Who Gains from Easier Credit: Price Capitalization and Buyer Sorting in Housing Markets

Yi-Ting Wang

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1 Introduction

Understanding the distributional consequences of mortgage credit expansions is essential for designing effective and equitable housing finance policies. This paper investigates a central question: when borrowing costs decrease, do lower-income buyers benefit through expanded access to homes in their targeted price tier, or are they instead crowded out by price increases and competition from higher-income households?

Empirically answering this question is challenging for three reasons. First, many credit-related policy shifts, such as changes in interest rates or underwriting standards, are endogenous to broader macroeconomic or household financial conditions, complicating causal inference. Second, households respond heterogeneously to easier credit: some increase leverage and divert resources from down payments toward non-housing consumption, while others use newly available borrowing capacity to upgrade to homes with better amenities, more space, or higher-quality schools. Third, expansions in mortgage credit often capitalize into house prices, generating general-equilibrium effects that influence not only directly treated buyers but also others in the local market.

I address these challenges in the context of the conforming loan limit (CLL), a annually adjusted threshold that determines eligibility for low-cost, government-backed mortgage credit. By linking CoreLogic transaction records, HMDA loan-level applications, and yearly

CLL updates, I construct a property-level dataset that integrates detailed housing characteristics, borrower demographics, and mortgage terms.

The analysis proceeds in three stages. First, I document a well-established stylized fact: increases in the CLL are capitalized into higher house prices. Second, I provide reduced-form evidence using an "ease-of-finance" measure—defined as the gap between a property's hedonic predicted price (based only on non-financial characteristics) and the prevailing CLL—to estimate how CLL-induced credit expansions affect buyer composition and borrowing behavior near the threshold. Finally, I develop a structural discrete choice model with an instrumental-variables strategy that embeds CLL eligibility directly into household choice sets.

Taken together, these components allow me to quantify whether increases in the CLL enable lower-income households to move into higher-quality or higher-priced segments of the market, or whether the resulting price capitalization instead crowds them out of the very tiers the policy is intended to make accessible. To highlight the broader applicability of the framework, I complement the empirical analysis with simulations that vary both the value households place on conforming status and the distribution of properties near the CLL. These exercises reveal conditions under which lower-income buyers upgrade when credit constraints are relaxed, as well as conditions in which higher-income buyers absorb the newly conforming units, leaving lower-income households no better off. In doing so, the simulations illustrate how the consequences of CLL expansions depend critically on local market structure and the strength of financing frictions across income groups.

2 Related Literature

This study relates to three strands of literature: (i) research on mortgage market frictions at the conforming loan limit, (ii) hedonic price modeling, and (iii) discrete choice and sorting models of housing demand.

Duca et al. (2011) argue that many standard house-price models fail when they omit credit supply shifts. By incorporating a cyclically adjusted loan-to-value (LTV) measure for first-time buyers, they show that accounting for credit constraints helps explain house price–to–rent ratios and improves the stability and fit of long-run housing demand models.

First, prior work exploits the sharp change in mortgage terms at the conforming loan limit (CLL) to study borrower behavior. DeFusco and Paciorek (2017) use bunching at the threshold to estimate the interest rate elasticity of mortgage demand, showing that borrowers adjust loan size to retain conforming status. Adelino et al. (2025) employ a difference-in-differences (DID) design to show that CLL increases raise house prices. These studies focus on loan size adjustments and price capitalization but leave open the question of how buyer composition changes when access to conforming credit expands.

Second, hedonic pricing models, pioneered by Rosen (1974), estimate the marginal willingness to pay for property attributes. I use a hedonic regression to construct predicted property prices based only on non-financial attributes, which serve as the basis for my "ease-of-finance" measure—the gap between predicted price and the applicable CLL. This approach follows extensions in Bajari and Benkard (2005) and Ekeland et al. (2002), which allow for flexible preferences, but here the hedonic stage serves primarily as an input for policy-induced variation in financing conditions rather than as a stand-alone valuation exercise.

Third, discrete choice and sorting models extend the hedonic framework to account for heterogeneous preferences and endogenous location choice. Bayer et al. (2009) show that incorporating mobility costs changes estimated willingness-to-pay. Dynamic extensions (e.g., Bayer et al., 2016) capture forward-looking behavior and tenure transitions. However, most such models abstract from financing constraints. The discrete choice model proposal in this paper adapts the Bayer et al. (2007) framework, in which ease of commute enters as a location attribute, by instead allowing a property's CLL status to enter the utility function as an "ease-of-finance" attribute.

By combining a hedonic prediction step with quasi-experimental variation from CLL adjustments, I link shifts in borrowing costs to changes in both prices and buyer composition. This approach bridges the gap between reduced-form estimates of CLL effects and structural models of housing demand, providing a framework for evaluating who benefits from mortgage credit expansions.

3 Institutional Background

The conforming loan limit is a dollar cap on the size of mortgages that can be purchased or guaranteed by the government-sponsored enterprises (GSEs) Fannie Mae and Freddie Mac. Loans below this threshold are known as "conforming loans". They qualify for GSE backing and thus typically enjoy lower interest rates, standardized underwriting, and broader lender participation due to lower capital and risk retention requirements. In contrast, loans above the limit, referred to as "jumbo loans", are ineligible for GSE securitization and must be financed through private channels, often resulting in higher rates and tighter credit standards. Conforming loans usually make up 60–70% of all new first-lien mortgages in the United States.

The CLL thus creates a clear boundary in the mortgage market, segmenting properties into distinct credit regimes. Each November, the Federal Housing Finance Agency (FHFA) sets the CLL for the upcoming year, applying county-level adjustments based on recent local housing price trends.

