Nonbank Growth and Local Housing Booms*

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Abstract

We study the effect of uneven nonbank mortgage expansion on localized housing market dynamics. Leveraging the local conforming loan-eligible share as an instrument for nonbank credit supply, we show that increased nonbank lending drives housing booms, characterized by rapid home price appreciation, rising transaction volumes, and intensified market competition. The effects of nonbank credit are especially persistent in census tracts near affluent neighborhoods, potentially by facilitating gentrification, while more short-lived in areas further from these neighborhoods. Additionally, we demonstrate that nonbank credit expansion has contributed to narrowing within-county price disparities across neighborhoods, thereby reshaping wealth distribution. Our findings highlight the crucial role of nonbank credit in housing market trends and household welfare.

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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 (Buchak et al., 2024). As the GSEs are purchasing conforming mortgages, mainly defined by the upper limit of loan amounts, nonbanks naturally concentrate their lending in areas where a larger share of home transaction prices fall below these limits. This uneven expansion of nonbank would work as a differential credit shock across neighborhoods within a county. In this paper, we study the role of uneven nonbank expansion as a shock for easier credit and explore how it explains the heterogeneity in the local housing market dynamics.

We use the Home Mortgage Disclosure Act (HMDA) data from 2013 to 2021 to identify the growth of nonbank lending, finding a significant variation in nonbank growth across census tracts within a county. However, the uneven nonbank growth within a county can be both demand- and supply-driven credit shock.[1] That is, nonbanks can passively meet the local loan demand, or nonbanks are actively choosing census tracts to expand, or both. To isolate the supply-driven credit shock from the nonbank growth, we propose a novel instrumental variable (IV) strategy using *Conforming Share*, the proportion of conforming loan-eligible housing transactions in a census tract, from CoreLogic Transaction Deeds data. All else being

[1] A prominent body of research argues that easier credit is preceded by shifts in market sentiment and expectations about future appreciation, and therefore, credit supply alone cannot account for the significant price booms in the early 2000s (DeFusco et al., 2022; Glaeser et al., 2013; Nathanson and Zwick, 2018).

equal, nonbanks are more likely to expand in the census tract with a higher *Conforming Share* as it would be a larger market for them.

To illustrate the validity of *Conforming Share* as an IV, consider two hypothetical census tracts, *A* and *B*. As shown in Panel A of Figure 1, these tracts have similar average home prices but differ in price distributions, which create distinct opportunities for lenders—particularly nonbanks that heavily rely on the OTD model. Tract *A*, with less dispersed home prices, has a higher share of conforming-eligible loans compared to tract *B*, which has more dispersed home prices. This difference makes tract *A* more attractive for nonbank expansion. By leveraging variations in local price distributions, measured by *Conforming Share*[2], we capture the different incentives driving nonbanks to expand their presence in local markets. This approach enables us to quantify the impact of nonbank credit growth on localized housing market dynamics.

Our key identifying assumption for the exclusion condition of our instrument is that given the same home price levels (i.e., holding the mean of the home price distribution across census tracts constant), the shape of the home price distribution (i.e., the left tail below the CLL representing the conforming share) does not directly drive a housing boom in subsequent years, except through the credit channel. To satisfy the identical housing market assumption, we include fixed effects for tract-level house price deciles, housing transaction volume deciles, and loan origination count deciles in our specifications. These stringent fixed effects ensure that we compare tracts with closely matched, if not identical, local housing market conditions.

We first confirm the relevance condition by showing that *Conforming Share* significantly increases the growth of nonbank shares with county-by-year fixed effects, with statistical significance of t-statistics larger than 13.69. The result is robust with different levels of fixed effect and various census tract characteristics as controls. We also find that a higher

[2]While *Conforming Share* might seem conceptually similar to the second moment (i.e., variance) of home prices within a neighborhood, the relationship between *Conforming Share* and price variance is not linear or one-to-one. Specifically, when the CLL exceeds the average home price, as illustrated in Figure 1, neighborhoods with smaller price dispersion would have larger *Conforming Share*. In contrast, when the CLL is below the average home price, as shown in Figure A1, neighborhoods with greater price dispersion would exhibit larger *Conforming Share*.

Conforming Share is associated with increased credit growth by both banks and nonbanks while the growth of nonbank origination is double the size of the growth of bank origination. This result indicates that the growth of nonbank shares is not entirely due to the withdrawal of traditional banks in the area (Benson et al., 2024; Buchak et al., 2018).

Having established the validity of the IV, we examine the impact of uneven nonbank growth on the local housing boom in the following year. We first find that the local home price significantly increases with the growth of nonbank origination. A one percentage point increase in nonbank origination share in a census tract results in a 0.793–0.876 percentage point greater growth rate in home values in the census tract. We also find that the price-to-rent ratio increases with the growth of nonbank origination, indicating that the price appreciation is above the fundamental growth in rental prices. Both results show that a higher nonbank growth, instrumented by a larger local *Conforming Share*, significantly increases home prices in a census tract relative to other tracts within the same county.

Nonbank growth not only increases the home price but also affects transaction volume and bidding behaviors, collectively indicating a localized housing boom. Using the CoreLogic Transaction Deeds data to measure the growth in home transaction volume, we find that the nonbank growth in a census tract significantly increases the transaction volumes in the census tract. Moreover, using the CoreLogic Multiple Listing Service (MLS) dataset, we find that the nonbank growth in a census tract increases the fraction of housing transactions sold above the listing prices, indicating the heated housing market (Han and Strange, 2016). A one percentage point increase in the nonbank origination share in a tract leads to an increase in the share of transactions above the listing price by 0.504 to 0.555 percentage points.

While our results suggest a housing boom followed by the growth of nonbank in a census tract, we find that the effect of nonbank growth on housing prices has heterogeneous long-term effects. On average, we find that positive home price growth has continued for several years. That is, the increased home price associated with nonbank credit growth seems to have a persistent effect in the local area. However, the results are starkly different by the pre-condition of neighborhoods. Drawing on Guerrieri et al. (2013) that housing demand spills over from affluent neighborhoods to nearby lower-income neighborhood—i.e., endogenous gentrification, we divide census tracts into two groups based on their proximity to the nearest neighborhood in the top quartile of median income. We find the long-term effect only at the census tracts near rich neighborhoods, whereas the effect disappears after a year in tracts far away from the rich neighborhoods. The difference might indicate that nonbank growth may trigger local gentrification only in neighborhoods close to rich areas, while in other locations, nonbank credit expansion may temporarily overheat home prices above their fundamental values.

Given the heterogeneous long-term effects of nonbank credit growth on local housing markets, we further explore how nonbank credit expansion influences mortgage performance.[3] To investigate this, we use the loan-year-quarter level performance data by merging the GSE performance dataset and HMDA. Leveraging local *Conforming Share* as an IV,[4] we find that loans originated by nonbanks or in areas experiencing greater nonbank credit-driven housing booms exhibit significantly lower 90+ day delinquency rates. This trend is particularly pronounced in census tracts near affluent neighborhoods, whereas the impact on delinquency is statistically insignificant in tracts farther from affluent areas. These heterogeneous effects once again present the critical role of neighborhood characteristics in shaping the long-term influence of nonbank credit growth.

Then, we study how localized housing dynamics influence price dispersions within counties. We find that within-county price dispersion decreases with nonbank credit growth. To show this, we use the predicted home price growth by the nonbank credit channel calculated from the estimated coefficients in previous analyses[5], and compute the trajectory of home price

[3]This analysis also provides valuable insights into the performance of nonbank-originated mortgages, a topic with mixed evidence in the literature. For instance, nonbanks may face higher default risks than traditional banks due to their stronger motivation to securitize mortgages more quickly (Kim et al., 2022), but their advanced screening technologies might mitigate these risks and lead to lower delinquency rates (Fuster et al., 2019).

[4]Our instrument, *Conforming Share*, remains valid in this context as it predicts the likelihood of nonbank-originated loans through exogenous factors unrelated to local housing market conditions or expectations.

[5]Specifically, we employ the coefficients estimated by each home price decile group using the specifications presented in the first columns of Table 2 and Table 4.

dispersions within counties.[6] The predicted path of within-county home price dispersion declines over time, with a similar reduction in price dispersion found in the actual data. The nonbank credit channel explains approximately 50% of the observed decline in price dispersion in the data, suggesting the significant role of nonbank growth in explaining the home price convergence within a city during the boom.

This reduction in home price dispersion driven by nonbank growth generates a wealth redistribution effect. By comparing the additional wealth accrued by homeowners in the bottom 20th percentile of census tracts to those in the top 20th percentile, our back-of-the-envelope calculation reveals that a homeowner in the bottom 20th percentile gains an additional $410.42 in home equity annually through the nonbank credit channel. This represents a 12.1% larger home equity gain compared to homeowners in the top 20th percentile tracts. Note that this wealth redistribution occurs without any increase in default risk as shown earlier.

Lastly, we investigate the broader implications of nonbank credit-driven housing booms for neighborhood transformation and rental market outcomes. We find that nonbank credit expansion is associated with an increase in the share of college-educated residents, indicating the onset of a gentrification process (Guerrieri et al., 2013). Rent prices also rise with nonbank credit growth, but rent burdens—measured by the rent-to-income ratio—remain unaffected, indicating that higher rents may be offset by rising local incomes. Importantly, we find no evidence of significant renter displacement to poorer neighborhoods, which is a key concern about gentrification (Qiang et al., 2021). Overall, our findings suggest that nonbank credit transforms neighborhood demographics and raises rental prices without significantly exacerbating financial pressures on renters.

Our paper contributes to three strands of literature. First, our findings add to the body of work on credit supply and its impact on housing price dynamics (Adelino et al., 2025; Di Maggio and Kermani, 2017; Favara and Imbs, 2015; Favilukis et al., 2017; Landvoigt, 2017). Our study complements these insights by showing that nonbank lending acts as a credit

[6] Neighborhood home price dispersion within a county is measured by the coefficient of variation of census tract home values (i.e., the standard deviation of census tract-level home values/the mean of home values).

shock, leading to localized housing booms characterized by rapid price appreciation, increased transaction volumes, and intensified market competition. We leverage the fact that nonbanks typically operate exclusively in the mortgage lending market with the OTD business model, giving them stronger incentives to expand into markets with higher conforming loan-eligible shares. To isolate the effect of the nonbank credit channel from other factors influencing housing markets, we use the local conforming loan-eligible share as an IV. Our approach is particularly aligned with the methodology of Adelino et al. (2025), who leverage annual changes in CLL and the 80% LTV threshold to capture changes in credit accessibility.

Second, our work is also highly relevant to the nonbank mortgage lending literature (Buchak et al., 2024; Gete and Reher, 2021; Irani et al., 2021; Benson et al., 2024). We add to this body of research by identifying an exogenous factor—local conforming loan-eligible share—that drives nonbank lending growth in local markets. This relationship is shaped by nonbanks' reliance on the OTD model and the structure of securitization markets. Additionally, our study provides new insights into the performance of nonbank-originated mortgages, a topic marked by mixed findings. For instance, Kim et al. (2022) argue that nonbanks, motivated by rapid securitization, may face higher default risks, while Fuster et al. (2019) show that fintech nonbank lenders achieve lower delinquency rates, likely due to advanced screening technologies. Our results indicate that nonbank credit supply may reduce delinquency risks by spurring local housing markets. However, note that this positive impact on loan performance is absent in neighborhoods farther from rich areas, which highlights the critical role of neighborhood characteristics in shaping the effects of nonbank lending on mortgage outcomes.

Third, we contribute to the literature on gentrification and housing wealth redistribution. Guerrieri et al. (2013) demonstrates that during city-wide housing booms, neighborhoods with initially lower housing prices tend to experience faster appreciation. Our findings build on this framework, showing that nonbank-driven credit shocks catalyze price appreciation in lower-income neighborhoods while also driving demographic shifts and higher rent prices. Crucially, we find no significant evidence of renter displacement, which is a major concern associated with gentrification. Over time, these dynamics foster convergence in housing prices within counties, redistributing housing wealth across neighborhoods. This aligns with Favilukis et al. (2017), who highlight how financial liberalization can reduce housing inequalities and reshape wealth distribution. Overall, our results emphasize the lasting impact of nonbank credit on local housing market dynamics and household welfare.

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 market dynamics. Section 4 concludes.

2. Data and Summary Statistics

The primary data sources for our analysis are the HMDA and CoreLogic, covering the period from 2013 to 2021. The HMDA dataset encompasses nearly the entire landscape of U.S. mortgage applications, offering detailed information on lender ID, loan application outcomes (approved or denied), applicant characteristics, and loan-level details such as 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 and construct key variables, including Δ*Nonbank Share*.

