low delinquency rate of the nonbank mortgage during the pre-2020 period does not validate the soundness of nonbank

the uneven price growth simply indicates a restoration of market efficiency by reinstating prices to the level of fundamentals.

lending but is due to the unwillingness to default, expecting a recovery in a bullish housing market. Our result would reconcile the recent mixed findings on the delinquency of nonbank lending, where nonbank mortgages have been demonstrated only marginally worse (Buchak et al., 2018) or even superior (Fuster et al., 2019) performances compared to traditional banks.

Our paper contributes to several strands of the literature. First, our findings contribute to the literature on the role of credit supply in elevating asset price, as well as subsequent busts (An and Yao, 2016; Di Maggio and Kermani, 2017; Favara and Imbs, 2015; Favilukis et al., 2017; Landvoigt, 2017). Our study shows that the local entry and expansion of nonbank lending create a positive supply shock, as in Benson et al. (2024), particularly in low-price neighborhoods, resulting in a rapid local home price appreciation. We instrument the expansion of nonbank shares by the conforming eligibility of the local market to avoid endogenous changes in credit supply driving our results. We find that the nonbank expansion creates homogeneity in housing prices in a county despite the difference in fundamentals, which leads to higher delinquency when the bullish housing market ends. The implications of nonbank expansion on the local housing market dynamics are a novel contribution of our paper to the existing literature.

Second, our study contributes to a growing literature on shadow bank lending, including the lending from FinTech lenders, in the residential mortgage market and the default performance of those loans. While various factors, such as technological advances, superior knowledge of local markets, and regulatory advantages, have been documented for the reasons of their rapid growth (Buchak et al., 2018; Gete and Reher, 2018; Irani et al., 2021; Moreira and Savov, 2017; Ordonez, 2013; Roberts et al., 2018), there is no consensus regarding the performance of those nonbank-originated mortgages. Despite credit risk concerns due to nonbanks' unique business model (i.e., OTD model, see (Buchak et al., 2023; Bosshardt et al., 2023)), several studies find either only marginally worse or even superior performance of nonbank originations in terms of their default rates (Buchak et al., 2018; Fuster et al., 2019; Kim et al., 2022).[3] Our study not

[3]The better performance of nonbanks in default rate is often attributed to the screening and monitoring skills of new technology-based nonbank lenders (Berg et al., 2022; Fuster et al., 2019). While there are few

only demonstrates that nonbank-originated mortgages are indeed riskier and more prone to default, even after controlling for loan risk profiles, but also provides a potential explanation for reconciling the results in previous research: nonbank borrowers are more reluctant to claim default during the bullish housing market, but they eventually are more likely to default when the bullish market ends. Thus, the weak evidence of nonbank default risk in the prior studies may be attributed to the limitation of the sample period in the mid-2010s.

The remainder of the paper is organized as follows. In Section 2, we explain the data and the key variables of interest with summary statistics. In Section 3, we empirically test our hypothesis on the localized housing prices and the consequence of nonbank expansion. Section 4 concludes.

2. Data and Summary Statistics

Our primary data source consists of loan application-level data obtained from the Home Mortgage Disclosure Act (HMDA) from 2013 to 2021. The HMDA data covers nearly the entire landscape of US mortgage applications, providing details on key aspects such as lender ID, loan application outcomes (approved or denied), applicant characteristics, and loan-level details including loan type, lien status, loan purpose, loan amount, and the census tract of the application. For our analysis, we focus on conventional, first-lien purchase mortgages for owner-occupied one-to-four-family homes. Based on the HMDA, we construct four distinct datasets, each designed to address specific questions in this study.

2.1. Loan Application-level Dataset

First, based on the HMDA data, we create the loan application-level dataset, covering the 2013–2021 period, to examine the impact of conforming loan eligibility of a loan application on

studies reporting a higher default risk for nonbank originations, their evidence is limited to non-GSE or non-residential loans, such as personal loans or corporate lending (Di Maggio and Yao, 2021; Johnson et al., 2023).

approval decisions, with a specific focus on the impact for nonbank lenders. Panel A of Table 1 reports summary statistics of the variables for the loan application-level analyses. Our main variable of interest is the determinants of approval decisions by lenders. We define *Approve* as a dummy variable that equals 1 if the loan application is approved and 0 otherwise. Among 21,972,413 loan applications, 91.5% are approved.

We also define the lenders in the HMDA data as *Nonbank* if the lenders are non-depository mortgage institutions, which are not regulated by any federal regulators[4], as in Demyanyk and Loutskina (2016) and Gete and Reher (2021). There are 7,764 number of lenders in the data and 1,376 (17.3%) are identified as nonbanks. In our sample, applications to nonbank lending institutions constitute 48.5% of total applications, which increases from 32.1% in the year 2013 to 56.8% in the year 2021, as plotted in Figure 1.

Since the Emergency Home Finance Act of 1970, the GSEs are only allowed to purchase conforming mortgage loans. The conforming status of the mortgage is based on the loan limit set by the FHFA.[5] Every year, the FHFA adjusts the county-level CLLs to accommodate mortgage supply with respect to the rise in housing prices. We define $Conforming$ as a dummy variable that equals 1 if the application's loan amount is below the CLL of the county in that year. In our sample, 90.7% of applications are conforming loans, meaning that the remaining 9.3% are jumbo loan applications.

While most of the counties in the U.S. follow the year's national CLL, there are some exceptions of a higher CLL applied to high-cost counties from the year 2008 to enhance housing affordability in high-cost areas.[6] Note that loan applications in those high-cost counties are still eligible for the GSE securitization as long as the loan amounts are smaller than the county-specific limits, which may be above the national limit. For the potential heterogeneity in lending behaviors, we further separate $Conforming$ into *Jumbo Conforming* and *Non-*

[4]Federal supervisors include the Office of the Comptroller of the Currency (OCC), the Federal Deposit Insurance Corporation (FDIC), the Consumer Financial Protection Bureau (CFPB), and the National Credit Union Administration (NCUA).

[5]https://www.fhfa.gov/DataTools/Downloads/Pages/Conforming-Loan-Limit.aspx.

[6]For more details, see https://www.fhfa.gov/AboutUs/Policies/Documents/Conforming-Loan-Limits/AREA_LIST_5_2008.pdf.

Jumbo Conforming, differentiating conforming loan applications by the loan sizes above and below the national CLL, respectively. In our data, the share of non-jumbo conforming loans and jumbo conforming loans are 85.8% and 4.9%, respectively, summing up to 90.7%, the proportion of total conforming loans.

Panel A also reports the loan application characteristics. The average log size of the loan is 12.398, which is $242,317, and the average value of log income is 11.449, which is $93,807. As the average loan size increased from $239,411 in the year 2013 to $380,689 in the year 2021, the average Loan-to-Income ratio also increased from 2.642 in the year 2013 to 3.456 in the year 2021. By ethnicity, Black, Asian, and non-white Hispanic borrowers account for 4.3%, 8.3%, and 1.2%, respectively, which makes White applicants account for 86.2%. Note that the shares of Black and non-white Hispanics are much lower than their fractions of the population in the U.S., which is 13.6% and 15.7%, respectively, while the fractions of White and Asian are higher than their fractions in the U.S. population of 61.2% and 5.8% in the 2021 Census. In addition, 31.3% of total applications are by Females, and 46.4% of applications have co-borrowers in the application.

2.2. Census tract-level Dataset

Second, we aggregate the HMDA data at the census tract level for constructing a tract-year panel dataset. While the CLLs are the same within a county but the local home price at the census tract can be diverse, we examine the effect of the conforming loan eligibility at the census tract level on the origination activities of nonbank lenders within the county. Panel B of Table 1 reports statistics of the census tract-level variables used in our second set of analyses.

We first aggregate our loan-level HMDA data for the fraction of nonbank originations, the applications that are approved, by year and census tracts. We define *Nonbank Share* as the share of nonbank mortgage originations in a census tract. In Panel B, we report that *Nonbank Share* has a mean of 46.5% with a relatively large standard deviation of 22.6%. With high growth rates in both the amount (*Growth_Loan Amount*) and count (*Growth_Loan Count*) of all mortgage originations—12.7% and 21.6% on average—a large variation in nonbank share across areas suggests uneven growth of nonbank origination across neighborhoods in our sample period.

We use the Zillow Home Value Index (ZHVI) to construct census tract-level home prices. We aggregate the ZIP code-level ZHVI to the census tract home price index, assigning the residential property shares from the HUD-USPS ZIP-TRACT Crosswalk file[7] as the weights. For measuring the price dynamics of census tracts, we use home price appreciation and price-to-rent ratio. *ZHVI Growth* is calculated as the home price growth rate of a census tract, with a mean of 7.8% and a standard deviation of 5.6%. Using the median rent data from the American Community Survey (ACS), we also construct the price-to-rent ratio for the census tracts. As there are some census tracts which the median rent values are not reported, note that our sample size for the price-to-rent ratio drops to 450,679. Δ*Price-to-Rent* is defined as the annual change in the census tract-level price-to-rent ratio, with a mean of 0.046.

We identify the conforming-eligible census tracts by comparing the county-level CLL to the census tract-level ZHVI. More specifically, we calculate $CLL-(ZHVI \times 0.8)$ to determine the conforming eligibility of the census tracts, as 80 percent loan-to-value ratios (LTV) are the most common practice in mortgage origination in the U.S (Adelino et al., 2012; An and Yao, 2016; Lilley and Rinaldi, 2021).[8] As $CLL-(ZHVI \times 0.8)$ measures the deviation of the home value in a census tract from its CLL, a large positive $CLL-(ZHVI \times 0.8)$ indicates that the price of an average house in a census tract is highly eligible for a conforming loan. We define *Conforming Eligibility* that equals to $CLL-(ZHVI \times 0.8)$ in the unit of \$100,000, having a mean of 2.596 (\$259,600) with a standard deviation of 1.635 (\$163,500).

Panel A of Figure 2 illustrates an example of the distribution of *Conforming Eligibility* within Orange County, CA, in the year 2015, by plotting $CLL-(ZHVI \times 0.8)$. Census

[7] https://www.huduser.gov/portal/datasets/usps_crosswalk.html.

[8] Residential mortgage loans with more than 80 percent LTV ratios are required to buy private mortgage insurance and this significantly increases the monthly amount of mortgage payment (Green and Wachter, 2005).

tracts with negative *Conforming Eligibility* are colored in red, while those with positive values are shown in blue. Note that the colors within the county vary by neighborhood. We can observe that the census tracts by the ocean are mostly red indicating that the home purchase mortgages in those census tracts are less likely to be conforming eligible. In contrast, the census tracts located inland are mostly blue indicating that the home purchase mortgages in the census tracts are likely to be conforming eligible. We use this variation to examine the uneven nonbank originations within a county.

Panel B of Table 1 also reports census tract-level variables we use for our analysis. Some variables are directly from the HMDA data. The log of census tract median income, log*(Median Income)*, has a mean of 11.028, which is $61,574. *Minority Application Share* is the share of loan applications from minorities in the census tract with a mean of 17.1%. Some variables are from our own computation from the loan application level data. *Female Application Share* is the fraction of female applicants by the census tract, which has a mean of 31.9%. *Average Loan-to-Income* is the average loan-to-income ratio aggregated by the census tract from the loan application level data with a mean of 2.859. Additionally, as a control variable, we compute the growth of income per capita and population in the past two years, *Per Cap Income Growth Last 2 Yrs* and *Population Growth Last 2 Yrs*, using the data from the ACS. We also compute the growth of ZHVI in the census tract in the past two years, *ZHVI Growth Last 2 Yrs*, using the census tract-level ZHVI.

2.3. County level Dataset

Third, we further aggregate the data at the county level to examine the changes within the counties due to the uneven growth of nonbank presence. Panel C of Table 1 reports the summary statistics of variables we use for the county-level analysis.

We define two variables that measure the dispersion of home values across different census tracts within a county. SD(*ZHVI*)/Mean(*ZHVI*) is the standard deviation of census tract-level ZHVI values within a county, normalized by the average ZHVI value, measuring the dispersion of home prices within a county. It has a mean of 0.177, indicating that the average standard deviation of home prices within a county is 17.7% of the average county home price. Alternatively, (Max($ZHVI$)$-$ Min($ZHVI$))/Mean($ZHVI$) is calculated as the difference between the maximum and the minimum census tract-level ZHVI within a county, normalized by the average ZHVI value. It has a mean of 0.555, indicating that the maximum difference in home price within a county is about 55.5% of the average county home price.

To measure the lending activities of nonbanks in the county, we first define *Nonbank Share (County)*, which is the share of nonbank mortgage originations in the county, similar to the definition in Panel B. *Nonbank Share (County)* has a mean of 44.5% with a standard deviation of 18.2%.

We also define a measure for conforming eligibility at the county level. As the CLLs are defined at the county level, we are not capturing the granular variation in the eligibility as in the census tract level measure. However, as a proxy measure for the overall conforming eligibility of the county, we define *Conforming Eligibility (County)*, which is $CLL - (ZHVI \times 0.8)$ using the county level ZHVI, in the unit of \$100,000. A higher *Conforming Eligibility (County)* indicates that the county is likely to have more census tracts with the home price under the CLLs. It has a mean of 2.806 (\$280,600) with a standard deviation of 0.993 (\$99,300).