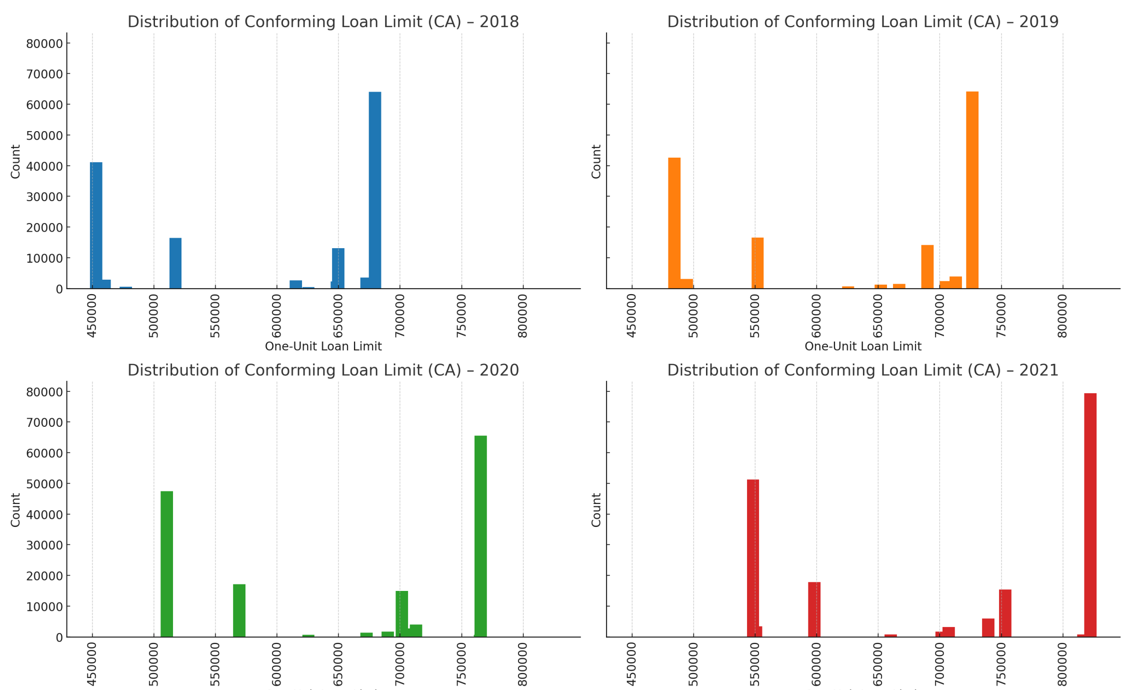


Figure 1: Single unit conforming loan limit (CA, 2018–2021)

Table 1: Conforming Loan Limits for Single-Unit Homes in California (2018–2021)[1]

Year	Baseline Limit (USD)	High-Cost Ceiling (USD)
2018	$453,100	$679,650
2019	$484,350	$726,525
2020	$510,400	$765,600
2021	$548,250	$822,375

As shown in Figure 1, adjustments to the conforming loan limit (CLL) vary both geographically (county level) and over time, but concentrates in a few value each year. Compared with fluctuations in actual market prices, these adjustments are relatively coarse, generating exogenous variation in the gap between market prices and the applicable CLL. This gap can be used to construct a property-level "ease-of-finance" indicator by comparing each property's predicted price, estimated using only non-financial characteristics, with the CLL for that property's county and year. Unlike interest rates or rate spreads, which are closely tied to borrower characteristics (e.g., FICO score, unobserved cash flows from savings or family support) and borrower choices (e.g., mortgage terms, points, down payments), the variation in the predicted-price, CLL gap provides a cleaner basis for defining treatment and control groups.

Importantly, a household's optimal housing choice, shaped by structural features like lot size, layout, or school district, is unlikely to shift dramatically in response to modest annual CLL adjustments. When the CLL increases, previously constrained households may either reduce their down payments and redirect funds toward other consumption, or use the expanded borrowing capacity to pay more for similar housing attributes, leading to price capitalization. This dynamic captures the tradeoff at the heart of the analysis: when some properties near the threshold become easier to finance, lower-income buyers may be able to move into this price tier. At the same time, higher-income buyers, who could already afford these properties, can use the freed-up funds from smaller down payments to bid more aggressively. The resulting demand pressure can fuel price capitalization, potentially offsetting any affordability gains. The central question, therefore, is whether lower-income buyers actually secure these newly conforming properties or whether they are instead crowded

[1]Source: Federal Housing Finance Agency (FHFA) Conforming Loan Limit Data; California-specific limits from `https://californiamortgagefinder.com/conforming-loan-limits/`.

out by wealthier competitors.

4 Data Sources

The primary data source is transaction-level housing listing and mortgage dataset from CoreLogic, which captures nearly all residential property transactions in the United States. It provides rich property-level attributes, such as sale price, square footage, lot size, year built, and location, along with mortgage details that include loan amount, interest rate, loan-to-value (LTV) ratio, and conforming loan status. Unique buyer identifiers allow differentiation between first-time and repeat purchasers.

To complement this, Home Mortgage Disclosure Act (HMDA) data offers loan-level application outcomes (approved, denied, withdrawn) and records loan purpose, lien status, and interest rate. Since 2018, HMDA has expanded to include underwriting measures such as debt-to-income ratio (DTI), combined loan-to-value ratio (CLTV), and automated underwriting system results. Crucially, HMDA also reports borrower demographics, including income, race, and age, allowing a detailed analysis of buyer composition.

In the empirical work, CoreLogic's Multiple Listing Service (MLS) and mortgage modules are linked through a property specific ID, while HMDA loan records are matched to CoreLogic's mortgage data via the mortgage composite transaction ID. This integration yields a unified dataset containing transaction prices, property characteristics, mortgage terms, and borrower demographics.

4.1 Sample Restriction

We focus on the single unit home transactions in California between 2018 and 2021. The sample is restricted to:

- Single-family home purchases matched with approved mortgage applications.
- Focus on home purchases, exclude refinances and home refinements.
- Excluded property for commercial purposes. Focus on occupancy type labelled as principal residence.

- Transaction years 2018–2021, chosen for data quality and policy variation.
- Properties with complete transaction, mortgage, and borrower demographic information.

4.2 Summary Statistics

Tables 2 and 3 report descriptive statistics for California homebuyers from 2018–2021 by borrower income quintile, using CoreLogic transaction records linked to HMDA mortgage application data. The income-based stratification highlights heterogeneity in how borrowers at different points of the income distribution finance their purchases and interact with the conforming loan limit (CLL).

