

Downpayment Relaxation, Mortgage Expansion and House Price Dynamics

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Abstract

This paper examines how relaxing down payment requirement affects house prices, exploiting geographical variation in eligibility conditions for a low-down-payment program introduced by GSEs in the United States. Using a regression discontinuity design, I show that easing down payment requirements increased origination of high loan-to-value (LTV) mortgages, with each \$1,000 reduction in average down payment associated with \$590 higher house price growth. The effect on high-LTV originations exhibits an inverse U-shaped relationship with housing affordability, being strongest in moderately priced housing markets and weaker in both low-cost and high-cost markets. The house price effect depends more on housing typology than on housing supply elasticity, with larger effects in housing markets where rental and owner-occupied housing are more segmented and units are harder to transition across tenure types.

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1 Introduction

Access to mortgage credit is a key determinant of homeownership, and down payment constraint remains the most significant barrier, particularly for first-time buyers. Mortgage financing generally requires a minimum cash contribution from the borrower at the time of closing. This downpayment requirement can often act as a hard constraint, preventing otherwise creditworthy households from purchasing homes (Ben-David, 2011). Policymakers worldwide have introduced numerous initiatives to expand homeownership, many of which aim to reduce downpayment requirement. Similarly, financial regulators adopt Loan-to-Value (LTV) cap (minimum down payment) as part of macro-prudential policy to maintain financial stability. Therefore, understanding how house prices respond to lower down payment is an important empirical question and whether factors such as housing market segmentation, housing supply elasticity and housing affordability affect this response.

The challenge in estimating the casual impact of down payment reduction is identifying a suitable natural experiment. Most programs that promote homeownership through down payment assistance or lower downpayment tend to target specific groups of borrowers. As a result, researchers often rely on the differential impact of such programs or regulations across geographic areas for identification. However, these areas can differ significantly in their underlying characteristics, and house prices may therefore respond differently across locations. In this paper, I overcome this challenge by leveraging the discontinuity in borrower eligibility at census tract level under the low downpayment mortgage programs, HomeReady (HR) and Home Possible (HP). The program design generates a discontinuous increase in the share of eligible borrowers at the threshold where tract income falls below 80% of the area median income.

These programs created an exogenous reduction in downpayment for borrowers, with average LTV ratio increasing by 0.55 and share of high LTV mortgages increasing by 1.34 percentage points, thereby providing the quasi-experimental setting to evaluate

the casual impact of downpayment reduction. I document four key findings. First, an average downpayment reduction of \$1000 generated a house price growth of \$590. Second, downpayment reduction was accompanied by change in mortgage composition with increase in high-LTV mortgages from first-time buyers partially offset by reduction in low-LTV mortgages from homemover, leaving the overall mortgage volume only marginally higher. Third, the effect on high-LTV mortgage originations exhibits an inverse U-curve with housing affordability, reflecting the strongest effect in moderately priced housing markets and weaker effects in low and high-cost markets. Fourth, effect on house price in a particular region depends on housing typology than on housing supply elasticity factors with strongest impact on housing markets with high friction in owner-rental conversion (lower share of single-family housing units).

HomeReady (HR) and Home Possible (HP) were launched by Fannie Mae and Freddie Mac in 2016 with the explicit objective of facilitating homeownership among low- and moderate-income borrowers. The programs offered borrowers mortgages with highest LTV loan (Loan-to-value (LTV) ratio of 97%). As the program had relaxed underwriting norms for highest LTV loans, most of the borrowers participating in the program become eligible for 97% LTV mortgages. Another feature was their reduction of upfront borrowing costs in the form of waivers on loan-level price adjustments (LLPAs), which are risk-based guarantee fees typically charged upfront by Fannie Mae and Freddie Mac to lenders, and passed on to borrowers([Bartlett et al., 2022](#)).

HR and HP programs had a unique eligibility rule where borrower income had to be below 100% of area median income (AMI). However, this income limit was exempted in low-income census tracts, which are defined as tracts where median income is below 80% of AMI. In other words, any borrower purchasing a home in a low-income tract was eligible for HR or HP regardless of income. This creates a sharp geographic discontinuity in program eligibility, allowing for identification of causal effects of reduced downpayment requirement using a regression discontinuity design (RDD). Tracts with median income below 80% of AMI experienced full borrower eligibility for the programs, while those above 80% of AMI retained eligibility only for

borrowers with income under 100% of AMI.

These programs were initiated in 2016 and expanded nationally by 2017. However, in mid-2019, the income limit exemptions for low-income census tracts were removed, leading to a decline in program uptake. Thus, the period from 2017 to 2018 provides a clean window to evaluate the effect of downpayment using the specified identification strategy. This paper combines loan-level data from the FHFA, Fannie Mae, Freddie Mac, and HMDA with tract-level socioeconomic and housing data from the American Community Survey (ACS) and house price data from FHFA House Price Index (HPI).

I begin by examining whether program features generate an exogenous reduction in downpayment requirement. RDD estimates report discontinuity in the LTV ratio of 0.347 to 0.652 percentage points at the threshold. These effects translate to an average reduction in borrower down payment of approximately \$1,041 to \$1,956. The relaxation in underwriting standards under the HR and HP programs led to a substantial increase in high-LTV (LTV above 95%) mortgage originations. Specifically, the share of high-LTV mortgage originations increases by 1.44 percentage points for treated tracts, and treated tracts exhibit 0.0817(13.9%) higher high-LTV originations per 1000 residents

While these programs increase the share of high LTV originations by 4.78%, the total originations increase by 1.28%. The primary impact of downpayment policy appears to operate through changes in the composition of mortgage originations than on overall mortgage volume. The increase in the share of high-loan-to-value (LTV) originations is driven mainly by first-time buyers, while the decline in the share of low-LTV originations is concentrated among existing homeowners. Consequently, even in the absence of a substantial expansion in total mortgage originations, compositional shifts alone can affect housing market outcomes.

Next, I assess whether this expansion in mortgage credit translated into increased housing demand and upward pressure on local house prices. Using tract-level house price indices from FHFA, I find that treated tracts experienced significantly faster house price growth between 2016 and 2018. Estimates suggest a 0.271 percentage

point increase in annualized house price growth, equivalent to a 5.98% gain relative to control tracts within the same MSA. This finding provides compelling evidence that easing downpayment constraint can appreciate house prices.

The geographic distribution of the effects of relaxing down payment requirements on high-LTV mortgage originations remains unclear. Low down payment programs are often intended to expand mortgage access in high-cost housing markets where households struggle to accumulate sufficient savings for a down payment. To study heterogeneous effects across housing markets, I measure housing affordability using the price-to-rent ratio and the price-to-income ratio at the MSA level. Using these measures, I divide markets into terciles and quartiles and estimate the RDD separately for each group. The results reveal an inverse U-shaped relationship between housing affordability and the response of high-LTV originations to down payment relaxation. The largest effects occur in moderately priced housing markets, while the responses are smaller in both low-cost and high-cost markets. This pattern suggests that in low-cost markets, existing down payment constraints were not binding as most borrowers had enough savings to meet down payment, whereas in high-cost markets income constraints and higher user costs limit the impact of down payment relaxation. However, in moderately priced markets, the existing downpayment constraints were binding enough to attract more borrowers on downpayment relaxation, while the user costs were not large enough to discourage participation.

While prior research suggests that house price responses to mortgage credit expansion depend on housing supply elasticity, most evidence comes from the pre-Global Financial Crisis period when construction activity was relatively high ([Saiz, 2010](#)). In the post-GFC environment, reduced construction activity and tighter regulations make it unclear whether supply elasticity still plays a dominant role. In addition to supply conditions, segmentation between rental and owner-occupied housing markets may influence how credit expansion affects house prices. This segmentation is largely determined by housing typology: owner-occupiers predominantly demand single-family homes, while renters are more likely to live in multi-family units. When the housing

stock contains a larger share of single-family homes, renter-occupied units can more easily transition to owner-occupied use, reducing frictions between the two segments. Consistent with this mechanism, the results show that house price responses to down payment relaxation are larger in markets with lower shares of single-family housing, where such conversion frictions are greater, while traditional measures of housing supply elasticity play a smaller role.

Finally, I examine which category of borrowers obtained high-LTV mortgages when down payment requirement was relaxed. To do so, I implement a borrower-level regression discontinuity design (RDD) using a sample of census tracts with median income above 80% of AMI, where eligibility for HR and HP programs is restricted to borrowers with income exceeding 100% of AMI. The baseline results indicate that treatment increases the probability of obtaining a high-LTV mortgage by 1.84 percentage points. Subsample analyses across demographic groups reveal that this effect is most pronounced among first-time homebuyers, young adults aged 25–34, Black and Hispanic borrowers, and lower-income borrowers (annual income below \$80,000).

This paper contributes to a growing literature on credit conditions and their influence on mortgage origination and housing markets. Foundational work by (Mian and Sufi, 2009, 2011; Purnanandam, 2011; Keys et al., 2010) emphasized how shifts in credit supply, especially through securitization shaped access to mortgages and household leverage prior to the financial crisis. More recent studies (Beraja et al., 2019; Corbae and Quintin, 2015; Dagher and Fu, 2017) have explored credit constraints and the effects of regulatory changes on mortgage originations. This paper complements these studies by isolating the role of the down payment requirement, a specific liquidity constraint, and evaluating its effects through the means of high LTV mortgage originations.

It also adds to the literature examining the impact of credit supply on house prices. Several studies (Favara and Imbs, 2015; Di Maggio and Kermani, 2017; Ferreira and Gyourko, 2023; Greenwald, 2018; Mian and Sufi, 2022; Landier et al., 2017; Blickle,

2022; Adelino et al., 2025; Carozzi et al., 2024) have documented strong house price responses to credit expansions. I build on this work by demonstrating how local housing market segmentation often plays a role in the magnitude of house price responses. Finally, the paper contributes to the literature on GSE interventions (Foote et al., 2012; Adelino et al., 2013; Bhutta, 2015). Unlike broad policy changes, I examine targeted, scalable GSE programs, HomeReady and Home Possible that indirectly alter down payment requirements, offering new insight into their effects on mortgage and housing market.

2 Institutional Setting and Data

2.1 Low Downpayment Mortgage Program

HomeReady and Home Possible are the low down-payment programs that serve as a quasi-experimental setting to study the effect of relaxing down-payment constraint. In December 2015, Fannie Mae launched HomeReady (HR) and Freddie Mac launched Home Possible (HP), with the shared objective of enabling low- and moderate-income borrowers to achieve homeownership. These programs were developed and introduced in coordination and feature identical benefits and eligibility criteria. There are many benefits in the programs, which are designed to assist borrowers with limited savings.

First, it offered borrowers mortgages with lowest down payment option (LTV of 97%). Borrowers ineligible for these programs had to meet a strict underwriting guidelines to secure 97% LTV mortgages. However, HR and HP programs had relaxed underwriting norms for income, employment and personal funds to obtain 97% LTV mortgages.¹ As a result, more borrowers became eligible for 97% LTV mortgages and around 50% of borrowers participating in HR program secured mortgages with LTV of 97%.

¹Rental income from non-occupant borrower to be considered for estimating income to meet DTI criteria. Borrowers can meet their down payment using funds from secondary loans, gifts from friends or family. Outside the HR and HP program, borrowers had to use their own personal funds for downpayment. Self-employed homebuyers who were earlier ineligible for 97% LTV mortgage will be eligible under HR and HP programs

Second, the programs waived risk-based loan-level price adjustments (LLPAs)² for mortgages with loan-to-value (LTV) ratios above 80% and borrower credit scores exceeding 680 and capped LLPAs at 150 basis points for rest of the mortgages. It also reduced mortgage insurance coverage requirements for high-LTV loans: standard coverage was lowered from 35% to 25% for loans above 95% LTV and from 30% to 25% for loans above 90% LTV³. These pricing benefits reduced the mortgage costs and had the additional effect of reducing the DTI, thereby making more borrowers eligible for the 97% LTV mortgages.

2.2 Borrower Eligibility for HomeReady and Home Possible Program

Although Fannie Mae and Freddie Mac launched HomeReady (HR) and Home Possible (HP) respectively in December 2015, similar programs directed at low- and moderate-income homebuyers existed previously in different names⁴. While these older programs had similar features and benefits, what was different about HomeReady and Home Possible was its unique eligibility criteria where borrowers in certain geographical areas were exempt from income-based limits to be eligible for the programs. The eligibility for HR and HP programs was based on borrower income, where Borrower income must be below 100 percent of the area median income (AMI). However, geography-based exceptions applied: there were no income limits for borrowers in low-income census tracts. In other words, every borrower with properties in low-income census tracts were eligible for this program while only borrowers with income below 100% AMI were eligible in other census tracts. Although many borrowers are eligible based on income criteria, Fannie Mae and Freddie Mac apply various underwriting rules to approve and select borrowers for these programs.⁵ In

²LLPAs are risk-based fees charged by Fannie Mae and Freddie Mac to compensate them for the default risk associated with borrower. LLPAs are applied based on specific risk factors and LLPAs increase with credit score and LTV ratio.

³All conventional loans with LTV ratio greater than 80% have mandatory requirement of mortgage insurance.

⁴Fannie Mae's program MyCommunityMortgage was replaced by Homeready and Freddie Mac's Home Possible Advantage was replaced by Home Possible

⁵The selection of borrowers for these programs are based on a combination of factors such as income, employment, credit score, cash holding, collateral quality

June 2019, Fannie Mae and Freddie Mac revised their programs to remove income limit exemptions applicable to low-income census tracts. Accordingly, our empirical tests are restricted to the period till 2019.

2.3 Evolution of HomeReady Program

HomeReady was announced in December 2015 and launched on a pilot basis in a limited number of locations during the first quarter of 2016. The program was then expanded nationwide by 2017. Figure [A.I](#) tracks the number of mortgages originated under the HomeReady program from 2016 onwards. As shown, the number of HomeReady mortgages increased from a very small base in 2016Q1 to over 20,000 by 2017Q2. The share of HomeReady loans relative to total Fannie Mae mortgage originations also rose steadily, peaking at approximately 18% in 2019Q1. Following the removal of income limit exemptions for low-income census tracts in 2019Q2, this share declined, falling below 10% by 2020Q1. Given this timeline, our empirical analysis focuses on the years 2017 and 2018, with particular emphasis on 2018, for which loan-to-value (LTV) data are available.

2.4 Low Income Census Tracts

Legally, the states within US are subdivided into counties, which are subdivided into census tracts. However, for many statistical applications, various institutions employ Metropolitan Statistical Areas (MSAs) as a geographical unit of analysis. MSAs are regions with an urban area at its core and could span across multiple cities or towns, often across different states. Each MSA would on average consist of xxx census tracts. A low-income census tract is defined as a census tract in which the median income of the tract does not exceed 80 percent of the MSA median income (AMI). US Census Bureau publishes the median income of MSA based on American Community Survey conducted every year. Prior studies ([Agarwal et al., 2012](#); [Bhutta, 2011](#); [Saadi, 2020](#)) have employed either a difference-in-differences approach or a regression discontinuity design (RDD) using low-income census tracts as a treatment

group. While their identification is based on low-income tracts being eligible for ratings under Community Reinvestment Act and FHFA housing goals, to the best of my knowledge, I am the first to apply this identification strategy to capture an exogenous reduction in the downpayment requirement based on the eligibility criteria of the HR and HP programs.

2.5 Data

Mortgage-level data comes from four sources – FHFA enterprise database, Fannie Mae Data Dynamics, Freddie Mac Clarity Data Intelligence loan-level dataset and HMDA dataset. The primary dataset for the study was the FHFA enterprise database Single-Family Census tract file; It provides loan-level data of single-family mortgage acquisitions of Fannie Mae and Freddie Mac with tract level details. It includes data regarding income, race, gender, age, first-time buyer status, unpaid principal balance, loan purpose, occupancy status and more. Starting from 2018, FHFA included debt-to-income (DTI) ratio, Loan-to-value (LTV) ratio, and property value along with several other data elements. The empirical analysis on high LTV mortgage acquisition relies on dataset that became available on 2018, as the FHFA dataset before 2018 didn't include data on LTV. There is a separate FHFA dataset – single-family mortgage level dataset (File A) that provides LTV categories, but without the census tract details. I use that dataset to track the high LTV acquisition before 2018.

I rely on Fannie Mae Data Dynamics, Freddie Mac Clarity Data Intelligence to obtain data on credit score, delinquencies, HomeReady and Home Possible status for each mortgage. Similarly, I gather data on origination fees, loan denials and denial reasons from HMDA dataset. HMDA also provides loan-level data reported by all agencies including those other than Fannie Mae and Freddie Mac, thereby providing comprehensive data across all loan purchasers. The FHFA data is merged with Fannie Mae's Data Dynamics and Freddie Mac's Clarity Data Intelligence to construct a consolidated dataset, the details of which are provided in Appendix.