The CoreLogic Deeds data includes comprehensive information on all deed transfers, and coverage of CoreLogic is known to be very high, reportedly capturing over 90% of U.S. property transactions. We use the deeds data to construct census tract-level variables such as *Conforming Share* and *Transaction Volume Growth*. Additionally, the CoreLogic MLS data provides detailed information on housing listings, including listing prices and final contract prices. Using the MLS data, we construct variables such as Δ*Overbid Share*.

Based on the HMDA and CoreLogic datasets, we construct the following datasets to address specific questions in this study.

2.1. Census tract-level Dataset

First, we construct a tract-year panel dataset by aggregating loan-level data from HMDA and housing transaction deeds and listings data from CoreLogic. For the conforming eligibility of mortgage origination or housing transaction, we use the CLL set by the Federal Housing Finance Agency (FHFA), annually adjusting the county-level CLL to accommodate mortgage supply under the rising housing prices.[7] While the CLLs are constant within counties, the share of housing transactions eligible for conforming loans varies across census tracts within a county. This allows us to examine the impact of conforming loan eligibility on nonbank lending activities, as well as on local housing market conditions, at the census tract level. Panel A of Table 1 reports summary statistics for the census tract-level variables used in our analyses.

We define *Conforming Share*, which captures the proportion of housing transactions eligible for conforming mortgages, as the share of housing transaction records where 80% of the sale prices fall below the CLL from CoreLogic Transaction Deeds data.[8][9] *Conforming Share* has a mean of 92.0% with a standard deviation of 18.7%, indicating substantial variation in conforming loan eligibility across tracts.

To measure the increase in nonbank origination activity, we begin by identifying nonbank lenders within the HMDA data. We classify lenders as nonbanks if they are non-depository mortgage originators that are not regulated by any federal regulators, following Demyanyk and Loutskina (2016) and Gete and Reher (2021). Our sample shows a steady increase in the nonbank market share, growing from 32.1% in 2013 to 56.8% in 2021, as illustrated in

[7] 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.

[8] We apply an 80% multiplier to the sale price because it is generally "easier" to finance with a conforming mortgage when the loan amount is below an 80% LTV ratio (Adelino et al., 2025). Residential mortgage loans with an LTV ratio above 80% require private mortgage insurance, which significantly increases the monthly mortgage payment (Green and Wachter, 2005).

[9] Notably, when calculating *Conforming Share*, we include all housing transactions, regardless of whether a mortgage was actually involved. This is because our measure focuses on conforming loan eligibility—reflecting the potential for a property to qualify for conforming loans—rather than the actual share of conforming loans originated.

Figure 2. We then aggregate loan-level data to calculate Δ*Nonbank Share*, the annual change in the fraction of nonbank mortgage originations within each census tract. The average value of Δ*Nonbank Share* across tracts is 2.6%, with substantial variability (standard deviation of 16.3%), again indicating heterogeneity in the growth of nonbank lending across neighborhoods.

To capture housing market dynamics, we measure the annual growth rate of home prices at the census tract level (*HP Growth*) using the FHFA House Price Index, with an average of 6.5% and a standard deviation of 6.9%. The annual growth in home transaction volume (*Transaction Volume Growth*) is derived from CoreLogic Transaction Deed data, averaging 12.4% across tracts. To calculate the change in the price-to-rent ratio (Δ*Price-To-Rent*), we first divide the Zillow Observed Rent Index (ZORI) by the FHFA House Price Index to obtain the *Price-To-Rent* ratio, then calculate its annual changes. Since ZORI is available at the ZIP Code level, we convert ZORI values to the census tract level using the HUD-USPS ZIP-TRACT Crosswalk file.[10] Δ*Overbid Share* is an additional measure of demand-driven housing market boom, calculated as the annual change in the percentage of transactions sold above the listing price using data from the CoreLogic MLS dataset. The mean and standard deviation of Δ*Overbid Share* are 4.3% and 15.7%, respectively.[11]

Panel A of Table 1 also reports additional census tract-level control variables used in our analysis, most of which are derived directly from HMDA data. *Avg. Applicant Income* has a mean of 1.099 and a standard deviation of 1.286 (measured in $100,000). *Avg. Female Applicant Share* captures the fraction of female applicants in the census tract, with an average of 31.8%. Similarly, *Avg. Minority Applicant Share* measures the share of loan applications from minority borrowers, with a mean of 8.3%. *Avg. Loan-to-Income* is the average loan-to-income ratio within each census tract, with a mean of 2.816.

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

[11] Note that due to the limited coverage of the ZORI and CoreLogic MLS dataset, the sample sizes of Δ*Price-To-Rent* and Δ*Overbid Share* are smaller than other tract-year level variables.

2.2. Loan-year-quarter Performance Dataset

In addition to the tract-year panel, we construct a loan-year-quarter level loan performance dataset to examine the delinquency rate of loans by nonbank lenders. We merge the HMDA data with the GSE performance data, tracing the quarterly performance of loans bought by the GSEs to the end of the year 2022.[12] After the matching, our sample is restricted to fixed rate purchase mortgages for single-family owner-occupied housing, and we have 4,371,874 observations in a panel performance structure with multiple time-series observations of a mortgage loan, with the average loan continuation of 12.4 quarters. Panel B of Table 1 reports the summary statistics of the variables at the loan-year-quarter level.

We construct *90+ Delinquency* to measure the loan performances, as a dummy variable that equals 1 if the loan has been delinquent for more than 90 days in a given quarter. It has a mean of 0.236%, and the number translates into 2.89% when we take the average loan continuation of 12.4 quarters into account.[13]

As in the tract-level dataset, *Conforming Share* represents the proportion of housing transactions within a census tract eligible for conforming loans in the year of origination. We identify whether a loan is originated by a nonbank lender (*Nonbank*) and find that 40.3% of observations in our sample are originated by nonbanks.

Since we match HMDA with the GSE performance data, we can include a rich set of loan-level characteristics at the time of origination that are known to well-proxy the credit risk of loans. The average FICO score of the loans in the sample is relatively high, 755.4, as all the matched loans are purchased by the GSEs. The share of observations with the initial loan-to-value ratio (LTV) larger than 95% is 10.1%. The current LTV ratio is calculated by dividing the remaining loan balance by the current market value of the home, which is estimated by

[12] As there is 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.

[13] $1-(1-0.00236)^{12.4}=0.0289$

adjusting the initial purchase price according to changes in the tract-level home price index. The average current LTV ratio is 70.2%. *Loan Age* is on average 8.5 quarters. Minority and female borrower shares are 8.4% and 31.2%, respectively. 74.0% of loans in the sample have co-borrowers. The logarithm of the applicant's income at origination is 11.3 ($83,283.02).

To correctly understand the default decision, it is important to control the borrowers' incentive to default and refinance. We borrow the measures of borrower's incentive on default and refinance from the literature (Deng and Quigley, 2012; Deng et al., 2000), measuring the in-the-moneyness of a loan for the default prepayment option. First, we define *Default Incentive* as the difference between the present value of the remaining loan on the property and the current market value of the property, normalized by the property's current market value. On average, loans in our sample are at 27.9% out-of-money for the default option. Second, 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. The mean of *Refinance Incentive* is 0.6%, indicating that the average mortgages are slightly in-the-money for the refinancing option due to the long regime of low-interest-rate until 2021.

Additionally, for alternative measures of the default and refinance option values, we use *Underwater*, a dummy equal to 1 if the property's current market value is lower than the loan balance, and *Rate Gap*, the difference between the contracted coupon rate and the predicted current market rate on similar mortgages.[14] The proportion of properties that are underwater is, on average, 5.1%, and the average value of *Rate Gap* is 0.146 percentage points.

[14] We predict the current available market rate using a quadratic in FICO, a quadratic in current LTV, and a quadratic in loan age following Berger et al. (2021).

3. Empirical Results

3.1. Nonbank Growth and Local Housing Market Dynamics

We begin our analysis by examining the effect of uneven credit supply on heterogeneous dynamics in local housing markets. All else equal, an increase in credit supply can affect housing prices, potentially sparking a localized housing boom, as observed during the last global financial crisis (Chinco and Mayer, 2016; Choi et al., 2016; Gao et al., 2021). However, identifying the impact of credit supply on local home price growth is challenging because regressing home price changes on credit supply may suffer from endogeneity due to the nonrandom nature of credit distribution (Adelino et al., 2025; Benson et al., 2024; Di Maggio and Kermani, 2017; Favara and Imbs, 2015). For instance, an anticipated housing boom in a given area could simultaneously drive both an increase in credit supply and home price appreciation.

To address potential endogeneity, we propose a novel IV strategy using *Conforming Share*—the proportion of conforming loan-eligible housing transactions in a census tract—as an instrument for nonbank growth in an area. Unlike banks with diversified product lines, nonbank lenders focus exclusively on the mortgage lending business, making their incentives to expand credit strongly tied to the securitizability of loans (Gete and Reher, 2021; Gissler et al., 2020).[15] This reliance on securitization is a crucial feature of nonbanks' OTD business model, which heavily reliant on the liquidity advantages provided by MBS markets. This institutional feature suggests that *Conforming Share* may be a strong and plausible instrument for nonbank mortgage activity, as it captures local variation in the attractiveness of markets to nonbanks.

Panel A of Figure 1 hypothetically illustrates how differences in price dispersion may influence nonbanks' expansion into local markets. In this example, the less dispersed area, tract A, has a higher conforming loan-eligible share than the more dispersed area, tract B. This higher share would incentivize lenders—particularly nonbank lenders relying on the OTD

[15]Gete and Reher (2021) document that regulatory changes that are favorable to nonbanks for securitized loans increased the scale of nonbank lending in the FHA loan segment.

model—to supply more credit in tract A over tract B. As a result, the increased credit supply in tract A could drive a localized housing boom. Panel B of Figure 1 provides a real-world example of such variations. The figure shows the distribution of $\log(\textit{Sale Price} \times 80\%)$ for two census tracts: 114.05 in Baldwin County, AL (blue bars), and 513.03 in Sussex County, DE (red bars), in 2018. While the average values of $\log(\textit{Sale Price} \times 80\%)$ are nearly identical (12.61 in the tract in Baldwin County and 12.62 in the tract in Sussex County), and the same CLL is applied in both tracts, there is a notable difference in how prices are distributed. Home prices in the blue-colored tract are densely concentrated around the mean value, whereas the red-colored tract shows a distribution with heavier tails. Consequently, the share of transactions with 80% of values below the CLL differs significantly: 95.33% in the blue tract and 78.12% in the red tract. Thus, we leverage variations in local price distributions, measured by *Conforming Share*, to capture the different incentives driving nonbanks to expand their business in local markets.

Our key identifying assumption for using *Conforming Share* as an instrument for nonbank credit growth is that, given the same home price levels, the shape of the distribution of home prices does not directly drive a housing boom in subsequent years other than credit channel. Therefore, conditional on identical housing market conditions aside from distributional differences, any housing market dynamics associated with *Conforming Share* can be attributed to the additional credit supplied to the area. To meet the identical housing market assumption, we include tract-level fixed effects for house price deciles, housing transaction volume deciles, and loan origination count deciles. These stringent fixed effects ensure we are comparing tracts with closely matched, if not identical, local housing market conditions.

Specifically, we estimate the following regression equation:

(First Stage)

$$\Delta Nonbank\ Share_{tract,t} = \alpha + \beta \cdot Conforming\ Share_{tract,t} + \delta \cdot X_{tract,t} + \eta_{hp\ decile} + \eta_{transaction\ volume\ decile} + \eta_{loan\ count\ decile} + \eta_{county \times t} + \epsilon_{tract,t}, \quad (1)$$

(Second Stage)

$$Y_{tract,t+1} = \alpha + \beta \cdot \Delta \widehat{Nonbank\ Share}_{tract,t} + \delta \cdot X_{tract,t} + \eta_{hp\ decile} + \eta_{transaction\ volume\ decile} + \eta_{loan\ count\ decile} + \eta_{county \times t} + \epsilon_{tract,t}. \quad (2)$$

In the first stage, we define $\Delta Nonbank\ Share_{tract,t}$ as the changes in the nonbank mortgage origination share within a tract in year t. $Conforming\ Share_{\text{tract},t}$ represents the share of housing transactions in a census tract where 80% of the sale price falls below the CLL, measuring the share of conforming-eligible loans. $X_{tract,t}$ denotes a list of controls, such as log(*Avg. Applicant Income*), *Female Application Share*, *Minority Application Share*, and *Avg. Loan-to-Income*. Additionally, we account for tract-level housing market conditions by including fixed effects for house price deciles, housing transaction volume deciles, loan origination count deciles, and county-year fixed effects to control for time-varying county-level shocks. Standard errors are clustered at the county level.