Table 2: Close Price, Loan Amount, and Conforming Share by Income Quintile (CA, 2018–2021)

Quintile	Close Price (USD)	Loan Amount (USD)	Share Conforming	Income Range (k USD)
Q1 (lowest)	725,857	479,239	0.891	50 – 120
Q2	789,014	577,671	0.811	121 – 150
Q3	823,092	600,978	0.756	151 – 182
Q4	842,554	612,506	0.722	183 – 229
Q5 (highest)	859,997	629,414	0.686	230 – 513,750

Table 3: CLTV, DTI, and Interest Rate by Income Quintile (CA, 2018–2021)

Quintile	Mean CLTV (%)	Mean DTI (%)	Mean Interest Rate (%)
Q1 (lowest)	68.24	42.41	3.626
Q2	76.57	38.82	3.731
Q3	79.04	35.74	3.819
Q4	80.16	32.13	3.884
Q5 (highest)	80.53	27.12	3.908

Several patterns emerge across income quintiles that are highly informative for understanding differential exposure to credit constraints and CLL eligibility:

1. **Home and loan sizes rise with income.** Close prices and loan amounts both increase monotonically from Q1 to Q5, consistent with standard income-elastic housing demand.

2. **Lower-income buyers rely disproportionately on conforming loans.** Conforming shares fall from 89% in Q1 to 69% in Q5. This reflects both the lower price points of homes purchased by Q1–Q2 households and their stronger sensitivity to financing costs. Consequently, CLL adjustments directly affect the borrowing costs of lower-income buyers much more than higher-income buyers.

3. **Combined Loan-to-Value ratio (CLTV) rises with income, while Debt-to-Income ratio (DTI) falls.** Lower-income buyers exhibit lower CLTV but much higher DTI, while higher-income buyers show the opposite pattern. This suggests that lower-income buyers are constrained not by collateral limits but by monthly-payment (DTI) underwriting caps.

4. **Interest rates rise slightly with income.** Higher-income borrowers pay marginally higher rates, consistent with greater use of jumbo products and reduced reliance on GSE-backed conforming loans.

Since conforming shares decline with income and DTI constraints bind most sharply for lower-income borrowers, increases in the CLL are likely to ease financing constraints most directly for Q1–Q2 households. Yet any gains in borrowing capacity may be attenuated, or even reversed, by price capitalization if expanded credit shifts demand upward. This creates a clear distributional tension: the households that stand to benefit most from improved access to conforming credit are also those most susceptible to being priced out when market prices adjust. These considerations motivate the reduced-form and structural analyses that follow.

5 Reduced Form Analysis

5.1 Hedonic Regression

The central objective of the reduced form analysis is to assess whether changes in the ease of finance, driven by adjustments to the conforming loan limit, alter the composition of homebuyers for properties near the threshold. Buyer composition is measured using mean buyer income and debt-to-income (DTI) ratio. Since most properties transact only once within the sample period, the comparison relies on properties with similar observable characteristics.

Following Adelino et al. (2025), the first step prior to defining treatment and control groups is to estimate a hedonic price. This step isolates the role of housing quality, allowing us to distinguish whether observed price changes after conforming loan limit adjustments simply reflect differences in property quality, or whether differences in buyer composition persist even after controlling for quality.

We estimate hedonic regressions of value per square foot and log house price on a set of property characteristics, along with year and ZIP code fixed effects. The residuals from these regressions, denoted

$$LHS_i = \gamma_0 + \beta X_i + \text{year}_i + \text{zipcode}_i + \varepsilon_i \tag{1}$$

includes housing attributes such as size, number of bedrooms and bathrooms. The residuals from these regressions provide quality-adjusted measures of housing prices, isolating variation unrelated to structural or locational characteristics. In the analysis that follows, we use predicted values based on the log house price specification to construct our measure of ease of finance.

Table 4: Average Actual and Predicted Prices in 2021 by Top 5 MSAs

MSA (ZIP Prefix)	**Actual Price**	**Predicted Price**
LA–Long Beach–Anaheim (90210)	$5,645,063	$5,621,424
SF–Oakland–Berkeley (94123)	$5,298,587	$5,304,052
LA–Long Beach–Anaheim (90077)	$4,776,373	$4,797,297
LA–Long Beach–Anaheim (92660)	$2,739,685	$2,740,923
SF–Oakland–Berkeley (94027)	$7,729,629	$7,586,158

5.2 Empirical Strategy

Following Green and Wachter (2005), we assume that most lenders require an LTV ratio of 80% or below for a loan to qualify as conforming. Under this assumption, treatment status is assigned when a property becomes easier to finance relative to the previous year, as defined by:

$$\text{Treatment}_{jt} = 1 \quad \text{if} \quad 0.8 \cdot \hat{P}_{jt} > C_{t-1,j} \quad \text{and} \quad 0.8 \cdot \hat{P}_{jt} \leq C_{t,j}$$

The sample is restricted to properties transacted at prices near the conforming loan limit in the transaction year, using two alternative bandwidths around the cutoff based on predicted and actual prices:

1. Sample 1: $\left|0.8 \cdot \hat{P}_{jt} - \text{CLL}\right| \leq 50{,}000$
2. Sample 2: $\left|0.8 \cdot \hat{P}_{jt} - \text{CLL}\right| \leq 10{,}000$
3. Sample 3: $|0.8 \cdot P_{jt} - \text{CLL}| \leq 50{,}000$
4. Sample 4: $|0.8 \cdot P_{jt} - \text{CLL}| \leq 10{,}000$

Table 5: Test for Price Capitalization

	(1) No Controls	(2) With Property Controls
Treated	107,245.7*	86,000.21*
	(55,773.63)	(45,256.11)
Total Baths		37,587.84***
		(9,084.28)
Number of Bedrooms		-13,424.98**
		(6,566.36)
Year Built		-235.21
		(524.86)
Living Area Square Feet		274.60***
		(16.05)
Control Mean	904,789.6	904,789.6
Observations	5,261	5,261
Zip Code FE	Yes	Yes
Year FE	Yes	Yes
R-squared	0.7197	0.7684

Testing for Price Capitalization We begin by testing whether becoming easier to finance leads to an increase in a property's actual transaction price. Results are reported in Table 5. The sample compares properties that were always below the conforming loan limit in both years (control group) with those that were above the limit in the previous year but became easier to finance in the current year (treatment group). Properties that were always above the limit are excluded from the control group.

The estimates show that easier access to financing is associated with a sizeable market price increase. Without property controls, treated properties sell for about \$107,246 more than comparable control properties (significant at the 10% level). Adding controls for structural attributes slightly reduces the estimate to \$86,000, which remains significant at the 10% level. Relative to a mean sale price of \$904,790 in the control group, this corresponds to a 9–12% price increase. For a typical 20% down payment, this implies an additional \$17,000–\$21,000 in upfront cash—or, if fully financed, an equivalent increase in mortgage principal.