I obtain house price data from multiple sources. My primary source is FHFA

house price index (HPI) for single-family homes. FHFA HPI is a weighted repeat-sales index and measures average price changes in repeat sales or refinancings on the same properties. FHFA HPI is available at various geographical levels, including at the level of census tract. Second, I obtain proxies for house price changes from FHFA uniform appraisal dataset (UAD) aggregate statistics. I construct different measures of house price changes based on changes in median, mean, 25th percentile and 75th percentile of appraisal values in the census tract.

I use employment, income, education, and housing related data at census tract level from American Community Survey (ACS). ACS provides tract level data based on estimate arrived by the Census Bureau based on monthly survey conducted in previous 5 years. As the census tracts are smaller in size and as sample sizes are expected to be small, census bureau provides only 5-year estimates. Each month, the survey targets 1/400th of the population, effectively implying that the 5-year estimates are based on 13% of the population, which is a reasonable sample. These estimates from ACS are primarily used in cross-sectional results, where variation of these variables across time is not a factor.

2.6 Sample Construction

The sample was refined to exclude some observations. While the HR and HP programs apply to rural areas, my focus is solely on urban areas. Housing markets where homebuyers face liquidity constraints are primarily urban areas, and HMDA data from rural census tracts tends to be unreliable. Hence, I exclude rural census tracts from my sample. Urban tracts constitute around 84% of all tracts within US. In the loan-level HMDA sample, I restrict my sample to loans with purchase type and owner-occupied properties as only single-unit, owner-occupied primary residences are allowed under HR and HP programs. I exclude loans with manufactured housing, as manufactured housing mortgages are allowed only with an LTV up to 95 percent under HR and HP programs.

3 Empirical Strategy

The eligibility criteria for the HR and HP programs introduce two thresholds: one at the census tract level and another at the borrower level. At the tract level, there is a discontinuity in the share of eligible borrowers at the 80% Area Median Income (AMI) cutoff. In census tracts with median incomes below 80% of AMI, all borrowers are eligible for the programs. In contrast, in tracts above this threshold, only borrowers with incomes below 100% of AMI are eligible. At the borrower level, a threshold of 100% AMI determines eligibility for borrowers residing in tracts other than low-income census tracts. These institutional rules enable two quasi-experimental regression discontinuity designs (RDDs): one exploiting the 80% AMI threshold at the tract level, and another using the 100% AMI threshold at the borrower level in non-low-income tracts. Most of the empirical analysis focuses on the tract level, as the impact on house prices can only be observed at this level of aggregation.

3.1 Regression Discontinuity Design

I obtain the casual identification by exploiting eligibility criteria for the HomeReady and Home possible programs. As detailed earlier, these programs created a sharp discontinuity in the share of eligible borrowers at census tracts with median income of 80% of AMI. Tracts below the 80% AMI threshold have 100% borrower eligibility, whereas tracts above the threshold have only eligibility restricted to borrowers with incomes below 100% AMI. Accordingly, there is a discontinuity at the 80 percent AMI threshold in the share of borrowers eligible for reduced payment requirements.

The prevailing convention on regression discontinuity design requires me to adopt sharp regression discontinuity to estimate the local average treatment effect of relaxation of downpayment constraint. The running variable for the RDD would be the ratio of median income of census tract to area median income, which I would refer now as tract-to-area income ratio or TAI ratio. The threshold for the running variable would be 0.8. Tracts with TAI ratio below or equal to 0.8 are defined as treated, while

those above 0.8 are defined as control. My empirical specification would be local linear regression within a given bandwidth of the threshold. As the outcome variable defined at the census tract level is very likely to vary with tract-to-area income ratio, it is necessary to use our running variable, tract-to-area income (TAI) ratio as a control in either side of the threshold.

$$Y_{cm} = \alpha + \beta_0 \mathbb{1}[I_{cm} < 0.8] + \beta_1 I_{cm} + \beta_2 \mathbb{1}[I_{cm} < 0.8] I_{cm} + \mu_m + X_{cm} \gamma + \epsilon_{cm} \quad (1)$$

I use the above specification for RDD at tract level, where Y_{cm} is the outcome variable in census tract c and Metropolitan Statistical Area (MSA) m , I_{cm} is the tract-to-area income ratio, and X_{cm} is a vector of tract level controls. Tract level controls include demographic and economic variables such as log of population, employment rate, share of rented, the share of vacant houses, and share of college-educated population. I include μ_m , MSA fixed effects to compare tracts within the same MSAs to control for local economic factors. I cluster the standard errors at the tract level.

To proceed with this research design, I first need to verify that discontinuity in the share of eligible borrowers at the cutoff of 80% AMI reflects in the discontinuity in the share of borrowers participating in the HomeReady program. I apply the above RDD specification, where the outcome variable is the number of HomeReady Mortgages as a share of mortgages originated by Fannie Mae. Figure A.II provides evidence of sharp discontinuity in the share of HomeReady mortgages and shows that share of HomeReady mortgages increases by 5.5 percentage points at the threshold.

3.2 Identifying Assumptions

The identification assumption of the RDD is the continuity of all other tract characteristics other than share of borrowers eligible for downpayment relaxation at the treatment threshold. If there are tract characteristics that are discontinuous at this threshold that are potentially likely to affect the outcome variables such as high LTV

mortgage acquisition or house price, then the identification assumption is violated. For instance, unemployed individuals are less likely to be qualified for mortgages and if there was a discontinuity in the unemployment rate across the threshold, it can create discontinuity in the rate of high LTV mortgage acquisition. I test for the continuity of tract characteristics such as unemployment rate, share of college educated, share of minority population, share of young population, share of single-family housing units, share of vacant units using the RDD empirical specification. I obtain data for these variables from ACS survey 2018, which provides the 5-year estimates from 2011-2016. The results depicted in Table A.VII report the coefficients of beta, which are statistically insignificant. As expected, the RDD plots in Figure A.VI show that these characteristics are smooth and continuous across the threshold.

While I argue that the relaxation of the down payment requirement led to various outcomes, it is important to consider that other mortgage-related characteristics may have also changed and contributed to these outcomes. For instance, there could have been a loosening of debt-to-income (DTI) requirements, reductions in credit score thresholds, or lower interest rates, which could have affected mortgage acquisition rate and, consequently, house prices. Therefore, for the RDD specification to be valid, these mortgage characteristics must also remain continuous at the policy threshold.

I test this assumption by examining the smoothness of key mortgage characteristics. I estimate the share of high-DTI borrowers, the share of low FICO score borrowers, and the average interest rate at the census tract level for mortgages acquired by Fannie Mae and Freddie Mac. I define low FICO borrowers as near-prime borrowers, which are those with credit scores below 660. High DTI borrowers are borrowers with DTI ratio above 43, as GSEs consider DTI above 43 as high risk in their assessment. None of these variables exhibit significant discontinuities at the threshold, as depicted in Figures A.VII and A.VIII. The RDD coefficients for these variables are statistically insignificant and reported in Table A.VIII. The mean interest rate is slightly discontinuous at threshold, as depicted in Figure A.VIII and is statistically significant at 10% confidence interval at one of the specifications (Panel C) in Table A.VIII. This could be due to some

of the waivers in upfront costs being passed to borrowers in the form of reduction in interest rates for HR and HP borrowers. Overall, these tests supports the validity of the RDD design by suggesting that any observed discontinuities in house prices or high-LTV mortgage acquisitions are unlikely to be driven by changes in other mortgage characteristics.

Second condition for validity of the identification assumption is the absence of manipulation around the cutoff. If tracts manipulate their median income to fall below the threshold, there would be significant difference in the number of tracts between just above and just below the cutoff. The histogram plot with density of tracts does not appear to show any jump or discontinuity in the density across the threshold. I use the ([McCrory, 2008](#)) density test to formally prove the absence of manipulation. As shown in Figure [A.IX](#), the test confirms the absence of any significant discontinuity in tract density at the threshold, suggesting that manipulation is unlikely.

Third condition that could threaten identification assumption is presence of other policies that use the same cutoff. There are two policies using the same cutoff that are cause of concern – the FHFA housing goals and Community Reinvestment Act. The FHFA sets loan purchase targets for Fannie Mae and Freddie Mac every three years, specifying the proportion of loans that must come from three groups: low-income borrowers, very low-income borrowers, and residents of low-income areas. Notably, the definition of low-income areas under the FHFA goals aligns with the threshold used in the HomeReady (HR) and Home Possible (HP) programs. I address this concern by choosing strategy that disentangles the effects of the HomeReady (HR) and Home Possible (HP) programs from those of the FHFA goals. The details of this approach are discussed below.

The FHFA sets a subgoal requiring that 18% of its loan purchases originate in low-income areas. These areas include low-income census tracts and minority census tracts. Minority census tracts are tracts that have at least 30% minority population and have tract median income below 100% of AMI. In other words, FHFA goals apply to all census tracts with incomes below 80% of AMI, as well as tracts with at least

30% minority population and incomes between 80% and 100% of AMI. This structure allows me to focus on a subsample of minority census tracts for empirical analysis: within this subsample, FHFA housing goals apply on both sides of the low-income census tract threshold, whereas the HR and HP exemptions are confined to tracts below the threshold. Hence, I perform robustness tests using a sample of only minority census tracts to isolate the effect of HR and HP program from FHFA housing goals. Minority census tracts constitute around 54% of all census tracts with income below 100 percent AMI.

Next, I address concerns about the Community Reinvestment Act (CRA) using the same threshold as the HR and HP programs in its implementation. The CRA is designed to encourage banks to meet the credit needs of low- and moderate-income (LMI) neighborhoods, which are defined as census tracts with median incomes below 80% of the area median income (AMI).

While the CRA does not mandate specific lending targets or volumes for LMI neighborhoods, it requires regulators to periodically assess a bank's lending performance in these areas. Banks receive a rating on a four-tier scale, ranging from Outstanding to Substantial Noncompliance. Although CRA ratings are not legally enforceable, they are taken into account when banks seek approval for branch openings, mergers, or acquisitions. However, due to significant examiner discretion and limited enforcement, it remains unclear whether the CRA has meaningfully increased mortgage lending in LMI neighborhoods. The existing literature provides mixed evidence—some studies find no effect, while others report only marginal and temporary increases in originations. Despite the limited impact of the CRA, it is important to verify that it does not introduce a discontinuity in mortgage originations at the 80% AMI threshold. To test this, I employ a regression discontinuity (RDD) design using data from 2013 to 2015—a period when the CRA was active, but the HR and HP programs were not yet implemented. The outcome variables are mortgage originations normalized by population, number of households, and adult population in each tract, to account for tract size variation.

An additional consideration is that the CRA does not apply to independent mortgage companies or non-bank lenders, often referred to as "shadow banks." Since the share of loans originated by such entities increased significantly after the 2008 financial crisis, the effectiveness of the CRA likely declined during the 2017–2019 period. To disentangle the effects of the CRA from those of the HR and HP programs, I conduct robustness checks on a subsample of tracts where independent mortgage companies dominate loan originations. The main findings on high-LTV mortgage acquisitions and house prices remain robust in this subsample.

4 Baseline Results

4.1 Effect on downpayment reduction

I begin by examining the effect of HR and HP programs on reduction of the downpayment requirement for borrowers. HR and HP programs relaxed their underwriting standards to qualify more borrowers for mortgages with the lowest downpayment at LTV of 97. Thus, many borrowers who were ineligible to receive mortgages earlier due to insufficient cash were able to secure low-downpayment mortgages in HR and HP programs.

I will estimate the reduction in downpayment as a result of these programs by measuring the increase in loan-to-value (LTV) using the RDD specification in Equation 1. Given that LTV data is available only from 2018 onwards, I utilize FHFA loan dataset for 2018. As described in Section 2.3, the HR and HP programs achieved their peak in 2018, making this year the most suitable for measuring their effects.

The results are reported in Table 1. Panel A presents estimates from weighted least squares (WLS) regressions, while Panel B reports ordinary least squares (OLS) estimates. The use of WLS is warranted because tract-level observations differ in the number of loans. Accordingly, WLS regressions weight each tract by the number of mortgages originated.

Table 1: Impact on Loan-to-Value Ratio

	(1)	(2)	(3)	(4)
Panel A: Weighted Least Squares				
$\mathbb{1}[I_{cm} \leq 0.8]$	0.652*** (0.192)	0.449*** (0.161)	0.347*** (0.133)	0.449*** (0.107)
Control Mean	85.07	85.12	81.31	81.42
Observations	18,113	18,113	18,028	27,966
R-squared	0.038	0.336	0.493	0.493
Panel B: Ordinary Least Squares				
$\mathbb{1}[I_{cm} \leq 0.8]$	0.428** (0.205)	0.316* (0.176)	0.395** (0.158)	0.258** (0.125)
Control Mean	85.14	85.2	81.98	82.71
Observations	18,113	18,113	18,028	27,966
R-squared	0.018	0.319	0.437	0.434
Bandwidth	0.179	0.179	0.179	0.286
Tract controls	No	No	Yes	Yes
MSA Fixed Effects	No	Yes	Yes	Yes

Notes: Table presents the results of the effect of HR and HP program on Loan-to-Value using RDD estimates of equation 1 at the tract level. The dependent variable is mean loan-to-value ratio at tract level. The sample is restricted to the optimal bandwidth in column (1) to (3), and bias-corrected bandwidth in column (4), based on (Calonico et al., 2014). $\mathbb{1}[I_{cm} \leq 0.8]$ is a dummy variable that carries a value of one for low-income census tracts, which are tracts with median income below or equal to 80% of Area Median Income (AMI). For each regression, the outcome mean for the control group (tracts with income above 80% AMI) is also shown. The specification includes tract-level controls for economy, demographics, and housing in columns (3) and (4) and MSA fixed effects in columns (2) to (4). The errors are clustered at the tract level and adjusted for heteroscedasticity. *, ** and *** represent 10%, 5%, and 1% levels of significance.

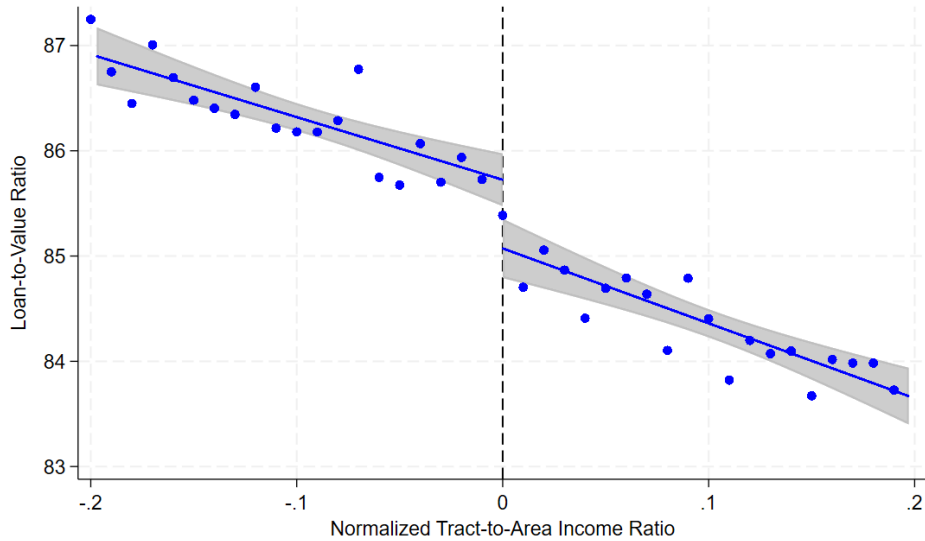


Figure 1: Impact on LTV Ratio

Notes: The figure plots the local linear regression to the left and right of the cutoff within the optimal bandwidth, with 95 percent confidence intervals in gray. The dots represent binned mean of LTV ratio. Tract-to-area income ratio is normalized by subtracting the cutoff value.

RDD estimates reported in Table 1 based on WLS regression suggest a substantial and significant increase in loan-to-value (LTV) ratios at the threshold. The estimated discontinuity ranges from 0.347 to 0.652 percentage points (pp). Figure 1 provides graphical evidence of how the LTV ratio changes across the threshold, displaying a clear discontinuity at the cutoff. Evaluated at a median house price of \$300,000 in 2018, these effects translate to an average reduction in borrower down payment of approximately \$1,041 to \$1,956 at the cutoff. The average of all estimates from Panel A of Table 1 suggests an increase in LTV by 0.474 pp, which is a reduction of downpayment requirement by \$1,422.

While these estimates represent average effects, not every borrower below the threshold experienced a down payment reduction of \$1,422. Only borrowers participating in the HomeReady and Home Possible programs would have received a lower down payment. As shown in Figure A.II, the share of HomeReady loans exhibits a discontinuity of 5.6 percentage points at the threshold. This increase in program participation is associated with a discontinuity in the loan-to-value (LTV) ratio of 0.474 pp.