Panel C also reports the other control variables at the county level. The log of county median income, log*(Median Income) (County)*, has a mean of 10.964, which is \$57,757. *Minority Application Share (County)* is the share of loan applications from minorities in the county with a mean of 13.5%. *Female Application Share (County)* is the fraction of female applicants by the county, which has a mean of 31.0%. *Average Loan-to-Income (County)* is the average loan-to-income ratio aggregated by the county from the loan application level data with a mean of 2.949. The average growth rates for county-level per capita income, population, and home prices over the past 2 years are 3.1%, 0.7%, and 5%, respectively.

2.4. Loan-year-month Dataset

Lastly, we construct a loan-year-month level panel dataset to examine the performance of loans by nonbank lenders. We merge the HMDA data with the GSE monthly performance data, tracing the monthly performance of loans bought by the GSEs to the end of the year 2022.[9] The matching procedure reduces the number of unique loan observations to 1,878,437. As the data has a panel structure with multiple time-series observations of a mortgage loan, our sample observations are 53,254,707 and the average loan continuation is about 28.3 months.[10] Panel D of Table 1 reports the summary statistics of the variables at the loan–year-month level.

We define two variables, *Underwater* and *Distance-to-Underwater*, to measure the loan's distance to underwater, by comparing the current market value of the underlying property and the present value of the loan. More specifically, *Underwater* is a dummy variable that equals 1 if the current market value of the underlying property is below the present value of the loan, indicating a negative equity position. In some sense, the measure captures the loans with zero distance to underwater. Over our sample period, 2.9% of loans are labeled as *Underwater*.

Distance-to-Underwater is the difference between the current market value of the property and the present value of the loan on the property, normalized by the property's current market value (Deng and Quigley, 2012; Deng et al., 2000).[11]. This variable works as one minus mark-to-market LTV and measures the distance to underwater. As the variable is defined only for

[9]As there exists no identifier to match the two datasets, we use the loan characteristics for the merge, following the methodology outlined in An et al. (2021). Specifically, we use key loan characteristics such as origination year, the presence of co-borrower(s), loan purpose, geography (state, MSA, and 3-digit ZIP code), owner occupancy status, purchaser type, loan amount, and property value. For the loans after 2018, when the HMDA starts to have more variables on the loan characteristics, we also use mortgage rates as an additional matching variable. For the quality of the matching, we use the uniquely matched loan observations only.

[10]The relative short average loan continuation is partly due to 1) an increase in the number of new loans, 2) an increase number of matched loans from the HMDA data and the GSE performance data after 2018 due to the enhanced list of variables of match. The constructed data may have more loadings in the later year in our sample period.

[11]This concept is very similar to Distance-to-Default (DD), which quantifies how far a firm's asset value is from its debt obligations. Since first introduced by Merton (1974), DD has been empirically shown to be a reliable measure for ranking firms' default risk (Duffie et al., 2007).

the loans above water, which has a positive distance to underwater, the number of observations is 2.9% smaller than other variables (51,726,819). In Panel D, we report that *Distance-to-Underwater* has a mean of 36.4% with a standard deviation of 19.4%, which indicates that the current market value of a property is 36.4% higher than the loan value on average for the homes with positive equity left.

We also construct *90+ Delinquency* for the actual delinquency events, as a dummy variable that equals 1 if the loan has been delinquent for more than 90 days. It has a mean of 0.084% in a given loan–year-month, but the number increases to 2.35% when we take the average loan continuation of 28.3 months into account.[12]

For a loan default, note that being underwater is not a sufficient but a necessary condition. To correctly understand the default decision, it is important to control the borrowers' incentive to default. We borrow the measures of borrower's incentive on refinance and default from the literature (Deng and Quigley, 2012; Deng et al., 2000), measuring the in-the-moneyness of a loan for the prepayment and default option. First, we define *Refinance Incentive* as the difference between the present value of the remaining mortgage when refinancing the amounts today (PV with Refinance) and the present discount value of the remaining mortgage without the refinancing (PV without Refinance), normalized by the PV with Refinance. While the mean of *Refinance Incentive* is slightly negative indicating that the average mortgages are out-of-the-money for the refinancing option, the median is 0.023 indicating where the median loan is at the in-the-money position by 2.3% due to the long regime of low-interest-rate until 2020.

Second, we define *Default Incentive* as the difference between the present value of the loan on the property and the current market value of the property, normalized by the property's current market value. By construction, the measure is very similar to *Distance-to-Underwater* except it works as mark-to-market LTV minus one so that a higher number of *Default Incentive* implies a higher default incentive. *Default Incentive* also includes the underwater loans with

[12] $1 - (1 - 0.00084)^{28.3} = 0.0235$

positive option value. On average, loans in our sample are at 35.7% out-of-money for the default option.

Matching HMDA with the GSE performance data allows us to include a rich set of loan-level characteristics at the time of origination that are known to well-proxy the credit risk of loans such as the FICO score. The average FICO score of the loans in the sample is 752.76, as all the matched loans are purchased by the GSEs. 26.3% of loans have a loan-to-value ratio between 80%–95% at the origination and 4.7% have above 95% loan-to-value ratio at the origination. The log loan amount is on average 12.099 ($179,692), and the average mortgage rate is 3.929%. Minority and female shares are 9.3% and 30.6%, respectively. 67.6% of loans in the sample have co-borrowers.

3. Empirical Results

3.1. Conforming Loan Eligibility and Loan Approval

We start our analyses by examining the relationship between conforming loan eligibility and mortgage approval decisions, especially focusing on loan applications to nonbank lenders. Specifically, we run the following loan-level linear probability model:

$$\begin{aligned} Approve_{i,t} =& \alpha + \beta \cdot Conforming_{i,t} + \gamma \cdot Conforming_{i,t} \times Nonbank_{i,t} + \delta \cdot X_{i,t} \\ &+ \eta_j + \eta_{\text{tract}} + \eta_t + \epsilon_{i,t}, \end{aligned} \tag{1}$$

where $Approve_{i,t}$ is a dummy variable that equals 1 if a loan application i is approved at time t and 0 if rejected. $Conforming_{i,t}$ denotes a dummy variable that equals 1 if the loan application amount is below the CLL of the county in that year. $Nonbank_{i,t}$ represents a dummy variable that equals 1 if the lender who received the loan application i is a nonbank lending institution. $X_{i,t}$ is a vector of loan and applicant level characteristics, including log(*Loan Amount*), log($Income$), *Black*, *Asian*, $Hispanic$, $Female$, and *Co-borrower*. Lastly, we also include lender fixed effects (η_j), census tract fixed effects (η_{tract}), and year fixed effects (η_t). We cluster the standard errors by the county.

Our variables of interest are $Conforming_{i,t}$ and its interaction with $Nonbank_{i,t}$. As conforming loans can be easily sold to the GSEs, originating conforming loans has been simple and straightforward for all lenders, which sometimes even creates an issue of lax lending standards (Dell'ariccia et al., 2012; Demyanyk and Van Hemert, 2011; Kim et al., 2022; Mian and Sufi, 2009). However, because of the institutional funding structure, nonbanks are more reliant on the OTD business model and their likelihood of loan origination heavily depends on the conforming eligibility of the mortgage than the bank lenders. This is consistent with Bosshardt et al. (2023), who find that (i) lenders employ their screening mechanisms rather than passively following the GSE underwriting standard, and (ii) nonbanks take even more risks due to their lower expected loss given default. Recently, the relatively weaker regulatory burden compared to traditional banks from the after crisis recovery (Buchak et al., 2018; Gete and Reher, 2018; Irani et al., 2021; Roberts et al., 2018) and the advanced technological adoption in the origination and securitization through the FinTech development (Buchak et al., 2018; Fuster et al., 2019) have made nonbanks more aggressive on their lending based on the conforming eligibility of the loan. As a result, we expect that (i) lenders, in general, disproportionately approve more loan applications below the CLL (positive β), and (ii) the effect of (i) would be larger for nonbank lenders (positive γ).

Table 2 reports the estimated coefficients of the regression. In Column (1), the coefficient estimate for $Conforming$ is 0.0061 with a t-statistic of 3.03, suggesting that lenders are 0.61% more likely to approve a loan application if the application amount is eligible for sale to the GSEs. Moreover, the coefficient of $Conforming \times Nonbank$ is also significantly positive (0.0455) with a t-statistic of 16.27. This indicates that the positive effect of conforming loan eligibility on loan approval is more pronounced for nonbank lenders, additionally increasing the mortgage approval rate by 4.55 percentage points.

Column (2) reports the regression coefficients with additional controls on loan- and borrower-level characteristics. Here, the coefficients for the main variables remain positive, and both the magnitude and the statistical significance of $Conforming$ increase substantially. After controlling the risk profile of borrowers and loan characteristics, lenders are more likely to approve conforming mortgages by 4.58 percentage points and even further approve by 3.71 percentage points when they are nonbank lenders as the coefficient of $Conforming \times Nonbank$ remains at a similar level to the previous column.

To address the potential concerns on the demand side factors, i.e. some areas being hit by positive productivity shocks, Columns (3)–(4) repeat the first two specifications replacing census tract fixed effects and year fixed effects with census tract×year fixed effects. As the census tract×year fixed effects absorb all the variations by the census tract and year, the results are robust to any local changes by year. Our results are the same as the first two specifications, showing the robustness of the results from potential demand shocks.

Next, we examine the potential heterogeneity in the effect of conforming loan status on loan approval. We separate *Conforming* into *Jumbo Conforming* and *Non-Jumbo Conforming. Jumbo Conforming* refer to the mortgages with loan amounts below the CLL of the county but above the national CLL. *Non-Jumbo Conforming* are the mortgages with loan amounts below the national CLL. While the GSEs would purchase both the *Jumbo Conforming* and *Non-Jumbo Conforming* as they are all conforming loans, lenders might treat the two differently due to the practices in the agency mortgage-backed securities (MBS) market that agency MBS with more than 10 percent of jumbo-conforming loans are not allowed to be sold in the to-be-announced (TBA) market (Huh and Kim, 2022). MBS that cannot be traded in the TBA market will be traded in the less-liquid specified pool (SP) market, discouraging the origination of jumbo-conforming mortgages.

We replace *Conforming* in equation (1) with *Jumbo Conforming* and *Non-Jumbo Con-*

forming and run the following model:

$$
\begin{aligned}
Approve_{i,t} =& \alpha + \beta_0 \cdot \textit{Jumbo Conforming}_{i,t} + \gamma_0 \cdot \textit{Jumbo Conforming}_{i,t} \times Nonbank_{i,t} \\
&+ \beta_1 \cdot \textit{Non-Jumbo Conforming}_{i,t} + \gamma_1 \cdot \textit{Non-Jumbo Conforming}_{i,t} \times Nonbank_{i,t} \\
&+ \delta \cdot X_{i,t} + \eta_j + \eta_{\text{tract}} + \eta_t + \epsilon_{i,t}.
\end{aligned} \tag{2}
$$

Table 3 reports the regression results. We find significantly positive coefficients for both *Non-Jumbo Conforming* and *Jumbo Conforming*, as well as their interactions with $Nonbank$. In particular, according to the result in Column (1) of Table 3, lenders are more likely to approve loan applications that are non-jumbo conforming (by 0.43 percentage points), or jumbo-conforming (by 1.87 percentage points), statistically significant at the 1% level. Furthermore, nonbank lenders provide additional approvals for those non-jumbo conforming and jumbo conforming applications by 4.72 percentage points and 2.91 percentage points, respectively. In Column (2), the signs of the coefficients remain the same when we include borrower and loan characteristics that are associated with the riskiness of the application. In Columns (3)–(4), we find the tighter fixed effects do not significantly affect our estimate results.

Additionally, in Table 3, we report t-test estimates for the coefficients of *Non-Jumbo Conforming* and *Jumbo Conforming* by nonbank lenders being statistically different (*Non-Jumbo Conforming* + *Non-Jumbo Conforming* × *Nonbank* - *Jumbo Conforming* - *Jumbo Conforming* × *Nonbank* = *Non-Jumbo Conforming by Nonbank* - *Jumbo Conforming by Nonbank*). We find that the loan approval of nonbank lenders is significantly higher for non-jumbo than jumbo mortgages, the difference ranging from 0.3 to 2.4 percentage points. This would suggest that nonbank lenders exploit the regulatory arbitrage across the markets aggressively focusing on the non-jumbo conforming loan market.