In the second stage, we examine how changes in nonbank origination share affect various housing market outcomes in the following year. The dependent variable $Y_{tract,t+1}$ represents key housing market indicators, including *HP Growth*, Δ*Price-To-Rent*, *Transaction Volume Growth*, and Δ*Overbid Share*. Using predicted nonbank share changes, $\Delta \widehat{Nonbank\ Share}_{tract,t}$ from the first stage, we can identify the effect of the exogenous increase of nonbank credit expansion on these outcomes. The second stage model also includes the same set of controls and fixed effects a in the first stage.

3.1.1. First Stage: Conforming Loan Share and Nonbank Credit Growth

Table 2 presents the estimation results of the first-stage regression. We find that census tracts with a higher conforming share exhibit a significant growth of nonbanks. In Column (1), the univariate regression—incorporating house price deciles, transaction volume deciles, loan origination count deciles, and county-by-year fixed effects—shows that the coefficient for *Conforming Share* is 0.033. This indicates that a one percentage point increase in the conforming share within a census tract is associated with a 0.033 percentage point increase in the nonbank origination share in the same year. Columns (2) and (3) present results with different combinations of fixed effects, and the findings remain consistent. In Columns (4)–(6), we replicate the regression of Δ*Nonbank Share* on *Conforming Share*, this time including various census tract characteristics as controls to find the results hold true. The strong positive correlation between *Conforming Share* and the growth of nonbank presence in the neighborhood confirms the relevance condition of the instrument.

While our results indicate that credit supply through nonbanks increases in markets with higher eligibility for conforming loans, this could be driven by nonbanks filling the gap left by traditional banks withdrawing from the mortgage market, rather than by additional credit supply in the neighborhood. For example, Buchak et al. (2018) argue that approximately 60% of the growth in shadow banking during the mid-2010s can be attributed to traditional banks responding to increased regulatory burdens. Also, Benson et al. (2024) shows that variation in exposure to the nationwide exit shock of JPMorgan Chase in 2013 explains the exogenous growth of nonbank lenders in the local mortgage market.

Table 3 explores this possibility. Columns (1)–(3) report results using *Bank Loan Growth*, defined as the growth rate of the aggregate loan count originated by banks in a census tract, as the dependent variable. Similarly, Columns (4)–(6) present results from regressing *Nonbank Loan Growth*, the growth rate of the aggregate loan count by nonbanks, on *Conforming Share*. We find that a higher *Conforming Share* is associated with increased growth rates of loan originations for both banks and nonbanks. Specifically, a one percentage point increase in *Conforming Share* leads to an additional 0.069 to 0.098 percentage point growth in bank-originated mortgages (Columns (1)–(3)) and an additional 0.125 to 0.144 percentage point growth in nonbank-originated loans (Columns (4)–(6)). Therefore, the faster increase in nonbank origination share observed in Table 2 is explained by the stronger impact of local conforming-eligible loan share on nonbank activities compared to banks, rather than massive withdrawal of banks in the local mortgage markets.

3.1.2. Second Stage: Nonbank Credit Growth and Local Housing Booms

Next, we examine the impact of uneven nonbank growth, instrumented by *Conforming Share*, on the local housing boom in the following year. We start by examining the intensive margin effect, i.e., the impact on home prices. In Table 4, the dependent variable is *HP Growth*, the growth rate of the FHFA tract-level home price index from year t to $t+1$. Across all combinations of fixed effects and with the inclusion of tract-level controls, we find that an increase in nonbank origination share leads to a rise in home values in the subsequent year. Specifically, the coefficients for $\Delta\widehat{Nonbank\ Share}$ are estimated to be 0.793–0.876, meaning that an additional one percentage point increase in nonbank origination share results in a 0.793 to 0.876 percentage point greater growth rate in home values. This indicates there is a localized housing boom driven by nonbank expansions.

In Table 5, we replace the dependent variable with Δ*Price-to-Rent*, which represents the change in the price-to-rent ratio from year t to $t+1$.[16] The growth in the price-to-rent ratio differs from the growth in home prices, as the price-to-rent ratio measures home prices relative to their annual rent, reflecting the fundamental cash flow from the property. We find that the increased credit supply from nonbanks, instrumented by the local conforming eligible share, raises local home prices above the level supported by rental prices. The coefficients for $\Delta\widehat{Nonbank\ Share}$ range from 0.361 to 0.412, indicating that the uneven increase in housing

[16] To calculate the price-to-rent ratio, we utilize ZIP code-level Zillow Observed Rent Index (ZORI) and convert it for the census tracts. As there are some census tracts that are not covered by ZORI, note that our sample size for the price-to-rent ratio drops to 91,467.

prices is aligned with the uneven growth of nonbanks.

We next examine the extensive margin effect of nonbank credit growth. Table 6 presents the IV regression results using *Transaction Volume Growth*, the growth rate of housing transactions from year t to $t{+}1$, as the dependent variable. The results consistently suggest that an increase in local nonbank share results in a rise in greater growth in housing transaction volume in the following year, the estimated coefficients ranging from 0.866 to 1.414.

Another measure we use to study the local housing price response is Δ*Overbid Share*, which represents the change in the share of housing transactions sold above the listing price. Transactions that exceed the listing price—typically caused by bidding wars—rise in the booming housing markets (Han and Strange, 2016). As long as listing prices reflect the seller's fair market evaluation, Δ*Overbid Share* captures the demand-side forces driving local housing booms.[17] Table 7 presents the estimates, showing consistent results with previous findings: a one percentage point increase in the nonbank origination share in a tract leads to an increase in the share of transactions above the listing price by 0.504 to 0.555 percentage points.

Overall, our results suggest that the growth of nonbank lenders is strongly associated with increased home purchase demand, which in turn contributes to a local housing boom. This increased demand drives home price appreciation even beyond the fundamental rent flow values, a higher transaction volume, and more frequent bidding wars in the following year.

3.1.3. Heterogeneous Long-Run Impact of Nonbank Credit

Having established that nonbank credit growth influences the local housing market in the year following the shock, we now assess its long-term effects. We estimate regressions similar to those in Column (1) of Table 4, replacing the dependent variable with $HP\ Growth_{t,t+n}$ to capture cumulative housing price growth from year t (the year of the nonbank shock) to year

[17] The higher *HP Growth* and Δ*Price-to-Rent* values could be attributed to either an increase in demand or a decrease in supply.

$t+n$, where n ranges from 1 to 6.[18]

Panel A of Figure 3 plots the estimated coefficients, showing that the impact of nonbank credit shocks indeed persists in the long run. The coefficients for $HP\ Growth_{t,t+n}$ remain significantly positive across different values of n, indicating that the effect of nonbank credit expansion on housing prices extends beyond the short-term continuing to influence housing markets for several years. This persistence suggests that credit supply shocks from nonbanks create sustained upward pressure on housing prices.

Next, we explore whether this long-run effect varies by neighborhood characteristics. Motivated by the finding of Guerrieri et al. (2013) that housing demand spills over from rich neighborhoods to nearby poor neighborhoods, we divide census tracts into two groups based on their proximity to the nearest neighborhood in the top quartile of median income. We examine heterogeneities in the long-term effects of nonbank credit shocks across different subgroups.

Panel B of Figure 3 shows the same regression coefficients as Panel A, separately estimated by tracts' proximity to rich neighborhoods. The figure indicates that the long-term impact of nonbank credit growth on local home price growth is primarily observed in tracts close to rich neighborhoods (below median distance). In these tracts, nonbank credit shocks have a persistent influence on housing price growth across all values of $n = 1, 2, \cdots, 6$. In contrast, for tracts farther from rich neighborhoods (above-median distance), the effect of nonbank credit growth on *HP Growth* is positive only for the first year ($n = 1$) and disappears for $n \geq 2$.

This finding suggests that proximity to wealthier neighborhoods may prolong the effects of credit-driven housing booms, possibly by fostering gentrification processes. In census tracts near affluent areas, nonbank credit expansion may lead to demand spillovers, triggering a feedback loop in which increased housing demand attracts further demand and investment. Conversely, census tracts located farther from affluent neighborhoods may not attract addi-

[18]To examine the long-run impact while maintaining a consistent sample across estimations, we utilize census tract data from 2013 to 2018.

tional investment, limiting the credit shock's effect to the short term. Overall, this spatially uneven pattern highlights the importance of locational factors in shaping the long-term impact of nonbank credit shocks on the local housing market.

3.2. The Effect on Mortgage Default Risks

So far, we have shown that nonbank credit has grown unevenly across neighborhoods, with greater expansion in areas with higher *Conforming Share*, all else being equal in terms of housing market conditions. This uneven growth has led to localized housing booms, characterized by faster home price appreciation and increased transaction volumes. Building on these findings, we now examine whether nonbank credit expansion also influences mortgage performance in affected areas.

The literature presents two contrasting perspectives on the performance of nonbank-originated loans. Kim et al. (2022) argue that nonbanks, driven by stronger motivations or capabilities to securitize mortgages more quickly, may bear higher default risks than traditional banks. In contrast, Fuster et al. (2019) find that loans originated by fintech nonbank lenders are associated with lower delinquency rates, potentially due to advanced screening technologies. Given these mixed findings, we hypothesize that housing market conditions resulting from increased nonbank lending might also play a critical role in shaping mortgage performance outcomes.

To investigate this hypothesis, we analyze loan-year-quarter-level performance data and use *Conforming Share* as an instrument for nonbank-originated mortgages, consistent with the approach in earlier sections. *Conforming Share* remains a valid instrument in this context, as it predicts the likelihood of loans being originated by nonbanks due to exogenous factors unrelated to local housing market conditions or expectations.

We estimate a two-stage panel regression at the loan-year-quarter level as follows:

(First Stage)

$$\begin{aligned} Nonbank_i = &\alpha + \beta \cdot \mathit{Conforming\ Share}_i + \delta \cdot X_i + \eta_{hp\ decile} + \eta_{transaction\ volume\ decile} \\ &+ \eta_{loan\ count\ decile} + \eta_{\text{county} \times origin\ year} + \eta_{report\ year} + \epsilon_{i,yq}, \end{aligned} \tag{3}$$

(Second Stage)

$$\begin{aligned} \mathit{90+\ Delinquency}_{i,yq} = &\alpha + \beta \cdot \widehat{Nonbank_i} + \delta \cdot X_i + \eta_{hp\ decile} + \eta_{transaction\ volume\ decile} \\ &+ \eta_{loan\ count\ decile} + \eta_{county \times origin\ year} + \eta_{report\ year} + \epsilon_{i,yq}. \end{aligned} \tag{4}$$

where the first stage models the probability of a loan being originated by a nonbank lender ($Nonbank_i$) as a function of *Conforming Share*, alongside a set of loan-level controls (X_i) such as FICO score, LTV ratio, DTI ratio, and borrower characteristics. The second stage assesses the effect of nonbank originations ($\widehat{Nonbank_i}$) on the likelihood of a severe delinquency event ($\mathit{90+\ Delinquency}_{i,yq}$). Fixed effects and clustering account for tract-level housing market conditions and time-varying county-level shocks.

The results are presented in Table 8, suggesting that nonbank-originated loans are overall associated with lower 90+ day delinquency rates, with differences observed across neighborhood types. In the full sample (Columns (1) and (2)), the coefficient for $\widehat{Nonbank}$ is negative in both specifications, while statistically weak, indicating a general trend toward lower delinquency for nonbank loans. Across different measures of default and refinance incentives, the coefficients are negative, ranging from -5.979 to -5.143.

Columns (3) and (4) focus on the performance of loans originated in census tracts near high-income areas. For these loans, the impact of nonbank originations on 90+ delinquency is statistically significant. In Column (3), $\widehat{Nonbank}$ is associated with a 3.567 percentage point reduction in severe delinquency every quarter, and Column (4) shows a similar result with a comparable effect size (-3.297). These results align with our previous findings that proximity to wealthier areas amplifies the positive effect of nonbank credit expansion on the housing market, possibly leading to improved loan performance. Importantly, since we control for the incentive measures, the observed effect of nonbank originations on loan performance likely reflects broader local housing market conditions rather than factors tied specifically to individual properties. This suggests that nonbank credit expansion may transform the overall neighborhood environment (e.g., gentrification), thereby reducing delinquency risk.