Table 2: High LTV Mortgage Originations

Panel A						
	Share of High LTV Mortgage Originations					
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}[I_{cm} \leq 0.8]$	0.0148** -0.00621	0.0112** -0.00545	0.0131*** -0.00501	0.0178*** (0.00589)	0.0114** (0.00515)	0.00936** (0.00435)
Control Mean	0.199	0.2	0.16	0.194	0.195	0.142
Observations	13,037	13,033	12,973	13,037	13,033	12,973
R-squared	0.024	0.289	0.382	0.038	0.305	0.447
Regression	OLS	OLS	OLS	WLS	WLS	WLS
Bandwidth	0.14	0.14	0.14	0.14	0.14	0.14
Panel B						
	High-LTV Loans Population			High-LTV Loans Households		
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}[I_{cm} \leq 0.8]$	0.0912*** (0.0342)	0.0614** (0.0275)	0.0673** (0.0268)	0.249*** (0.0880)	0.158** (0.0719)	0.187*** (0.0680)
Control Mean	1.001	1.009	0.514	2.643	2.681	0.899
Observations	14,571	14,570	14,501	15,543	15,543	15,543
R-squared	0.002	0.380	0.416	0.002	0.360	0.425
Bandwidth	0.157	0.157	0.157	0.169	0.169	0.169
Tract controls	No	No	Yes	No	No	Yes
MSA Fixed Effects	No	Yes	Yes	No	Yes	Yes

Notes: Table presents the results of the effect of HR and HP program on High LTV Mortgage originations using RDD estimates of equation 1 at the tract level. The dependent variable in Panel A is share of high LTV mortgage originations and Panel B is high LTV loan per population(in thousands) in columns (1) to (3) and high LTV loan per households(in thousands). The sample is restricted to the optimal bandwidth based on (Calonico et al., 2014). $\mathbb{1}[I_{cm} \leq 0.8]$ is a dummy variable that carries a value of one for low-income census tracts, which are tracts with median income below or equal to 80% of Area Median Income (AMI). For each regression, the outcome mean for the control group (tracts with income above 80% AMI) is also shown. The errors are clustered at the tract level and adjusted for heteroscedasticity. *, ** and *** represent 10%, 5%, and 1% levels of significance.

If we attribute the entire increase in the LTV ratio at the threshold to the HomeReady program, this implies an increase in the LTV ratio of 8.3 pp per HomeReady borrower. This corresponds to a substantial reduction in the required down payment of approximately \$23,700. Thus, the median HomeReady borrower, who would otherwise have qualified for a mortgage with an LTV ratio of 90 percent, obtains a mortgage with an LTV ratio of 97 percent in the presence of the HomeReady program.

4.2 Effect on High LTV Mortgage Originations

Mortgages with reduced down payment requirements offered by Government-Sponsored Enterprises (GSEs) typically fall within the loan-to-value (LTV) range of 95 to 97 percent. As expected, the results presented in Table 2 indicate that relaxation in underwriting standards under the HR and HP programs led to a substantial increase in high-LTV mortgage originations. I define high-LTV loans as those with an LTV ratio exceeding 95 percent.

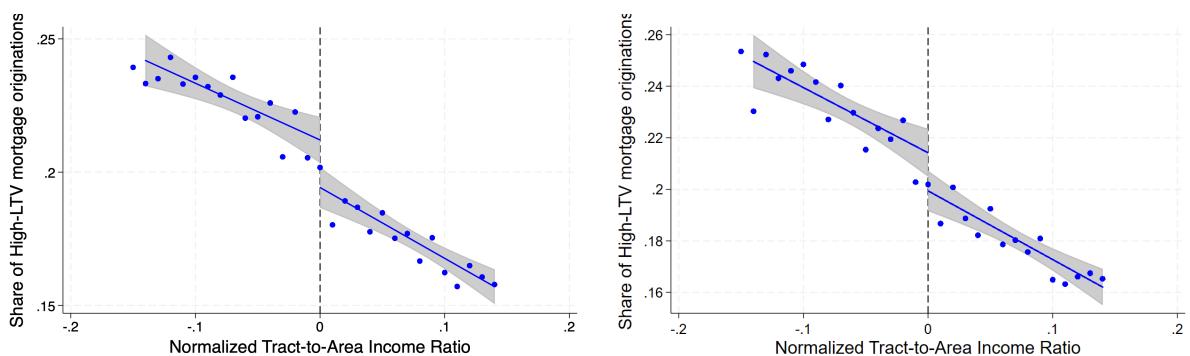


Figure 2: Share of High LTV Mortgage Originations

Notes: The figure plots the local linear regression to the left and right of the cutoff within the optimal bandwidth, with 95 percent confidence intervals in gray. The dots represent binned mean of share of high LTV originations. Tract-to-area income ratio is normalized by subtracting the cutoff value. The left figure represents estimates based on WLS and right figure based on OLS.

Figure 2 provides graphical evidence of how the share of high-LTV originations changes across the threshold, displaying a clear discontinuity at the cutoff. On either side of the threshold, the share of high-LTV loans declines as the tract income-to-AMI ratio increases. This is a pattern consistent with the expectation that borrowers in lower-income tracts are more likely to face liquidity constraints and, thus, prefer

high-LTV loans over other loans.

Since census tract sizes vary significantly, it is necessary to normalize the dependent variable to ensure comparability across tracts. Accordingly, I normalize high-LTV mortgage originations by: dividing high-LTV loans by all originations in Panel A, total population in Columns (1) to (3) in Panel B, and number of households in Columns (4) to (6) in Panel B.

The results in Panel A of Table 2 show that the coefficient in Column 1 is positive and statistically significant, indicating a discontinuity in the share of high-LTV loans at the cutoff. Specifically, the share of high-LTV mortgage originations increases by 1.44 percentage points for treated tracts, representing an 7.43% higher share relative to control tracts. Similarly, Columns (3) and (6) of Panel B reveals that treated tracts exhibit 0.0817(13.9%) higher high-LTV originations per 1000 residents and 0.195(19.4%) higher originations per 1000 households compared to control tracts.

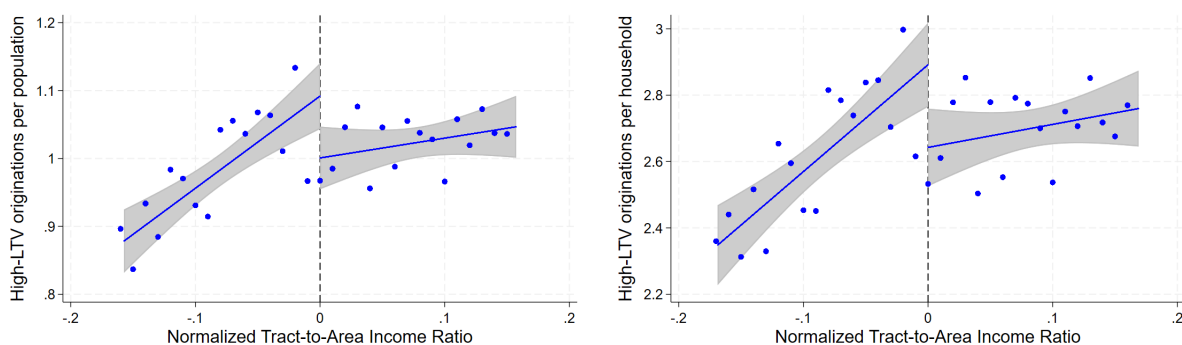


Figure 3: High LTV Mortgage Origination Density

Notes: The figure plots the local linear regression to the left and right of the cutoff within the optimal bandwidth, with 95 percent confidence intervals in gray. The dots represent binned mean of share of high LTV originations per population in left figure and per household in right figure. Tract-to-area income ratio is normalized by subtracting the cutoff value.

Figure 3 provides graphical evidence of discontinuity in high-LTV origination density changes across the threshold. Above the threshold, there is no clear pattern in the relationship between high-LTV originations density and tract income-to-AMI ratio. One possible explanation for this relationship is that total mortgage origination density is likely to decrease with tract income due to income constraints posed on borrowers during mortgage originations. However, the share of high LTV loans increases with

tract income-to-AMI ratio as observed in Figure 2. These two factors combine to ensure that there is non-monotonic relationship between high-LTV originations density and tract income-to-AMI ratio. The effect of the program is reflected in the clear jump observed in high-LTV originations density at the threshold after which it reduces with tract income-to-AMI ratio.

Table 3: Effect on Mortgage Originations

	High-LTV Originations		Total Originations	
	(1)	(2)	(3)	(4)
$\mathbb{1}[I_{cm} \leq 0.8]$	0.0500** (0.0232)	0.0478** (0.0200)	0.0228 (0.0259)	0.0128 (0.0204)
Observations	14,712	14,642	14,656	14,586
R-squared	0.412	0.559	0.405	0.629
Bandwidth	0.159	0.159	0.158	0.158
Tract controls	No	Yes	No	Yes
MSA Fixed Effects	Yes	Yes	Yes	Yes

Notes: Table presents the results of the effect of HR and HP program on total and High LTV Mortgage origination count using RDD estimates of equation 1 at the tract level. The dependent variable in columns (1) to (2) is the logarithm of high LTV first-time buyer mortgage originations, and columns (3) to (4) is the logarithm of total mortgage originations. The sample is restricted to the optimal bandwidth based on (Calonico et al., 2014). $\mathbb{1}[I_{cm} \leq 0.8]$ is a dummy variable that carries a value of one for low-income census tracts, which are tracts with median income below or equal to 80% of Area Median Income (AMI). The errors are clustered at the tract level and adjusted for heteroscedasticity. *, ** and *** represent 10%, 5%, and 1% levels of significance.

How does the relaxation of down payment requirements under the HR and HP programs affect total mortgage originations, including loans with LTV ratio less than 95%. Table 3 addresses this question by estimating the same empirical specification using total mortgage originations and high-LTV mortgage originations as dependent variables. To account for differences in census tract size, columns (2) and (4) of Table 3 include the logarithm of population as an additional control variable.

The results indicate that the regression discontinuity (RDD) estimate for high-LTV originations is positive and significant, whereas the corresponding estimate for total mortgage originations is positive but statistically insignificant. High-LTV originations increase by 4.78%, while total originations increase by 1.28%, an effect that cannot be estimated with high levels of confidence. Overall, these findings suggest that total

mortgage originations either remain unchanged or increase only modestly following the introduction of low-down-payment programs. Instead, the primary impact appears to operate through changes in the composition of mortgage originations, particularly with respect to borrower leverage and borrower type, which is explored in the next section.

4.3 Effect on Mortgage Composition by First-Time Buyer Status

This section examines how the observed increase in the share of high-loan-to-value (LTV) originations is driven mainly by first-time buyers, while the decline in the share of low-LTV originations is concentrated among existing homeowners, whom I hereafter refer to as home movers. Changes in borrower composition can have important implications for the housing market because first-time buyers influence both the owner-occupied and rental segments. Consequently, even in the absence of a substantial expansion in total mortgage originations, compositional shifts alone can affect housing market outcomes.

It is not surprising that the increase in high-LTV originations following down payment relaxation is concentrated among first-time buyers. First-time buyers are more likely to face binding down payment constraints than existing homeowners, as the latter can refinance their current property to access the liquidity needed for a new mortgage. HMDA data indicate that insufficient cash or collateral accounts for 26% of loan denials among first-time buyers, compared to only 5% for existing homeowners. As a result, policies that relax down payment requirements are expected to substantially affect first-time buyers.

To examine changes in mortgage composition, I classify originations by borrower type (first-time buyers versus home movers) and leverage (high LTV versus low LTV). Specifically, I analyze the shares of (i) high-LTV first-time buyer originations, (ii) high-LTV home mover originations, (iii) low-LTV first-time buyer originations, and (iv) low-LTV home mover originations, where low-LTV loans are defined as having LTV ratios below 95%. Table [A.I](#) reports that relaxing down payment requirements

increases the share of high-LTV originations by 1.04 percentage points and decreases the share of low-LTV home mover originations by 1.09 percentage points, with little change in the remaining two categories. Because these outcomes are expressed as shares, an increase in one category necessarily implies a decline in another. Therefore, these results do not by themselves imply a reduction in the level of low-LTV home mover originations. I examine this issue directly in the next set of results.

Table 4: Effect on Mortgage Composition

	First-time High-LTV		HomeMover Low-LTV	
	(1)	(2)	(3)	(4)
$\mathbb{1}[I_{cm} \leq 0.8]$	0.142** (0.0639)	0.644** (0.307)	-0.295** (0.146)	-0.879** (0.425)
Control Mean	0.653	1.511	4.781	5.919
Observations	14,987	13,892	15,056	12,353
R-squared	0.405	0.331	0.448	0.300
Bandwidth	0.163	0.150	0.164	0.133
Tract controls	Yes	Yes	Yes	Yes
MSA Fixed Effects	Yes	Yes	Yes	Yes

Notes: Table presents the results of the effect of HR and HP program on mortgage composition using RDD estimates of equation 1 at the tract level. Columns (1)–(2) use the number of high-LTV first-time-buyer mortgage originations, measured per total households and per renter households (in thousands), respectively. Columns (3)–(4) use the number of low-LTV non-first-time-buyer mortgage originations, measured per total households and per owner households (in thousands), respectively. The sample is restricted to the optimal bandwidth based on (Calonico et al., 2014). $\mathbb{1}[I_{cm} \leq 0.8]$ is a dummy variable that carries a value of one for low-income census tracts, which are tracts with median income below or equal to 80% of Area Median Income (AMI). The errors are clustered at the tract level and adjusted for heteroscedasticity. *, ** and *** represent 10%, 5%, and 1% levels of significance.

Using the same RDD specification, data, and sample as in the previous section, I focus on high-LTV first-time buyer mortgage originations and low-LTV homemover originations as variable of interest in Table 4. As in earlier regressions, columns (1) and (3) adjust originations for tract size by scaling them by the total number of households. In addition, because first-time buyers predominantly originate from renter households and home movers from owner-occupied households, columns (2) and (4) scale first-time buyer originations by renter-occupied households and home mover originations by owner-occupied households, respectively.

Table 4 shows a positive and statistically significant effect on high-LTV first-time

buyer originations and a negative and statistically significant effect on low-LTV home mover originations. Specifically, high-LTV first-time buyer originations per renter-occupied household increase by 41.4% in treated tracts relative to control tracts (column 2), while low-LTV home mover originations per owner-occupied household decline by 14.9% (column 4). The RDD plots depicting this discontinuity at the threshold is provided in Figure A.III. These results suggest that the expansion in mortgage originations among first-time buyers occurs, at least in part, at the expense of home movers. This raises the question of why mortgage originations decline among home movers.

Even if GSEs expanded low down-payment lending to first-time buyers while holding overall securitization volumes fixed, such a policy change would be expected to generate a uniform reduction in home-mover originations across all tracts, rather than a decline concentrated in treated tracts. The fact that the reduction in home-mover originations is observed only at the treatment threshold therefore suggests that the effect is not driven by a mechanical reallocation of GSE lending, but instead reflects equilibrium responses to the relaxation of down payment requirements.

As shown earlier, most tract-level covariates that could directly affect mortgage demand evolve smoothly at the threshold. In contrast, house prices exhibit a discontinuity at the threshold following the introduction of low-down-payment programs. This price response provides a natural mechanism linking relaxation of down payment requirements to the decline in low-LTV home-mover originations. Specifically, by stimulating first-time buyer demand, down payment relaxation puts upward pressure on house prices, which in equilibrium reduces mortgage demand among borrowers requiring low-LTV loans, which are predominantly home movers.

4.4 Effect on House Prices

The HR and HP programs led to an exogenous reduction in the down payment requirement, which increased high LTV mortgages originations. This section examines whether this increase in high LTV origination driven by first time buyers affects

house prices. House price growth depends on various demand-related factors such as income, demographics, housing supply mix, and amenities (Glaeser et al., 2006; Gyourko et al., 2013; Favara and Song, 2014). As established earlier, these factors exhibit no discontinuities at the threshold, making them unlikely confounders in our RDD framework. (Favara and Imbs, 2015) demonstrate that exogenous credit supply shocks can influence house prices. While their study focuses on heterogeneity in branching regulations, this paper isolates shocks to mortgage originations arising purely from a relaxation of down payment constraints.