3.2. Conforming Loan Eligibility and Growth of Nonbank Origination Share

We have demonstrated that nonbank lenders are more inclined to originate mortgages under the CLL. The natural question that arises from this result is whether the nonbank origination share has grown more in areas where a larger proportion of loan applications are eligible for conforming mortgages. To address this question, we examine the relationship between conforming eligibility and nonbank origination in the census tracts. Specifically, we estimate the following regression equation:

$$
\begin{aligned}
Nonbank\ Share_{\text{tract},t+1} = & \alpha + \beta \cdot Conforming\ Eligibility_{\text{tract},t} + \delta \cdot X_{\text{tract},t} \\
& + \eta_{\text{county}} + \eta_t + \epsilon_{\text{tract},t},
\end{aligned} \tag{3}
$$

where $Nonbank\ Share_{\text{tract},t+1}$ is the nonbank mortgage origination share within a tract in year $t+1$. $Conforming\ Eligibility_{\text{tract},t}$ is the distance of the county's CLL to the 80% of home price level at the census tract (ZHVI $\times$ 0.8), represented as $CLL - (ZHVI \times 0.8)$ in the unit of \$100,000, measuring the conforming loan eligibility for a typical loan in the census tract. $X_{tract,t}$ denotes a list of controls, such as $\log(Median\ Income)$, *Minority Application Share*, *Female Application Share*, and *Average Loan-to-Income*, as well as *Per Cap Income Growth Last 2 Yrs*, *Population Growth Last 2 Yrs*, and *ZHVI Growth Last 2 Yrs*. The last three variables denote the growth rates of per capita income, population, and the tract-level Zillow Home Value Index (ZHVI) in the past two years, respectively. We also include county fixed effects (η_{county}) and year fixed effects (η_t), thus comparing census tracts within the same county and the same year. The estimations are weighted by the total population of the census tracts and we cluster the standard errors at the county level.

Table 4 reports the estimation results. We find that census tracts with higher conforming loan eligibility exhibit a significant increase in nonbank origination shares. Specifically, in Column (1), univariate regression with county and year fixed effects shows that the coefficients of *Conforming Eligibility* is 0.0429, indicating that a \$100,000 larger gap between the CLL and 80% of the census tract home value is associated with a 4.29 percentage point greater nonbank origination share. Column (2) reports the results including various census tract characteristics as controls. The result remains the same. Interestingly, we find that nonbank share grows in the neighborhoods with a higher home price growth and population growth but also a higher average loan-to-income ratio with more female applications. In Columns (3)–(4), we repeat the regression of *Nonbank Share* on *Conforming Eligibility* with county×year fixed effects to find the same results.

Figure 2 provides an example of Orange County, CA in 2015. Given the variation of *Conforming Eligibility* in 2015 of Panel A, we observe the uneven shares of nonbank lenders within the county in the following year of 2016 as seen in Panel B. Note that, with the same level of CLL within the county, *Conforming Eligibility* is a function of a lower home price. In other words, nonbank is more concentrated in the lower home-price neighborhoods. We reconfirm this in Figure 3, where we present the binned scatter plot of nonbank origination share according to census tract-level home values using data from 2003 to 2021. We find a clear downward-sloping relationship suggesting that the nonbank origination expands more in the lower-priced neighborhoods.

While we find that the credit supply through nonbanks increases in the conforming eligible area, it can be driven not by the additional credit supply in the neighborhood but by nonbanks filling the gap due to the withdrawal of traditional banks from the mortgage market. Table 5 presents the results. Columns (1)–(2) report the results using *Growth_Loan Amount*, the growth rate of the aggregate loan amount in a census tract, as a dependent variable. In Column (1), we find a 1 SD increase in the gap between the CLL and 80% of the census tract home value is associated with a 1.13 percentage point higher growth rate in loan amount ($0.69 \times 1.635 = 1.13$). In Column (2), we replace county and year fixed effects with county×year fixed effects to absorb any county-level time-varying factors. While the magnitude is smaller than the results in Column (1), the estimated coefficient of *Conforming Eligibility* is significantly positive, with a value of 0.0047.

As *Growth_Loan Amount* also captures the effect from the average loan size, in Columns (3)–(4), we report the results using *Growth_Loan Count*, the growth rate of the total number of loan originations in a census tract, as the dependent variable. The results are similar to the results in Columns (1)–(2). In Column (3), a 1 SD increase in *Conforming Eligibility* is associated with an additional 1.13 percentage points growth in the number of originated loans ($0.69 \times 1.635 = 1.13$). Column (4) with the granular fixed effects also shows a similar result. That is, we find that the uneven mortgage origination activities of nonbanks across neighborhoods were not driven by filling the gap of withdrawal of banks in the neighborhood. This is consistent with Benson et al. (2024), who show that regional changes in Ginnie Mae MBS securitizability lead to heterogeneous credit growth from both bank and nonbank originators.

3.3. Uneven Nonbank Growth and Local Home Prices

We find that the degree of conforming eligibility of a neighborhood increases the intensity of nonbanks's origination in the area. In this section, we examine the effect of this uneven additional supply of credit on the heterogeneous local price dynamics.

We first examine the effect of uneven credit shock on local home prices. All else equal, additional credit supply can generate a price impact on the local housing market, which potentially leads to a localized bubble as we observed in the last global financial crisis (Chinco and Mayer, 2016; Choi et al., 2016; Gao et al., 2021). However, identifying the credit supply effect on local home price growth is challenging as regressing the change in credit supply on the home price is likely to suffer endogeneity problem due to the nonrandomness of credit supply (Adelino et al., 2012; An and Yao, 2016; Di Maggio and Kermani, 2017; Favara and Imbs, 2015). For example, an expectation of a housing boom in an area may cause both an increase in credit supply and home price appreciation.

To address the potential endogeneity, we use *Conforming Eligibility* as an instrument variable for the nonbank growth in an area. As in Table 4, *Conforming Eligibility* is positively correlated with the nonbank presence in the neighborhood in the near future, which confirms the relevance condition. For exclusion restriction, we claim that the local home price appreciation from *Conforming Eligibility* is only through the nonbank growth in the neighborhood. One of the few possible channels that challenge the exclusion restriction is the future home price expectation that the conforming eligible neighborhoods, where the home price is on average lower, have on average a higher expected home price appreciation. However, as the local housing supply elasticity is the key determinant of the housing price sensitivity, a higher home price appreciation is expected in the low housing supply elasticity areas for any demand shock (Glaeser et al., 2008; Saiz, 2010), where the home price level is likely to be on average higher.

Another possible challenge will be the change in the composition of the local housing market. For example, gentrification, which is likely to occur in lower-priced areas, would bring a structural change in the housing demand such as the composition of buyers in the neighborhood or the economic fundamentals of the area. While sudden structural changes are unlikely, we include extensive controls at the neighborhood level that might have an impact on the changes in buyer composition and housing market expectation such as median income, minority share, and the growth rates of per capita income, population, and census tract-level home values in the previous two years. That is, we use the variation in *Conforming Eligibility* that attracts nonbank presence in the neighborhood after controlling other potential factors.

We instrument *Nonbank Share* with *Conforming Eligibility*, as in Section 3.2, and run the following regression model:

$$Y_{\text{tract},t+1} = \alpha + \beta \cdot \widehat{Nonbank\ Share}_{\text{tract},t} + \delta \cdot X_{\text{tract},t} + \eta_{\text{county}} + \eta_t + \epsilon_{\text{tract},t}, \tag{4}$$

where $\widehat{Nonbank\ Share}$ is the instrumented *Nonbank Share*, and $X_{\text{tract},t}$ is a vector of census tract-level control variables, including log(*Median Income*), *Minority Application Share*, *Female Application Share*, *Average Loan-to-Income*, *Per Cap Income Growth Last 2 Yrs*, *Pop-*

ulation Growth Last 2 Yrs, and *ZHVI Growth Last 2 Yrs*. We also include county (η_{county}) and year (η_t) fixed effects. We cluster the standard errors at the county level.

We examine the effect of the uneven nonbank growth on local home prices. Table 6 documents the IV regression estimates of the effect of *Nonbank Share*, instrumented by *Conforming Eligibility*, on the local home prices. The dependent variable in Columns (1)–(2) is *ZHVI Growth*, the growth rate of tract-level housing price (ZHVI) from t to $t+1$. In Column (1), we include county and year fixed effects to find that the increase in nonbank origination share raises the home value of the census tract. Given the top 25th percentile value of *Nonbank Share* is 62.8% and the bottom 25th percentile is 29.1%, the top 25th percentile census tract will experience about 2.69 percentage point $((62.8-29.1)\times 0.0799)$ larger growth rate in home values than the bottom 25th percentile census tract.

In Column (2), we replace county and year fixed effects with county×year fixed effects to find similar results. Also, a back-of-the-envelope calculation based on the estimates in Column (2) of Table 5 and Table 6 suggests that an exogenous 1% increase in aggregate credit supply in a neighborhood leads to 0.3267% increase in home prices $(0.0394/0.1206 = 0.3267)$. This estimate is close to the magnitude in the previous studies on the effect of aggregate credit increase on the home price, which typically ranges around 0.3–0.35% (Di Maggio and Kermani, 2017; Favara and Imbs, 2015; Lilley and Rinaldi, 2021).

In Panel C of Figure 2, we visualize our regression results using the example of Orange County, CA in 2015. Given the variation of conforming eligibility in Panel A, we find the uneven nonbank originations across census tracts within a county in Panel B, and the geographical heterogeneity in the growth of nonbank origination matches well with the home price appreciation across census tracts in a county as in Panel C.

In Columns (3)–(4) of Table 6, we use Δ*Price-to-Rent*, the change in price-to-rent ratio from t to $t+1$, as the dependent variable. The growth in the price-to-rent ratio is different from the growth of home prices as the price-to-rent ratio measures the home price relative to its annual rent, which is the fundamental cash flow from the house. We find that the increased credit supply of nonbank, instrumented by local conforming eligibility, increases local home prices above the level of the fundamental measured by the rental price. In Column (3), the coefficient of $\widehat{Nonbank\ Share}$ is 0.145 indicating that a 1 SD increase in nonbank origination share is associated with a 0.033 additional increase in the price-to-rent ratio. The results are the same in Column (4) where we include county×year fixed effects. That is, even after controlling for the local rental prices, we find the uneven increase in housing prices in accordance with the uneven growth of nonbank.

Lastly, we examine the consequence of uneven home price growth. From our previous findings, as nonbanks are more likely to supply credit to the neighborhoods with low home prices so that the loans qualify for conforming status, we predict that the lower-priced area would have price appreciation that is relatively higher than the higher-priced area *within a county*, where the same CLL is being applied. As a result, the heterogeneity in home prices within a county would decrease.

We regress various measures of house price dispersion across census tracts within a county on nonbank growth in the county, using a similar IV strategy as in Section 3.2 but changing the unit of analysis to the county. Regression specification is as follows:

$$\begin{aligned} Dispersion_{\text{county},t+1} = & \alpha + \beta \cdot \widehat{Nonbank\ Share}_{\text{county},t} + \delta \cdot X_{\text{county},t} + \eta_{\text{state}} + \eta_t \\ & + \epsilon_{\text{county},t}, \end{aligned} \tag{5}$$

where $Dispersion_{\text{county},t+1}$ measures the house price dispersion across census tracts within a county, either by (i) the standard deviation of census tract-level ZHVI within a county normalized by the average ZHVI of the county ($\text{SD}(ZHVI)/\text{Mean}(ZHVI)$) or (ii) the difference between the maximum and minimum tract-level ZHVI within a county normalized by the average ZHVI of the county ($(\text{Max}(ZHVI) - \text{Min}(ZHVI))/\text{Mean}(ZHVI)$).

To measure the share of nonbank mortgage origination within a county, we define *Nonbank*

Share (County) as the fraction of nonbank share among the aggregated mortgage origination in the county, which we instrument by *Conforming Eligibility (County)*, defined as the difference between the county CLL and the 80% of county-level ZHVI. $X_{\text{county},t}$ is a set of county-level controls, including $\log(Median\ Income)$ $(County)$, *Minority Application Share (County)*, *Female Application Share (County)*, and *Average Loan-to-Income (County)*, as well as *Per Cap Income Growth Last 2 Yrs (County)*, *Population Growth Last 2 Yrs (County)*, and *ZHVI Growth Last 2 Yrs (County)*. State (η_{state}) and year (η_t) fixed effects are included for the comparison between counties in the same state and the same year. The estimations are weighted by the total population of the county and we cluster the standard errors at the state level.

In Columns (1)–(2) of Table 7, we use SD($ZHVI$)/Mean($ZHVI$) as the dependent variable. Column (1) uses $\widehat{Nonbank\ Share}$ $(County)$ as the main independent variable, instrumented by *Conforming Eligibility*, to find that the increase in $\widehat{Nonbank\ Share}$ $(County)$ reduces the price dispersion within a county. Column (2) includes state×year fixed effects to find a stronger effect. That is, when comparing two counties within a state and year with different levels of nonbank share, a county with a higher nonbank share experiences a stronger price convergence as low-priced census tracts in the county experience a higher price growth than the other census tracts in the county, which narrows the price heterogeneity within the county. For a 1 SD increase in nonbank share in a county, the dispersion would decrease by 41.0% to 44.6% of a 1 SD of the dispersion measure. Columns (3)–(4) use (Max($ZHVI$) − Min($ZHVI$))/Mean($ZHVI$) as the dependent variable. Column (3) includes state and year fixed effects and Column (4) includes state×year fixed effects to find a similar convergence in housing prices within a county.

3.4. The Effect on Mortgage Default Risks

So far, we find that nonbank has been unevenly grown in the neighborhoods with lower housing prices that qualify for GSE's conforming eligibility, resulting in an uneven housing price appreciation across the neighborhood that low-priced neighborhoods experience a much higher appreciation than the high-priced ones. As a result, given a CLL, we find that census tracts in a county show a price convergence within the county.