Conversely, in census tracts farther from affluent areas (Columns (5) and (6)), the results show positive and no statistically significant effect of nonbank originations on 90+ day delinquency. The coefficients for $\widehat{\textit{Nonbank}}$ are 3.219 in Column (5) and 3.399 in Column (6), both with t-statistics below 1. This weak statistical significance indicates a lack of reliability of the estimates, emphasizing that the beneficial impact of nonbank credit expansion on loan performance is primarily concentrated in areas near rich neighborhoods.

We corroborate our results by examining the relationship between the nonbank credit-driven home price growth and mortgage delinquency. To do so, we replace the first-stage outcome variable with *HP Growth*, the tract-level home price growth. Table 9 presents the IV regression results. In the full sample (Columns (1) and (2)), $\widehat{\textit{HP Growth}}$ is significantly negatively associated with delinquency rates, indicating that a 100 percentage point increase in credit-driven home price growth reduces severe mortgage distress by roughly 5 percentage points. The effects are especially pronounced in tracts near affluent neighborhoods (Columns (3) and (4)), where a 100 percentage point increase in $\widehat{\textit{HP Growth}}$ lowers delinquency rates by 7.673–7.799 percentage points. In contrast, for tracts farther from affluent areas (Columns (5) and (6)), the effects are statistically insignificant. Our consistent findings on mortgage performance highlight the critical role of neighborhood characteristics in shaping the long-term influence of nonbank credit growth.

3.3. Within-County Price Convergence and Wealth Redistribution

City-wide home prices are essentially a composite of home prices within neighborhoods across the city. Thus, understanding neighborhood-level price trends can offer insights into overall city home price dynamics. In particular, Guerrieri et al. (2013) find that during city-wide housing booms, neighborhoods with initially lower home prices tend to appreciate at significantly higher rates than those with initially higher prices, implying that home values within cities converge during such periods. Building on this insight, we explore whether the nonbank credit channel contributed to this convergence pattern across neighborhoods within counties.

3.3.1. Home Price Convergence Among Neighborhoods Within Counties

To investigate home price convergence, we compute both the actual dispersion of home prices and the dispersion calculated using predicted home values from 2013 to 2021. Predicted home values are derived through the nonbank credit channel by estimating two key relationships: the coefficient of *Conforming Share* on Δ*Nonbank Share* within each house price decile group, and the coefficient of Δ*Nonbank Share* on *HP Growth* within these same groups.[19] Then, we measure the dispersion in home prices across census tracts within counties by the coefficient of variation of census tract home values (i.e., the standard deviation of census tract-level home values divided by the mean value).

Figure 4 illustrates the results, showing both actual and predicted dispersions. The solid blue line represents the observed dispersion in home values across census tracts within counties, showing a steady decline over the period. The dashed red line indicates the fitted values based on the estimated nonbank credit growth channel. While the predicted decline is somewhat smaller than the observed decline, it nonetheless shows a persistent reduction in home price dispersion within counties, suggesting that the nonbank credit channel has indeed contributed to within-county price convergence.

Between 2013 and 2021, the actual within-county dispersion dropped from 0.359 to 0.281, while the fitted model predicts a decline from 0.359 to 0.320. This implies that approximately 50% (i.e., $\frac{0.359-0.320}{0.359-0.281}$) of the observed decline in home price dispersion can be attributed to

[19] Using these estimated coefficients, alongside each census tract's house price decile group and *Conforming Share* value, we calculate the fitted house price growth rates for each census tract by year. These fitted growth rates enable us to trace the predicted price trajectory for each tract over time.

the nonbank credit channel during this period. This finding highlights the significant role of nonbank lending in narrowing price disparities within counties, as increased credit availability in lower-priced neighborhoods drives appreciation rates that help close the gap with higher-priced areas.

3.3.2. Back-of-the-Envelope Calculation of Wealth Redistribution

The housing price convergence within counties driven by nonbank credit growth also has a notable wealth redistribution effect. Importantly, this redistribution occurs without an associated increase in default risk in areas experiencing greater nonbank credit growth. As demonstrated in Section 3.2, nonbank lending and the resulting home price growth are linked to either unchanged or significantly reduced default probabilities in these neighborhoods.

To estimate the wealth redistribution impact of nonbank credit-driven housing price convergence, we perform a back-of-the-envelope calculation. Specifically, we approximate the additional wealth accrued by homeowners in the bottom 20th percentile of census tracts compared to those in the top 20th percentile. According to Zillow Home Value Index (ZHVI), in 2013, the average home value in the bottom 20 percentile tracts was \$100,253 with fitted annual growth rate of 3.783%[20], while the top 20 percentile tracts' home value was on average \$698,791 with the fitted growth rate of 0.484%.[21] Using these values, we calculate the annual wealth redistribution amount as follows:

$$\textit{Wealth Redistribution} = (\$100,253 \times 3.783\%) - (\$698,791 \times 0.484\%) = \$410.42.$$

The calculation indicates that, through the nonbank credit channel, a homeowner in the bottom 20th percentile of census tracts gains an additional \$410.42 in home equity annually.

[20]This is obtained by 0.989 (average *Conforming Share* for bottom 20 percentile tracts) × 0.070 (coefficient estimate of *Conforming Share* on Δ*Nonbank Share* for bottom 20 percentile tracts) × 0.546 (coefficient estimate of $\Delta\widehat{\textit{Nonbank Share}}$ on *HP Growth* for bottom 20 percentile tracts).

[21]Similarly, this value is obtained by 0.709 (average *Conforming Share* for top 20 percentile tracts) × 0.061 (coefficient estimate of *Conforming Share* on Δ*Nonbank Share* for top 20 percentile tracts) × 0.112 (coefficient estimate of $\Delta\widehat{\textit{Nonbank Share}}$ on *HP Growth* for top 20 percentile tracts).

This represents a 12.1% larger home equity gain compared to homeowners in the top 20th percentile of census tracts. Over the eight years of our sample period, this translates into \$3,283.38. This redistribution effect, driven by faster home price appreciation in lower-priced neighborhoods, suggests that nonbank lending plays a role in promoting wealth convergence over time. Moreover, our findings align with Favilukis et al. (2017), which demonstrate that financial liberalization can reduce housing inequality and reshape wealth distribution.

3.4. Neighborhood Transformation and Impact on Renters

Our results suggest that nonbank credit-driven housing booms may reduce housing inequality and redistribute wealth among homeowners. In this section, we explore the broader implications of these dynamics for neighborhood demographics and rental markets, particularly through potential gentrification effects. Specifically, we analyze how nonbank credit-driven housing booms influence demographic composition, rent prices, and renter displacement in affected neighborhoods.

3.4.1. Changes in Neighborhood Composition

We first examine how nonbank credit expansion influences neighborhood demographics, focusing on changes in the share of college-educated residents aged 25+, a widely recognized indicator of gentrification (Brummet and Reed, 2019; Qiang et al., 2021). The results, reported in Table 10, show that census tracts with greater nonbank credit growth experience a significant increase in the share of college-educated residents in the following year. A one percentage point increase in nonbank credit share is associated with a 0.036–0.067 percentage point rise in the college-educated share. These findings suggest that nonbank credit-driven housing booms may accompany with neighborhood gentrification, aligning with Guerrieri et al. (2013) that link local housing price booms to changes in neighborhood composition.

3.4.2. Rental Market Impacts

Next, we analyze how nonbank credit-driven growth affects rent prices and rent burdens among tenants.[22] Columns (1)–(3) of Table 11 reveal that nonbank credit growth is significantly associated with increases in rent prices across census tracts. However, we cannot determine whether this rise is driven by higher rents on existing units or the introduction of new, higher-end rental housing. To better understand the implications for renters, we examine rent burdens, measured by the rent-to-income ratio. Columns (4)–(6) of Table 11 show that rent burdens remain unaffected, suggesting that while nonbank credit-driven housing booms may raise rental prices, these increases are offset by comparable rises in local household incomes. Thus, nonbank credit expansion may not necessarily exacerbate rent burdens for tenants.

Displacement of Renters? Another key concern related to local gentrification is whether rising rents displace existing renters to less desirable neighborhoods. To address this, we analyze renter migration patterns using the InfoUSA dataset, focusing on the proportion of renters moving to neighborhoods with lower home prices or rents. As shown in Table 12, our findings indicate that nonbank credit growth does not significantly increase renter displacement. Specifically, we find no evidence of higher outflows of renters to neighborhoods with lower home prices (Columns (1)–(3)) or lower rents (Columns (4)–(6)). These results suggest that while nonbank credit-driven gentrification transforms neighborhood demographics and raises rent prices, it does not lead to the widespread displacement of renters to poorer or less desirable areas.

[22] While Section 3.1 shows a significant increase in the price-to-rent ratio, it is not immediately clear how rent prices are affected.

4. Conclusion

This paper investigates the impact of uneven nonbank expansion in the residential mortgage market on localized housing booms and associated mortgage performance. Given that nonbanks rely heavily on conforming loan originations due to their OTD model, nonbank origination growth is concentrated in census tracts with greater eligibility for conforming mortgages. Leveraging this pattern as a novel IV strategy, we show that nonbank credit expansion has driven localized housing booms characterized by faster home price appreciation, increased transaction volumes, and more competitive market conditions.

Our findings suggest that nonbank lending has a persistent impact on housing prices, particularly in census tracts near rich neighborhoods, where demand spillovers from nonbank credit may support gentrification and sustained price growth. In contrast, the effect of nonbank lending on home price appreciation is more limited and short-lived in neighborhoods farther from wealthy areas, underscoring the importance of locational characteristics in shaping the long-term effects of nonbank lending.

We also explore the effect of nonbank growth on mortgage default risks. Our IV regression estimations indicate that nonbank-originated mortgages exhibit lower rates of severe delinquency, especially in neighborhoods close to affluent areas. This improved performance likely reflects broader local market conditions and enhanced neighborhood stability due to nonbank-driven price appreciation. However, in areas farther from rich neighborhoods, the relationship between nonbank lending and mortgage performance is negligible, suggesting that the mortgage stability benefits of nonbank lending are primarily concentrated in high-demand areas.

We observe that nonbank credit expansion has contributed to a convergence in housing prices within counties. This convergence, driven by higher appreciation rates in lower-priced neighborhoods receiving more nonbank credit, implies that the nonbank lending channel has played a role in reducing disparities in housing values across neighborhoods within counties.

Finally, we find that nonbank growth leads to an increase in the share of college-educated residents and rent price growth. However, rent burdens—measured by the rent-to-income ratio—remain unaffected. More importantly, we find no evidence of significant renter displacement to poorer neighborhoods. Overall, our findings highlight the critical role of non-bank credit in shaping the housing market dynamics, from localized housing booms to home price convergence within counties.

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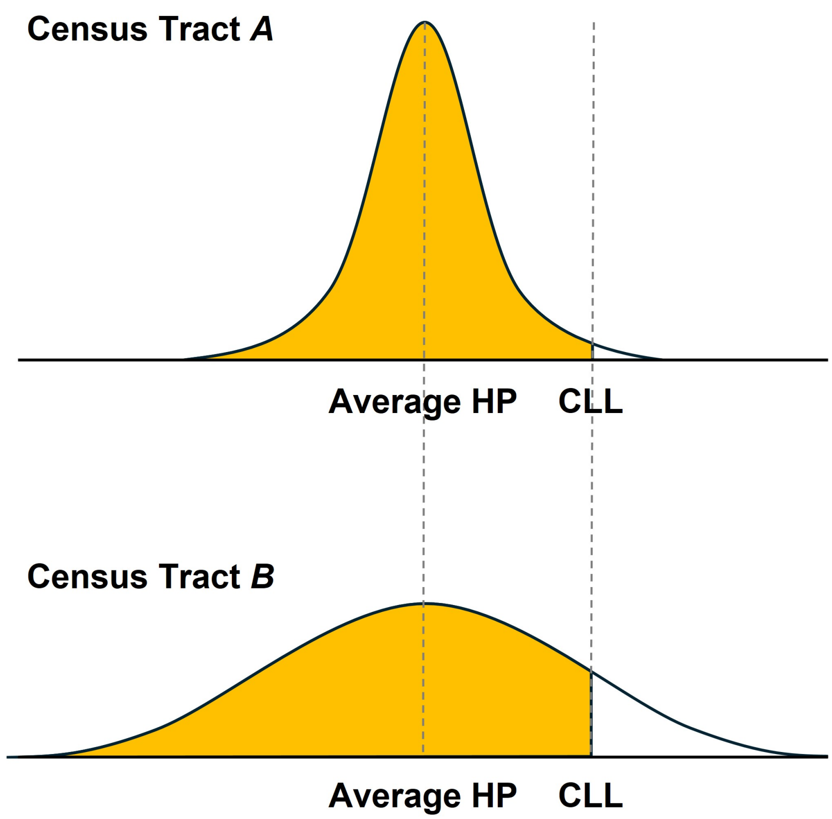
Figure 1: Home Price Distribution and Local Conforming Loan-Eligible Share

This figure illustrates both a conceptual and an actual example of home price distributions and conforming loan-eligible shares. Panel A provides a conceptual illustration using hypothetical census tracts, tract A and tract B. The distribution for census tract A, representing a neighborhood with a wider price distribution, is shown at the top, while census tract B, representing a narrower distribution, is shown below. Panel B provides a real-world example of census tracts with similar levels of average home prices but different levels of price dispersion in 2018. Census tract 114.05 in Baldwin County, AL, is represented with blue bars, and census tract 513.03 in Sussex County, DE, is represented with red bars. The blue and red lines indicate the kernel density estimates for tract 114.05 in Baldwin County, AL, and tract 513.03 in Sussex County, DE, respectively.