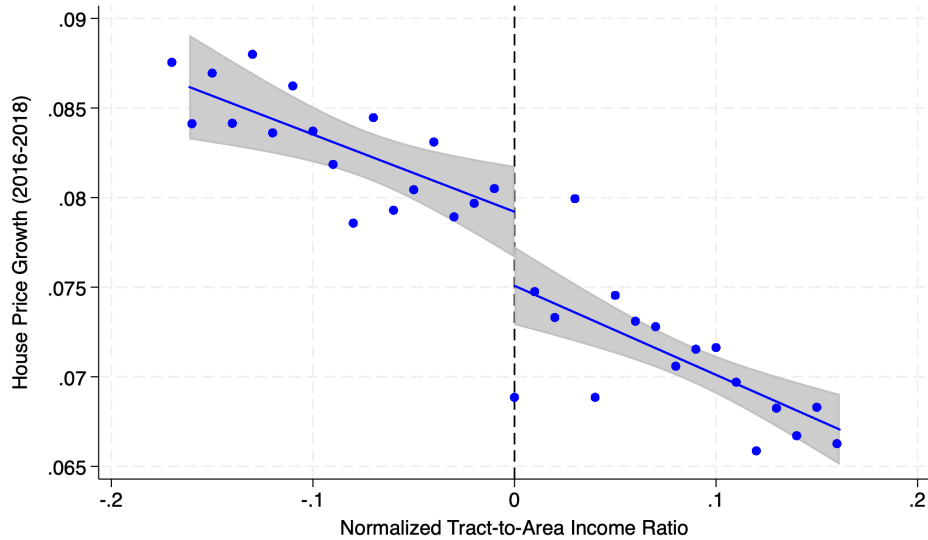
The empirics follow the treatment approach described in the RDD specifications outlined in 1. The outcome of interest is annualized house price growth from the end of 2016 to the end of 2018. The empirical analysis focuses on 2017 and 2018, as the HR and HP programs were fully implemented by late 2016, and exemptions for low-income census tracts ended in mid-2019. Tract-level house price data are obtained from the FHFA House Price Index (HPI), and cumulative growth over 2017–2018 is calculated accordingly. The specification includes tract-level covariates that may influence house price dynamics, including the unemployment rate, the share of college-educated residents, the share of young residents, the share of single-family housing units, the vacancy rate, and the share of minority residents.

Table 5 reports RDD estimates of house price growth. The coefficients capture the discontinuity in house price growth at the same threshold used to determine the exogenous reduction in down payment requirements. Across all specifications, the estimates are positive and statistically significant, indicating a robust increase in house price growth at the cutoff. Column (1), which excludes controls and fixed effects, indicates that treated tracts experienced a 0.413 percentage point increase in house price growth at the threshold, corresponding to a 5.45% rise relative to control tracts. Column (3), which includes tract-level controls and MSA fixed effects, yields a somewhat smaller estimate of 0.271 percentage points, equivalent to a 5.98% increase relative to control tracts. Figure 4 corroborates these findings by visually illustrating a clear discontinuity in house price growth at the threshold.

Table 5: Effect on House Price Growth

	(1)	(2)	(3)	(4)
$\mathbb{1}[I_{cm} \leq 0.8]$	0.00413** (0.00172)	0.00262* (0.00135)	0.00271** (0.00131)	0.00181* (0.00102)
Control	0.0751	0.0757	0.0443	0.0427
Observations	11,117	11,104	11,104	18,595
R-squared	0.019	0.426	0.455	0.436
Bandwidth	0.162	0.162	0.162	0.281
Tract controls	No	No	Yes	Yes
MSA Fixed Effects	No	Yes	Yes	Yes

Notes: Table presents the results of the effect of relaxing downpayment constraint on house prices using RDD estimates of equation 1 at the tract level. The dependent variable is the growth in house price from 2016 to 2018. The sample is restricted to the optimal bandwidth in column (1) to (3), and bias-corrected bandwidth in column (4), based on (Calonico et al., 2014). $\mathbb{1}[I_{cm} \leq 0.8]$ is a dummy variable that carries a value of one for low-income census tracts, which are tracts with median income below or equal to 80% of Area Median Income (AMI). For each regression, the outcome mean for the control group (tracts with income above 80% AMI) is also shown. The specification includes tract-level controls for economy, demographics, and housing in columns (3) and (4) and MSA fixed effects in columns (2) to (4). The errors are clustered at the tract level and adjusted for heteroscedasticity. *, ** and *** represent 10%, 5%, and 1% levels of significance.

**Figure 4: Impact on House Price Growth**

Notes: The figure plots the local linear regression to the left and right of the cutoff within the optimal bandwidth, with 95 percent confidence intervals in gray. The dots represent binned mean of house price growth. Tract-to-area income ratio is normalized by subtracting the cutoff value.

The average of all RDD estimates from Table 5 suggests an increase in house price by 0.282 pp. Evaluated at a median house price of \$300,000 in 2018, this translates to an annualized rise in house price by \$845. The RDD estimates from similar specification in Table 1 indicated an increase in LTV by 0.474 pp, which is a reduction of downpayment by \$1,422. Combining these estimates implies that an average down payment reduction of \$1,422 is associated with an annualized house price increase of \$845, or approximately \$0.59 in house price for every dollar reduction in down payment.

These results suggest attenuation rather than amplification in house prices following a relaxation of down payment requirements. Whether house prices amplify or attenuate in response to such policy changes depends on several factors, including the responsiveness of homebuyer demand, the elasticity of housing supply, and the degree of segmentation between rental and owner-occupied markets. For example, amplification could arise if a small reduction in down payment requirements substantially increases buyer demand in a market characterized by inelastic housing supply and strong segmentation between rental and owner-occupied sectors.

The evidence also points to modest demand responses. While high-LTV originations increase by about 5%, overall mortgage originations rise by only 1%, reflecting compositional shifts away from the low-LTV homemover segment. I will examine in subsequent sections whether housing supply elasticity and market segmentation can help explain the observed attenuation in house price responses.

4.5 Effect on Loan Applications and Loan Rejections

The next question I investigate is what causes high LTV originations to rise when the down payment constraint is relaxed. Two potential explanations may account for this increase. First, the relaxation may encourage a greater number of applications, as awareness of the HR and HP programs encourages previously constrained borrowers to enter the mortgage market. Second, the design features and underwriting standards of these programs may reduce the incidence of loan denials.

Table 6: Effect on Loan Applications and Loan Rejection

	Applications Population (1)	Applications Households (2)	Denial Rates (3)	Denial (Liquidity I) (4)	Denial (Liquidity II) (5)	Liquidity Denials All Denials (6)
$\mathbb{1}[I_{cm} \leq 0.8]$	0.260 (0.185)	0.706 (0.579)	-0.996** (0.420)	-0.355** (0.145)	-0.368** (0.188)	-1.628* (0.962)
Control Mean	7.9	17.62	24.27	2.822	3.869	13.91
Observations	10,858	9,309	12,299	11,836	9,258	9,388
R-squared	0.327	0.292	0.311	0.120	0.144	0.074
Bandwidth	0.195	0.167	0.222	0.213	0.166	0.178
MSA FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Table presents the results of the effect of relaxing downpayment constraint on loan applications and loan rejections using RDD estimates of equation 1 at the tract level based on HMDA dataset of loans purchased by Fannie Mae and Freddie Mac. The dependent variable in column 1 is loan applications per population, column 2 is loan applications per household, column 3 is number of loan rejected as a share of loan applications, column 4 is number of loans rejected due to insufficient cash or collateral as the primary reason, as a share of loan applications, column 5 is number of loans rejected due to insufficient cash or collateral as any one of the reason, as a share of loan applications and column 6 is number of loans rejected due to insufficient cash or collateral as the primary reason, as a share of all loan rejections. $\mathbb{1}[I_{cm} \leq 0.8]$ is a dummy variable that carries a value of one for low-income census tracts, which are tracts with median income below or equal to 80% of Area Median Income (AMI). For each regression, the outcome mean for the control group (tracts with income above 80% AMI) is also shown.

To assess which mechanism is primarily responsible for the observed increase in high-LTV originations, I estimate loan applications and denial rates at the tract level. HMDA loan-level dataset reports the approval status of each application and provides detailed reasons for loan denials. The five most cited reasons include: low credit score, high debt-to-income ratio, insufficient cash, insufficient collateral, and inadequate employment history. Of these, insufficient cash and insufficient collateral most directly reflect liquidity constraints faced by borrowers.

Loan rejections due to insufficient collateral typically indicate that the appraised property value was lower than expected, preventing the borrower from satisfying the LTV requirement given their available funds. Accordingly, I classify both insufficient cash and insufficient collateral as denials attributable to liquidity constraints.

Table 6 presents RDD estimates for loan application and loan denial rates. The RDD coefficient for loan applications per 1000 residents is positive but statistically insignificant, suggesting that the reduction in down payment requirements only led to

a marginal increase in mortgage applications. It also establishes that the HR and HP programs were not effective in stimulating additional loan applications. However, loan denial rates declined by 1 percentage points in treated tracts, representing a 4.12% reduction relative to the control group. This suggests that the primary mechanism through which HR and HP programs operated was by improving loan approval rates rather than increasing application volume. Notably, loan ejections due to liquidity constraints declined even further. Column 4 shows that the share of loans denied due to liquidity constraints (insufficient cash or collateral) fell by 0.355 percentage points, corresponding to a reduction of 12.6% compared to the control group.

These results provide evidence on how the HR and HP programs operated. Specifically, the programs enabled many borrowers who would not otherwise have qualified for the lowest-down-payment mortgages (LTV ratio of 97 percent) to become eligible under HR and HP. Importantly, meeting the formal eligibility criteria for HR or HP does not guarantee approval of a low down-payment loan, as loan approval also depends on additional factors such as income, credit history, employment, and property appraisals.⁶

The HR and HP programs effectively relaxed some of these underwriting constraints, allowing a larger share of borrowers to qualify for low-down-payment loans. This relaxation helps explain the observed reduction in loan denial rates associated with the programs. Although we do not find a statistically significant increase in loan application volume, the programs did lead to a modest increase in loan applications. This increase may reflect greater borrower awareness driven by outreach efforts by Fannie Mae and Freddie Mac, as well as marketing by mortgage lenders.

⁶Fannie Mae underwriting approval, often facilitated by the Desktop Underwriter (DU) system, involves a comprehensive review of credit, income, assets, and property value to meet standardized guidelines.

5 Heterogeneity Based on Housing Affordability

It remains unclear which geographic areas or housing markets experience the strongest effect on high LTV mortgage originations from relaxing down payment requirement. A key objective of low downpayment programs is to expand mortgage access in high-cost housing markets, where prospective buyers often struggle to accumulate sufficient funds for a down payment. Therefore, identifying the housing markets that exhibit the largest responses is central to evaluating the policy's effectiveness. To capture housing market conditions, I use a measure of housing affordability defined by the price-to-rent ratio, the ratio of median house prices to median rents and price-to-income ratio, the ratio of median house prices to median household income.

To capture heterogeneous effects of down payment relaxation on HLTV originations based on housing affordability, I divide the sample of tracts within the optimal bandwidths from threshold into terciles and quartiles based on price-to-rent ratio and price-to-income ratio and estimate the RDD specification separately for each tercile and quartile. Price-to-rent and Price-to-income is measured at the MSA level, as the real estate agencies and developers define housing markets at MSA level and variation of price-to-rent within a MSA is much smaller than variation across MSAs. Price-to-rent ratio is sourced from the 5-year average estimates median house price and median rent from 2011-2016 from the American Community Survey 2011-2016.

Figure 5 plots the RDD estimates by terciles of the price-to-rent and price-to-income ratios. For both measures, the largest effects are observed in the middle tercile. The bottom tercile for both measures exhibits a positive estimate, but it is substantially smaller than that of the middle tercile, and its confidence interval includes values below zero. Similarly, the estimate for top tercile of price-to-income is statistically insignificant and similar in magnitude to the estimate of bottom tercile; both are significantly smaller than the estimate of middle-tercile effect.

Quartile-based RDD estimates in Figure A.IV reveal similar patterns. The strongest effects occur in the third quartile of the price-to-rent distribution and the second

quartile of the price-to-income distribution. For both measures, the estimated effects in the two middle quartiles exceed those in the top and bottom quartiles. Table A.II reports the tercile-level RDD estimates shown in Figure 5. The key takeaway from these results is that the effect of relaxing down payment requirements on high-LTV mortgage originations exhibits an inverse U-shaped relationship with housing affordability. The effect is strongest in moderately priced housing markets and weaker in both low-cost and high-cost markets.

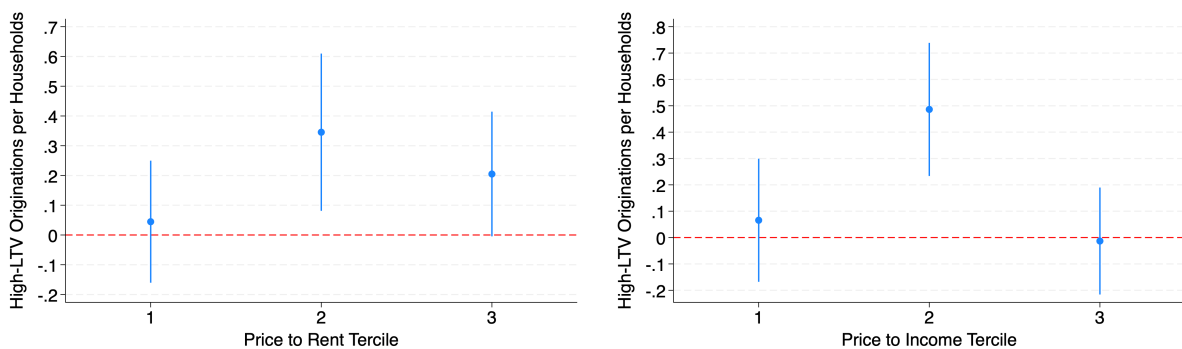


Figure 5: High-LTV Originations: Heterogeneity by Housing Affordability

Notes: The figure displays RDD estimates of impact of relaxing down payment constraint on high-LTV originations per households (in thousands) and their corresponding 95% confidence intervals. It plots coefficients corresponding to the bottom, middle, and top terciles based on ratio of MSA level median house price to median gross rent in the left figure and median house price to median income in the right figure.

I propose a simplified framework to explain the above results. The framework builds on the user cost model introduced by (Poterba, 1984), with modifications based on (Glaeser et al., 2012). Households choose between renting and owning based on the relative cost of each option. Renting involves a recurring payment of R_t , while homeownership entails a mortgage with periodic payments determined by the mortgage interest rate r_t , and a required down payment θ , proportional to the house price P_t . Homeowners also incur maintenance costs and property taxes equal to τP_t , but benefit from a mortgage interest tax deduction at a rate ϕ . Assuming that rents and maintenance costs grow at rate g and that the discount rate is equal to the mortgage rate, the household's indifference condition between renting and owning can be expressed as follows:

$$\frac{R_t}{P_t} = (1 - \phi)r_t - g + \tau$$

As the price-to-rent ratio increases, a greater proportion of households are expected to prefer renting over homeownership. Let S denote household savings and θ denote the down payment rate. Households must have sufficient savings to cover the required down payment to qualify for a mortgage.

$$S \geq \theta P_t$$

In addition to the down payment constraint, borrowers must also satisfy an income constraint tied to the debt-to-income (DTI) ratio, which I denote by κ . The minimum required income to meet this constraint is:

$$\text{Income} \geq \frac{\kappa}{P_t \cdot r}$$

In low-cost markets, the house prices are relatively low and the minimum down payment required, θP_t is low as well. As a result, the down payment constraint is non-binding for many potential homebuyers. Relaxing the down payment rate therefore expands eligibility only marginally, leading to a relatively small increase in high-LTV originations.

In high-cost markets, downpayment constraint is binding for most households and even a modest relaxation in downpayment rate, θ could make substantially more households eligible for mortgage. However, two offsetting mechanisms limit the response. First, as the price-to-rent ratio rises, the user cost of owning increases relative to renting, reducing the share of households that prefer homeownership. Many newly eligible households may therefore continue to rent despite qualifying for a mortgage. Second, as the price-to-income ratio increases, fewer households satisfy the debt-to-income (DTI) constraint. Although down payment relaxation expands eligibility along the LTV margin, many households in high-cost markets remain constrained by income requirements. Together, these user cost and income constraints

provide a plausible explanation for the weaker effects of down payment relaxation on high-LTV originations in high-cost markets.

While the RDD estimates for top tercile are significantly smaller than the middle tercile, the estimates for the top tercile differ slightly across the two measures (Figure 5). For price-to-rent, the RDD estimates for top tercile is positive and statistically significant. In contrast, for price-to-income, the RDD estimates for top tercile is statistically insignificant and similar in magnitude to the bottom-tercile estimate. One possible explanation is that income constraints exert a stronger limiting effect than user costs. Income-based eligibility rules are mechanical and depend directly on borrower earnings, whereas the user cost mechanism assumes frictionless optimization in the absence of behavioural biases. In practice, behavioral studies show that households may exhibit a preference for homeownership even when owning is more expensive than renting, attenuating the user cost channel. Consequently, high-LTV originations in high-cost markets may be more strongly constrained by income constraint than by user cost considerations.

In moderately priced markets, prices are sufficiently high that relaxing down payment requirements meaningfully expands mortgage eligibility, yet not so high as to render the DTI constraint broadly binding or to substantially tilt tenure decisions toward renting. As a result, these markets exhibit the largest increase in high-LTV originations following down payment relaxation.

6 Heterogeneous Effect on House Price

It is well established that the effect of mortgage credit expansion on house prices depends on housing supply elasticity. In areas with more elastic housing supply, higher housing demand induced by mortgage expansion is more likely to be met through new construction, which attenuates the resulting increase in house prices. However, most existing evidence on this relationship focuses on the pre-Global Financial Crisis (GFC) period, characterized by high construction activity, relatively light housing

regulation, and faster construction turnaround.