The results can be interpreted in two ways. First is the demand-side story that there was a large underserved population living in low-priced neighborhoods who were not able to be served by traditional banks, for example, because of the lack of enough credit history despite good creditworthiness. In this case, the growth of nonbanks helped borrowers in low-priced neighborhoods to finance themselves to purchase homes, fulfilling the underserved demands. Then the uneven price growth simply indicates a restoration of market efficiency by reinstating prices to the level of fundamentals.

However, the results can be also due to a supply-side story that the aggressive growth of nonbanks in the low-priced neighborhoods that suit their business model pushed the housing prices above the fundamentals in the neighborhoods, shaping a localized boom and bust cycle. The story is somewhat similar to the subprime lending during the 2008 financial crisis, where the rapid expansion of credit to the previously underserved population resulted in a massive run-up in housing prices and a significant drop afterward (Favilukis et al., 2017; Khandani et al., 2013; Mian and Sufi, 2009). It is also notable that the boom and bust patterns in the last crisis were significantly different across the neighborhoods as our findings on nonbank lending (Chinco and Mayer, 2016; Choi et al., 2016; Gao et al., 2021).

To distinguish the two compelling possibilities with the opposite conclusion, we examine the difference in delinquency rates across mortgage loans by the originators. If the extended loans in the low-priced neighborhoods were to the low-quality borrowers by aggressive nonbank lenders as the supply-side story, we are likely to observe an increase in mortgage delinquency (Di Maggio and Kermani, 2017; Iacoviello, 2005; Kiyotaki and Moore, 1997). Thus, we examine the effects of the growth in uneven nonbank lending on mortgage delinquency.

The findings in the literature on the delinquency of mortgages originated by nonbank lenders are mixed. Buchak et al. (2018) find that mortgages originated by nonbank lenders are more likely to be 60 days delinquent or more than those originated by banks, despite the small estimated magnitude. On the other hand, Fuster et al. (2019), focusing exclusively on fintech nonbank lenders, demonstrates that borrowers using fintechs are less likely to be delinquent. However, note that both studies analyze the data up to the mid-2010s when the market was bullish and delinquency was less likely. For our study on mortgage delinquency, we particularly focus on the mortgage performance in the post-2020 period, as the housing market became less bullish after 2020 and the realization of potential delinquency is more likely.

Specifically, we run the panel regression at loan–year-month level as follows:

$$Y_{i,\mathrm{ym}} = \alpha + \beta \cdot Nonbank_i + \delta \cdot X_i + \eta_{\mathrm{tract}} + \eta_{\text{origin-year}} + \eta_{\mathrm{y}} + \epsilon_{i,\mathrm{ym}}, \tag{6}$$

where $Nonbank_i$ is a dummy variable that equals 1 if loan i is originated by a nonbank lender. X_i presents a broad set of loan-level control variables at the origination that are widely known as important predictors of default propensity, such as FICO score, LTV ratio, loan amount, and mortgage rate. We also include census tract, origination year, and reporting year fixed effects to control for the time-invariant local conditions and unobserved time-varying market conditions that apply to all locations. All standard errors are clustered at the census tract level.

Our first dependent variable of interest is $Underwater_{i,\mathrm{ym}}$, which is a dummy variable that equals 1 if the current market value of the underlying property of loan i is lower than the present value of loan i and 0 otherwise. In other words, $Underwater_{i,\mathrm{ym}}$ is an indicator of being in a negative equity position. While different from the default, the negative equity position is a necessary condition for the "strategic default" (Foster and Van Order, 1984) and indeed associated with the majority of default events during the recent financial crisis by 30% to 70% (Bhutta et al., 2017; Gerardi et al., 2018; Guiso et al., 2013). Thus, we investigate whether the mortgages originated by nonbank lenders are more likely to be in the necessary condition for borrowers to default.

In Columns (1)–(2) of Table 8, we report the regression results of nonbank originations on $Underwater_{i,\mathrm{ym}}$ using equation (6). Column (1) includes census tract fixed effects, origination year fixed effects, and reporting year fixed effects, to find that the mortgage loans originated by nonbanks are 0.3 percentage points more likely to be underwater in a given year-month. Column (2) replaces census tract and reporting year fixed effects with census tract×reporting year fixed effects to find a similar result. That is, even after controlling for time-varying census tract characteristics, the origination by nonbanks is more likely to suffer the underwater situation. The estimated coefficients of other control variables are as expected. While higher LTV, loan amounts, and mortgage rates of a loan increase the likelihood of being underwater, a higher FICO score lowers the likelihood.

Our second dependent variable of interest is $Distance\text{-}to\text{-}Underwater_{i,\mathrm{ym}}$, which is the difference between the current market value of the property and the present value of the loan on the property, normalized by the property's current market value. This variable works as one minus mark-to-market LTV and measures the distance to underwater. We define the measure separately for the above-water mortgage loans to examine the effect on the distance to underwater. Given the historically low default rates since the mid-2010s due to the bullish housing market, $Distance\text{-}to\text{-}Underwater_{i,\mathrm{ym}}$ may better capture the potential risk of mortgage default than the underwater.

In Columns (3)–(4) of Table 8, we report the regression results of nonbank originations on $Distance\text{-}to\text{-}Underwater_{i,\mathrm{ym}}$. Column (3) includes census tract fixed effects, origination year fixed effects, and reporting year fixed effects, to find that the mortgage loans originated by nonbanks are 0.47% closer to underwater in a given year-month. Column (2) replaces census tract and reporting year fixed effects with census tract×reporting year fixed effects to find a similar result. That is, even after controlling for the time-varying census tract characteristics, the mortgage loans originated by nonbanks are much closer to underwater than the mortgages originated by traditional banks. The results in Columns (1)–(4) indicate that the mortgages originated by nonbanks are either more likely to be underwater or near to it, compared to the mortgages by banks.

Our third dependent variable of interest is *90+ Delinquency*$_{i,\mathrm{ym}}$, which is about the actual delinquency events, defined as a dummy variable that equals 1 if the loan has been delinquent for more than 90 days and 0 otherwise.[13] The 90+ delinquency is the most widely used measure to define severe delinquency because a loan is considered at risk of foreclosure once it becomes 90 days or more delinquent.[14]

In Columns (5)–(8), we report the results using the delinquency events as a dependent variable. Column (5) includes the census tract fixed effects, origination year fixed effects, and reporting year fixed effects, and Column (6) includes census tract$\times$reporting year fixed effects and origination year fixed effects. We find that mortgage originations by nonbanks are more likely to be delinquent than the loans originated by traditional banks. While the magnitude of the estimated coefficient is small, considering that the average loan continuation is as short as 28.3 months, our results indicate that nonbank origination increases the default by 0.079% to 0.096% for the 28.3 months of the loan continuation.[15]

As default decisions are known to be strongly affected by the incentive to default, we also control the incentive by the measures of in-the-moneyness of a loan for the prepayment and default option in the literature (Deng and Quigley, 2012; Deng et al., 2000). *Refinance Incentive* is the difference between the present value of the remaining mortgage when refinancing the amounts today (PV with Refinance) and the present discount value of the remaining mortgage without the refinancing (PV without Refinance), normalized by the PV with Refinance. *Default Incentive* is the difference between the present value of the loan on the property and the current market value of the property, normalized by the property's current market value. In Columns (7)–(8), we include *Default Incentive* and *Refinance Incentive* as control variables in the regression. As expected, *Default Incentive* is positively associated with actual

[13]In our tables, we scale the delinquency dummy to 100 for better readability, following the literature (Agarwal et al., 2015; Deng et al., 2023).

[14]For example, see https://www.gao.gov/products/gao-11-93.

[15]$1-(1-0.000028)^{28.3}=0.00079$ and $1-(1-0.000034)^{28.3}=0.00096$

90+ delinquency events, indicating that negative equity or near-underwater situations make borrowers more likely to default. Notably, we find that the nonbank origination increases the likelihood of default even after controlling for the incentives.

As we find that the mortgages originated by nonbanks show a higher likelihood of being underwater, a shorter distance to underwater, or a higher likelihood of delinquency, we further examine the time-series variation of these results, by interacting $Nonbank$ with year dummies as follows:

$$Y_{i,\mathrm{ym}} = \alpha + \sum_{\mathrm{t}=2013}^{2022} \beta_{\mathrm{t}} \cdot Nonbank_i \cdot \mathrm{I}(\text{year} = t) + \delta \cdot X_i + \eta_{\text{tract}} + \eta_{\text{origin-year}} + \eta_{\mathrm{y}} + \epsilon_{i,\mathrm{ym}}. \tag{7}$$

Table 9 reports the results on $Underwater$ in Columns (1)–(2) and the results on *Distance-to-Underwater* in Columns (3)–(4). We find that mortgage originations by nonbanks are more likely to be underwater or close to underwater for most of the years throughout our sample period. That is, the risk of being delinquent has been always higher in mortgage loans originated by nonbanks than in mortgage loans by banks.

In Columns (5)–(8), we report the results on *90+ Delinquency* with the same specifications as in Table 8. Interestingly, the coefficients of $Nonbank$ times year dummies are significantly negative during the pre-2020 period, but turn significantly positive after 2021, the year when the housing market slows down. Specifically, the estimated coefficients of the interactions between $Nonbank$ and the year dummies of 2021 and 2022 range from 0.0209 to 0.0265, suggesting that nonbank borrowers are on average 1.00–1.26 percentage points[16] more likely to default in 2021–2022 period.

Note that the time-series pattern of delinquency is different from the likelihood of being underwater, which is always higher for nonbanks' originations. It is possible that mortgage borrowers do not choose to default during the bullish housing market expecting forthcoming recovery from the underwater, but have to default when the bullish housing market ends. Figure 4 provides supportive evidence of our conjecture. Utilizing the specification in Table 6

[16] $1 - (1 - 0.000209)^{48} = 0.0100$ and $1 - (1 - 0.000265)^{48} = 0.0126$

but by year from 2013 to 2021, the figure shows that while census tracts with greater nonbank activities consistently experienced a higher home price appreciation by 2020, there was a significant decline in home prices in those tracts in 2021, indicating that there was a downward pressure in the neighborhood in 2021 and borrowers in the neighborhoods may start to default on their loans. Our result would reconcile the recent mixed findings on the delinquency of nonbank lending, where nonbank mortgages have been demonstrated only marginally worse (Buchak et al., 2018) or even superior (Fuster et al., 2019) performances compared to traditional banks.

4. Conclusion

In this paper, we examine the role of the uneven nonbank expansion in the residential mortgage market on the localized housing prices and its consequences. As nonbanks prefer conforming loans due to the OTD business model, we find that the expansion of nonbank origination is heavily concentrated in the census tracts that qualify for the conforming status, which are the low-price neighborhoods. We also find the localized housing prices within a county that the low-price neighborhoods show relatively higher home price appreciation than the other neighborhoods, resulting in a housing price convergence within a county despite the differences in the fundamentals. We find that the nonbank originations have been exposed to the risk of higher default and the risk realized after 2021 when the bullish housing market ends.

References

Adelino, M., A. Schoar, and F. Severino. 2012. Credit Supply and House Prices: Evidence from Mortgage Market Segmentation. Working Paper No.17832, National Bureau of Economic Research.

Agarwal, S., I. Ben-David, and V. Yao. 2015. Collateral Valuation and Borrower Financial Constraints: Evidence from the Residential Real Estate Market. *Management Science* 61:2220–2240.

An, X., Y. Deng, and S. A. Gabriel. 2021. Default Option Exercise over the Financial Crisis and Beyond. *Review of Finance* 25:153–187.

An, X., and V. Yao. 2016. Credit Expansion, Competition, and House Prices. Working Paper.

Benson, D., Y. S. Kim, and K. Pence. 2024. Nonbank Issuers and Mortgage Credit Supply. Working Paper.

Berg, T., A. Fuster, and M. Puri. 2022. FinTech Lending. *Annual Review of Financial Economics* 14:187–207.

Bhutta, N., J. Dokko, and H. Shan. 2017. Consumer Ruthlessness and Mortgage Default during the 2007 to 2009 Housing Bust. *Journal of Finance* 72:2433–2466.

Bosshardt, J., A. Kakhbod, and A. Kermani. 2023. The Value of Intermediaries for GSE Loans. Working Paper.

Buchak, G., G. Matvos, T. Piskorski, and A. Seru. 2018. Fintech, Regulatory Arbitrage, and the Rise of Shadow Banks. *Journal of Financial Economics* 130:453–483.

Buchak, G., G. Matvos, T. Piskorski, and A. Seru. 2023. Beyond the Balance Sheet Model of Banking: Implications for Bank Regulation and Monetary Policy. Working Paper No. 25149, National Bureau of Economic Research.

Chinco, A., and C. Mayer. 2016. Misinformed Speculators and Mispricing in the Housing Market. *Review of Financial Studies* 29:486–522.

Choi, H.-S., H. G. Hong, J. D. Kubik, and J. P. Thompson. 2016. Sand States and the US Housing Crisis. Working Paper.

Dell'ariccia, G., D. Igan, and L. Laeven. 2012. Credit Booms and Lending Standards: Evidence from the Subprime Mortgage Market. *Journal of Money, Credit and Banking* 44:367–384.

Demyanyk, Y., and E. Loutskina. 2016. Mortgage Companies and Regulatory Arbitrage. *Journal of Financial Economics* 122:328–351.