The property controls in Column (2) behave as expected: each additional bathroom adds about \$37,588 to price, each additional bedroom lowers price by about \$13,425 (holding square footage constant), and larger living area has a strong positive effect at roughly \$275 per square foot. Year built is not statistically significant once other characteristics are accounted for.

Taken together, the results indicate that moving from jumbo to conforming status, driven by CLL changes, induces a substantial price increase, even after controlling for structural property features.

Main Regression We then examine whether easier financing conditions influence buyer characteristics by estimating treatment effects at the individual–property level. This approach follows Adelino et al. (2025), with the modification that each property is assigned to the treatment or control group in only one year, avoiding repeated use across periods. The treatment group consists of properties that become easier to finance in the current year. For comparison, I consider three alternative control groups: (i) properties that are always easy to finance, as in Adelino et al. (2025); (ii) properties that are always hard to finance; and (iii) a combined sample including both.

For each buyer i that purchases housing property j,

$$Y_{jt} = \alpha_t \, Treated_{jt} + X_{jt} + \text{year}_t + \text{zipcode}_j + \zeta_{jt}, \tag{2}$$

Control variables include total baths, number of bedrooms, year built, and living area square feet. All regressions include zipcode and year fixed effects.

Our primary outcomes are: (i) buyer income, (ii) debt-to-income ratio (DTI), and (iii) combined loan-to-value ratio (CLTV)

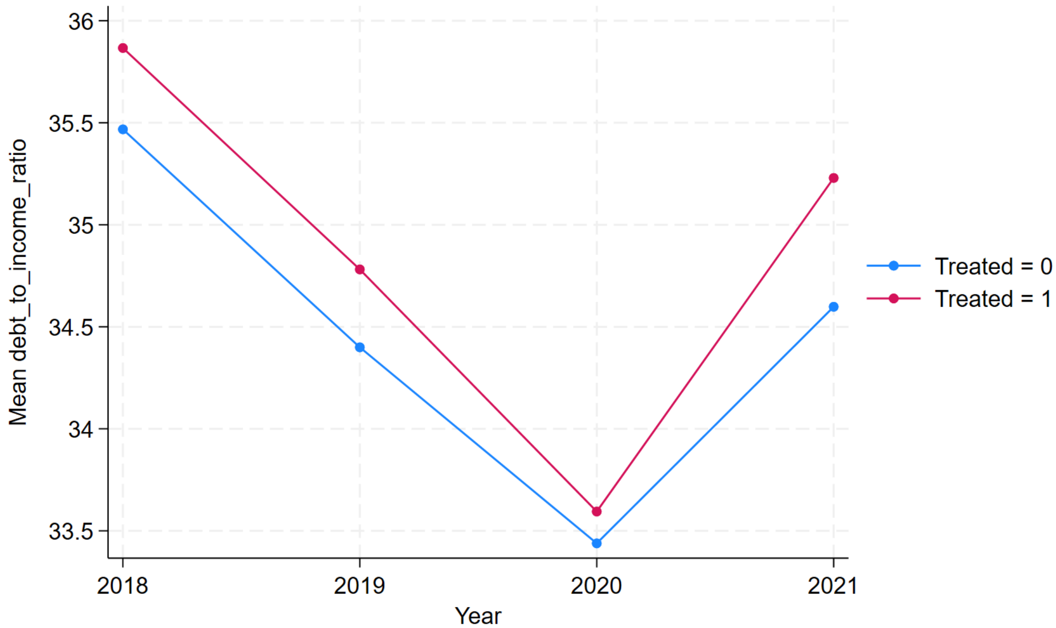
5.3 Overall Trend

Before presenting the regression results, we first plot the average buyer income and debt-to-income (DTI) ratio by treatment status and year. Figure 2 provides an overview of these outcomes. The treated group, representing properties with increased ease of finance, consistently exhibits lower average buyer income and higher DTI ratios relative to the control group. The gap only closed in 2020. The sharp decline in DTI observed in 2020 likely reflects the federal policy response to COVID-19, which included widespread mortgage and other loan forbearance programs. By temporarily suspending required payments, these programs substantially reduced many households' reported monthly debt obligations, thereby lowering measured DTI ratios. The year fixed effects in our regression specification account for such aggregate fluctuations, ensuring that identification relies on variation within years rather than on macroeconomic shocks.

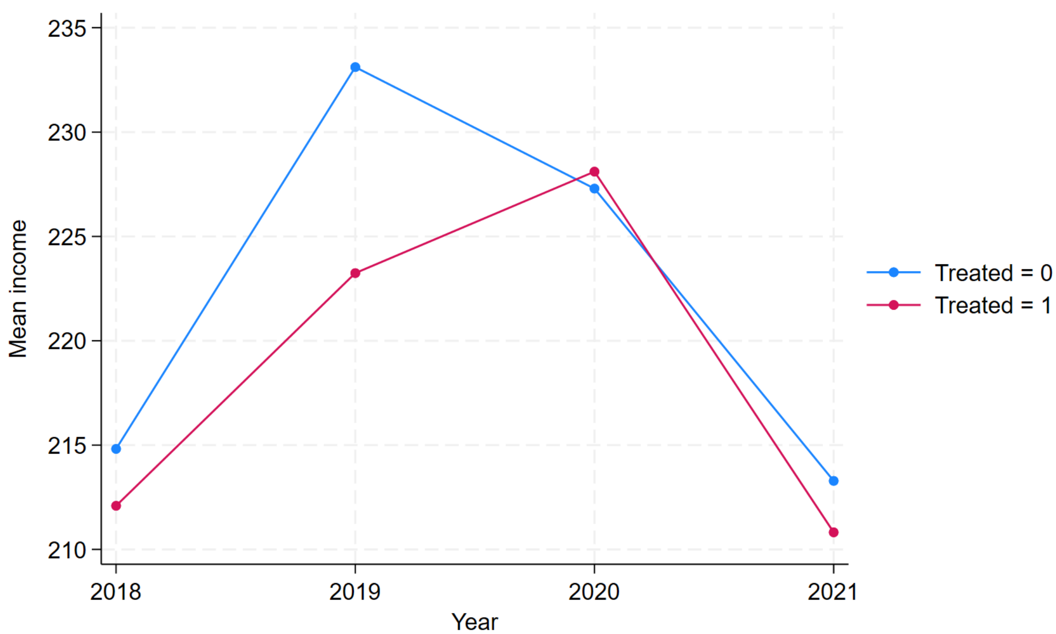
5.4 Regression Results

The baseline regression results are presented in Table 6.