Housing market conditions have changed substantially since the GFC. Residential construction activity has declined, reflecting the excess supply accumulated during the pre-GFC boom, rising construction costs, and tighter regulatory constraints. As a result, it remains an open empirical question to what extent housing supply elasticity continues to shape the price response to mortgage credit expansion in the post-GFC period.

Housing supply elasticity varies across geographies depending on how easily developers can build new housing. (Saiz, 2010) identifies two key determinants of supply elasticity: the share of undevelopable land and the land-use regulatory environment. Areas with a larger share of undevelopable land or stricter regulations tend to exhibit more inelastic housing supply. Following this approach, I obtain MSA-level measures of the share of undevelopable land and the Wharton Residential Land Use Regulatory Index (WRLURI) from (Saiz, 2010).

In contrast, there is limited empirical work examining the role of segmentation between owner-occupied and rental housing markets in shaping house price responses to credit expansion. This segmentation is potentially important in the context of down payment relaxation, as such policies primarily affect first-time buyers (FTBs). Indeed, the increase in high-LTV originations is concentrated among first-time buyers (Table 4), whose transition into homeownership implies an exit from the rental market Gete and Reher (2018). Consequently, down payment relaxation simultaneously affects both the owner-occupied and rental segments of the housing market.

The ultimate effect on house prices depends on the degree of friction between the owner-occupied and rental sectors. Greater frictions implies that it is difficult to convert rental units into owner-occupied housing, thereby limiting supply adjustments and amplifying price responses. (Greenwald, 2018) shows in a calibrated model that such rental market frictions play a key role in determining how credit conditions translate into house price movements.

These frictions largely arise from differences in housing structure preferences between owner-occupiers and investors. Owner-occupiers typically prefer detached single-family homes, while investors more frequently purchase multi-family properties, such as apartment buildings, which involve lower maintenance costs and reduced exposure to tenant-related risks. This pattern is evident in data from the American Community Survey: approximately 88% of owner-occupied units are detached single-family homes, whereas 45.2% of renter-occupied units are located in multi-unit apartment buildings. Table A.IX provides a glimpse of tenure status for each type of housing structure

Table 7: Impact on House Price: Heterogeneity by Housing Supply Factors

	(1)	(2)	(3)
$\mathbb{1}[I_{cm} \leq 0.8]$	0.0176** (0.00749)	0.000499 (0.00132)	0.00139 (0.00107)
$\mathbb{1}[I_{cm} \leq 0.8] \times \text{Single_family}$	-0.0206** (0.00973)		
$\mathbb{1}[I_{cm} \leq 0.8] \times \text{Undevelopable}$		0.00359 (0.00268)	
$\mathbb{1}[I_{cm} \leq 0.8] \times \text{Regulation}$			0.000852 (0.000836)
Observations	18,595	17,486	17,486
R-squared	0.436	0.425	0.425
Bandwidth	0.281	0.281	0.281
Tract controls	Yes	Yes	Yes
MSA Fixed Effects	Yes	Yes	Yes

Notes: Table presents the results of the heterogeneous effect of relaxing downpayment on house price growth based on RDD specification 2. The dependent variable is the growth in house prices from 2016 to 2018. $\mathbb{1}[I_{cm} \leq 0.8]$ is a dummy variable that carries a value of one for low-income census tracts, which are tracts with median income below or equal to 80% of Area Median Income (AMI). The heterogeneous variable that is interacted with $\mathbb{1}[I_{cm} \leq 0.8]$ is share of single-family housing units in column (1), share of undevelopable area in column (2), and Wharton Residential Land Use Regulatory Index in column (3). The sample is restricted to bias-corrected optimal bandwidth, based on (Calonico et al., 2014).

Because most owner-occupied units are single-family homes, the structure of the rental housing stock largely determines the degree of friction between rental and owner-occupied markets. In geographies with a higher share of single-family housing (SFH), a first-time buyer can easily purchase a unit that was previously renter-occupied,

as those are likely to be detached single-family housing units. Such transitions involve relatively little adjustment, implying lower conversion frictions between rental and owner-occupied segments. By contrast, in geographies with a lower share of single-family housing units, rental housing is dominated by multi-family housing structures, where transitions from renting to owning typically require a shift across housing types, generating higher frictions in the conversion process.

Motivated by this mechanism, I measure housing market friction using the share of single-family housing units in a local housing market. A higher SFH share implies lower friction between rental and owner-occupied sectors and therefore a smaller expected house price response to down payment relaxation. To construct this measure, I use tract-level counts of housing structure types from the American Community Survey.

To examine whether housing market frictions and housing supply elasticity help explain the observed house price effects, I estimate an RDD specification that interacts the treatment indicator with measures of the SFH share, the share of undevelopable land, and the Wharton Residential Land Use Regulatory Index (WRLURI). The results are reported in Table 7. In the specification, $HousingFriction_m$ denotes the tract-level integration measure and I_{cm} is the tract-to-area income ratio.

$$HP_{cm} = \alpha + \beta_0 \mathbb{1}[I_{cm} \leq 0.8] + \beta_1 I_{cm} + \beta_2 \mathbb{1}[I_{cm} \leq 0.8] \cdot I_{cm} + \beta_3 HousingFriction_m + \beta_4 \mathbb{1}[I_{cm} \leq 0.8] \cdot HousingFriction_m + \mu_m + X_{cm}\gamma + \epsilon_{cm}$$

The estimates in column (1), which focus on the housing market friction measure, show that the interaction between treatment and the SFH share is negative and statistically significant. This result indicates that the house price effect diminishes as housing market frictions decline (i.e., as the SFH share increases). At the same time, the main treatment coefficient is positive and statistically significant, suggesting that the price effects are strongest in markets with higher frictions between rental and

owner-occupied segments.

The housing supply elasticity measures are the share of undevelopable land and the land-use regulation index. Here, the interaction terms are positive and statistically significant, although the magnitude of the effects is small. The sign of the coefficients suggests that house price responses are somewhat larger in areas with greater geographic constraints or stricter land-use regulation, consistent with more inelastic housing supply, but the overall influence appears limited.

Table 8: Effect on House Price Growth: Heterogeneity By Housing Structure

	(1) Below Median	(2) Above Median	(3) Bottom	(4) Middle	(5) Top
$\mathbb{1}[I_{cm} \leq 0.8]$	0.00388*** (0.00133)	-0.000142 (0.00156)	0.00392** (0.00167)	0.00147 (0.00165)	0.000279 (0.00199)
Control Mean	0.0585	0.026	0.0573	0.0498	0.0174
Observations	9,432	9,163	6,374	6,195	6,026
R-squared	0.432	0.409	0.397	0.481	0.393
Bandwidth	0.281	0.281	0.281	0.281	0.281
Tract controls	Yes	Yes	Yes	Yes	Yes
MSA Fixed Effects	Yes	Yes	Yes	Yes	Yes

Notes: Table presents the results of the heterogeneous effect of relaxing downpayment on house price growth based on RDD specification 2. The dependent variable is the growth in house prices from 2016 to 2018. $\mathbb{1}[I_{cm} \leq 0.8]$ is a dummy variable that carries a value of one for low-income census tracts, which are tracts with median income below or equal to 80% of Area Median Income (AMI). The sample is sorted by the share of single-family housing units at the MSA level. Column (1) reports estimates for MSAs below the median, while column (2) reports estimates for MSAs above the median. Columns (3)–(5) report results for the bottom, middle, and top terciles, respectively. The sample is restricted to bias-corrected optimal bandwidth, based on (Calonico et al., 2014).

To provide additional evidence, I divide the sample within the optimal bandwidth into terciles and below/above-median groups based on the share of single-family housing and re-estimate the RDD specification separately for each subsample. The resulting coefficients, plotted in Figure 6, reveal a clear pattern. The house price RDD estimate for areas below the median SFH share (high-friction markets) is positive and significantly larger than the estimate for areas above the median SFH share (low-friction markets). Similarly, the estimated house price effect is largest in the bottom tercile of SFH share and declines monotonically across terciles. These findings are consistent with the hypothesis that lower housing market frictions moderate house

price responses.

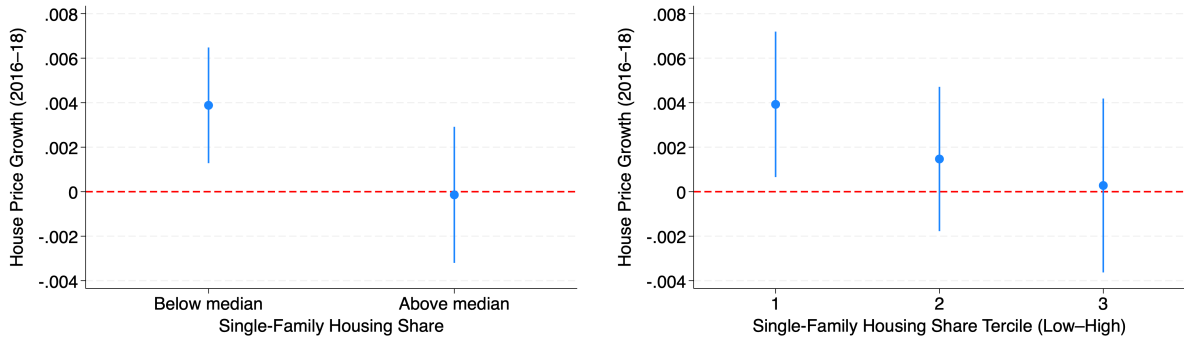


Figure 6: House Price Growth: Heterogeneity by Housing Market Integration

Notes: The figure displays RDD estimates of impact of downpayment constraint on house price growth and their corresponding 95% confidence intervals. The sample is sorted by the MSA-level share of single-family housing units. Figure on the right plots coefficients for MSAs below and above the median, respectively. Figure on the left plots coefficients for MSAs corresponding to the bottom, middle, and top terciles.

In contrast, tercile-level estimates based on the housing supply elasticity measures show no clear monotonic pattern. Although the top tercile, defined by the highest share of undevelopable land or the strictest land-use regulation exhibits the largest price response, the differences across groups are less systematic.

Overall, the results suggest that frictions between rental and owner-occupied housing markets play an important role in shaping house price responses to down payment relaxation, and that this mechanism appears to be more influential than differences in housing supply elasticity.

7 Borrower level Results

As detailed earlier, only borrowers with income above 100% AMI are eligible for HR and HP programs in tracts with median income greater than 80% AMI. This creates a clear and full discontinuity in eligibility for these programs at the threshold based on borrower income of 100% AMI for tracts with median income greater than 80% AMI. Consequently, the borrower level RDD tests would be restricted to tracts with median income greater than 80% AMI. The sample for the RDD test would be middle-income tracts (tracts with median income between 80% AMI and 120% AMI),

where there is a discontinuity at the 100% AMI threshold in borrowers eligible for reduced payment requirements.

Table 9: High LTV Mortgage Originations - Borrower Level

	LTV Ratio		High LTV	
	(1)	(2)	(3)	(4)
$\mathbb{1}[B_{im} \leq 1]$	0.265* (0.143)	0.304*** (0.118)	0.0184*** (0.00410)	0.0318*** (0.00275)
Control Mean	84.75	84.84	0.145	0.146
Observations	151,695	226,715	124,961	282,212
R-squared	0.047	0.046	0.041	0.051
Bandwidth	0.164	0.246	0.135	0.310
MSA Fixed Effects	Yes	Yes	Yes	Yes

Notes: Table presents the results of the effect of relaxing downpayment constraint on high LTV mortgage originations using RDD estimates of equation 2 at the borrower level. The dependent variable in columns (1) and (2) is the loan-to-value ratio and columns (3) and (4) is a dummy variable that carries a value of one for borrowers with high LTV (LTV greater than 95%) mortgages. $\mathbb{1}[B_{im} \leq 1]$ is a dummy variable that carries a value of one for borrowers with median income below or equal to 100% of Area Median Income (AMI). For each regression, the outcome mean for the control group (borrowers with income above 100% AMI) is also shown. The sample is restricted to the optimal bandwidth in columns (1) and (3), and bias-corrected bandwidth in columns (2) and (4), based on (Calonico et al., 2014). The errors are clustered at the tract level and adjusted for heteroscedasticity. *, ** and *** represent 10%, 5%, and 1% levels of significance.

The running variable for the RDD would be the ratio of borrower annual income to area median income, which I would refer now as borrower-to-area income ratio or BAI ratio. The threshold for the running variable would be 1. Borrowers with BAI ratio below or equal to 1 are defined as treated, while those above 1 are defined as control. My empirical specification would be local linear regression within a given bandwidth of the threshold.

$$Y_{icm} = \alpha + \beta_0 \mathbb{1}[B_{im} < 1] + \beta_1 B_{im} + \beta_2 \mathbb{1}[B_{im} < 1] B_{im} + \mu_m + \epsilon_{icm} \quad (2)$$

I use the above specification for RDD at borrower level, where Y_{icm} is the outcome variable of borrower i in census tract c and Metropolitan Statistical Area (MSA) m , B_{im} is the borrower-to-area income ratio. I include μ_m , MSA fixed effects to compare borrowers within the same MSAs to control for local economic factors. I cluster the

standard errors at the tract level.

7.1 Impact on High LTV Mortgage Originations

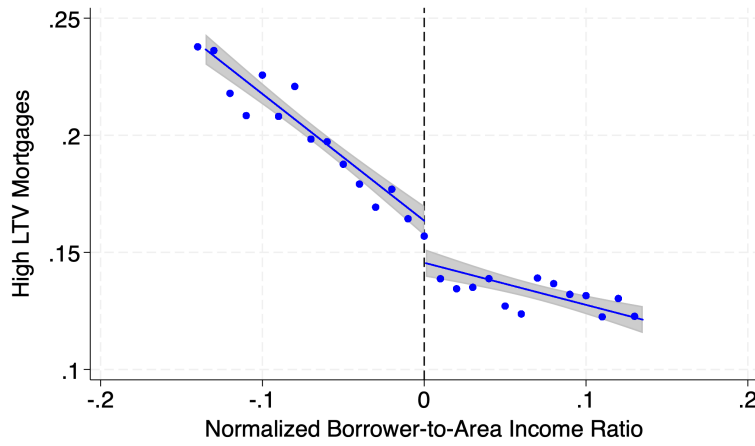
I investigate the impact on high-LTV mortgage originations by employing RDD specification as outlined in Equation 2. Table 9 reports discontinuity in LTV ratio of 0.256 (Column 1), reinforcing the fact that borrowers experience a reduction in downpayment at the eligibility threshold. Similarly, column (3) shows that the probability of a borrower having a high-LTV mortgage increases by 1.84 percentage points for treated borrowers, representing a 13.1% rise compared to control borrowers.

Figure 7 (a) provides graphical evidence of how the probability of a borrower having a high-LTV mortgage changes across the threshold, displaying a clear discontinuity at the cutoff. RDD estimates based on specification 2 at different intervals of tract to area income ratio is plotted in Figure 7 (b). As expected, the RDD estimates are insignificant at tract-to-area income ratio below 0.8, as all borrowers are eligible for HR and HP program and there is no discontinuity in the probability of a borrower having a high LTV mortgage at the threshold. As the tract-to-area income ratio goes above 0.8, RDD estimates become positive and significant.

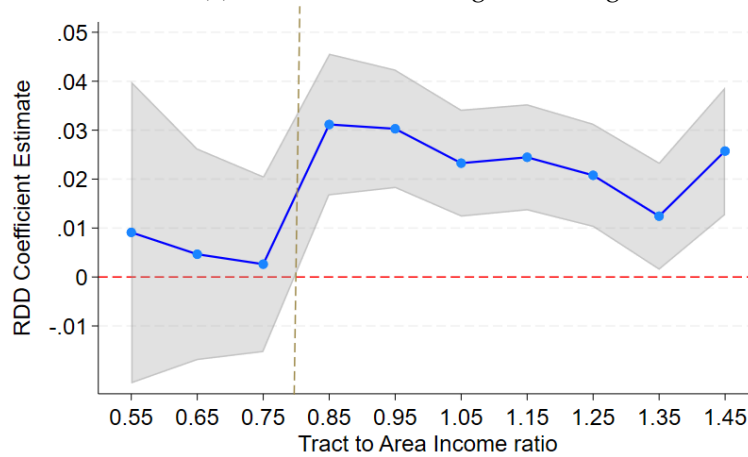
7.2 Heterogeneity by Borrower Demographics

In this section, I will explore the characteristics of borrowers that are most likely to obtain mortgages when down payment requirement is relaxed. This would provide additional evidence of how local demographics can influence the participation in low-downpayment mortgage programs. It can also provide some answers on whether demography-based, or place-based strategy should be adopted when designing low-downpayment program. The results show that place-based targeting will also benefit those demographic groups which are in most need of support to achieve homeownership.