Demyanyk, Y., and O. Van Hemert. 2011. Understanding the Subprime Mortgage Crisis. *Review of Financial Studies* 24:1848–1880.

Deng, Y., C. Han, T. Li, and T. J. Riddiough. 2023. Adaptation to Climate Change Through Mortgage Default and Prepayment. Working Paper.

Deng, Y., and J. M. Quigley. 2012. Woodhead Behavior and the Pricing of Residential Mortgages. Working Paper.

Deng, Y., J. M. Quigley, and R. Van Order. 2000. Mortgage Terminations, Heterogeneity and the Exercise of Mortgage Options. *Econometrica* 68:275–307.

Di Maggio, M., and A. Kermani. 2017. Credit-Induced Boom and Bust. *Review of Financial Studies* 30:3711–3758.

Di Maggio, M., and V. Yao. 2021. Fintech Borrowers: Lax Screening or Cream-Skimming? *Review of Financial Studies* 34:4565–4618.

Duffie, D., L. Saita, and K. Wang. 2007. Multi-Period Corporate Default Prediction with Stochastic Covariates. *Journal of Financial Economics* 83:635–665.

Favara, G., and J. Imbs. 2015. Credit Supply and the Price of Housing. *American Economic Review* 105:958–992.

Favilukis, J., S. C. Ludvigson, and S. Van Nieuwerburgh. 2017. The Macroeconomic Effects of Housing Wealth, Housing Finance, and Limited Risk Sharing in General Equilibrium. *Journal of Political Economy* 125:1–291.

Foster, C., and R. Van Order. 1984. An Option-Based Model of Mortgage Default. *Housing Finance Review* 3:351–372.

Fuster, A., M. Plosser, P. Schnabl, and J. Vickery. 2019. The Role of Technology in Mortgage Lending. *Review of Financial Studies* 32:1854–1899.

Gao, Z., M. Sockin, and W. Xiong. 2021. Learning about the Neighborhood. *Review of Financial Studies* 34:4323–4372.

Gerardi, K., K. F. Herkenhoff, L. E. Ohanian, and P. S. Willen. 2018. Can't Pay or Won't Pay? Unemployment, Negative Equity, and Strategic Default. *Review of Financial Studies* 31:1098–1131.

Gete, P., and M. Reher. 2018. Mortgage Supply and Housing Rents. *Review of Financial Studies* 31:4884–4911.

Gete, P., and M. Reher. 2021. Mortgage Securitization and Shadow Bank Lending. *Review of Financial Studies* 34:2236–2274.

Glaeser, E. L., J. Gyourko, and A. Saiz. 2008. Housing Supply and Housing Bubbles. *Journal of Urban Economics* 64:198–217.

Green, R. K., and S. M. Wachter. 2005. The American Mortgage in Historical and International Context. *Journal of Economic Perspectives* 19:93–114.

Guiso, L., P. Sapienza, and L. Zingales. 2013. The Determinants of Attitudes toward Strategic Default on Mortgages. *Journal of Finance* 68:1473–1515.

Huh, Y., and Y. S. Kim. 2022. The Real Effects of Secondary Market Trading Structure: Evidence from the Mortgage Market. *Review of Financial Studies* 35:3574–3616.

Iacoviello, M. 2005. House Prices, Borrowing Constraints, and Monetary Policy in the Business Cycle. *American Economic Review* 95:739–764.

Irani, R. M., R. Iyer, R. R. Meisenzahl, and J.-L. Peydró. 2021. The Rise of Shadow Banking: Evidence from Capital Regulation. *Review of Financial Studies* 34:2181–2235.

Johnson, M. J., I. Ben-David, J. Lee, and V. Yao. 2023. FinTech Lending with LowTech Pricing. Working Paper No. 31154, National Bureau of Economic Research.

Khandani, A. E., A. W. Lo, and R. C. Merton. 2013. Systemic Risk and the Refinancing Ratchet Effect. *Journal of Financial Economics* 108:29–45.

Kim, Y. S., K. Pence, R. Stanton, J. Walden, and N. Wallace. 2022. Nonbanks and Mortgage Securitization. *Annual Review of Financial Economics* 14:137–166.

Kiyotaki, N., and J. Moore. 1997. Credit Cycles. *Journal of Political Economy* 105:211–248.

Landvoigt, T. 2017. Housing Demand During the Boom: The Role of Expectations and Credit Constraints. *Review of Financial Studies* 30:1865–1902.

Lilley, M., and G. Rinaldi. 2021. Credit Supply and House Prices: Evidence from Conforming Loan Limits. Working Paper.

Merton, R. C. 1974. On the Pricing of Corporate Debt: The Risk Structure of Interest Rates. *The Journal of Finance* 29:449–470.

Mian, A., and A. Sufi. 2009. The Consequences of Mortgage Credit Expansion: Evidence from the U.S. Mortgage Default Crisis. *Quarterly Journal of Economics* 124:1449–1496.

Moreira, A., and A. Savov. 2017. The Macroeconomics of Shadow Banking. *Journal of Finance* 72:2381–2432.

Ordonez, G. 2013. Sustainable Shaodw Banking. Working Paper No. 19022, National Bureau of Economic Research.

Roberts, D., A. Sarkar, and O. Shachar. 2018. Bank Liquidity Provision and Basel Liquidity Regulations. FRBNY Staff Report No. 852.

Saiz, A. 2010. The Geographic Determinants of Housing Supply. *Quarterly Journal of Economics* 125:1253–1296.

Wall Street Journal. 2021. Nonbank Lenders Are Dominating the Mortgage Market URL `https://www.wsj.com/articles/nonbank-lenders-are-dominating-the-mortgage-market-11624367460`.

Figure 1: Mortgage Origination by Nonbanks and Banks

We report the time series of the aggregate share of loan originations by nonbank and bank lenders using the HMDA data.

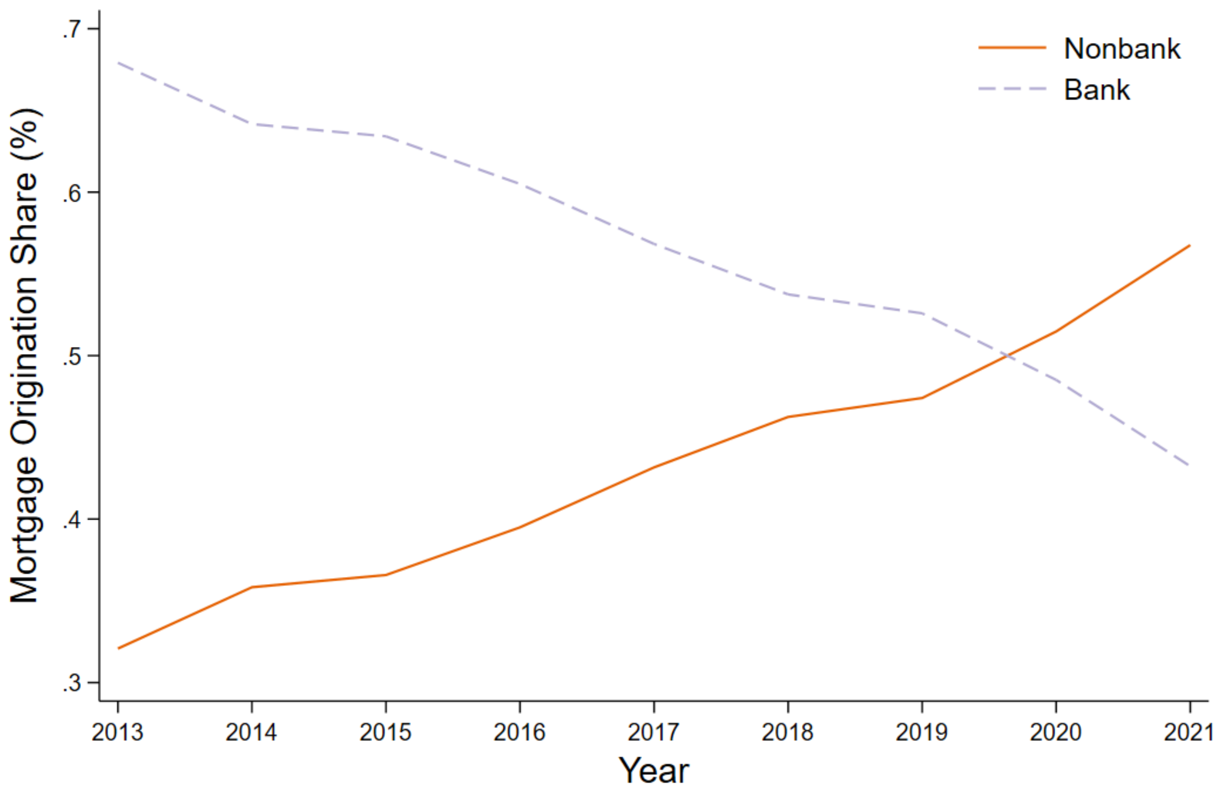
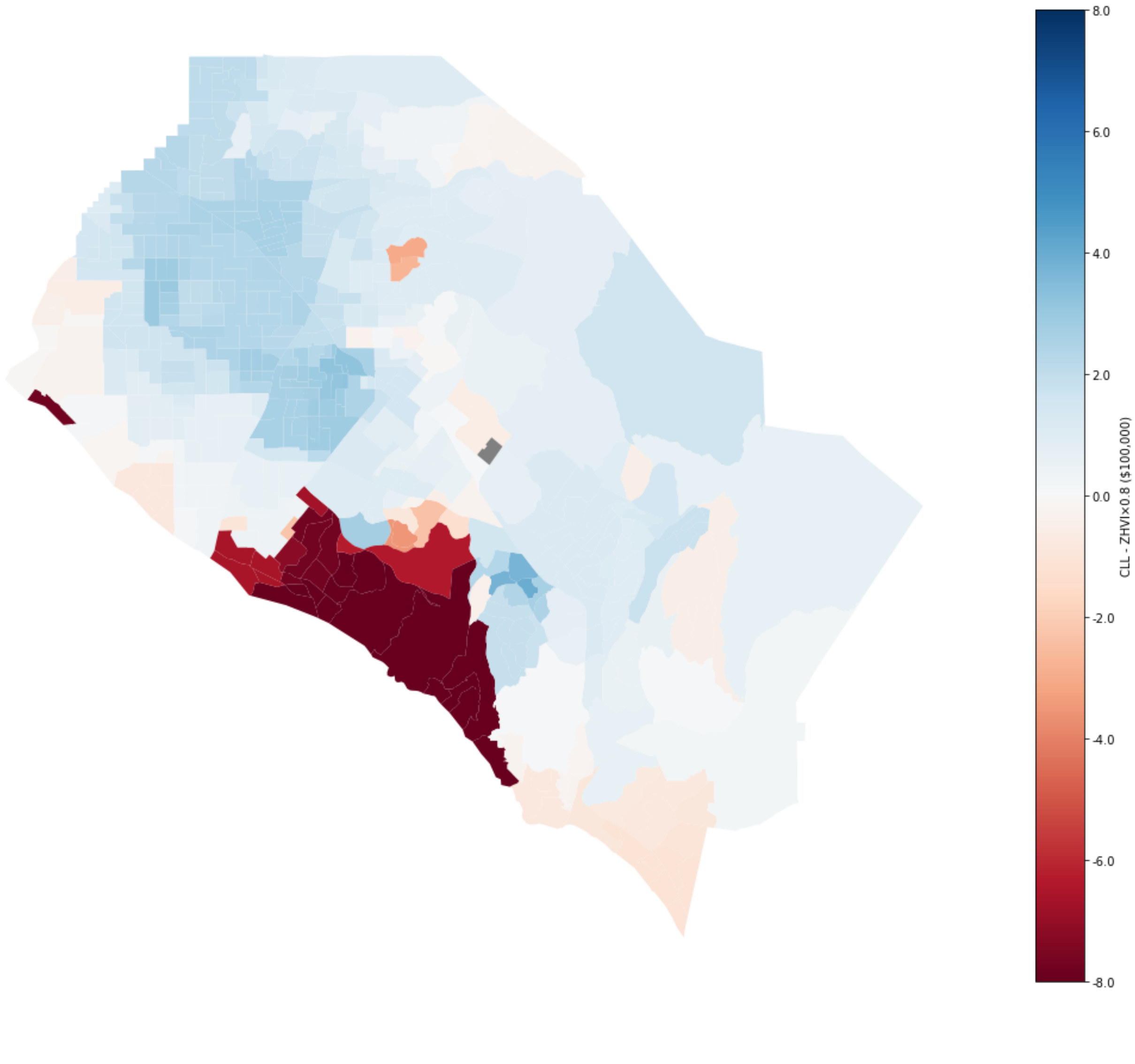


Figure 2: Conforming Loan Eligibility, Nonbank Mortgage Share, and Home Price Increases in Orange County, CA

We report the distribution of conforming loan eligibility, nonbank origination share, and annual home price appreciation across census tracts within Orange County, California. Panel A reports the conforming loan eligibility of census tracts, calculated by $CLL - (ZHVI \times 0.8)$, in the year 2015. Panel B reports nonbank mortgage origination share in 2016. Panel C reports the annual growth rate of ZHVI from 2015 to 2016.