Panel A: Conceptual Illustration



Panel B: Actual Example

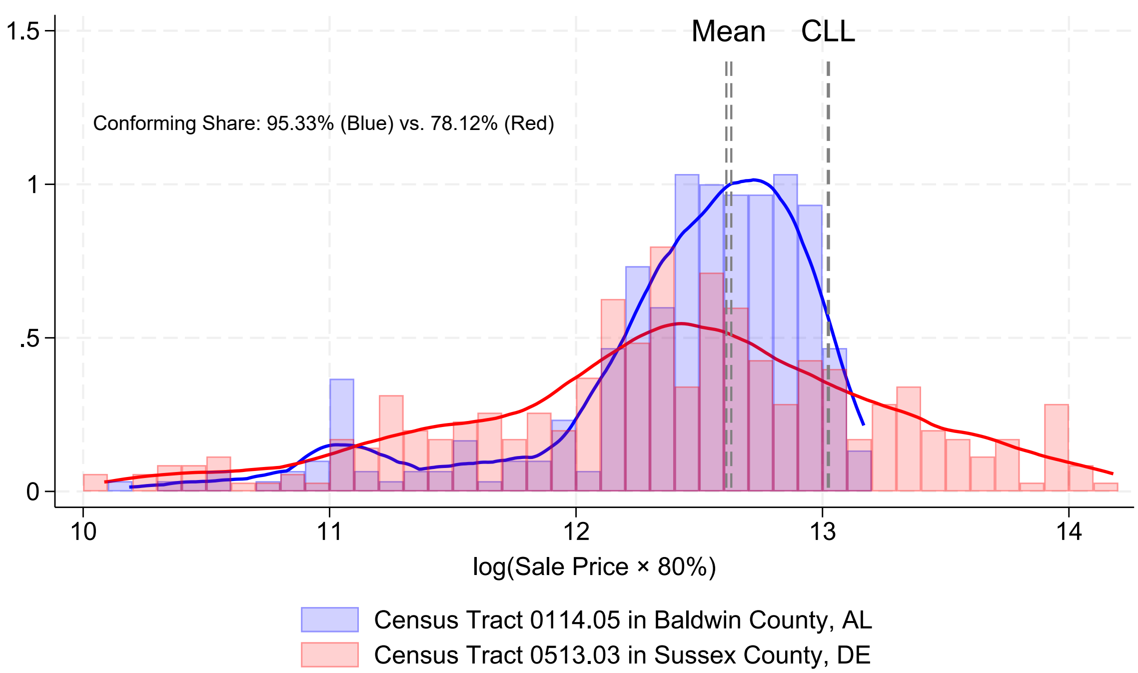


Figure 2: Mortgage Origination by Nonbanks and Banks

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

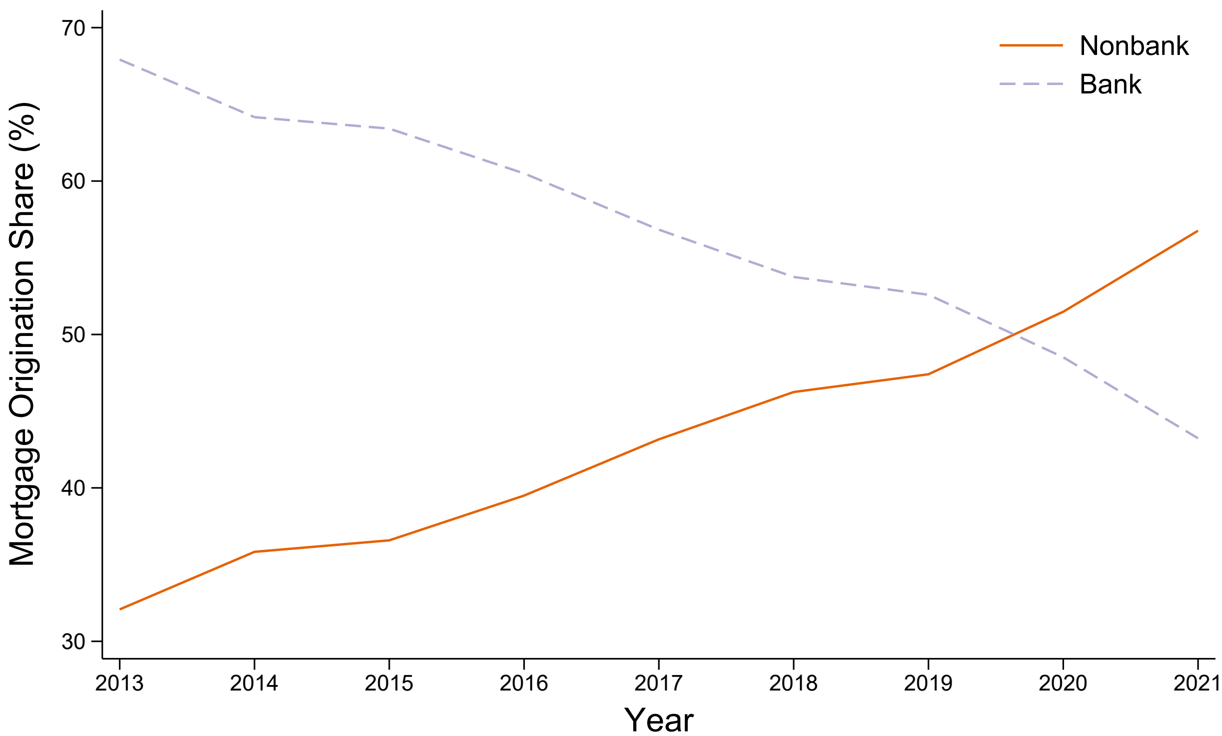
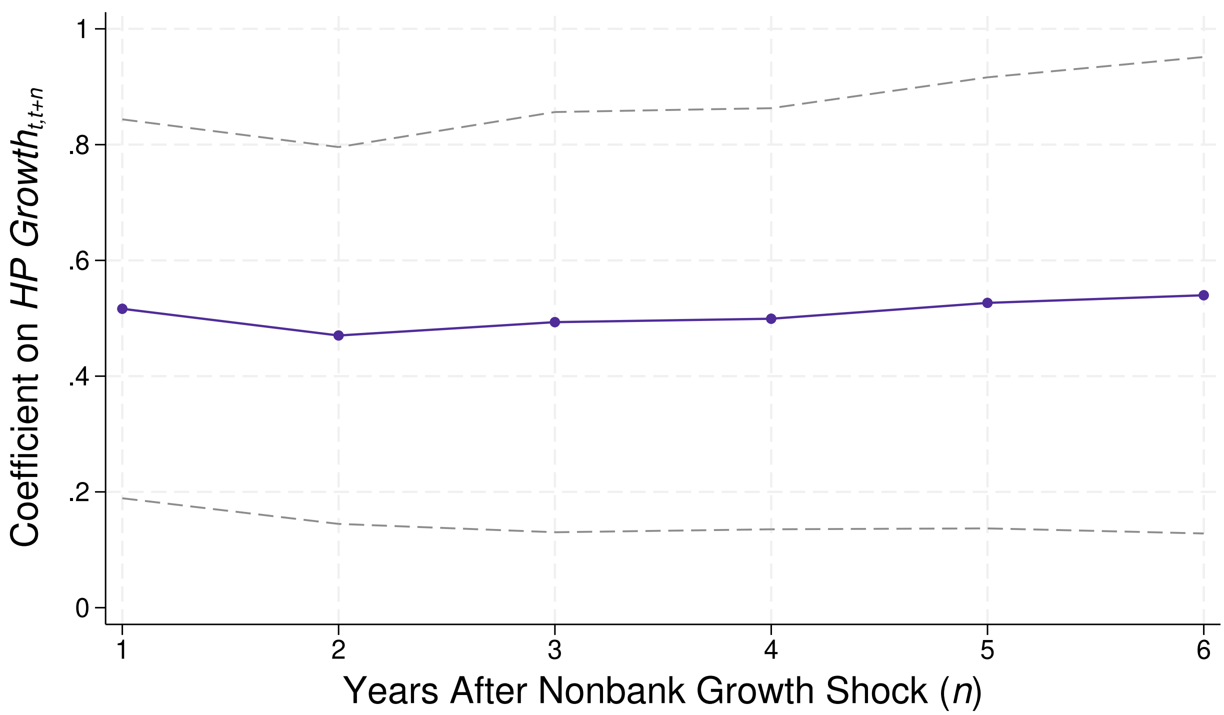


Figure 3: Nonbank Credit Shock and Cumulative HP Growth

We report the coefficient estimates from the regression in Column (1) of Table 4, replacing the dependent variable with $HP\ Growth_{t,t+n}$ to capture cumulative housing price growth from year t (the year of the nonbank shock) to year $t{+}n$, where n ranges from 1 to 6. To assess the long-term impact while maintaining a consistent sample across estimations, we use census tract data from 2013 to 2018. Panel A presents estimates based on the full census tract sample. Panel B reports estimates by census tract subgroups, classified according to their proximity to rich neighborhoods defined by median income levels.

Panel A: All Census Tracts



Panel B: Census Tracts By Proximity to Rich Neighborhood

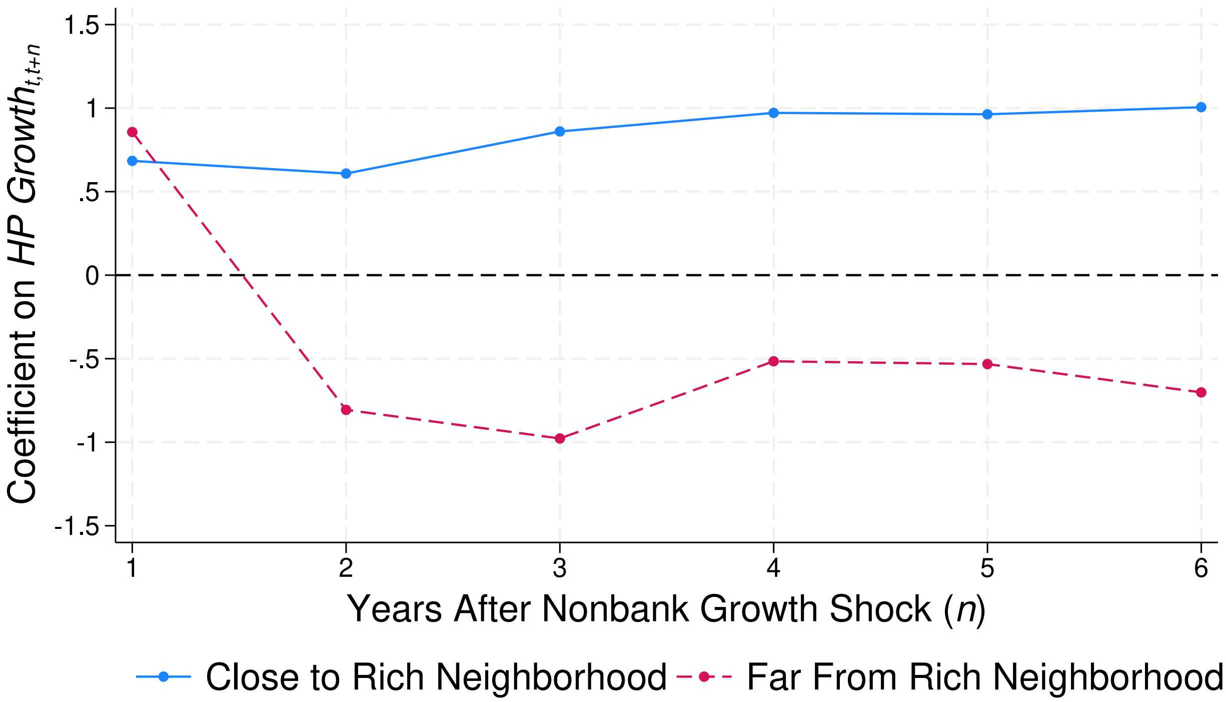


Figure 4: Neighborhood Price Convergence Within Counties

We report the actual and predicted paths of within-county home price dispersion from 2013 to 2021. The dispersions in home prices across census tracts within counties are measured as the coefficient of variation of census tract-level home values (i.e., the standard deviation of census tract home values divided by the mean value).