I examine whether effect of downpayment relaxation is particularly strong among



(a) RDD of Share of High LTV Originations



(b) RDD Estimates of High LTV Originations across tract-to-area income

Figure 7: High LTV Mortgage Originations - Borrower Level

Notes: The left figure plots the local linear regression to the left and right of the cutoff within the optimal bandwidth, with 95 percent confidence intervals in gray. The dots represent binned mean of share of high LTV originations. Borrower-to-area income ratio is normalized by subtracting the cutoff value. The right figure plots the RDD estimates and corresponding 95% confidence intervals at borrower level at a subsample of tract to area income ratio intervals of 0.1, starting from 0.5 to 1.5. For each subsample of tract to area income ratio intervals of 0.1, a separate RDD specification is estimated for optimal bandwidth.

first-time homebuyers. The RDD estimates based on borrower level specifications are results reported in Table [A.III](#), separately for a sample of only first time buyers and another sample consisting of rest of the home buyers. The RDD coefficient for first time buyers is 1.97 pp, while the coefficient for rest of the homebuyers is 1.17 pp.

Similarly, columns (3) to (6) report RDD estimates in Table [A.III](#), separately for a subsample of different age groups. While the youngest age group (19-24) witness no change in its share of high-LTV mortgages, young adults (25-34) encountered a 4.02 percentage points increase in the probability of having a high LTV loan, which was also the highest of all age groups. As age increases, the share of borrowers benefiting from program also reduces. Borrowers in age group (35-54) and age group (55 and above) increased their share of high LTV mortgages by 2.07 pp and 1.04 pp respectively. Young borrowers are more likely to be constrained for cash due to limited savings. Hence, it is not surprising that young adults benefited most from any relaxation of down payment and oldest borrowers benefited the least. The fact that youngest borrowers (age 19-24) were not impacted at all from the program can be explained by how few borrowers in this age-group are seeking homeownership, which is also reflected in the smaller sample size observed for this age-group. Most borrowers within this age-group are in the process of establishing their career or yet to start a family.

Next, I examine how the effect of downpayment relaxation varies across race. Many studies have shown that there is substantial racial gap in homeownership even after accounting for borrower characteristics such as income and credit score. Studies have documented race-based discrimination in lending ([Bartlett et al., 2022](#)). As Black and Hispanic communities have lower levels of homeownership and have historically encountered discrimination, it would be interesting to observe whether these communities could benefit from a place-based targeting program rather than one based on demography. RDD estimates reported in Table [A.IV](#) show that Black and Hispanic borrowers increased their share of high-LTV mortgages by 5.27 pp and 3.49 pp compared to White borrowers, who increased their share of high-LTV mortgages

by 1.37 pp. These results suggest that even place-based targeting program for low downpayment mortgages can benefit the demographic groups that have historically suffered from discrimination and have low levels of homeownership.

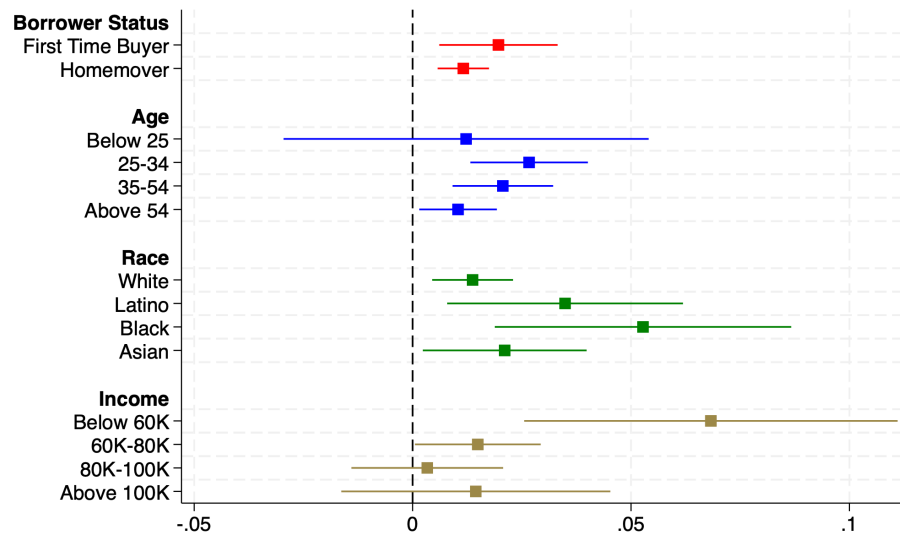


Figure 8: Impact on LTV Ratio

Notes: The figure plots the RDD estimates and corresponding 95% confidence intervals at borrower level for subsample of various borrower categories

Although the program was designed to target lower-income borrowers, I examine whether it successfully achieved that objective. To do so, I conduct borrower-level tests across multiple samples defined by different income categories, and the results are reported in Table A.V.

The result reveals a consistent pattern, where the probability of obtaining a high LTV mortgage due to HR and HP program is the highest for lowest income group and it progressively decreases as the income levels rise. The lowest income group consists of borrowers with annual income below \$60,000. For this group, the RDD estimates reported in Table A.V indicate a 6.83 percentage point increase in the probability of obtaining a high-LTV loan, suggesting that the program had a significant impact on its intended population. While borrowers with income between \$60,000 and \$80,000 reported an increase of 1.49 pp in the share of high-LTV mortgages, borrower groups with income above \$80,000 witnessed no effect on high-LTV mortgages due to the

programs. These results reinforce the fact that lowest-income borrowers with limited savings or cash-in-hand are most likely to benefit from any relaxation of down payment requirement.

8 Conclusion

Rising cost of housing has made homeownership difficult for many aspiring homebuyers. The average age of homeownership in United States has increased from 25 in 1980 to 36 in 2020. The most binding constraint in obtaining a mortgage for buying home is the down payment requirement. Hence, it is important to understand how relaxing downpayment requirements can affect mortgage and housing market. This paper investigates the impact of relaxing down payment constraints on house prices by exploiting a discontinuity at geographical level in borrower eligibility for low down payment programs. Using a regression discontinuity design, I establish four main findings. First, an average downpayment reduction of \$1000 per borrower generated a house price growth of \$590. Second, downpayment reduction was accompanied by change in mortgage composition with increase in high-LTV mortgages from first-time buyers partially offset by reduction in low-LTV mortgages from homemovers. Third, the effect on high-LTV mortgage originations exhibits an inverse U-curve with housing affordability, reflecting the strongest effect in moderately priced housing markets and weaker effects in low and high-cost markets. Fourth, effect on house price depends on existing distribution of housing structure than on housing supply elasticity factors with strongest price impact on housing markets with high friction in owner-rental conversion.

My findings highlight an underexplored aspect of how down payment relaxation affect mortgage and housing markets. As policymakers design newer program to provide downpayment assistance and support for aspiring homebuyers, I demonstrate that how effectiveness of the program could depend on regional housing affordability and how the price impact can depend on distribution of housing structures.

For policymakers addressing the issue of homeownership, my findings carry critical implications. The results suggest that housing affordability in terms of price-to-rent ratio and price-to-income ratio can affect participation in low-downpayment mortgage programs. As high-cost markets are less affected by these programs, policymakers must figure out the underlying factors for high price-to-rent ratio and initiate policy solutions to address those factors rather than depending on reduced downpayment requirements in mortgages to increase homeownership. My results have important implications for real estate development policies, as housing supply elasticity seems to play a lower role than housing structure distribution in determining house price. As lower frictions in rental-owner conversion moderates price impact, policymakers should consider designing and financing housing structures suitable for both renters and owners, especially within multi-unit apartments, which is currently dominated by renters.

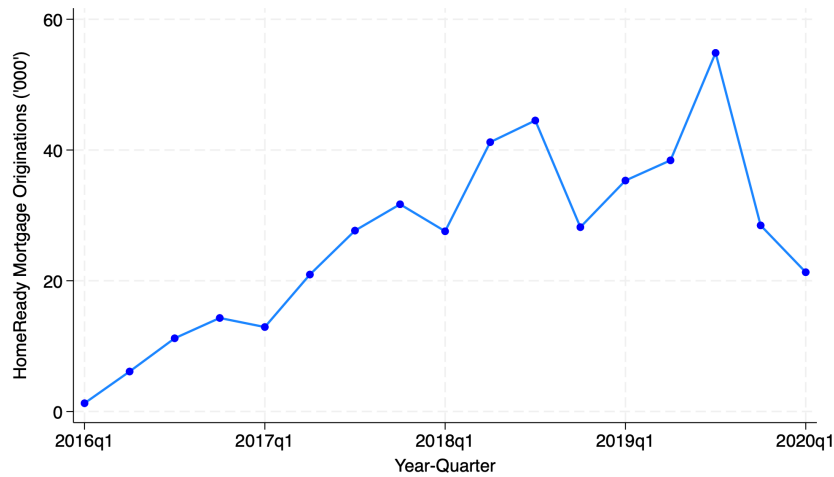
My findings also reveal that using LTV caps for macro-prudential policy for financial stability, could also affect house prices with heterogenous effects. This will have implications for Central Banks that pursue LTV caps to control credit supply. My results show that one can promote low-downpayment mortgages without substantially increasing the mortgage origination volume by change the composition of borrowers and loan characteristics.

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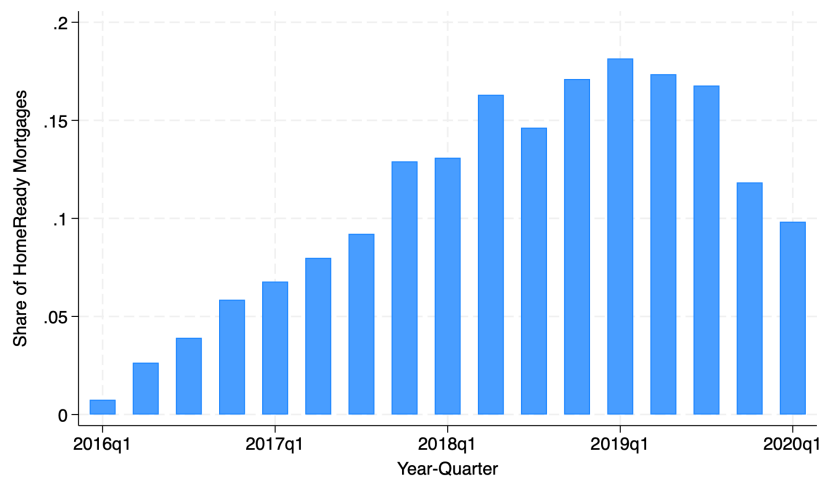
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Appendix



(a) HomeReady Originations



(b) Share of HomeReady Originations

Figure A.I: Evolution of HomeReady Program

Notes: Figure (a) plots the quarter-wise number of mortgages originated under HomeReady Program. Figure (b) plots the quarter-wise number mortgages originated under HomeReady Program as share of total mortgages originated by Fannie Mae

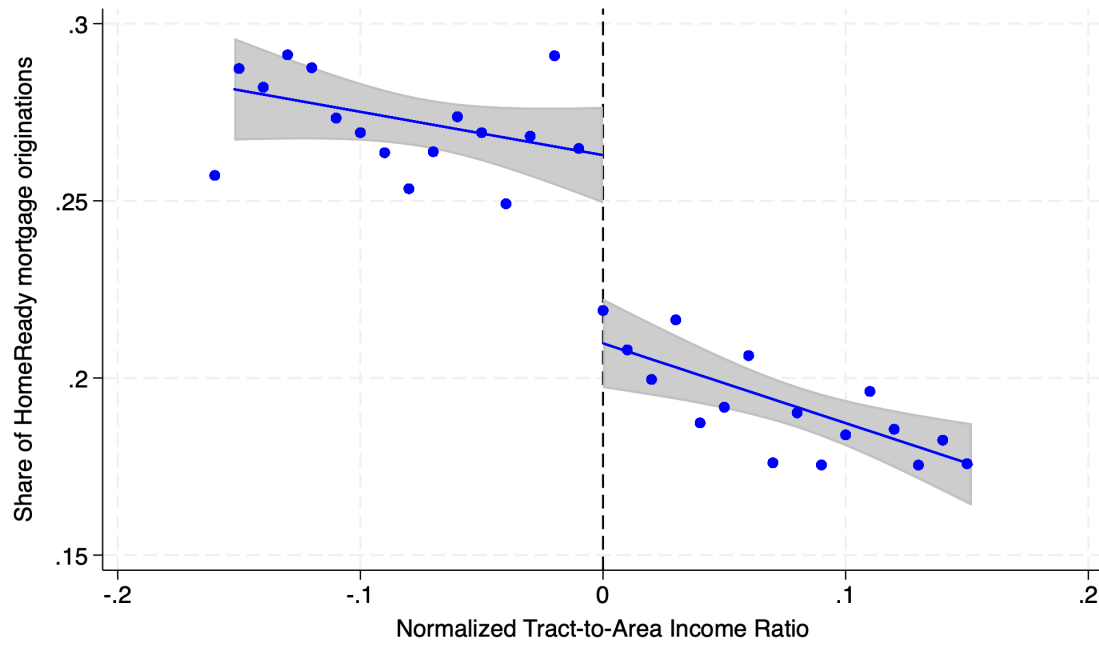
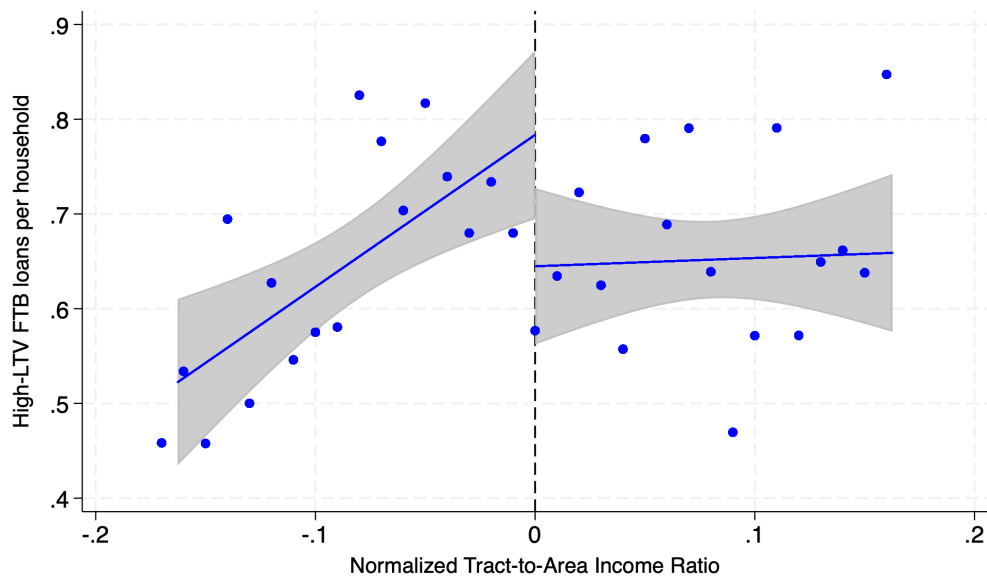
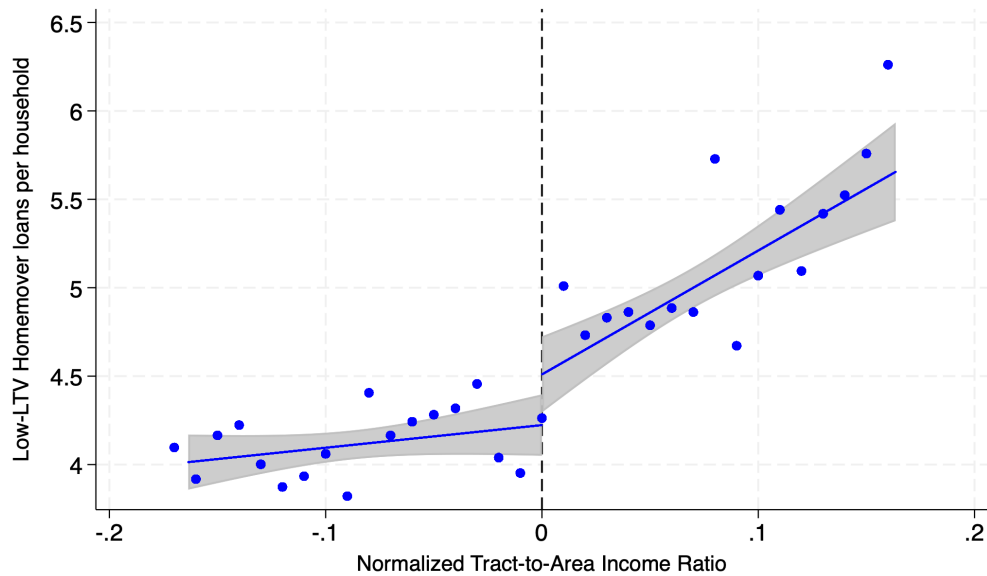


Figure A.II: Discontinuity in the share of HomeReady Mortgages at threshold

Notes: The figure plots the residualized values in the RDD specification after controlling for all variables other than tract to area income ratio. The residuals values are estimated separately for the right and left of the cutoff within the optimal bandwidth. The dots represent binned mean of the residual values. Tract to area income ratio is normalized by subtracting the cutoff value.