Panel A: Conforming Loan Eligibility in 2015



Panel B: Nonbank Origination Share in 2016

Panel C: Annual ZHVI Growth 2015–2016

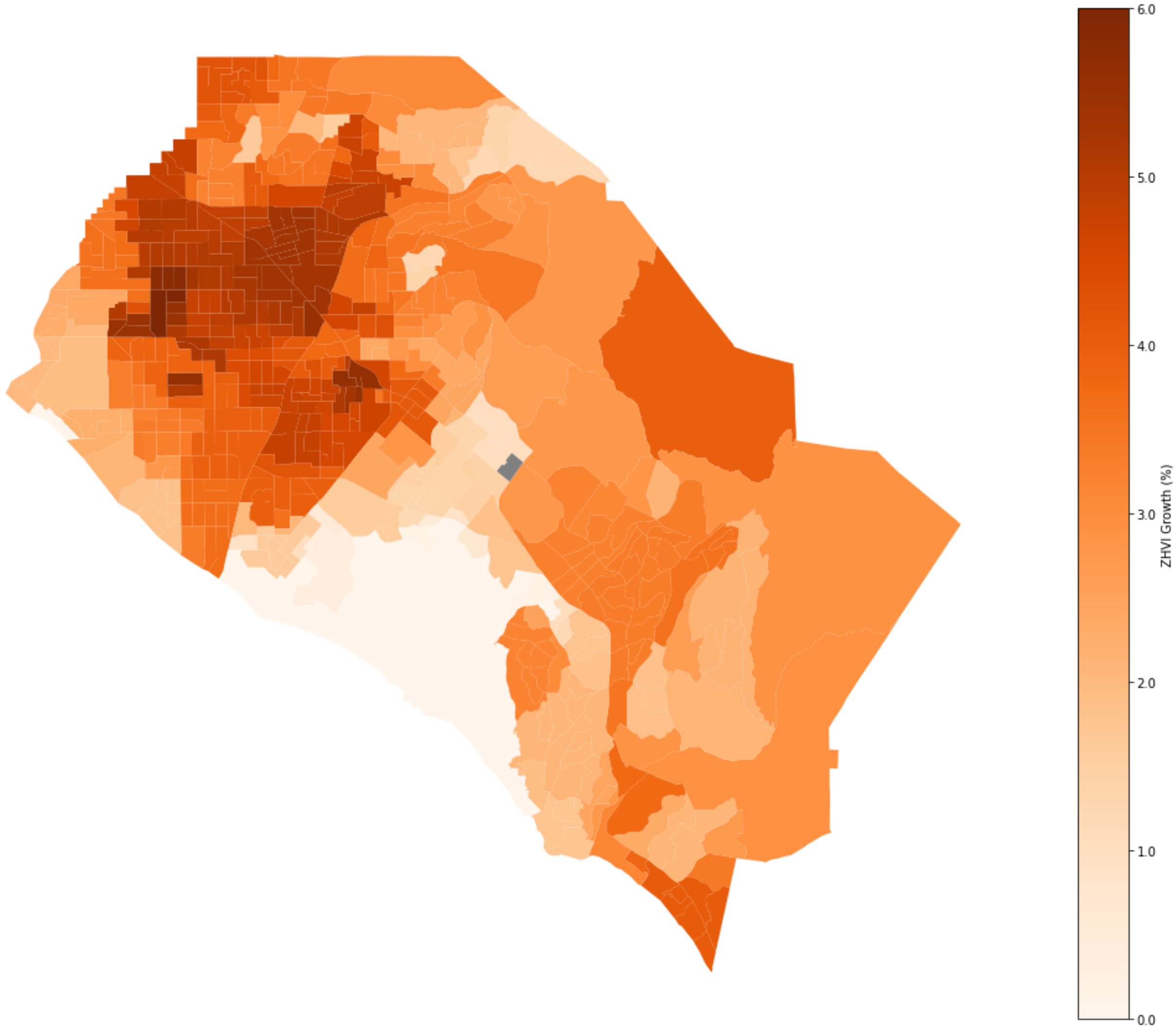


Figure 3: Binned Scatter Plot of Census Tract-level Nonbank Mortgage Share on Home Values

We report a binned scatter plot depicting nonbank mortgage origination share based on home values, using our census tract-level sample of the U.S. from 2013 to 2021. We categorize census tracts into 20 groups based on *ZHVI* values, with each bin containing an equal number of tracts, and illustrate *Nonbank Share*. Both *ZHVI* and *Nonbank Share* are residualized using county and year fixed effects. The red line draws the linear fit between *Nonbank Share* and *ZHVI*.

Figure 4: Coefficient Estimates of Home Price Appreciation in Table 6 by Year

We report the coefficient estimates of $\widehat{Nonbank\ Share}$ by running census tract-level IV regressions presented in Table 6 separately for each year, from 2013 to 2021. The dependent variables are *ZHVI Growth*, the growth rate of Zillow Home Value Index from the current year to the next. The main independent variable is $\widehat{Nonbank\ Share}$, the nonbank mortgage origination share in a census tract instrumented by *Conforming Eligibility*, tract-level difference between the conforming loan limit and ZHVI value. We include control variables such as log($Median\ Income$), $Minority\ Application\ Share$, $Female\ Application\ Share$, and *Average Loan-to-Income*, as well as *Per Cap Income Growth Last 2 Yrs*, *Population Growth Last 2 Yrs*, and *ZHVI Growth Last 2 Yrs*. We also include county fixed effects, and all estimations are weighted by the total population of the census tract. The 99% confidence intervals are provided along with the coefficient values.

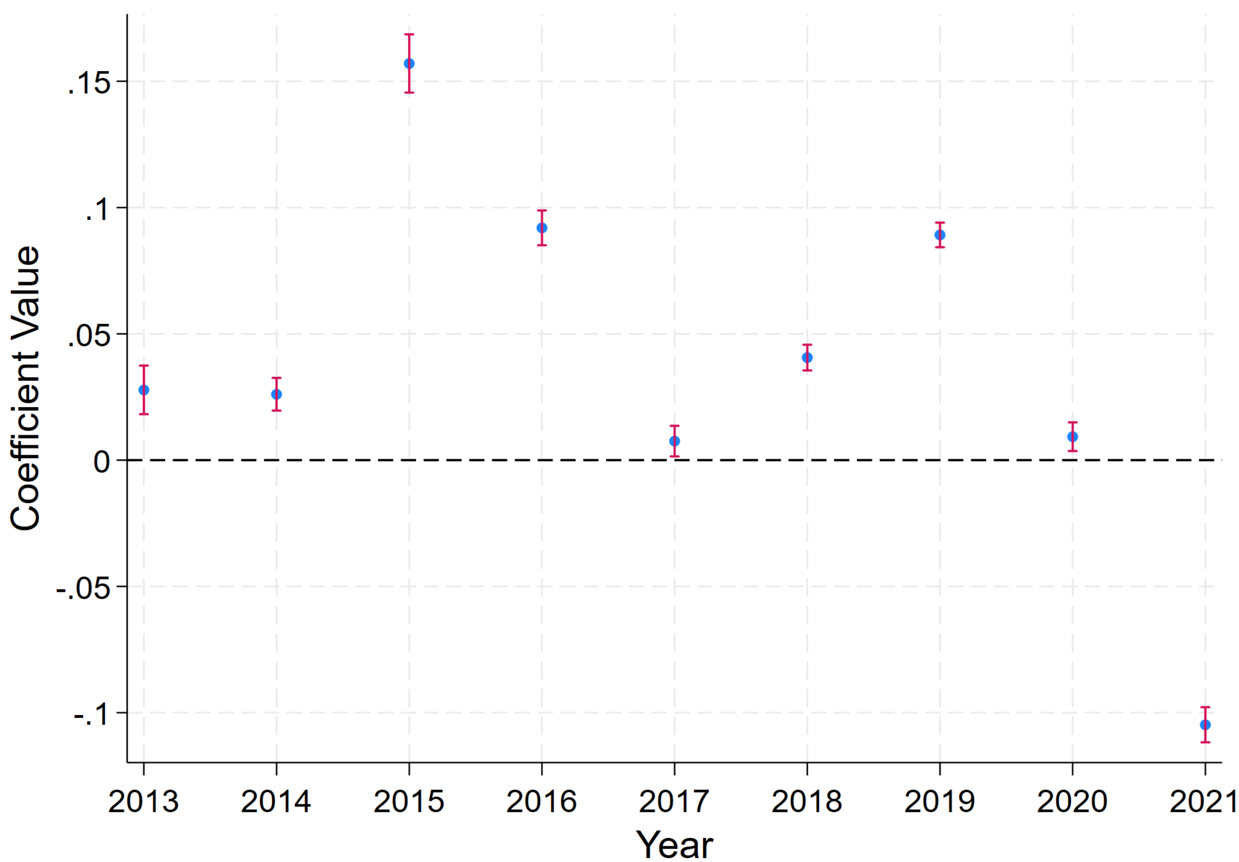


Table 1: Summary Statistics

The table reports the summary statistics of the variables. Panel A reports the loan application-level data: *Approve*, *Nonbank*, *Conforming*, *Non-Jumbo Conforming*, *Jumbo Conforming*, log(*Loan Amount*), log(*Income*), *Black*, *Asian*, *Hispanic*, *Female*, and *Co-borrower*. Panel B reports the summary statistics of the census tract-level data: *Nonbank Share*, *Growth_Loan Amount*, *Growth_Loan Count*, *ZHVI Growth*, Δ*Price-to-Rent*, *Conforming Eligibility*, log(*Median Income*), *Minority Application Share*, *Female Application Share*, *Average Loan-to-Income*, *Per Cap Income Growth Last 2 Yrs*, *Population Growth Last 2 Yrs*, and *ZHVI Growth Last 2 Yrs*. Panel C reports the county-level panel data: SD(*ZHVI*)/Mean(*ZHVI*), (Max(*ZHVI*)−Min(*ZHVI*)/Mean(*ZHVI*), *Nonbank Share (County)*, *Conforming Eligibility (County)*, log(*Median Income*) *(County)*, *Minority Application Share (County)*, *Female Application Share (County)*, and *Average Loan-to-Income (County)*, *Per Cap Income Growth Last 2 Yrs (County)*, *Population Growth Last 2 Yrs (County)*, and *ZHVI Growth Last 2 Yrs (County)*. Panel D reports the loan-year-month level data: *Underwater*, *Distance-to-Underwater*, *90+ Delinquency*, *Nonbank*, *Refinance Incentive*, *Default Incentive*, *FICO*, *LTV b/w 80%–95%*, *LTV above 95%*, log(*Loan Amount*), *Mortgage Rate*, *Minority*, *Female*, and *Co-borrower*.

	Obs.	Mean	S.D.	P25	P50	P75
Panel A: Loan Application-Level Dataset						
Approve	21,972,413	0.915	0.279	1.000	1.000	1.000
Nonbank	21,972,413	0.485	0.500	0.000	0.000	1.000
Conforming	21,972,413	0.907	0.291	1.000	1.000	1.000
Non-Jumbo Conforming	21,972,413	0.858	0.349	1.000	1.000	1.000
Jumbo Conforming	21,972,413	0.049	0.216	0.000	0.000	0.000
log(Loan Amount)	21,972,413	12.398	0.686	11.964	12.409	12.835
log(Income)	21,972,413	11.449	0.692	10.985	11.430	11.864
Black	21,972,413	0.043	0.204	0.000	0.000	0.000
Asian	21,972,413	0.083	0.276	0.000	0.000	0.000
Hispanic	21,972,413	0.012	0.109	0.000	0.000	0.000
Female	21,972,413	0.313	0.464	0.000	0.000	1.000
Co-borrower	21,972,413	0.464	0.499	0.000	0.000	1.000
Panel B: Census Tract Level Dataset						
Nonbank Share	528,604	0.465	0.226	0.291	0.462	0.628
Growth_Loan Amount	528,604	0.127	0.416	-0.146	0.054	0.308
Growth_Loan Count	528,604	0.216	0.499	-0.109	0.123	0.419
ZHVI Growth	528,604	0.078	0.056	0.040	0.066	0.106
ΔPrice-to-Rent	450,679	0.046	0.115	-0.007	0.041	0.093
Conforming Eligibility	528,604	2.596	1.635	2.215	2.891	3.397
log(Median Income)	528,604	11.028	0.397	10.746	11.022	11.324
Minority Application Share	528,604	0.171	0.224	0.025	0.080	0.219
Female Application Share	528,604	0.319	0.134	0.234	0.311	0.396
Average Loan-to-Income	528,604	2.859	0.704	2.345	2.763	3.329
Per Cap Income Growth Last 2 Yrs	528,604	0.031	0.057	-0.002	0.028	0.060
Population Growth Last 2 Yrs	528,604	0.010	0.042	-0.011	0.007	0.029
ZHVI Growth Last 2 Yrs	528,604	0.052	0.055	0.022	0.049	0.080