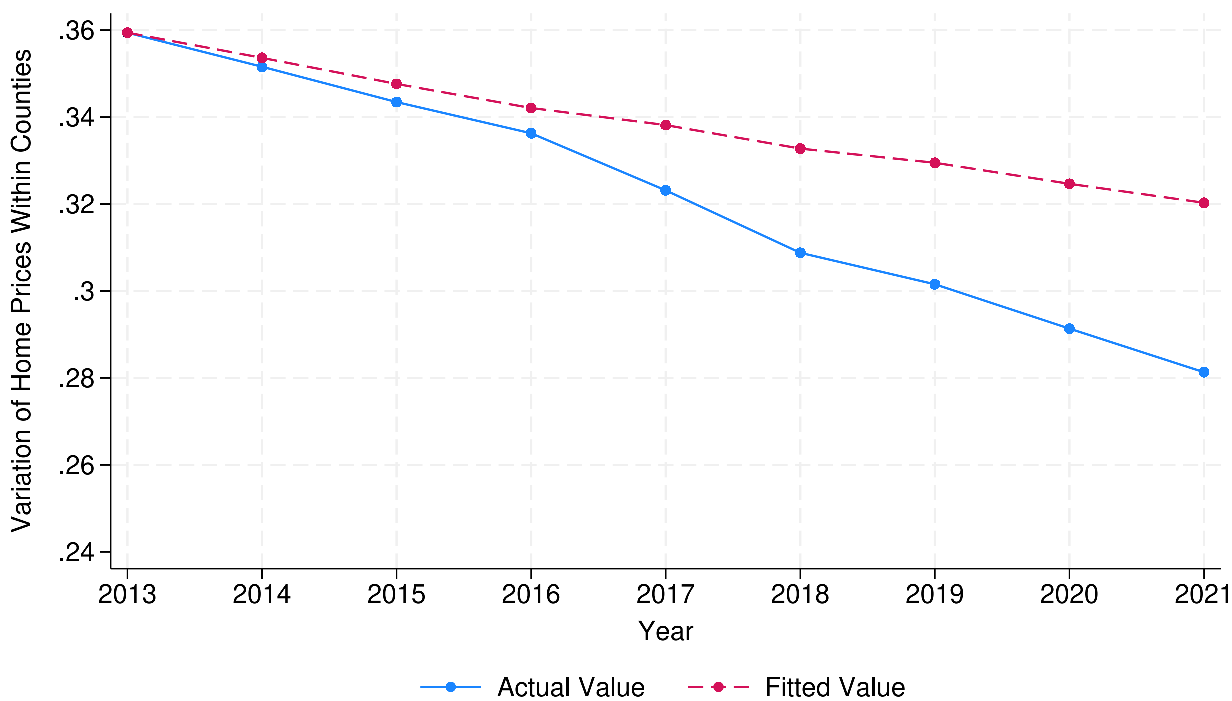


Table 1: Summary Statistics

The table reports the summary statistics of the variables. Panel A reports the summary statistics of the census tract-level data: Δ*Nonbank Share*, *Conforming Share*, *HP Growth*, *Transaction Volume Growth*, Δ*Price-To-Rent*, Δ*Overbid Share*, *Avg. Applicant Income*, *Avg. Female Applicant Share*, *Avg. Minority Applicant Share*, and *Avg. Loan-To-Income*. Panel B reports the summary statistics of the loan-year-quarter level data: *90+ Delinquency* $\times$ 100, *Nonbank*, *Conforming Share*, *FICO*, *Current LTV*, *Loan Age*, *Minority*, *Female*, *Co-borrower*, log *(Income)*, *Default Incentive*, *Refinance Incentive*, *Underwater*, and *Rate Gap*.

	Obs.	Mean	S.D.	P25	P50	P75
Panel A: Census Tract Level Dataset						
Conforming Share	299,701	0.920	0.187	0.950	1.000	1.000
ΔNonbank Share	299,701	0.026	0.163	-0.067	0.025	0.119
HP Growth	299,701	0.065	0.069	0.023	0.059	0.102
Transaction Volume Growth	299,701	0.124	1.544	-0.125	0.026	0.200
ΔPrice-To-Rent	91,467	0.005	0.015	-0.003	0.004	0.011
ΔOverbid Share	242,393	0.043	0.157	-0.032	0.029	0.117
Avg. Applicant Income	299,701	1.099	1.286	0.709	0.928	1.258
Avg. Female Applicant Share	299,701	0.318	0.136	0.231	0.312	0.400
Avg. Minority Applicant Share	299,701	0.083	0.148	0.000	0.029	0.091
Avg. Loan-To-Income	299,701	2.816	0.859	2.309	2.694	3.216
Panel B: Loan-Year-Quarter Dataset						
90+ Delinquency$\times$100	4,371,874	0.236	4.850	0.000	0.000	0.000
Conforming Share	4,371,874	0.960	0.092	0.966	1.000	1.000
Nonbank	4,371,874	0.403	0.491	0.000	0.000	1.000
FICO	4,371,874	755.438	44.549	726.000	766.000	792.000
Initial LTV > 95	4,371,874	0.101	0.301	0.000	0.000	0.000
Current LTV	4,371,874	70.215	15.672	60.672	72.084	81.235
Loan Age	4,371,874	8.502	7.448	3.000	6.000	12.000
Minority	4,371,874	0.084	0.281	0.000	0.000	0.000
Female	4,371,874	0.312	0.463	0.000	0.000	1.000
Co-borrower	4,371,874	0.740	0.439	0.000	1.000	1.000
log(Income)	4,371,874	11.330	0.624	10.897	11.327	11.728
Default Incentive	4,371,874	-0.279	0.189	-0.406	-0.259	-0.142
Refinance Incentive	4,371,874	0.006	0.146	-0.037	0.035	0.095
Underwater	4,371,874	0.051	0.219	0.000	0.000	0.000
Rate Gap	4,371,874	0.146	1.123	-0.358	0.220	0.826

Table 2: Local Conforming Eligible Transaction Share and Nonbank Share Growth

This table presents the panel regression results examining the impact of the conforming loan-eligible share within a census tract on the growth of nonbank mortgage origination shares. We utilize census tract-level data from 2013 to 2021. The dependent variable is Δ*Nonbank Share*, the annual change in nonbank mortgage origination share within a census tract. The primary independent variable, *Conforming Share*, is calculated as the proportion of housing transaction records where 80% of sale prices fall below the CLL. In Columns (4)–(6), we include control variables such as *Avg. Applicant Income*, *Avg. Female Applicant Share*, *Avg. Minority Applicant Share*, and *Avg. Loan-To-Income*. Columns (1) and (4) include tract-level fixed effects for house price deciles, housing transaction volume deciles, and loan origination count deciles. Columns (2) and (5) include tract-level fixed effects for house price decile by housing transaction volume decile and for loan origination count decile. Columns (3) and (6) include tract-level fixed effects for house price decile by housing transaction volume decile by loan origination count decile. All columns include county-by-year fixed effects. t-statistics are reported in parentheses, and all standard errors are clustered at the county level. ***, **, and * denote significance of the parameter estimates at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	ΔNonbank Share$_t$					
Conforming Share$_t$	0.0333***	0.0341***	0.0332***	0.0288***	0.0298***	0.0292***
	(16.19)	(16.14)	(15.69)	(13.69)	(14.30)	(14.20)
Avg. Applicant Income				-0.0003	-0.0002	-0.0003
				(-1.03)	(-0.88)	(-1.09)
Avg. Female Applicant Share				0.0028	0.0018	0.0025
				(0.62)	(0.40)	(0.56)
Avg. Minority Applicant Share				0.0224*	0.0212*	0.0163*
				(1.91)	(1.94)	(1.66)
Avg. Loan-To-Income				0.0062***	0.0062***	0.0057***
				(8.35)	(8.25)	(7.66)
HP Decile FE	✓			✓		
Transaction Volume Decile FE	✓			✓		
Loan Count Decile FE	✓	✓		✓	✓	
HP Decile × Transaction Volume Decile FE		✓			✓	
HP Decile × Transaction Volume Decile × Loan Count Decile FE			✓			✓
County × Year FE	✓	✓	✓	✓	✓	✓
Dep. Var. Mean	0.026	0.026	0.026	0.026	0.026	0.026
R-Squared	0.094	0.094	0.099	0.095	0.095	0.099
Obs.	299,701	299,701	299,701	299,701	299,701	299,701

Table 3: Local Conforming Eligible Transaction Share and the Growth of Bank and Nonbank Credit

This table presents the panel regression results examining the impact of the conforming loan-eligible share within a census tract on the growth of nonbank mortgage origination shares. We utilize census tract-level data from 2013 to 2021. The dependent variables are *Bank Loan Growth*, the growth rate of loan originations by traditional banks (Columns (1)–(3)), and *Nonbank Loan Growth*, the growth rate of loan originations by nonbanks (Columns (4)–(6)). The primary independent variable, *Conforming Share*, is calculated as the proportion of housing transaction records where 80% of sale prices fall below the CLL. In Columns (1) and (4) include tract-level fixed effects for house price deciles, housing transaction volume deciles, and loan origination count deciles. Columns (2) and (5) include tract-level fixed effects for house price decile by housing transaction volume decile and for loan origination count decile. Columns (3) and (6) include tract-level fixed effects for house price decile by housing transaction volume decile by loan origination count decile. All columns include county-by-year fixed effects. t-statistics are reported in parentheses, and all standard errors are clustered at the county level. ***, **, and * denote significance of the parameter estimates at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Bank Loan Growth$_t$			Nonbank Loan Growth$_t$		
Conforming Share$_t$	0.0692***	0.0757***	0.0977***	0.1250***	0.1275***	0.1443***
	(3.69)	(4.27)	(5.24)	(7.90)	(8.77)	(7.39)
HP Decile FE	✓			✓		
Transaction Volume Decile FE	✓			✓		
Loan Count Decile FE	✓	✓		✓	✓	
HP Decile × Transaction Volume Decile FE		✓			✓	
HP Decile × Transaction Volume Decile × Loan Count Decile FE			✓			✓
County × Year FE	✓	✓	✓	✓	✓	✓
Dep. Var. Mean	0.194	0.194	0.194	0.399	0.399	0.399
R-Squared	0.057	0.062	0.116	0.054	0.060	0.131
Obs.	299,701	299,701	299,701	299,701	299,701	299,701