Buyer Income Starting with buyer income, the estimates show a consistent negative treatment effect across bandwidths, with magnitudes ranging from −55.89k to −128.91k in the full sample. For example, in sample 1, treated buyers have incomes about $128.9k lower than the control group on average ($p < 0.10$), which is 32% lower than the control mean. The effect is even larger in the "Always Above" group ($p < 0.05$). In sample 3, the



(a) Debt-to-Income Ratio (CA, 2018–2021)



(b) Income (CA, 2018–2021)

Figure 2: Debt-to-Income Ratio and Income Trends in California (2018–2021)

Table 6: Effect of Treatment on Buyer Outcomes Near the CLL

	Panel A: Outcome = Income			Panel B: Outcome = Debt-to-Income Ratio		
	All	Always Below	Always Above	All	Always Below	Always Above
Sample 1						
Treated	-128.91*	-62.73	-223.75**	0.15	0.10	0.24
	(66.55)	(125.98)	(95.69)	(0.11)	(0.19)	(0.17)
Control Mean	402.90	340.44	425.93	34.62	35.31	34.37
Observations	51,171	28,770	42,921	51,523	28,955	43,220
Sample 2						
Treated	-55.89	92.15	-51.21	0.20	-0.56	0.21
	(150.49)	(105.01)	(153.28)	(0.23)	(1.85)	(0.23)
Control Mean	544.40	208.28	550.48	34.49	34.64	34.49
Observations	10,211	5,238	10,120	10,267	5,266	10,175
Sample 3						
Treated	-96.54***	-128.80**	-22.93	0.12	0.21	-0.27
	(30.12)	(56.29)	(59.10)	(0.18)	(0.22)	(0.28)
Control Mean	311.71	310.26	316.67	35.33	35.56	34.56
Observations	50,783	40,481	15,252	51,129	40,756	15,353
Sample 4						
Treated	-91.39	-25.56	-297.18	-0.01	0.22	-0.33
	(70.11)	(48.36)	(224.22)	(0.40)	(0.50)	(0.66)
Control Mean	285.59	264.03	358.37	35.42	35.60	34.82
Observations	9,952	7,900	3,014	10,016	7,953	3,033
Panel C: Outcome = Combined Loan-to-Value Ratio						
Sample 1						
Treated	-0.24	-0.13	-0.57			
	(0.16)	(0.23)	(0.32)			
Control Mean	76.79	76.16	76.90			
Observations	51,120	28,770	42,921			
Sample 2						
Treated	-0.55*	-0.57*	-0.57*			
	(0.32)	(0.32)	(0.32)			
Control Mean	76.89	76.90	76.90			
Observations	10,210	5,238	10,119			
Sample 3						
Treated	-0.19	-0.58	-0.58			
	(0.23)	(0.36)	(0.36)			
Control Mean	76.73	76.87	76.87			
Observations	50,603	40,481	15,228			
Sample 4						
Treated	-0.21	-0.98	-0.98			
	(0.53)	(0.85)	(0.85)			
Control Mean	76.64	77.13	77.13			
Observations	9,906	7,900	3,011			
Zip Code FE			Yes			
Year FE			Yes			

96.54k reduction in income is 31% lower than the control mean. These reductions, while are consistent with the intuition that treated properties becoming easier to finance compared to their counterparts draws in somewhat lower-income borrowers, is relative large to average buyer incomes of $285k–$545k across bandwidths. To check whether the results are mainly driven by the top income buyers within each sample, we drop the transactions conducted by top decile income buyers and reestimate. The results are presented below. In both samples, treated effect is negative but statistically insignificant. The control group means are both around 210–215k, so the estimated effects are small relative to mean income. Therefore, although properties around the threshold seems to become more affordable and does attract relatively lower income buyers, the main impact in the original regressions comes from very rich borrowers moving away to neigboring price tiers, which is not an actual improvement of affordability.

Table 7: Robustness Test for Income

	Outcome = Income (Robustness: Drop Top Decile)			
	Sample 1	Sample 2	Sample 3	Sample 4
Treated	-0.53	-3.38	-2.39**	-0.40
	(0.96)	(2.10)	(1.05)	(2.47)
Control Mean	210.16	214.56	176.08	177.38
Observations	50,657	10,119	50,274	9,848
Zip Code FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Income measured in $1,000s.

Debt to Income Ratio (DTI) Turning to Debt to Income Ratio (DTI), we find modest increases in the treatment group, though none are statistically significant at conventional levels. These increases could arise through two channels: (a) the entry of lower-income borrowers, which mechanically raises DTI for a given loan size, or (b) existing/new buyers reducing their down payments because the higher CLL removes the incentive for strategic bunching just below the limit. Overall, a raise in ease of finance has a positive impact on debt to income ratio, which may result from two sources (a) borrowers of lower income entering (b) buyers lowering their downpayment since the conforming loan limit has increased, no longer need to strategic bunching. If buyers lowering their downpayment is the main source of decreasing DTI, we should observe people borrow more (holding property value equal) in the treatment group. However, the treatment impact on combined loan to value ratio is not significant, and even has a negative sign.

Combined Loan-to-Value Ratio (CLTV) If the primary channel driving higher DTI in treated areas were a reduction in down payments (mechanism b), we would expect a significant positive treatment effect on CLTV, indicating that buyers are financing a larger share of the purchase price through debt, holding property values constant. However, regression estimates show no statistically significant CLTV effects; in most cases, point estimates are small and even negative. This pattern suggests that treated buyers are not systematically increasing leverage relative to property value. The absence of a CLTV effect weakens the down-payment channel explanation and instead supports a buyer-composition mechanism: the modest DTI increases are more plausibly driven by the entry of lower-income borrowers rather than by existing buyers taking on higher leverage. Moreover, we find no significant tendency for CLTV ratios to revert to 80% when the incentive to bunch diminishes.