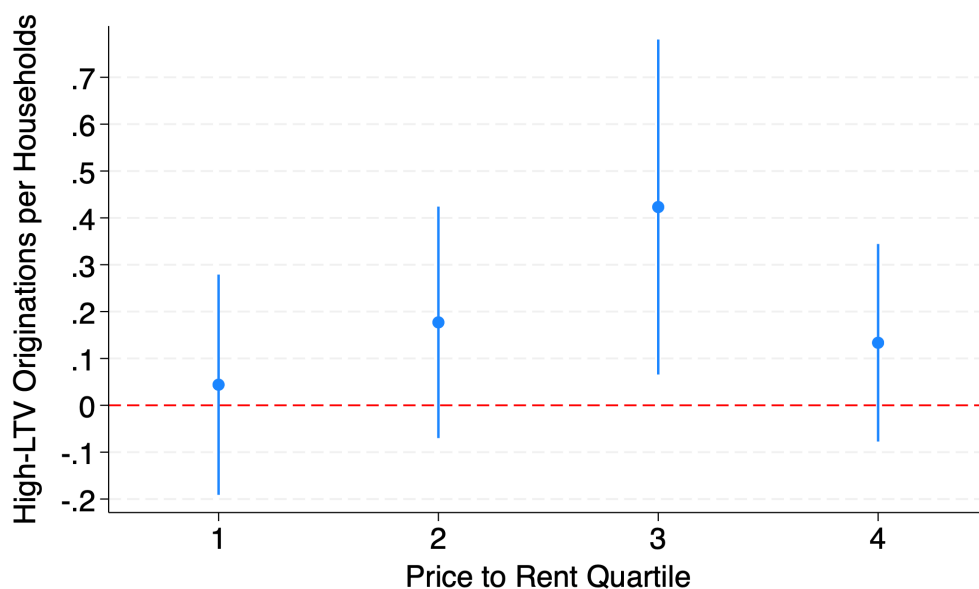
(a) First-time buyer High LTV Originations per households(in thousands)



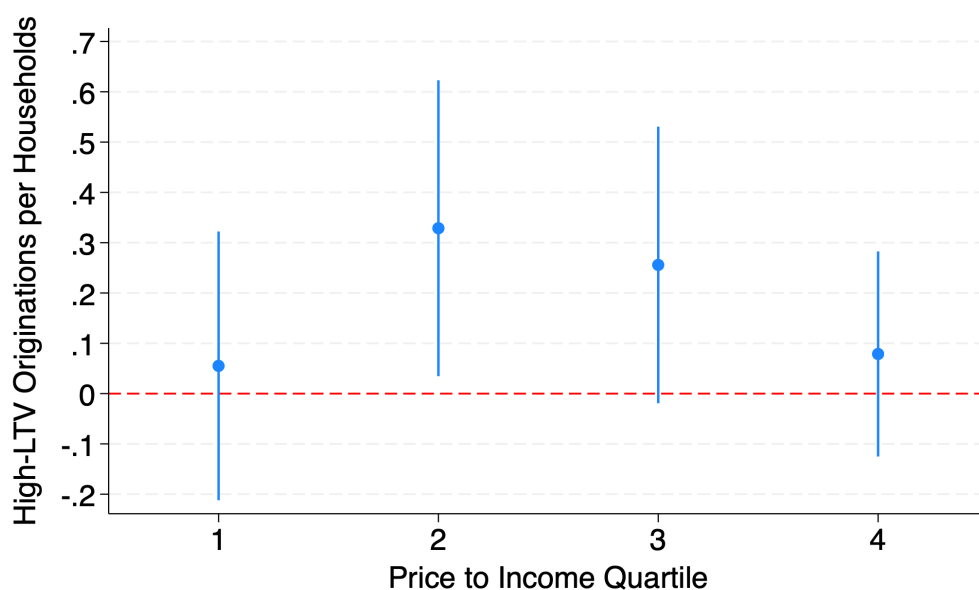
(b) Home-mover Low LTV Originations per households(in thousands)

Figure A.III: Impact on Mortgage Composition

Notes: The figure plots the residualized values in the RDD specification after controlling for all variables other than tract to area income ratio. The residuals values are estimated separately for the right and left of the cutoff within the optimal bandwidth. The dots represent binned mean of the residual values. Tract to area income ratio is normalized by subtracting the cutoff value.



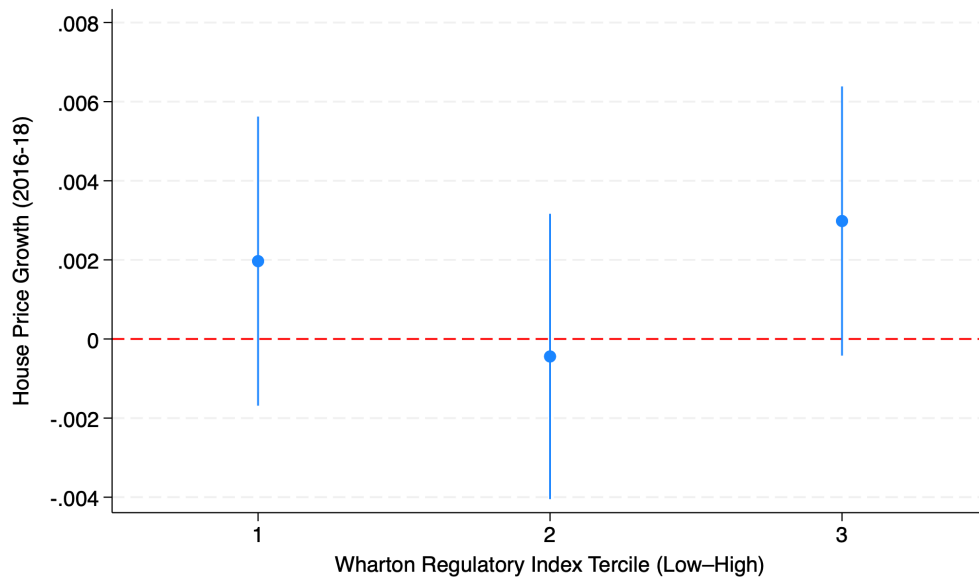
(a) House Price to Rent Quartile



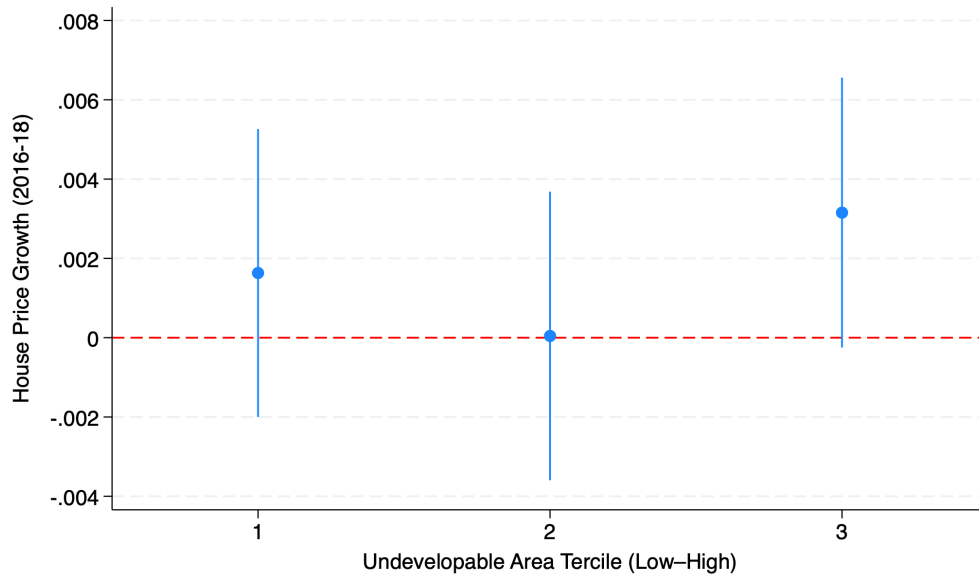
(b) House Price to Income Quartile

Figure A.IV: HLTV Originations: Heterogeneity by Housing Affordability (Quartile)

Notes: The figure displays RDD estimates of impact of relaxing down payment constraint on high-LTV originations per households (in thousands) and their corresponding 95% confidence intervals. It plots coefficients corresponding to quartiles defined based on ratio of MSA level median house price to median gross rent in Figure (a) and median house price to median income in Figure (b)



(a) RDD Estimates By Regulation Index



(b) RDD Estimates By Undevelopable Area

Figure A.V: Impact on House Price: Heterogeneity by Housing Supply Elasticity

Notes: The figure displays RDD estimates and their corresponding 95% confidence intervals across tercile of Wharton Residential Land Use Regulatory Index (WRLURI) in (a) and share of undevelopable area in (b). The sample is divided into three subsamples based on the tercile distribution of Wharton Regulation Index and Share of Undevelopable Area at MSA level. For each quartile, a separate RDD specification is estimated for optimal bandwidth, and the resulting coefficient is plotted against the corresponding quartile.

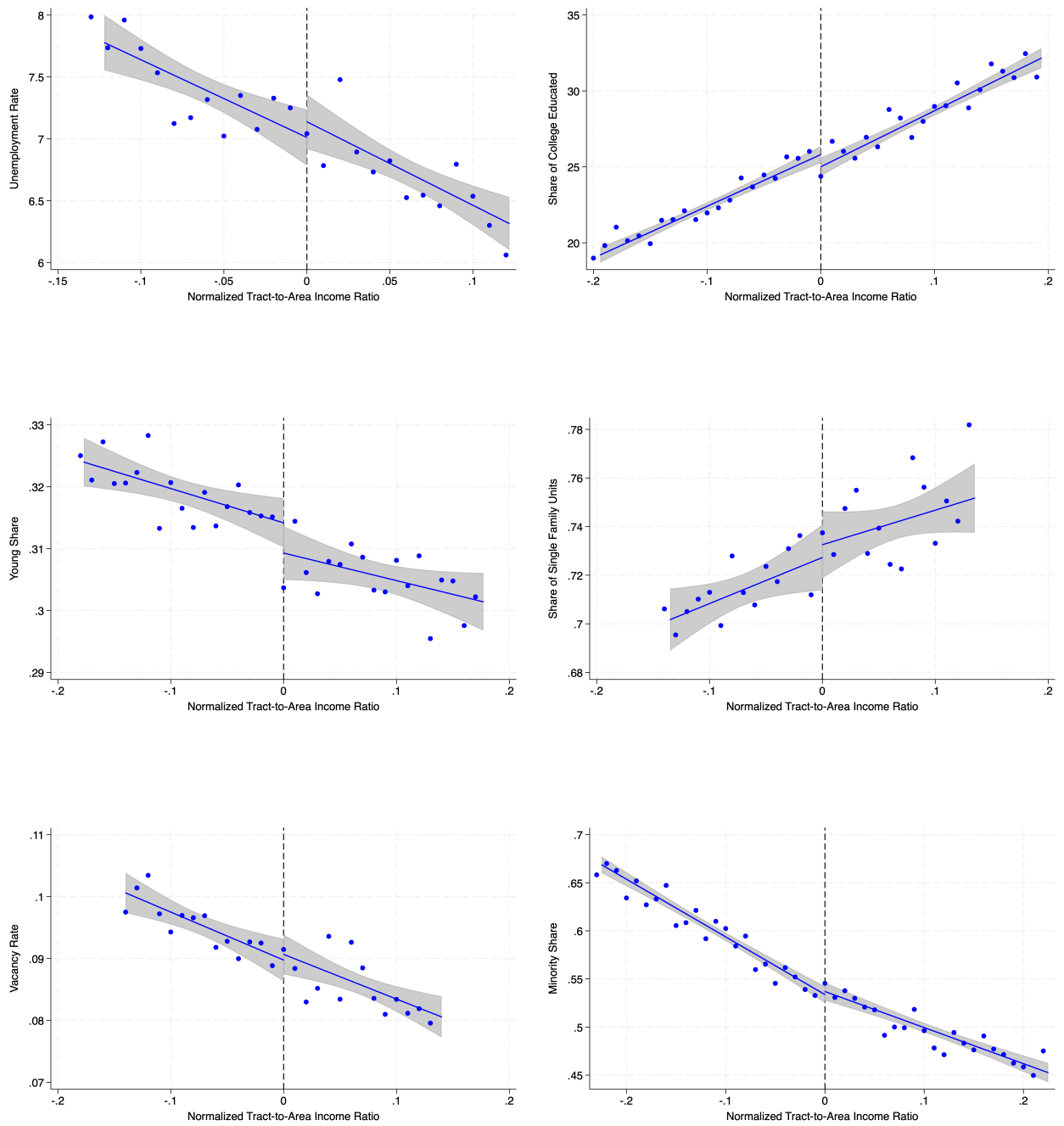
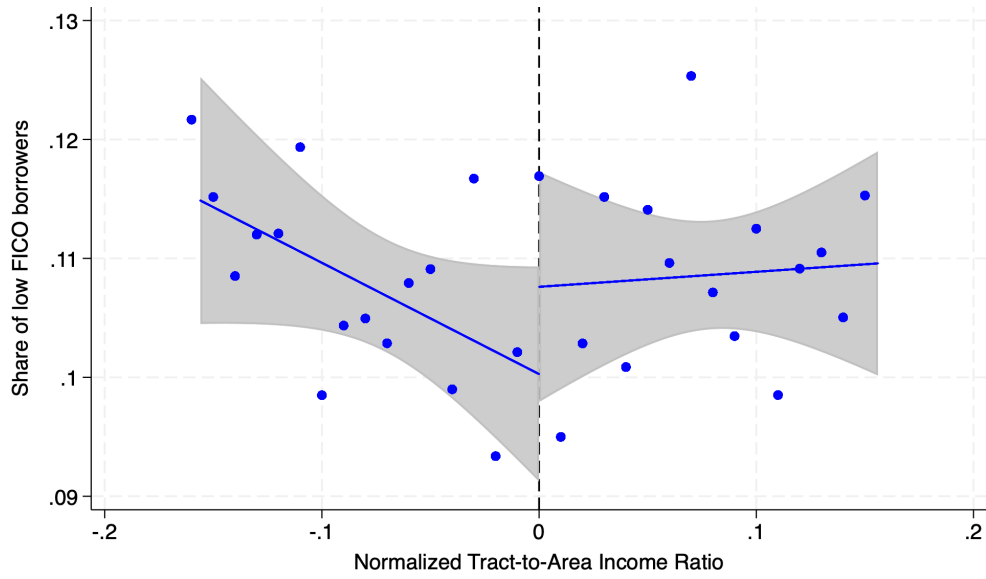
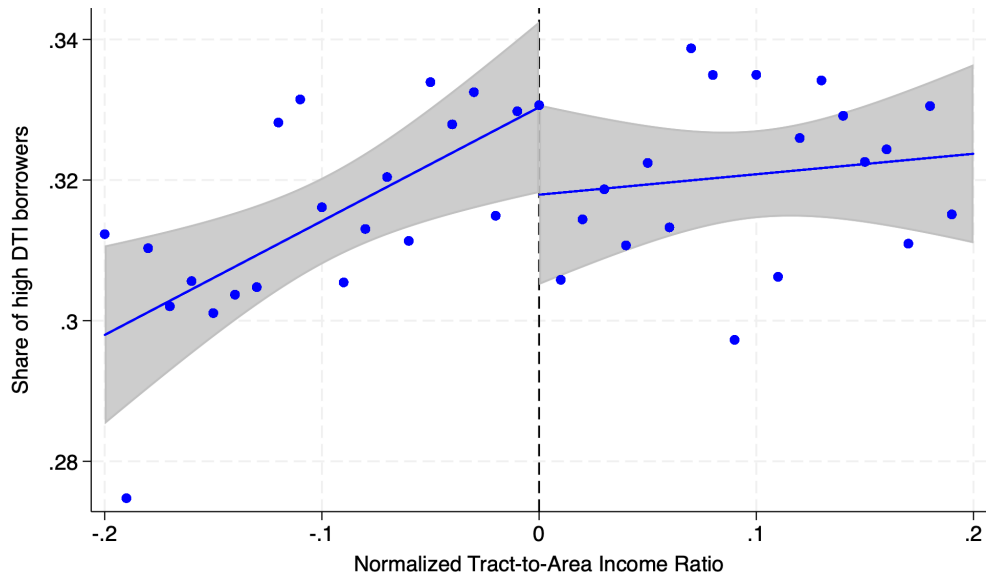


Figure A.VI: The figure plots the residualized values in the RDD specification after controlling for MSA fixed effects. The residuals values are estimated separately for the right and left of the cutoff within the optimal bandwidth. The dots represent binned mean of the residual values. Tract to area income ratio is normalized by subtracting the cutoff value



(a) Share of low FICO borrowers (FICO score < 680)



(b) Share of high DTI borrowers (DTI > 43)

Figure A.VII: Continuity in other mortgage characteristics at threshold

Notes: The figure plots the residualized values in the RDD specification after controlling for all variables other than tract to area income ratio. The residuals values are estimated separately for the right and left of the cutoff within the optimal bandwidth. The dots represent binned mean of the residual values. Tract to area income ratio is normalized by subtracting the cutoff value.