Table 4: Nonbank Credit and Local Home Price Growth

This table presents the IV regression results using *Conforming Share*. We use the census tract-level observations from 2013 to 2021. The dependent variable is *HP Growth*, the growth rate of home prices at the census tract level using the FHFA House Price Index from year t to $t+1$. The main independent variable is $\Delta\widehat{\textit{Nonbank Share}}$, the annual change in nonbank mortgage origination share within a census tract instrumented by *Conforming Share*, the proportion of housing transaction records where 80% of sale prices fall below the CLL. In Columns (4)–(6), we include control variables such as *Avg. Applicant Income*, *Avg. Female Applicant Share*, *Avg. Minority Applicant Share*, and *Avg. Loan-To-Income*. Columns (1) and (4) include tract-level fixed effects for house price deciles, housing transaction volume deciles, and loan origination count deciles. Columns (2) and (5) include tract-level fixed effects for house price decile by housing transaction volume decile and for loan origination count decile. Columns (3) and (6) include tract-level fixed effects for house price decile by housing transaction volume decile by loan origination count decile. All columns include county-by-year fixed effects. t-statistics are reported in parentheses, and all standard errors are clustered at the county level. ***, **, and * denote significance of the parameter estimates at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
				HP Growth$_{t+1}$		
$\Delta\widehat{\text{Nonbank Share}}_t$	0.8265***	0.8075***	0.8759***	0.8198***	0.7929***	0.8615***
	(11.50)	(10.90)	(11.93)	(8.81)	(8.68)	(9.48)
Avg. Applicant Income				-0.0003	-0.0004	-0.0002
				(-1.15)	(-1.23)	(-0.80)
Avg. Female Applicant Share				0.0061	0.0067*	0.0055
				(1.51)	(1.72)	(1.36)
Avg. Minority Applicant Share				0.0088	0.0102	0.0122
				(0.65)	(0.82)	(0.99)
Avg. Loan-To-Income				-0.0050***	-0.0048***	-0.0048***
				(-6.44)	(-6.28)	(-6.25)
HP Decile FE	✓			✓		
Transaction Volume Decile FE	✓			✓		
Loan Count Decile FE	✓	✓		✓	✓	
HP Decile × Transaction Volume Decile FE		✓			✓	
HP Decile × Transaction Volume Decile × Loan Count Decile FE			✓			✓
County × Year FE	✓	✓	✓	✓	✓	✓
Dep. Var. Mean	0.065	0.065	0.065	0.065	0.065	0.065
First Stage F-Stat.	192.080	199.633	184.672	134.574	142.614	133.406
Obs.	299,701	299,701	299,701	299,701	299,701	299,701

Table 5: Nonbank Credit and Local Home Price-To-Rent Ratio

This table presents the IV regression results using *Conforming Share*. We use the census tract-level observations from 2013 to 2021. The dependent variable is Δ*Price-To-Rent*, the change in *Price-To-Rent* from year t to $t+1$ measured by the FHFA House Price Index divided by Zillow Observed Rent Index (ZORI). The main independent variable is $\Delta\widehat{\textit{Nonbank Share}}$, the annual change in nonbank mortgage origination share within a census tract instrumented by *Conforming Share*, the proportion of housing transaction records where 80% of sale prices fall below the CLL. In Columns (4)–(6), we include control variables such as *Avg. Applicant Income*, *Avg. Female Applicant Share*, *Avg. Minority Applicant Share*, and *Avg. Loan-To-Income*. Columns (1) and (4) include tract-level fixed effects for house price deciles, housing transaction volume deciles, and loan origination count deciles. Columns (2) and (5) include tract-level fixed effects for house price decile by housing transaction volume decile and for loan origination count decile. Columns (3) and (6) include tract-level fixed effects for house price decile by housing transaction volume decile by loan origination count decile. All columns include county-by-year fixed effects. t-statistics are reported in parentheses, and all standard errors are clustered at the county level. ***, **, and * denote significance of the parameter estimates at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
				ΔPrice-To-Rent$_{t+1}$		
$\Delta\widehat{\text{Nonbank Share}}_t$	0.3631***	0.3614***	0.3619***	0.4116***	0.4086***	0.4082***
	(4.27)	(4.44)	(5.24)	(3.15)	(3.28)	(3.83)
Avg. Applicant Income				-0.0000	-0.0000	0.0000
				(-0.04)	(-0.02)	(0.22)
Avg. Female Applicant Share				-0.0019	-0.0017	-0.0013
				(-0.61)	(-0.55)	(-0.42)
Avg. Minority Applicant Share				-0.0001	-0.0003	-0.0003
				(-0.02)	(-0.07)	(-0.06)
Avg. Loan-To-Income				-0.0014**	-0.0014**	-0.0014***
				(-2.34)	(-2.43)	(-2.73)
HP Decile FE	✓			✓		
Transaction Volume Decile FE	✓			✓		
Loan Count Decile FE	✓	✓		✓	✓	
HP Decile × Transaction Volume Decile FE		✓			✓	
HP Decile × Transaction Volume Decile × Loan Count Decile FE			✓			✓
County × Year FE	✓	✓	✓	✓	✓	✓
Dep. Var. Mean	0.005	0.005	0.005	0.005	0.005	0.005
First Stage F-Stat.	21.152	21.281	21.591	12.403	12.718	13.143
Obs.	91,467	91,467	91,467	91,467	91,467	91,467

Table 6: Nonbank Credit and Local Housing Transaction Volume

This table presents the IV regression results using *Conforming Share*. We use the census tract-level observations from 2013 to 2021. The dependent variable is *Transaction Volume Growth*, the annual growth in home transaction volume from year t to $t+1$ derived from CoreLogic Transaction Deed Data. The main independent variable is $\Delta\widehat{\textit{Nonbank Share}}$, the annual change in nonbank mortgage origination share within a census tract instrumented by *Conforming Share*, the proportion of housing transaction records where 80% of sale prices fall below the CLL. In Columns (4)–(6), we include control variables such as *Avg. Applicant Income*, *Avg. Female Applicant Share*, *Avg. Minority Applicant Share*, and *Avg. Loan-To-Income*. Columns (1) and (4) include tract-level fixed effects for house price deciles, housing transaction volume deciles, and loan origination count deciles. Columns (2) and (5) include tract-level fixed effects for house price decile by housing transaction volume decile and for loan origination count decile. Columns (3) and (6) include tract-level fixed effects for house price decile by housing transaction volume decile by loan origination count decile. All columns include county-by-year fixed effects. t-statistics are reported in parentheses, and all standard errors are clustered at the county level. ***, **, and * denote significance of the parameter estimates at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Transaction Volume Growth$_{t+1}$					
$\Delta\widehat{\text{Nonbank Share}}_t$	0.9185**	0.9149**	0.8660	1.4066***	1.3962***	1.4141**
	(1.99)	(1.99)	(1.59)	(2.93)	(2.96)	(2.36)
Avg. Applicant Income				0.0005	0.0004	0.0010
				(0.59)	(0.48)	(0.96)
Avg. Female Applicant Share				0.0107	0.0100	0.0057
				(0.78)	(0.72)	(0.39)
Avg. Minority Applicant Share				-0.0928***	-0.0932***	-0.0961***
				(-5.16)	(-5.13)	(-5.62)
Avg. Loan-To-Income				-0.0164***	-0.0162***	-0.0157***
				(-4.38)	(-4.40)	(-3.43)
HP Decile FE	✓			✓		
Transaction Volume Decile FE	✓			✓		
Loan Count Decile FE	✓	✓		✓	✓	
HP Decile × Transaction Volume Decile FE		✓			✓	
HP Decile × Transaction Volume Decile × Loan Count Decile FE			✓			✓
County × Year FE	✓	✓	✓	✓	✓	✓
Dep. Var. Mean	0.124	0.124	0.124	0.124	0.124	0.124
First Stage F-Stat.	192.080	199.633	184.672	134.574	142.614	133.406
Obs.	299,701	299,701	299,701	299,701	299,701	299,701

Table 7: Nonbank Credit and Share of Transactions Sold Above the Listing Price

This table presents the IV regression results using *Conforming Share*. We use the census tract-level observations from 2013 to 2021. The dependent variable is Δ*Overbid Share*, the annual change in the percentage of transactions sold above the listing price from year t to $t+1$ derived from CoreLogic MLS Data. The main independent variable is $\Delta\widehat{\textit{Nonbank Share}}$, the annual change in nonbank mortgage origination share within a census tract instrumented by *Conforming Share*, the proportion of housing transaction records where 80% of sale prices fall below the CLL. In Columns (4)–(6), we include control variables such as *Avg. Applicant Income*, *Avg. Female Applicant Share*, *Avg. Minority Applicant Share*, and *Avg. Loan-To-Income*. Columns (1) and (4) include tract-level fixed effects for house price deciles, housing transaction volume deciles, and loan origination count deciles. Columns (2) and (5) include tract-level fixed effects for house price decile by housing transaction volume decile and for loan origination count decile. Columns (3) and (6) include tract-level fixed effects for house price decile by housing transaction volume decile by loan origination count decile. All columns include county-by-year fixed effects. t-statistics are reported in parentheses, and all standard errors are clustered at the county level. ***, **, and * denote significance of the parameter estimates at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	ΔOverbid Share$_{t+1}$					
$\Delta\widehat{\text{Nonbank Share}}_t$	0.5046***	0.5038***	0.5247***	0.5476***	0.5412***	0.5553***
	(7.17)	(7.62)	(7.57)	(6.76)	(7.06)	(6.85)
Avg. Applicant Income				-0.0003	-0.0003*	-0.0003*
				(-1.58)	(-1.94)	(-1.67)
Avg. Female Applicant Share				0.0013	0.0021	0.0021
				(0.36)	(0.60)	(0.60)
Avg. Minority Applicant Share				-0.0114**	-0.0110**	-0.0077*
				(-2.13)	(-2.31)	(-1.68)
Avg. Loan-To-Income				-0.0040***	-0.0040***	-0.0039***
				(-3.69)	(-3.56)	(-3.39)
HP Decile FE	✓			✓		
Transaction Volume Decile FE	✓			✓		
Loan Count Decile FE	✓	✓		✓	✓	
HP Decile × Transaction Volume Decile FE		✓			✓	
HP Decile × Transaction Volume Decile × Loan Count Decile FE			✓			✓
County × Year FE	✓	✓	✓	✓	✓	✓
Dep. Var. Mean	0.043	0.043	0.043	0.043	0.043	0.043
First Stage F-Stat.	177.009	183.875	173.267	125.917	133.185	127.546
Obs.	242,393	242,393	242,393	242,393	242,393	242,393

Table 8: Nonbank Credit and Mortgage Delinquency

This table presents the IV 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 *90+ Delinquency*, a dummy variable that equals 1 if the loan has been delinquent for more than 90 days. The main independent variable is $\widehat{Nonbank}$, a dummy variable that equals 1 if a loan is originated by nonbank lenders, instrumented by *Conforming Share*, the proportion of housing transaction records where 80% of sale prices fall below the CLL in a census tract. In all columns, we include control variables such as *FICO*, *Initial LTV* > 95 *Current LTV*, *Minority*, *Female*, *Co-borrower*, log(*Income*), and *Loan Age*, as well as the squared terms of *FICO*, *Current LTV*, *Loan Age*. Odd columns control *Default Incentive* and *Refinance Incentive*, which measures borrower's in-the-moneyness of default and refinance options, respectively. Even columns control *Underwater* and *Rate Gap*, which are alternative measures for borrower's incentive of default and refinance, respectively. In all specifications, we include tract-level fixed effects for house price deciles, housing transaction volume deciles, loan origination count deciles, and county by origination year fixed effects 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)
	90+ Delinquency×100					
	All Sample		Close to Rich Neighborhood		Far from Rich Neighborhood	
$\widehat{\text{Nonbank}}$	-5.9799	-5.1434	-3.5674*	-3.2970*	3.2186	3.3995
	(-1.04)	(-1.16)	(-1.66)	(-1.73)	(0.91)	(0.83)
FICO	-0.0242	-0.0346**	-0.0416***	-0.0475***	-0.0661***	-0.0661***
	(-0.99)	(-2.35)	(-5.41)	(-8.43)	(-3.47)	(-3.61)
Initial LTV > 95	0.1660*	0.1134**	0.1275***	0.0903***	0.0399	0.0381
	(1.75)	(2.08)	(2.71)	(2.59)	(0.83)	(1.03)
Current LTV	-8.0450	2.0183***	-5.6744***	1.4321***	-0.2195	0.5084
	(-1.59)	(2.69)	(-2.98)	(4.82)	(-0.07)	(0.51)
Minority	0.0483	0.0612	0.0982**	0.1028***	0.1188***	0.1196***
	(0.70)	(1.16)	(2.53)	(2.90)	(2.93)	(2.80)
Female	0.0299	0.0230	0.0011	0.0001	-0.0488	-0.0505
	(0.69)	(0.69)	(0.08)	(0.01)	(-1.24)	(-1.14)
Co-borrower	-0.2649	-0.2380*	-0.2005***	-0.1920***	0.0234	0.0288
	(-1.56)	(-1.84)	(-3.35)	(-3.62)	(0.22)	(0.23)
log(Income)	-0.0507***	-0.0387***	-0.0759***	-0.0655***	-0.0489***	-0.0505**
	(-2.99)	(-2.92)	(-3.65)	(-3.85)	(-3.04)	(-2.26)
Loan Age	-0.0260	0.0013	-0.0030	0.0151	0.0678**	0.0723**
	(-0.44)	(0.04)	(-0.13)	(0.91)	(2.01)	(2.29)
Default Incentive	9.4181*		6.7245***		0.6195	
	(1.67)		(3.24)		(0.17)	
Refinance Incentive	-2.6875***		-2.0935***		-1.1210	
	(-2.64)		(-5.54)		(-1.58)	
Underwater		0.5876**		0.4644***		0.0647
		(2.30)		(4.50)		(0.24)
Rate Gap		0.2096		0.1434**		-0.0682
		(1.41)		(2.27)		(-0.51)
Square of FICO, Current LTV, Loan Age	✓	✓	✓	✓	✓	✓
HP Decile FE	✓	✓	✓	✓	✓	✓
Transaction Volume Decile FE	✓	✓	✓	✓	✓	✓
Loan Count Decile FE	✓	✓	✓	✓	✓	✓
County × Origin. Year FE	✓	✓	✓	✓	✓	✓
Report Year FE	✓	✓	✓	✓	✓	✓
Dep. Var. Mean	0.236	0.236	0.220	0.220	0.255	0.255
First Stage F-Stat.	27.619	35.809	74.401	84.291	26.539	21.220
Obs.	4,371,874	4,371,874	2,406,774	2,406,774	1,965,100	1,965,100