Given that the estimated treatment effects on combined loan-to-value (CLTV) ratios are statistically insignificant and even slightly negative across specifications, we do not find evidence that relaxed borrowing constraints systematically increase leverage relative to property value. This suggests that changes in down payment behavior are not the primary channel through which conforming loan limit adjustments influence buyer outcomes. Instead, the more salient margins of adjustment appear to be buyer income and debt-to-income (DTI) ratios, which show consistent directional responses to credit expansion. We therefore focus the remainder of the analysis on these two outcomes, with down payment included as a control, as they more directly capture shifts in buyer composition and borrowing behavior driven by policy-induced changes in financing conditions.

5.5 Identification

Key Assumptions Identification relies on comparing treated and control properties within a narrow price bandwidth around the conforming loan limit (CLL). The central assumption is that, conditional on rich property-level controls and zipcode-by-year fixed effects, properties on either side of the cutoff are similar in all economically relevant respects except for their access to conforming credit. Because prices within this window are tightly clustered, remaining unobserved heterogeneity in housing quality should be limited, reducing concerns that physical amenities or locational attributes drive systematic differences in buyer composition.

Addressing Endogeneity Even within this restricted window, two forms of endogeneity may bias estimates. (1) *Buyer-side selection*: Higher-income households may self-select into the jumbo segment regardless of financing conditions, causing compositional changes that reflect endogenous sorting rather than the causal impact of credit access. (2) *Unobserved property quality*: Houses near the CLL may differ along unobserved dimensions that correlate with both price and buyer characteristics.

To address these concerns, we strengthen identification by adopting a two-stage least squares (2SLS) framework that isolates exogenous variation in financing status. We make three adjustments relative to the baseline specification. First, treatment is defined directly from the actual closing price relative to the CLL rather than predicted prices or year-to-year transitions in conforming status. Second, because transaction prices are endogenous, we instrument for treatment using exogenous measures of proximity to the CLL. Third, treatment depends solely on financing status in the transaction year, eliminating dependence on prior-year outcomes.

Formally, a property is classified as treated if and only if its transacted price falls below the conforming limit:

$$\text{Treated}_{jt} = \mathbf{1}\{0.8P_{jt} \leq C_{jt}\},$$

where P_{jt} is the closing price for property j in year t, and C_{jt} is the county-level CLL.

The second stage estimates:

$$Y_{ijt} = \alpha\,\widehat{\text{Treated}}_{jt} + X_{jt}\beta + \text{year}_t + \text{zipcode}_j + \zeta_{ijt}, \tag{3}$$

where Y_{ijt} is a buyer characteristic (income, DTI, or CLTV), and X_{jt} includes bathrooms, bedrooms, home age, living area, and downpayment.

Because Treated_{jt} depends on the endogenous price P_{jt}, we instrument using two sources of plausibly exogenous variation: (i) hedonic-predicted proximity to the CLL, and (ii) local exposure to county-level CLL shifts.

Hedonic Distance-to-CLL Instrument. Let $\widehat{P}_{jt}$ denote the predicted price from a hedonic model using only structural attributes and zipcode-by-year fixed effects. We construct:

$$Z_{jt}^{(1)} = 0.8\widehat{P}_{jt} - C_{jt},$$

which captures "mechanical" distance to the limit absent buyer-specific demand shocks. Because $\widehat{P}_{jt}$ excludes buyer characteristics, $Z_{jt}^{(1)}$ offers variation that is orthogonal to endogenous sorting.

Shift–Share (Bartik-Style) Instrument. Adjustments to the CLL relax financing constraints for households whose preferred loan size lies near the threshold, but the magnitude of this effect varies across neighborhoods. Let $s_{z,t-1}$ denote the lagged conforming-loan share in ZIP code z. When the CLL grows at rate $g_t = C_t/C_{t-1}$, ZIP codes with a high $s_{z,t-1}$ experience larger effective shifts in financing access. The resulting shift–share instrument is:

$$Z_{zt}^{(2)} = s_{z,t-1} \times g_t.$$

As shown in the placebo tests, this instrument does not predict lagged income, supporting its exclusion validity.

First Stage and Estimation Window. To maintain comparability and minimize extrapolation, the estimation sample is restricted to:

$$|0.8P_{jt} - C_{jt}| \leq 50{,}000.$$

The first-stage equation is:

$$\text{Treated}_{jt} = \pi_0 + \pi_1 Z_{jt} + X_{jt}\rho + \text{FE}_{\text{year}} + \text{FE}_{\text{zipcode}} + \nu_{jt}.$$

Second Stage Interpretation. The fitted treatment indicator $\widehat{\text{Treated}}_{jt}$ captures the exogenous component of conforming-loan eligibility arising from policy-driven shifts and mechanical distance to the CLL. The second-stage estimates thus reflect causal effects of financing access rather than endogenous sorting or unobserved property quality. As shown in Table 8, IV estimates indicate that expanded access to conforming credit shifts buyer composition toward lower-income and higher-DTI households. Combined with placebo evidence in Table 9, these results support the credibility of the identification strategy.

Table 8: Effects of Conforming Loan Limits on Income and DTI

	ln(Income)				**DTI Ratio**			
	OLS	Hedonic-IV	IV-FE	Bartik-IV	OLS	Hedonic-IV	IV-FE	Bartik-IV
Treated$_{ijt}$	-0.101^{***}	-0.339^{***}	0.633^{***}	-0.695^{***}	0.477^{***}	2.994^{***}	-5.380^{***}	5.048
	(0.005)	(0.032)	(0.111)	(0.231)	(0.111)	(0.665)	(2.057)	(4.872)
Total baths	-0.001	0.011^{***}	0.010	-0.008	0.250^{***}	0.024	0.162	0.303^{**}
	(0.005)	(0.004)	(0.006)	(0.007)	(0.093)	(0.088)	(0.104)	(0.140)
Bedrooms	-0.006^{*}	-0.018^{***}	-0.006	-0.005	0.089	0.393^{***}	0.089	0.097
	(0.003)	(0.003)	(0.004)	(0.005)	(0.083)	(0.073)	(0.081)	(0.096)
Home age (/10)	-0.001	0.020^{***}	-0.001	0.000	0.060^{*}	-0.013	0.058	0.002
	(0.001)	(0.001)	(0.002)	(0.000)	(0.031)	(0.025)	(0.034)	(0.004)
Sqft (per 100)	0.002^{***}	-0.002^{***}	0.019^{***}	-0.011^{**}	0.079^{***}	0.092^{***}	-0.060	0.183
	(0.001)	(0.001)	(0.003)	(0.005)	(0.015)	(0.012)	(0.051)	(0.111)
Downpayment (10k$)	-0.004^{***}	-0.003^{***}	-0.001^{**}	-0.006^{***}	-0.039^{***}	-0.028^{***}	-0.062^{***}	-0.024
	(0.000)	(0.000)	(0.000)	(0.001)	(0.004)	(0.004)	(0.008)	(0.019)
Observations	50,782	50,929	50,782	38,080	50,782	50,929	50,782	38,080
Control mean	5.159	5.159	5.159	5.159	35.014	35.014	35.014	35.014
Root MSE	0.471	0.506	0.584	0.513	10.444	10.670	10.800	10.800
Year FE	✓		✓	✓	✓		✓	✓
Zipcode FE	✓		✓	✓	✓		✓	✓
First-stage F-stat	—	1108.734	125.407	22.349	—	1108.734	125.407	22.349
Anderson LM	—	1085.257	127.408	22.872	—	1085.257	127.408	22.872
Adj. R^2	0.112	—	—	—	0.042	—	—	—