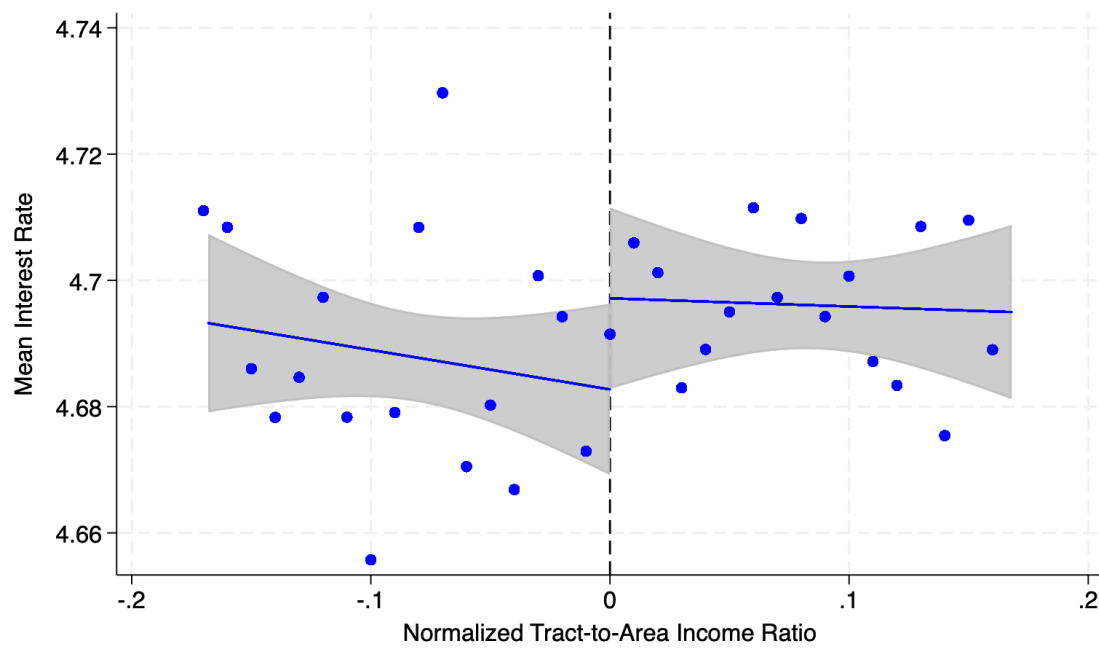


Figure A.VIII: Continuity in interest rate at threshold

Notes: The figure plots the residualized values in the RDD specification after controlling for all variables other than tract to area income ratio. The residuals values are estimated separately for the right and left of the cutoff within the optimal bandwidth. The dots represent binned mean of the residual values. Tract to area income ratio is normalized by subtracting the cutoff value.

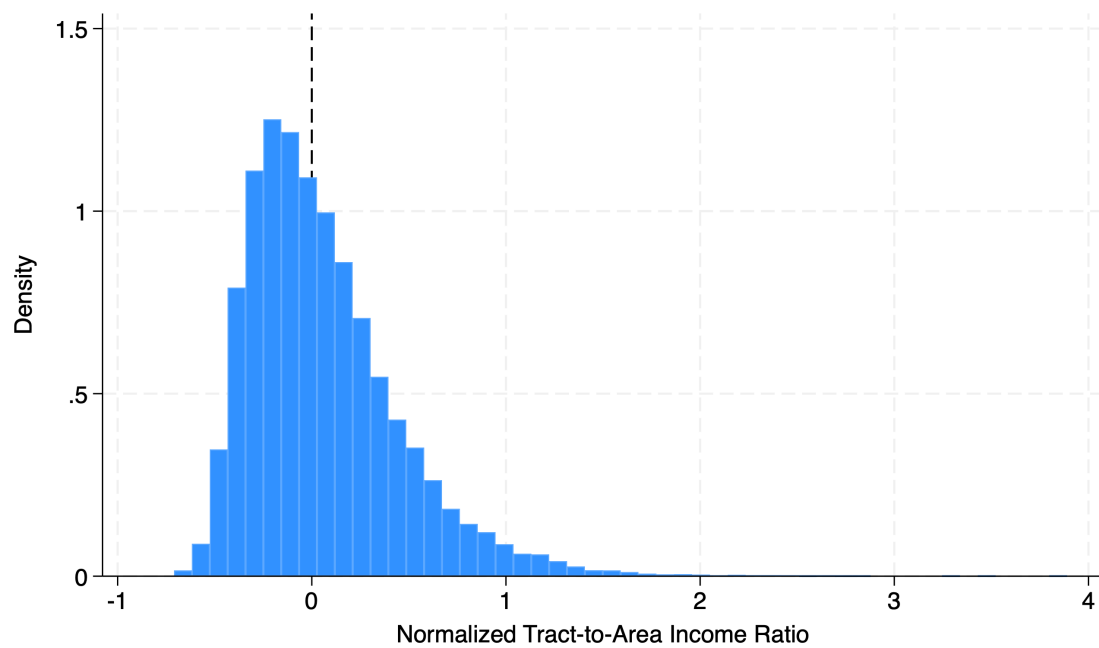


Figure A.IX: Histogram

Additional Tables

Table A.I: Effect on Mortgage Composition

	First-time High-LTV	HomeMover Low-LTV	HomeMover High-LTV	First-time Low-LTV
	(1)	(2)	(3)	(4)
$\mathbb{1}[I_{cm} \leq 0.8]$	0.0104** (0.00504)	-0.0109* (0.00628)	0.00123 (0.00197)	-0.00214 (0.00540)
Control Mean	0.134	0.536	0.0257	0.314
Observations	11,852	13,678	12,372	17,036
R-squared	0.357	0.262	0.107	0.346
Bandwidth	0.128	0.148	0.134	0.186
Tract controls	Yes	Yes	Yes	Yes
MSA Fixed Effects	Yes	Yes	Yes	Yes

Notes: Table presents the results of the effect of HR and HP program on mortgage Composition using RDD estimates of equation 1 at the tract level. The dependent variable is the share of First-time buyer High-LTV originations in column (1), share of Non-First-time buyer Low-LTV originations in column (2), share of Non-First-time buyer High-LTV originations in column (3), and share of First-time buyer Low-LTV originations in column (4). The sample is restricted to the optimal bandwidth based on (Calonico et al., 2014). $\mathbb{1}[I_{cm} \leq 0.8]$ is a dummy variable that carries a value of one for low-income census tracts, which are tracts with median income below or equal to 80% of Area Median Income (AMI). The errors are clustered at the tract level and adjusted for heteroscedasticity. *, ** and *** represent 10%, 5%, and 1% levels of significance.

Table A.II: High-LTV Originations: Heterogeneity by Housing Affordability

	Price-to-Rent Tercile			Price-to-Income Tercile		
	Bottom (1)	Middle (2)	Top (3)	Bottom (4)	Middle (5)	Top (6)
$\mathbb{1}[I_{cm} \leq 0.8]$	0.0447 (0.105)	0.345** (0.135)	0.205* (0.107)	0.0657 (0.119)	0.486*** (0.129)	-0.0131 (0.104)
Observations	5,188	5,177	5,178	5,198	5,192	5,153
R-squared	0.394	0.358	0.495	0.428	0.311	0.471
Bandwidth	0.169	0.169	0.169	0.169	0.169	0.169
Tract controls	Yes	Yes	Yes	Yes	Yes	Yes
MSA Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Table presents the results of the heterogenous effect of relaxing downpayment constraint on high LTV mortgage originations using RDD estimates of equation 1 at the tract level by classifying sample into terciles based on ratio of MSA level median house price to median gross rent in columns (1) to (3) and median house price to median income in columns (4) to (6). The dependent variable is high LTV originations per households(in thousands). The sample is restricted to the optimal bandwidth based on (Calonico et al., 2014). $\mathbb{1}[I_{cm} \leq 0.8]$ is a dummy variable that carries a value of one for low-income census tracts, which are tracts with median income below or equal to 80% of Area Median Income (AMI).

Table A.III: High LTV Mortgages: Borrower Heterogeneity by Buyer Status and Age

	Borrower Status		Borrower Age			
	First-time Buyer (1)	Homemover (2)	<25 (3)	25-34 (4)	34-55 (5)	>55 (6)
$\mathbb{1}[B_{im} \leq 1]$	0.0197*** (0.00691)	0.0116*** (0.00300)	0.0122 (0.0213)	0.0267*** (0.00686)	0.0207*** (0.00587)	0.0104** (0.00453)
Control Mean	0.254***	0.0279***	0.314***	0.194***	0.128***	0.0479***
Observations	63,863	62,062	8,000	57,476	54,227	41,008
R-squared	0.068	0.027	0.118	0.055	0.045	0.029
Bandwidth	0.131	0.144	0.189	0.162	0.155	0.231
MSA Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Table presents the results of the heterogenous effect of relaxing downpayment constraint on high LTV mortgage originations using RDD estimates of equation 2 at the borrower level by classifying sample based on borrower age and status categories. The dependent variable is a dummy variable that carries a value of one for borrowers with high LTV (LTV greater than 95%) mortgages. $\mathbb{1}[B_{im} \leq 1]$ is a dummy variable that carries a value of one for borrowers with median income below or equal to 100% of Area Median Income (AMI). The sample is restricted to the optimal bandwidth based on (Calonico et al., 2014).

Table A.IV: High LTV Mortgages: Heterogeneity by Borrower Race

Borrower Race	White (1)	Latino (2)	Black (3)	Asian (4)
$\mathbb{1}[B_{im} \leq 1]$	0.0137*** (0.00472)	0.0349** (0.0138)	0.0527*** (0.0173)	0.0211** (0.00957)
Control Mean	0.13	0.225	0.274	0.0672
Observations	87,229	15,018	10,668	12,369
R-squared	0.036	0.081	0.090	0.076
Bandwidth	0.149	0.185	0.231	0.196
MSA Fixed Effects	Yes	Yes	Yes	Yes

Notes: Table presents the results of the heterogeneous effect of relaxing downpayment constraint on high LTV mortgage originations using RDD estimates of equation 2 at the borrower level by classifying sample based on borrower race categories. The dependent variable is a dummy variable that carries a value of one for borrowers with high LTV (LTV greater than 95%) mortgages. $\mathbb{1}[B_{im} \leq 1]$ is a dummy variable that carries a value of one for borrowers with median income below or equal to 100% of Area Median Income (AMI). The sample is restricted to the optimal bandwidth based on (Calonico et al., 2014).

Table A.V: High LTV Mortgages: Heterogeneity by Borrower Income

Borrower Income	<60K (1)	60K-80K (2)	80K-100K (3)	>100K (4)
$\mathbb{1}[B_{im} \leq 1]$	0.0683*** (0.0218)	0.0149** (0.00734)	0.00336 (0.00886)	0.0145 (0.0157)
Control Mean	0.161	0.163	0.126	0.104
Observations	12,141	43,867	22,550	6,130
R-squared	0.047	0.037	0.023	0.02
Bandwidth	0.144	0.093	0.091	0.078
MSA Fixed Effects	Yes	Yes	Yes	Yes

Notes: Table presents the results of the heterogenous effect of relaxing downpayment constraint on high LTV mortgage originations using RDD estimates of equation 2 at the borrower level by classifying sample based on borrower income categories. The dependent variable is a dummy variable that carries a value of one for borrowers with high LTV (LTV greater than 95%) mortgages. $\mathbb{1}[B_{im} \leq 1]$ is a dummy variable that carries a value of one for borrowers with median income below or equal to 100% of Area Median Income (AMI). The sample is restricted to the optimal bandwidth based on (Calonico et al., 2014).

Table A.VI: High LTV Mortgages: Heterogeneity by Housing Affordability

	Undevelopable area			Land Regulation Index		
	Bottom (1)	Middle (2)	Top (3)	Bottom (4)	Middle (5)	Top (6)
$\mathbb{1}[I_{cm} \leq 0.8]$	0.00163 (0.00185)	4.41e-05 (0.00186)	0.00315* (0.00174)	0.00197 (0.00186)	-0.000442 (0.00184)	0.00298* (0.00174)
Control Mean	0.0288***	0.0461***	0.0551***	0.0362***	0.0394***	0.0514***
Observations	6,010	5,758	5,718	6,423	5,523	5,540
R-squared	0.406	0.440	0.414	0.436	0.414	0.406
Bandwidth	0.281	0.281	0.281	0.281	0.281	0.281
Tract controls	Yes	Yes	Yes	Yes	Yes	Yes
MSA Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Table presents the results of the heterogeneous effect of relaxing downpayment on house price growth based on RDD specification 2. The dependent variable is the growth in house prices from 2016 to 2018. $\mathbb{1}[I_{cm} \leq 0.8]$ is a dummy variable that carries a value of one for low-income census tracts, which are tracts with median income below or equal to 80% of Area Median Income (AMI). The sample is sorted by classifying it into terciles based on share of undevelopable area in columns (1) to (3) and Wharton Residential Land Use Regulatory Index (WRLURI) in columns (4) to (6). The sample is restricted to bias-corrected optimal bandwidth, based on (Calonico et al., 2014).

Table A.VII: RDD Estimates of Co-variates

	Unemployment Rate (1)	College Educated (2)	Young (3)	Single Family Units (4)	Vacancy Rate (5)	Minority Share (6)
Treated	-0.132 (0.168)	0.823* (0.433)	0.00503 (0.00309)	-0.00539 (0.0102)	-0.000942 (0.00247)	-0.00287 (0.00670)
Control Group	7.138	25.04	0.309	0.733	0.0906	0.536
Observations	6,874	10,804	9,980	7,613	7,899	12,567
R-squared	0.284	0.381	0.149	0.077	0.346	0.427
Bandwidth	0.122	0.194	0.177	0.135	0.14	0.225
MSA Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

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Notes: Table presents the results of the effect of relaxing downpayment constraint on covariates using RDD estimates of equation 1 at the tract level. $\mathbb{1}[I_{cm} \leq 0.8]$ is a dummy variable that carries a value of one for low-income census tracts, which are tracts with median income below or equal to 80% of Area Median Income (AMI). For each regression, the outcome mean for the control group (tracts with income above 80% AMI) is also shown. The specification includes tract-level controls for economy, demographics, and housing, as well as MSA fixed effects. The errors are clustered at the tract level and adjusted for heteroscedasticity. *, ** and *** represent 10%, 5%, and 1% levels of significance.

Table A.VIII: Continuity in Other Mortgage Characteristics at threshold

Panel A			
Dependent Variable	Low Credit Score (1)	High DTI (2)	Interest rate (3)
$\mathbb{1}[I_{cm} \leq 0.8]$	-0.00757 (0.00697)	0.0129 (0.00929)	-0.0148 (0.0104)
Control	0.107	0.322	4.698
Bandwidth	0.156	0.2	0.168
Observations	8,384	10,693	8,998
R-squared	0.133	0.164	0.221
Panel B (Bandwidth - 20)			
$\mathbb{1}[I_{cm} \leq 0.8]$	0.000294 (0.00868)	0.0119 (0.0136)	-0.00152 (0.0136)
Control	0.131	0.284	4.703
Observations	5,361	5,361	5,361
R-squared	0.155	0.166	0.232
Panel C (Bandwidth - 10)			
$\mathbb{1}[I_{cm} \leq 0.8]$	-0.00518 (0.00610)	0.0129 (0.00929)	-0.0182* (0.00963)
Control	0.119	0.322	4.71
Observations	10,693	10,693	10,693
R-squared	0.118	0.164	0.212

Notes: Table presents the results of RDD estimates of other mortgage characteristics based on equation 1 at the tract level. Panel A restricts sample within the optimal bandwidth, while Panel B and C restricts the sample within bandwidths of 0.1 and 0.2 from the cutoff respectively. The dependent variable for column (1) is the share of low FICO score borrowers (FICO < 680), column (2) is the share of high DTI borrowers (DTI > 43) and column (3) is the mean interest rate. $\mathbb{1}[I_{cm} \leq 0.8]$ is a dummy variable that carries a value of one for low-income census tracts, which are tracts with median income below or equal to 80% of Area Median Income (AMI). For each regression, the outcome mean for the control group (tracts with income above 80% AMI) is also shown. The specification includes tract-level controls for economy, demographics, and housing, as well as MSA fixed effects. The errors are clustered at the tract level and adjusted for heteroscedasticity. *, ** and *** represent 10%, 5%, and 1% levels of significance.

Table A.IX: Composition of Housing Structures by tenure status

Structure Type	Always Owner	Always Rental	Own/Rent
Detached, 1 unit	73.5%	2.4%	24.1%
Attached, 1–4 units	23.7%	41.9%	34.5%
Apartment, 5–19 units	4.1%	78.1%	17.8%
Apartment, 20–49 units	4.6%	77.2%	18.2%
Apartment, 50+ units	7.4%	70.5%	22.2%

Notes: This table provides the shares of housing units which have remained always owner, always rental and either owned/rental for each housing structure category