Table 9: Nonbank-Driven Home Price Growth and Mortgage Delinquency

This table presents the IV regression results that examine the effect of nonbank-driven housing boom on mortgage delinquency. We use the loan-year-month level observations from 2013 to 2022. The dependent variables are *90+ Delinquency*, a dummy variable that equals 1 if the loan has been delinquent for more than 90 days. The main independent variable is $\widehat{\textit{HP Growth}}$, the census tract level home price growth rate, instrumented by *Conforming Share*, the proportion of housing transaction records where 80% of sale prices fall below the CLL in a census tract. In all columns, we include control variables such as *FICO*, *Initial LTV* > 95 *Current LTV*, *Minority*, *Female*, *Co-borrower*, log(*Income*), and *Loan Age*, as well as the squared terms of *FICO*, *Current LTV*, *Loan Age*. Odd columns control *Default Incentive* and *Refinance Incentive*, which measures borrower's in-the-moneyness of default and refinance options, respectively. Even columns control *Underwater* and *Rate Gap*, which are alternative measures for borrower's incentive of default and refinance, respectively. In all specifications, we include tract-level fixed effects for house price deciles, housing transaction volume deciles, loan origination count deciles, and county by origination year fixed effects 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)
	90+ Delinquency×100					
	All Sample		Close to Rich Neighborhood		Far from Rich Neighborhood	
$\widehat{\text{HP Growth}}$	-5.0844***	-4.9468***	-7.7998***	-7.6725***	-6.0542	-5.6494
	(-2.75)	(-2.71)	(-2.94)	(-2.92)	(-1.18)	(-1.11)
FICO	-0.0477***	-0.0498***	-0.0472***	-0.0493***	-0.0493***	-0.0515***
	(-19.77)	(-20.82)	(-14.08)	(-14.82)	(-13.71)	(-14.40)
Initial LTV > 95	0.0760***	0.0593***	0.0701***	0.0527***	0.0863***	0.0689***
	(8.38)	(6.71)	(6.17)	(4.74)	(6.35)	(5.20)
Current LTV	-2.7515***	1.2430***	-2.5197***	1.2311***	-3.0221***	1.3294***
	(-15.52)	(11.40)	(-11.33)	(7.88)	(-11.20)	(7.74)
Minority	0.1199***	0.1205***	0.1317***	0.1319***	0.1027***	0.1034***
	(8.90)	(8.98)	(7.06)	(7.10)	(4.92)	(4.99)
Female	-0.0115**	-0.0119**	-0.0069	-0.0072	-0.0167**	-0.0171**
	(-2.24)	(-2.32)	(-0.95)	(-0.99)	(-2.04)	(-2.10)
Co-borrower	-0.0961***	-0.0950***	-0.0989***	-0.0977***	-0.0945***	-0.0931***
	(-12.23)	(-12.05)	(-9.90)	(-9.78)	(-7.01)	(-6.93)
log(Income)	-0.0455***	-0.0418***	-0.0488***	-0.0451***	-0.0463***	-0.0422***
	(-9.17)	(-8.48)	(-6.85)	(-6.46)	(-6.26)	(-5.72)
Loan Age	0.0354***	0.0442***	0.0357***	0.0445***	0.0362***	0.0451***
	(18.08)	(21.75)	(13.43)	(16.48)	(11.55)	(14.26)
Default Incentive	3.5973***		3.4555***		3.8395***	
	(23.50)		(17.32)		(16.85)	
Refinance Incentive	-1.6138***		-1.5058***		-1.7567***	
	(-20.24)		(-14.95)		(-14.32)	
Underwater		0.2946***		0.2889***		0.3002***
		(12.90)		(10.56)		(8.94)
Rate Gap		0.0410***		0.0417***		0.0424***
		(12.41)		(9.42)		(7.75)
Square of FICO, Current LTV, Loan Age	✓	✓	✓	✓	✓	✓
HP Decile FE	✓	✓	✓	✓	✓	✓
Transaction Volume Decile FE	✓	✓	✓	✓	✓	✓
Loan Count Decile FE	✓	✓	✓	✓	✓	✓
County × Origin. Year FE	✓	✓	✓	✓	✓	✓
Report Year FE	✓	✓	✓	✓	✓	✓
Dep. Var. Mean	0.234	0.234	0.220	0.220	0.252	0.252
First Stage F-Stat.	3340.609	3355.796	2733.888	2745.587	315.275	317.027
Obs.	4,307,107	4,307,107	2,413,507	2,413,507	1,893,600	1,893,600

Table 10: Nonbank Credit and Change in College-Educated Population Share

This table presents the IV regression results using *Conforming Share*. We use the census tract-level observations from 2013 to 2021. The dependent variable is Δ*College Share*, the annual change in the share of college-educated residents aged 25+ from year t to $t+1$ derived from the American Community Survey (ACS) Data. The main independent variable is $\Delta\widehat{\textit{Nonbank Share}}$, the annual change in nonbank mortgage origination share within a census tract instrumented by *Conforming Share*, the proportion of housing transaction records where 80% of sale prices fall below the CLL. In Columns (4)–(6), we include control variables such as *Avg. Applicant Income*, *Avg. Female Applicant Share*, *Avg. Minority Applicant Share*, and *Avg. Loan-To-Income*. Columns (1) and (4) include tract-level fixed effects for house price deciles, housing transaction volume deciles, and loan origination count deciles. Columns (2) and (5) include tract-level fixed effects for house price decile by housing transaction volume decile and for loan origination count decile. Columns (3) and (6) include tract-level fixed effects for house price decile by housing transaction volume decile by loan origination count decile. All columns include county-by-year fixed effects. t-statistics are reported in parentheses, and all standard errors are clustered at the county level. ***, **, and * denote significance of the parameter estimates at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
				ΔCollege Share		
$\Delta\widehat{\text{Nonbank Share}}_t$	0.0408**	0.0370**	0.0359**	0.0667***	0.0614***	0.0598***
	(2.41)	(2.23)	(1.99)	(3.23)	(3.08)	(2.81)
Avg. Applicant Income				0.0001***	0.0001***	0.0001***
				(2.78)	(2.79)	(2.73)
Avg. Female Applicant Share				-0.0004	-0.0003	-0.0003
				(-0.82)	(-0.63)	(-0.61)
Avg. Minority Applicant Share				-0.0057***	-0.0054***	-0.0049***
				(-5.83)	(-6.40)	(-6.64)
Avg. Loan-To-Income				-0.0004***	-0.0004**	-0.0004**
				(-2.77)	(-2.57)	(-2.35)
HP Decile FE	✓			✓		
Transaction Volume Decile FE	✓			✓		
Loan Count Decile FE	✓	✓		✓	✓	
HP Decile × Transaction Volume Decile FE		✓			✓	
HP Decile × Transaction Volume Decile × Loan Count Decile FE			✓			✓
County × Year FE	✓	✓	✓	✓	✓	✓
Dep. Var. Mean	0.006	0.006	0.006	0.006	0.006	0.006
First Stage F-Stat.	186.566	194.621	180.085	130.705	139.012	130.199
Obs.	298,855	298,855	298,855	298,855	298,855	298,855

Table 11: Nonbank Credit and Rent Price Changes

This table presents the IV regression results using *Conforming Share*. We use the census tract-level observations from 2013 to 2021. The dependent variables are *Rent Growth*, the growth rate of Zillow Observed Rent Index (ZORI) (Columns (1)–(3)), and Δ*Rent-To-Income*, the annual change in the ZORI divided by median income (Columns (4)–(6)). The main independent variable is $\Delta \widehat{\textit{Nonbank Share}}$, the annual change in nonbank mortgage origination share within a census tract instrumented by *Conforming Share*, the proportion of housing transaction records where 80% of sale prices fall below the CLL. In Columns (1) and (4) include tract-level fixed effects for house price deciles, housing transaction volume deciles, and loan origination count deciles. Columns (2) and (5) include tract-level fixed effects for house price decile by housing transaction volume decile and for loan origination count decile. Columns (3) and (6) include tract-level fixed effects for house price decile by housing transaction volume decile by loan origination count decile. All columns include county-by-year fixed effects. t-statistics are reported in parentheses, and all standard errors are clustered at the county level. ***, **, and * denote significance of the parameter estimates at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Rent Growth$_{t+1}$			ΔRent-To-Income$_{t+1}$		
$\Delta\widehat{\text{Nonbank Share}}_t$	0.2086**	0.2170***	0.2182***	0.0201	0.0266	0.0465
	(2.54)	(2.69)	(2.70)	(0.54)	(0.74)	(1.25)
HP Decile FE	✓			✓		
Transaction Volume Decile FE	✓			✓		
Loan Count Decile FE	✓	✓		✓	✓	
HP Decile × Transaction Volume Decile FE		✓			✓	
HP Decile × Transaction Volume Decile × Loan Count Decile FE			✓			✓
County × Year FE	✓	✓	✓	✓	✓	✓
Dep. Var. Mean	0.054	0.054	0.054	0.003	0.003	0.003
First Stage F-Stat.	20.560	20.711	21.167	20.524	20.679	21.162
Obs.	90,614	90,614	90,614	90,596	90,596	90,596

Table 12: Nonbank Credit and Change in Share of Movers to Worse Neighborhoods

This table presents the IV regression results using *Conforming Share*. We use the census tract-level observations from 2013 to 2021. The dependent variables are Δ*Mover Share to Lower HP*, the annual change in the the proportion of renters moving to neighborhoods with lower home prices (Columns (1)–(3)), and Δ*Mover Share to Lower Rent*, the annual change in the the proportion of renters moving to neighborhoods with lower rent prices (Columns (4)–(6)). The main independent variable is $\Delta\widehat{Nonbank\ Share}$, the annual change in nonbank mortgage origination share within a census tract instrumented by *Conforming Share*, the proportion of housing transaction records where 80% of sale prices fall below the CLL. In Columns (1) and (4) include tract-level fixed effects for house price deciles, housing transaction volume deciles, and loan origination count deciles. Columns (2) and (5) include tract-level fixed effects for house price decile by housing transaction volume decile and for loan origination count decile. Columns (3) and (6) include tract-level fixed effects for house price decile by housing transaction volume decile by loan origination count decile. All columns include county-by-year fixed effects. t-statistics are reported in parentheses, and all standard errors are clustered at the county level. ***, **, and * denote significance of the parameter estimates at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	ΔMover Share to Lower HP$_{t+1}$			ΔMover Share to Lower Rent$_{t+1}$		
$\Delta\widehat{\text{Nonbank Share}}_t$	-0.1076	-0.1054	-0.1427	0.0189	0.0344	0.0133
	(-1.05)	(-1.08)	(-1.28)	(0.11)	(0.21)	(0.08)
HP Decile FE	✓			✓		
Transaction Volume Decile FE	✓			✓		
Loan Count Decile FE	✓	✓		✓	✓	
HP Decile × Transaction Volume Decile FE		✓			✓	
HP Decile × Transaction Volume Decile × Loan Count Decile FE			✓			✓
County × Year FE	✓	✓	✓	✓	✓	✓
Dep. Var. Mean	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
First Stage F-Stat.	126.587	134.524	124.209	34.101	36.477	34.043
Obs.	192,770	192,770	192,766	58,976	58,976	58,948

Figure A1: Home Price Distribution and Local Conforming Loan-Eligible Share

This figure illustrates a conceptual example of home price distributions and conforming loan-eligible shares when tract avaerage home prices are greater than the CLL.