Notes: Dependent variables: ln(Income) (cols 1–4) and Debt-to-Income Ratio (cols 5–8, in percentage). Bartik-IV uses $Z_{zt} = \text{share}_{z,t-1} \times (\text{CLL}_t/\text{CLL}_{t-1})$ as the instrument. Window restricted to $\mid 0.8 \times \text{Price} - \text{CLL} \mid \leq \$50{,}000$. Standard errors in parentheses, clustered by zipcode. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 9: Placebo Test: Predictive Power of IV on Pre-Treatment Income

	(1) Bartik IV	(2) Hedonic IV
Instrument	-106.671	0.008***
	(73.148)	(0.0004)
Observations	38,071	38,071
R-squared	0.450	0.457
Within R^2	0.0005	0.0134
Zipcode FE	Yes	Yes
Year FE	Yes	Yes
Controls	Yes	Yes

Notes: This table reports placebo regressions testing whether the instrumental variables predict *lagged median income at the zipcode level*. Standard errors clustered at the zipcode level are reported in parentheses. $^{***}p < 0.01$.

6 Discrete Choice Model Framework

The reduced-form evidence indicates that increases in the CLL primarily alter the composition of buyers near the threshold, rather than uniformly increasing leverage through smaller down payments. To assess whether these compositional changes reflect genuine "upgrading" into higher-quality or higher-priced homes, consistent with heterogeneous willingness to pay under relaxed credit constraints, we turn to a discrete choice framework. This model allows us to explicitly link financing eligibility (conforming vs. jumbo status) to household choice behavior, quantify preference heterogeneity across income groups, and simulate counterfactual CLL adjustments to measure how policy-induced shifts in credit access redistribute buyers across the housing market.

Let m index markets, where a market is defined as a **county–year**. Individuals i choose property h in market m. Utility is given by

$$U_{ihm} = \delta_{hm} + \mu_{ihm} + \varepsilon_{ihm}, \tag{4}$$

where:

- δ_{hm}: mean utility for property h in market m, common across individuals.
- μ_{ihm}: individual-specific deviation from mean utility due to heterogeneous tastes
- ε_{ihm}: i.i.d. idiosyncratic shock.

The mean utility is specified as:

$$\delta_{hm} = X_{hm}\beta - \alpha_i P_{hm} + \gamma_i B_{hm} + \xi_{hm}. \tag{5}$$

The components are:

- X_{hm}: observed property characteristics (including location fixed effects within m).
- P_{hm}: actual transaction price (endogenous).
- $B_{hm} \equiv \mathbf{1}\{P_{hm} \leq \text{CLL}_m\}$: indicator that the *actual* price is at or below the conforming loan limit in market m.
- ξ_{hm}: unobserved demand shifter.
- α_i, γ_i: coefficients that can vary with buyer characteristics (e.g., income group k).

6.1 Instrumental Variable Strategy

Because B_{hm} depends on endogenous P_{hm}, we construct instruments from *predicted prices* $\widehat{P}_{hm}$ estimated from a hedonic model using only property attributes (e.g., square footage, building age, number of rooms, number of bathrooms, etc.) and zipcode $\times$ year fixed effects:

$$\widehat{P}_{hm} = g(X_{hm}^{\text{hed}}). \tag{6}$$

Instruments:

$$Z_{hm}^{(1)} \equiv \mathbf{1}\{\widehat{P}_{hm} \leq \text{CLL}_m\}, \tag{7}$$

$$Z_{hm}^{(2)} \equiv s\big(\text{CLL}_m - \widehat{P}_{hm}\big), \tag{8}$$

where $s(\cdot)$ is a flexible function of the *distance to the CLL*.

Define the *distance to the conforming loan limit* as

$$D_{hm} \equiv \mathrm{CLL}_m - \widehat{P}_{hm}, \tag{9}$$

The *shift–share (Bartik-style) exposure* to county level shocks is given by

$$Z_{hm}^{\mathrm{Bartik}} \equiv w_{g(h),\,m-1} \cdot \Delta\mathrm{CLL}_m, \tag{10}$$

where $w_{g(h),\,m-1}$ denotes the *pre-policy exposure* of market $g(h)$ (e.g., the share of properties in $g(h)$ with $|D_{hm}| \leq \bar{\tau}$ in $m-1$), and $\Delta\mathrm{CLL}_m \equiv \mathrm{CLL}_m - \mathrm{CLL}_{m-1}$ is the change in the conforming loan limit.

6.2 First Stage

Estimate the first stage for B_{hm}:

$$B_{hm} = \pi_0 + \pi_1 Z_{hm}^{(1)} + \pi_2 Z_{hm}^{(2)} + \pi_3 Z_{hm}^{\mathrm{Bartik}} + X_{hm}\rho + \nu_{hm}, \tag{11}$$

where X_{hm} are all exogenous variables that enter the utility function. μ_{ihm} is *not* included in the first stage, because it is unobserved and individual-specific. Let $\widehat{\nu}_{hm}$ be the residual.