	Obs.	Mean	S.D.	P25	P50	P75
Panel C: County Level Dataset						
SD(ZHVI)/Mean(ZHVI)	19,302	0.177	0.127	0.080	0.151	0.249
(Max(ZHVI)-Min(ZHVI))/Mean(ZHVI)	19,302	0.555	0.491	0.195	0.412	0.756
Nonbank Share (County)	19,302	0.445	0.182	0.315	0.459	0.578
Conforming Eligibility (County)	19,302	2.806	0.993	2.403	2.912	3.343
log(Median Income) (County)	19,302	10.964	0.207	10.822	10.968	11.166
Minority Application Share (County)	19,302	0.135	0.123	0.053	0.103	0.179
Female Application Share (County)	19,302	0.310	0.050	0.280	0.311	0.343
Average Loan-to-Income (County)	19,302	2.949	3.912	2.431	2.796	3.309
Per Cap Income Growth Last 2 Yrs (County)	19,302	0.031	0.020	0.014	0.033	0.046
Population Growth Last 2 Yrs (County)	19,302	0.007	0.009	0.001	0.006	0.013
ZHVI Growth Last 2 Yrs (County)	19,302	0.050	0.045	0.025	0.050	0.076
Panel D: Loan-Year-Month Dataset						
Underwater	53,254,707	0.029	0.167	0.000	0.000	0.000
Distance-to-Underwater	51,726,819	0.364	0.194	0.212	0.347	0.507
90+ Delinquency×100	53,254,707	0.084	2.904	0.000	0.000	0.000
Nonbank	53,254,707	0.457	0.498	0.000	0.000	1.000
Refinance Incentive	53,254,707	-0.018	0.167	-0.066	0.023	0.089
Default Incentive	53,254,707	-0.352	0.204	-0.502	-0.338	-0.200
FICO	53,254,707	752.764	46.121	721.000	762.000	791.000
LTV b/w 80%–95%	53,254,707	0.263	0.440	0.000	0.000	1.000
LTV above 95%	53,254,707	0.047	0.212	0.000	0.000	0.000
log(Loan Amount)	53,254,707	12.099	0.580	11.712	12.128	12.525
Mortgage Rate	53,254,707	3.929	0.748	3.375	3.875	4.500
Minority	53,254,707	0.093	0.293	0.000	0.000	0.000
Female	53,254,707	0.306	0.461	0.000	0.000	1.000
Co-borrower	53,254,707	0.676	0.468	0.000	1.000	1.000

Table 2: Conforming Loan, Nonbanks, and Mortgage Approvals

This table presents the panel regression results that examine the effect of conforming loan eligibility on mortgage approval decisions. We use the loan application-level observations from 2013 to 2021. The dependent variable is *Approve*, a dummy variable that equals 1 if a loan applicaton is approved. The primary independent variables are *Conforming*, a dummy variable that equals 1 if the loan amount of an application is less than the conforming loan limit of the county, and *Conforming* × *Nonbank*, an interaction of *Conforming* and *Nonbank*, a dummy variable that equals 1 if a loan is applied to nonbank lenders. In Columns (2) and (4), we include control variables such as log(*Loan Amount*), log(*Income*), *Black*, *Asian*, *Hispanic*, *Female*, and *Co-borrower*. Columns (1)–(2) include lender, census tract, and year fixed effects and Columns (3)–(4) include lender and census tract×year fixed effects. The *t*-statistics are reported in parentheses and all standard errors are clustered at the county level. ***, **, and * denote the significance of the parameter estimates at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	Approve			
Conforming	0.0061**	0.0458***	0.0064**	0.0449***
	(3.03)	(15.49)	(3.28)	(15.46)
Conforming×Nonbank	0.0455***	0.0371***	0.0451***	0.0371***
	(16.27)	(12.29)	(16.21)	(12.22)
log(Loan Amount)		-0.0045***		-0.0060***
		(-3.43)		(-5.15)
log(Income)		0.0555***		0.0557***
		(44.00)		(43.90)
Black		-0.0560***		-0.0549***
		(-18.77)		(-19.09)
Asian		-0.0123***		-0.0120***
		(-13.33)		(-12.84)
Hispanic		-0.0413***		-0.0418***
		(-10.53)		(-10.53)
Female		0.0040***		0.0039***
		(12.64)		(13.52)
Co-borrower		-0.0007		-0.0008
		(-0.88)		(-0.96)
Lender FE	✓	✓	✓	✓
Tract FE, Year FE	✓	✓		
Tract×Year FE			✓	✓
Obs.	21,972,413	21,972,413	21,972,413	21,972,413
R-Squared	0.076	0.088	0.109	0.120

Table 3: Jumbo Conforming and Non-Jumbo Conforming Loans, Nonbanks, and Mortgage Approvals

This table presents the panel regression results that examine the effect of jumbo conforming and non-jumbo conforming loan eligibility on mortgage approval decisions. We use the loan application-level observations from 2013 to 2021. The dependent variable is *Approve*, a dummy variable that equals 1 if a loan applicaton is approved. The primary independent variables are *Jumbo Conforming*, a dummy variable that equals 1 if the loan amount of an application is less than the conforming loan limit of the county but greater than the national conforming loan limit, *Non-Jumbo Conforming*, a dummy variable that equals 1 if the loan amount of an application is less than the national conforming loan limit, and their interactions with *Nonbank*, a dummy variable that equals 1 if a loan is applied to nonbank lenders. In Columns (2) and (4), we include control variables such as log(*Loan Amount*), log(*Income*), *Black*, *Asian*, *Hispanic*, *Female*, and *Co-borrower*. We also report the t-test results for differences in coefficient estimates. Columns (1)–(2) include lender, census tract, and year fixed effects and Columns (3)–(4) include lender and census tract×year fixed effects. The t-statistics are reported in parentheses and all standard errors are clustered at the county level. ***, **, and * denote the significance of the parameter estimates at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	Approve			
Non-Jumbo Conforming (A)	0.0043*	0.0493***	0.0046*	0.0480***
	(2.12)	(15.65)	(2.30)	(15.47)
Non-Jumbo Conforming×Nonbank (B)	0.0472***	0.0381***	0.0468***	0.0382***
	(17.06)	(12.91)	(17.09)	(12.75)
Jumbo Conforming (C)	0.0187***	0.0419***	0.0191***	0.0417***
	(11.14)	(20.76)	(12.83)	(23.57)
Jumbo Conforming×Nonbank (D)	0.0291***	0.0214***	0.0289***	0.0216***
	(7.36)	(5.45)	(7.20)	(5.43)
Loan and Borrower-level Characteristics		✓		✓
Lender FE	✓	✓	✓	✓
Tract FE, Year FE	✓	✓		
Tract×Year FE			✓	✓
Obs.	21,972,413	21,972,413	21,972,413	21,972,413
R-Squared	0.076	0.088	0.109	0.121
Non-Jumbo Conforming by Nonbank − Jumbo Conforming by Nonbank				
$A+B-C-D$	0.004***	0.024***	0.003**	0.023***
	(3.907)	(17.201)	(2.589)	(15.850)

Table 4: Conforming Loan Eligibility and Nonbank Mortgage Shares in Census Tract

This table presents the panel regression results that investigate the impact of conforming loan eligibility in a census tract on the share of nonbank mortgage originations. We use the census tract-level observations from 2013 to 2021. The dependent variable is *Nonbank Share*, the nonbank mortgage origination share in a census tract in the next year. The main independent variable is *Conforming Eligibility*, calculated by $CLL - (ZHVI \times 0.8)$. In Columns (2) and (4), we include control variables such as log($Median\ Income$), $Minority\ Application\ Share$, $Female\ Application\ Share$, and *Average Loan-to-Income*, as well as *Per Cap Income Growth Last 2 Yrs*, *Population Growth Last 2 Yrs*, and *ZHVI Growth Last 2 Yrs*. In Columns (1)–(2), we include county and year fixed effects, and in Columns (3)–(4) we use county×year fixed effects. All estimations are weighted by the total population of the census tract. The t-statistics are reported in parentheses and all standard errors are clustered at the county level. ***, **, and * denote the significance of the parameter estimates at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	Nonbank Share			
Conforming Eligibility	0.0429***	0.0422***	0.0430***	0.0423***
	(17.29)	(14.77)	(16.41)	(13.89)
log(Median Income)		0.0002		-0.0005
		(0.03)		(-0.11)
Minority Application Share		-0.0060		-0.0025
		(-0.27)		(-0.11)
Female Application Share		0.0320***		0.0327***
		(3.74)		(3.73)
Average Loan-to-Income		0.0297***		0.0299***
		(11.46)		(11.21)
Per Cap Income Growth Last 2 Yrs		-0.0052		-0.0079
		(-0.93)		(-1.47)
Population Growth Last 2 Yrs		0.0802***		0.0749***
		(4.44)		(4.27)
ZHVI Growth Last 2 Yrs		0.0818***		-0.0098
		(4.29)		(-0.33)
County FE, Year FE	✓	✓		
County×Year FE			✓	✓
Obs.	528,604	528,604	528,604	528,604
R-Squared	0.571	0.575	0.605	0.608

Table 5: Conforming Loan Eligibility and Aggregate Mortgage Origination Growth in Census Tract

This table presents the panel regression results that investigate the impact of conforming loan eligibility in a census tract on the growth of aggregate loan originations. We use the census tract-level observations from 2013 to 2021. The dependent variables are *Growth_Loan Amount*, the growth rate of aggregate loan amount in a census tract from the current year to the next (Columns (1)–(2)), and *Growth_Loan Count*, the growth rate of the total number of loan originations in a census tract from the current year to the next (Columns (3)–(4)). The main independent variable is *Conforming Eligibility*, calculated by $CLL - (ZHVI \times 0.8)$. In all columns, we include control variables such as log($Median\ Income$), $Minority\ Application\ Share$, $Female\ Application\ Share$, and *Average Loan-to-Income*, as well as *Per Cap Income Growth Last 2 Yrs*, *Population Growth Last 2 Yrs*, and *ZHVI Growth Last 2 Yrs*. We include county and year fixed effects in Columns (1) and (3), and county×year fixed effects in Columns (2) and (4). All estimations are weighted by the total population of the census tract. The *t*-statistics are reported in parentheses and all standard errors are clustered at the county level. ***, **, and * denote the significance of the parameter estimates at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	Growth_Loan Amount		Growth_Loan Count	
Conforming Eligibility	0.0069***	0.0047***	0.0069**	0.0033*
	(2.75)	(2.79)	(2.54)	(1.92)
log(Median Income)	-0.1041***	-0.1049***	-0.1315***	-0.1321***
	(-38.74)	(-42.29)	(-39.46)	(-42.67)
Minority Application Share	0.1065***	0.1134***	0.1756***	0.1845***
	(15.88)	(16.17)	(20.94)	(20.64)
Female Application Share	0.0175**	0.0135**	0.0919***	0.0842***
	(2.55)	(2.00)	(11.07)	(10.34)
Average Loan-to-Income	-0.0135***	-0.0015	-0.0546***	-0.0417***
	(-4.47)	(-0.55)	(-17.20)	(-12.67)
Per Cap Income Growth Last 2 Yrs	0.0147	0.0500***	0.0155	0.0561***
	(1.39)	(4.90)	(1.37)	(4.66)
Population Growth Last 2 Yrs	0.0182	0.0423**	0.0084	0.0290
	(0.85)	(2.42)	(0.32)	(1.25)
ZHVI Growth Last 2 Yrs	0.0205	0.1016**	0.1187*	0.2547***
	(0.32)	(2.13)	(1.84)	(4.51)
County FE, Year FE	✓		✓	
County×Year FE		✓		✓
Obs.	528,604	528,604	528,604	528,604
R-Squared	0.075	0.149	0.080	0.150

Table 6: Nonbank Mortgage Share and Home Price Appreciations in a Census Tract

This table reports the IV regression results using *Conforming Eligibility*. We use the census tract-level observations from 2013 to 2021. The dependent variables are *ZHVI Growth*, the growth rate of Zillow Home Value Index from the current year to the next (Columns (1)–(2)), and Δ*Price-to-Rent*, the change in price-to-rent ratio from the current year to the next (Columns (3)–(4)). The main independent variable is $\widehat{\textit{Nonbank Share}}$, the nonbank mortgage origination share in a census tract instrumented by *Conforming Eligibility*, tract-level difference between the conforming loan limit and ZHVI value. In all columns, we include control variables such as log($Median\ Income$), $Minority\ Application\ Share$, $Female\ Application\ Share$, and *Average Loan-to-Income*, as well as *Per Cap Income Growth Last 2 Yrs*, *Population Growth Last 2 Yrs*, and *ZHVI Growth Last 2 Yrs*. We include county and year fixed effects in Columns (1) and (3), and county×year fixed effects in Columns (2) and (4). All estimations are weighted by the total population of the census tract. The t-statistics are reported in parentheses and all standard errors are clustered at the county level. ***, **, and * denote the significance of the parameter estimates at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	ZHVI Growth		ΔPrice-to-Rent	
$\widehat{\text{Nonbank Share}}$	0.0799***	0.0394***	0.1450***	0.0916***
	(58.67)	(47.92)	(35.24)	(23.23)
log(Median Income)	-0.0141***	-0.0123***	-0.0036***	-0.0024***
	(-65.10)	(-94.06)	(-5.48)	(-3.89)
Minority Application Share	0.0206***	0.0236***	0.0287***	0.0320***
	(52.96)	(99.90)	(25.08)	(29.28)
Female Application Share	-0.0051***	-0.0036***	-0.0061***	-0.0053***
	(-10.77)	(-12.57)	(-4.42)	(-4.06)
Average Loan-to-Income	-0.0021***	-0.0014***	-0.0064***	-0.0032***
	(-14.36)	(-14.92)	(-14.47)	(-7.56)
Per Cap Income Growth Last 2 Yrs	-0.0069***	-0.0006	-0.0239***	-0.0073**
	(-6.58)	(-1.02)	(-7.28)	(-2.34)
Population Growth Last 2 Yrs	-0.0066***	-0.0052***	-0.0460***	-0.0378***
	(-4.74)	(-6.28)	(-9.80)	(-8.56)
ZHVI Growth Last 2 Yrs	0.0152***	0.1879***	-0.0330***	0.1886***
	(10.26)	(141.87)	(-7.58)	(31.64)
County FE, Year FE	✓		✓	
County×Year FE		✓		✓
Obs.	528,604	528,604	450,679	450,679
First-Stage F-Statistics	120.78	114.35	144.88	134.08