6.3 Second Stage: Control Function

Following Petrin and Train (2010), include the first-stage residual in the mean utility:

$$\delta_{hm} = X_{hm}\beta - \alpha_i P_{hm} + \gamma_i B_{hm} + \lambda\,\widehat{\nu}_{hm} + \xi_{hm}. \tag{12}$$

6.4 Heterogeneity and Upgrading Effect

Allow heterogeneous responses by interacting α_i and γ_i with income group k:

$$\gamma_i = \gamma_0 + \sum_k \gamma_k \cdot \mathbf{1}\{i \in k\}, \tag{13}$$

$$\alpha_i = \alpha_0 + \sum_k \alpha_k \cdot \mathbf{1}\{i \in k\}. \tag{14}$$

6.5 Aggregating to Income–Price Tier Shares

After estimation:

1. Compute baseline choice probabilities $\Pr_{ihm}$ using observed P_{hm} and B_{hm}.

2. Simulate a counterfactual CLL increase, update B'_{hm} and recompute $\Pr'_{ihm}$.

3. Aggregate to income group k and price tier g:

$$s_{kg} = \frac{1}{N_k} \sum_{i \in k} \sum_{h \in g} \Pr_{ihm}, \tag{15}$$

$$s'_{kg} = \frac{1}{N_k} \sum_{i \in k} \sum_{h \in g} \Pr'_{ihm}. \tag{16}$$

4. The change $s'_{kg} - s_{kg}$ measures the extent of "upgrading" for group k into price tier g.

7 Simulation

This section presents a stylized simulation of the heterogeneous demand system introduced in Section 6. The goal is to illustrate how income-group–specific price sensitivities (α_k) and the conforming-loan bonus (γ_k) interact with a Conforming Loan Limit (CLL) increase to generate either *upgrading* or *crowd-out* among lower-income buyers.

(a) Parameter Calibration: α_k and Baseline γ_k

We simulate 30 markets with heterogeneous house prices and quality characteristics. Buyers from five income quintiles $k = 1, \ldots, 5$ face indirect utility

$$U_{ih} = \beta X_h - \alpha_k P_h + \gamma_k B_h + \varepsilon_{ih},$$

where $B_h = 1$ if house h is conforming under the relevant CLL. The calibrated price sensitivities are:

$$\alpha_1 = 3.0, \quad \alpha_2 = 2.5, \quad \alpha_3 = 2.0, \quad \alpha_4 = 1.5, \quad \alpha_5 = 1.0.$$

Thus, lower income groups ($k = 1, 2$) are more price sensitive than higher-income groups.

For the conforming-loan "bonus," we impose

$$\gamma_1 = \gamma_2 = \gamma_{\text{low}}, \qquad \gamma_3 = \gamma_4 = \gamma_5 = 0.5,$$

and treat γ_{low} as the key parameter determining whether lower-income buyers upgrade or become crowded out when the CLL increases.

(b) Upgrading vs. Crowd-Out Regions for γ_{low}

We increase the CLL from the 30th to the 60th percentile of each market's price distribution. Houses that become newly conforming experience a 15% price capitalization. For each value of γ_{low}, we compute the *change in expected purchase price for the lowest-income group*:

$$\Delta P_1(\gamma_{\text{low}}) = \mathbb{E}[P \mid \text{new CLL}, k = 1] - \mathbb{E}[P \mid \text{old CLL}, k = 1].$$

Interpretation:

$$\Delta P_1 > 0 \Rightarrow \text{Upgrading}, \qquad \Delta P_1 < 0 \Rightarrow \text{Crowd-Out}.$$

The simulation generates two distinct regimes:

- **Crowd-Out Region: $\gamma_{\text{low}} \lesssim 0.7$.** When the conforming-loan bonus is small, lower-income buyers do not strongly value newly conformed mid-tier houses. Price capitalization discourages them, and they remain in the always-conforming lower-price segment. Higher-income buyers absorb the newly conformed units. Thus $\Delta P_1 < 0$.

- **Upgrading Region:** $\boldsymbol{\gamma_{\text{low}} \gtrsim 0.7}$**.** When γ_{low} is sufficiently large, the gain from being conforming outweighs the price penalty, causing lower-income buyers to move into higher-quality, higher-priced homes. Thus $\Delta P_1 > 0$.

When the gain from being newly conforming is sufficiently large for lower-income households, the upgrading effect dominates: these buyers shift toward higher-quality homes even though they are highly price sensitive. When the gain is small, lower-income buyers remain focused on the always-conforming lower-priced segment, and higher-income buyers absorb the newly conformed assets. In this case, the crowd-out effect dominates. Thus, whether a CLL expansion benefits the marginal buyer depends critically on the interaction between price sensitivity and the value of conforming status.

8 Conclusion

This paper examines how mortgage credit expansions, implemented through increases in the conforming loan limit (CLL), affect both house prices and the composition of buyers near the policy threshold. Using linked CoreLogic–HMDA data and a combination of hedonic predictions, reduced-form comparisons, and instrumental variable approaches, the analysis uncovers several key findings.

First, consistent with prior work, credit expansions are capitalized into housing prices. Properties that transition from jumbo to conforming status experience meaningful price increases, even after carefully controlling for property quality. This confirms that the reduced cost of mortgage credit transmits quickly into equilibrium prices.

Second, the distributional effects of CLL increases are more nuanced. Reduced-form estimates initially indicate that treated properties attract lower-income buyers on average, but most of this effect is driven by very high-income households shifting away from the newly conforming tier. After removing the top income decile, treatment effects remain directionally consistent—suggesting some improvement in access for marginal borrowers—though the magnitudes diminish. Likewise, DTI ratios rise modestly among treated buyers, while combined loan-to-value measures do not, implying that relaxed credit constraints draw in payment-constrained buyers rather than encouraging systematic reductions in down payments.

Third, the structural discrete choice framework provides a unified interpretation of these results by explicitly embedding financing eligibility into household utility. The model highlights how the value of conforming status interacts with heterogeneous price sensitivities to produce either upgrading (when lower-income households move into higher-tier homes under an expanded CLL) or crowd-out (when price capitalization offsets the benefits of cheaper credit). The simulation results illustrate that the direction of the effect depends critically on the relative strength of these forces.

Taken together, the evidence suggests that CLL increases expand access for some marginal buyers but do not uniformly improve affordability, particularly in high-cost regions where price capitalization is strong. The distributional incidence of mortgage credit expansions is therefore sensitive to local market structure and to the strength of financing frictions among lower-income households.

By combining reduced-form and structural approaches, this paper provides a framework for evaluating not only the average effects of mortgage credit policies but also their distributional consequences.

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