Table 7: Nonbank Mortgage Share and Home Price Dispersion within a County

This table reports the IV regression results using *Conforming Eligibility (County)*. We use the county level observations from 2013 to 2021. The dependent variable are SD($ZHVI$)/Mean($ZHVI$), the standard deviation of tract-level ZHVI values as a proportion of the average ZHVI value in the next year, and (Max($ZHVI$)−Min($ZHVI$))/Mean($ZHVI$), the difference between the maximum and minimum tract-level ZHVI values as a proportion of the average ZHVI value in the next year. The main independent variable is $\widehat{\textit{Nonbank Share}}$, the nonbank mortgage share in a county, instrumented by *Conforming Eligibility (County)*, county-level difference between the conforming loan limit and ZHVI value. In all columns, we include control variables such as log($Median\ Income$) ($County$), *Minority Application Share (County)*, *Female Application Share (County)*, and *Average Loan-to-Income (County)*, as well as *Per Cap Income Growth Last 2 Yrs (County)*, *Population Growth Last 2 Yrs (County)*, and *ZHVI Growth Last 2 Yrs (County)*. We include state and year fixed effects in odd columns, and state×year fixed effects in even columns. All estimations are weighted by the total population of the county. The t-statistics are reported in parentheses and all standard errors are clustered at the state level. ***, **, and * denote the significance of the parameter estimates at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	$\frac{\text{SD(ZHVI)}}{\text{Mean(ZHVI)}}$		$\frac{\text{(Max(ZHVI)-Min(ZHVI))}}{\text{Mean(ZHVI)}}$	
$\widehat{\text{Nonbank Share}}$ (County)	-0.2863**	-0.3111**	-0.8886*	-0.9389**
	(-2.31)	(-2.32)	(-1.97)	(-2.22)
log(Median Income) (County)	0.3020***	0.2025***	1.3025***	0.8273***
	(5.70)	(4.59)	(6.43)	(5.90)
Minority Application Share (County)	0.2833***	0.1776*	1.4851***	0.9629***
	(3.46)	(1.94)	(5.80)	(4.11)
Female Application Share (County)	1.1440***	0.8600***	4.9579***	3.6218***
	(5.37)	(4.94)	(5.57)	(5.19)
Average Loan-to-Income (County)	0.1372***	0.1046***	0.5709***	0.4199***
	(4.23)	(2.95)	(5.09)	(3.53)
Per Cap Income Growth Last 2 Yrs (County)	0.1775	0.2219	0.4220	0.4750
	(0.61)	(0.97)	(0.36)	(0.59)
Population Growth Last 2 Yrs (County)	-0.1635	-1.3490	3.9517	-1.6773
	(-0.17)	(-1.38)	(1.24)	(-0.54)
ZHVI Growth Last 2 Yrs (County)	0.2763	0.4629*	0.8292	1.5502*
	(1.22)	(2.00)	(0.98)	(1.88)
State FE, Year FE	✓		✓	
State×Year FE		✓		✓
Obs.	19,302	19,302	19,302	19,302
First-Stage F-Statistics	20.75	22.05	20.75	22.05

Table 8: Nonbank and Mortgage Delinquency

This table presents the panel regression results that examine the effect of nonbank mortgage origination on mortgage delinquency. We use the loan-year-month level observations from 2013 to 2022. The dependent variables are *Underwater*, a dummy variable that equals 1 if the current market value of the underlying property is below than the present value of the loan (i.e., negative equity), *Distance-to-Underwater*, the difference between the current market value of the property and the present value of the loan as a proportion of the current market value of the property, and *90+ Delinquency*, a dummy variable that equals 1 if the loan has been delinquent for more than 90 days. The main independent variable is *Nonbank*, a dummy variable that equals 1 if a loan is originated by nonbank lenders. In Columns (7)–(8), we include *Refinance Incentive* and *Default Incentive*, which measures borrower's incentive on refinance and default, respectively. In all columns, we include control variables such as *FICO*, *LTV b/w 80%–95%*, *LTV above 95%*, log(*Loan Amount*), *Mortgage Rate*, *Minority*, *Female*, and *Co-borrower*. Odd columns include census tract, origination year, and reporting year fixed effects and even columns include census tract×origination year and reporting year fixed effects. The t-statistics are reported in parentheses and all standard errors are clustered at the census tract and year level. ***, **, and * denote the significance of the parameter estimates at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Underwater		Distance-to-Underwater		90+ Delinquency×100			
Nonbank	0.0030***	0.0036***	-0.0047***	-0.0053***	0.0034***	0.0028*	0.0028**	0.0021
	(10.82)	(13.30)	(-17.43)	(-19.69)	(2.78)	(1.94)	(2.19)	(1.43)
Refinance Incentive							-0.0800***	-0.0679***
							(-12.42)	(-10.41)
Default Incentive							0.1256***	0.1159***
							(17.68)	(14.74)
FICO	-0.0000***	-0.0000***	0.0001***	0.0001***	-0.0013***	-0.0013***	-0.0013***	-0.0013***
	(-12.29)	(-13.67)	(23.95)	(25.64)	(-81.42)	(-74.69)	(-81.05)	(-74.35)
LTV b/w 80%–95%	0.0104***	0.0103***	-0.1464***	-0.1479***	0.0037***	0.0059***	-0.0149***	-0.0115***
	(28.65)	(28.01)	(-294.80)	(-302.88)	(3.44)	(4.71)	(-11.85)	(-8.08)
LTV above 95%	0.1356***	0.1371***	-0.2328***	-0.2348***	0.0290***	0.0345***	-0.0018	0.0059**
	(84.07)	(80.25)	(-361.97)	(-342.06)	(17.15)	(17.47)	(-0.87)	(2.55)
log(Loan Amount)	0.0008***	0.0006**	-0.0827***	-0.0869***	0.0324***	0.0320***	0.0222***	0.0221***
	(2.82)	(2.14)	(-29.79)	(-28.53)	(24.04)	(21.40)	(17.04)	(14.60)
Mortgage Rate	0.0525***	0.0520***	-0.0896***	-0.0891***	0.0433***	0.0460***	0.0404***	0.0428***
	(68.00)	(65.16)	(-317.18)	(-330.31)	(34.25)	(32.57)	(29.28)	(27.42)
Minority	0.0047***	0.0042***	-0.0057***	-0.0057***	0.0251***	0.0254***	0.0243***	0.0246***
	(11.43)	(9.97)	(-15.52)	(-15.77)	(11.94)	(10.46)	(11.60)	(10.18)
Female	0.0005**	0.0005**	0.0004**	0.0002	-0.0023**	-0.0032***	-0.0022**	-0.0031***
	(2.55)	(2.28)	(2.28)	(1.32)	(-2.45)	(-2.94)	(-2.40)	(-2.91)
Co-borrower	0.0015***	0.0021***	0.0064***	0.0066***	-0.0355***	-0.0364***	-0.0348***	-0.0357***
	(6.03)	(8.93)	(31.40)	(33.01)	(-30.28)	(-27.38)	(-29.77)	(-26.88)
Reporting Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Census Tract FE, Origination Year FE	✓		✓		✓		✓	
Census Tract×Origination Year FE		✓		✓		✓		✓
Obs.	53,254,707	53,254,707	51,726,818	51,726,694	53,254,707	53,254,707	53,254,707	53,254,707
R-Squared	0.184	0.262	0.776	0.812	0.003	0.010	0.003	0.010

Table 9: Nonbank and Mortgage Delinquency, by Year

This table presents the panel regression results that examine the effect of nonbank mortgage origination on mortgage delinquency by year. We use the loan-year-month level observations from 2013 to 2022. The dependent variables are *Underwater*, a dummy variable that equals 1 if the current market value of the underlying property is below than the present value of the loan (i.e., negative equity), *Distance-to-Underwater*, the difference between the current market value of the property and the present value of the loan as a proportion of the current market value of the property, and *90+ Delinquency*, a dummy variable that equals 1 if the loan has been delinquent for more than 90 days. The main independent variables are the interactions between *Nonbank*, a dummy variable that equals 1 if a loan is originated by nonbank lenders, and dummy variables for reporting year. In Columns (7)–(8), we include *Refinance Incentive* and *Default Incentive*, which measures borrower's incentive on refinance and default, respectively. In all columns, we include control variables such as *FICO*, *LTV b/w 80%–95%*, *LTV above 95%*, log(*Loan Amount*), *Mortgage Rate*, *Minority*, *Female*, and *Co-borrower*. Odd columns include census tract, origination year, and reporting year fixed effects and even columns include census tract×origination year and reporting year fixed effects. The t-statistics are reported in parentheses and all standard errors are clustered at the census tract and year level. ***, **, and * denote the significance of the parameter estimates at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Underwater		Distance-to-Underwater		90+ Delinquency×100			
Nonbank×I(Year=2013)	0.0046***	0.0107***	-0.0080***	-0.0122***	-0.0209***	-0.0276***	-0.0217***	-0.0289***
	(4.51)	(9.76)	(-5.75)	(-6.66)	(-7.41)	(-7.28)	(-7.73)	(-7.64)
Nonbank×I(Year=2014)	0.0206***	0.0245***	-0.0087***	-0.0118***	-0.0211***	-0.0302***	-0.0221***	-0.0315***
	(14.14)	(16.61)	(-7.22)	(-7.84)	(-6.83)	(-7.84)	(-7.18)	(-8.21)
Nonbank×I(Year=2015)	0.0161***	0.0190***	-0.0078***	-0.0104***	-0.0173***	-0.0260***	-0.0184***	-0.0273***
	(13.39)	(15.82)	(-7.75)	(-8.71)	(-6.39)	(-8.14)	(-6.77)	(-8.53)
Nonbank×I(Year=2016)	0.0135***	0.0158***	-0.0065***	-0.0087***	-0.0084***	-0.0187***	-0.0093***	-0.0198***
	(10.86)	(12.53)	(-8.55)	(-10.57)	(-2.93)	(-5.92)	(-3.24)	(-6.24)
Nonbank×I(Year=2017)	-0.0012*	0.0009	-0.0048***	-0.0065***	0.0074**	-0.0024	0.0069*	-0.0031
	(-1.96)	(1.54)	(-7.62)	(-10.96)	(1.99)	(-0.66)	(1.85)	(-0.84)
Nonbank×I(Year=2018)	-0.0064***	-0.0033***	-0.0009**	-0.0019***	-0.0231***	-0.0322***	-0.0232***	-0.0324***
	(-14.21)	(-6.67)	(-1.98)	(-4.35)	(-9.98)	(-11.27)	(-10.01)	(-11.32)
Nonbank×I(Year=2019)	0.0078***	0.0107***	-0.0048***	-0.0056***	-0.0186***	-0.0290***	-0.0193***	-0.0297***
	(9.16)	(13.12)	(-8.29)	(-10.90)	(-8.64)	(-10.47)	(-8.82)	(-10.60)
Nonbank×I(Year=2020)	0.0052***	0.0067***	-0.0091***	-0.0096***	-0.0129***	-0.0167***	-0.0138***	-0.0176***
	(5.40)	(7.84)	(-19.10)	(-20.83)	(-2.63)	(-3.37)	(-2.81)	(-3.54)
Nonbank×I(Year=2021)	0.0013***	0.0009***	-0.0058***	-0.0061***	0.0240***	0.0263***	0.0234***	0.0257***
	(3.62)	(2.58)	(-13.05)	(-15.43)	(13.64)	(14.14)	(13.30)	(13.79)
Nonbank×I(Year=2022)	0.0001	-0.0007	-0.0011*	-0.0013**	0.0217***	0.0265***	0.0209***	0.0258***
	(0.18)	(-1.50)	(-1.96)	(-2.38)	(14.10)	(16.59)	(13.50)	(16.00)
Loan-level Charateristics	✓	✓	✓	✓	✓	✓	✓	✓
Reporting Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Census Tract FE, Origination Year FE	✓		✓		✓		✓	
Census Tract×Origination Year FE		✓		✓		✓		✓
Default Incentive & Refi Incentive							✓	✓
Obs.	53,254,707	53,254,707	51,726,818	51,726,694	53,254,707	53,254,707	53,254,707	53,254,707
R-Squared	0.184	0.262	0.776	0.812	0.003	0.010	0.003	0.010