Linking Asset Values to Financing:
The Role of Small-Dollar Mortgages in Cash vs. Mortgage Property Price Disparities*

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Abstract

All-cash transactions and their associated price discounts in the housing market have increased following the Great Financial Crisis. We document that cash discounts vary substantially across property price levels, with the largest discounts occurring in the lowest-priced market segment. Using the expansion of enforcement actions on mortgage fraud post-GFC as an instrument for local small credit supply, we find that a one-percentage-point decrease in small loan approvals increases cash discounts by 11.43%. The impact is larger in low-cost houses and disadvantaged communities. The results point to the cause for the observed overall decrease in relative prices for low-cost houses, highlighting the importance of small loan availability for wealth-building through homeownership among lower-income households.

Keywords: Small-dollar mortgage, Credit supply, Cash discount, House prices
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1. Introduction

In a perfectly efficient market, an asset's value is independent of the way it is financed (Modigliani and Miller, 1958). Yet, in the housing market, the way a transaction is financed can influence the purchase price, with properties acquired in cash-financed transactions often securing price discounts compared to similar properties purchased with mortgages. While existing literature suggests that these "cash discounts" compensate for a variety of market frictions (Han and Hong, 2024; Reher and Valkanov, 2023), they are much larger than those predicted by traditional economic models. For example, Reher and Valkanov (2023) develop a model incorporating market frictions, but it explains only 27% of the observed cash discount and they attribute the remaining to behavioral factors. In contrast to these demand side channels, we explore an alternative channel based on credit supply as a mechanism to explain this difference.

In contrast to the literature, which focuses on average cash discounts, we document substantial heterogeneity in cash discounts across properties based on price levels, with the largest discounts reaching 16.3% for the lowest-valued properties where credit supply plays a crucial role in facilitating purchases by prospective homeowners. Using data on mortgage approvals and housing transactions, we investigate the impact of lenders curtailing the supply of small-dollar mortgages on cash discounts. Our findings reveal that this change in lending activity amplified cash discounts for low-cost housing, thereby disproportionately dampening the values of these properties relative to their higher-priced counterparts.

To motivate our analysis, we document several facts regarding the U.S. mortgage and housing markets in Figure 1. First, we show in Panel A substantial variation in cash discounts across price deciles based on an unconditional quantile regression approach, with discounts declining monotonically across price deciles. Second, we observe in Panel B that properties in the lowest price decile experienced a substantial increase in all-cash transactions since 2012, a

trend not observed in higher-value segments. In addition, this rise in all-cash transactions corresponds to an increase in cash discounts for low-cost houses (Panel C). Finally, during the same period, we also note a declining trend in small-dollar mortgage approval rates compared to larger loans (Panel D). This decline corresponds to an increase in origination costs resulting from various government programs and regulatory interventions targeting lenders' mortgage origination behaviors after the Global Financial Crisis (Agarwal et al., 2017; Agarwal et al., 2022; D'Acunto and Rossi, 2022; Haughwout et. al., 2016; Mayer et al., 2014).[1]

Based on these insights, we examine and quantify how the supply of small dollar mortgage credit impacts price discounts, utilizing mortgage approval data from the Home Mortgage Disclosure Act (HMDA) and housing transaction data from CoreLogic. Our main empirical approach addresses potential confounding factors that may simultaneously influence small credit supply and cash discounts through a two-step approach: first, we create a measure of cash discounts adjusted for differences in hedonic attributes that may affect financing choices, and second, we apply an Instrumental Variable (IV) method to account for potential endogeneity in small credit supply.

First, considering that credit supply information is available at the census tract-year level, we create an annual measure of cash discounts for each census tract. Our goal is to compare the difference in sales prices between cash and mortgage financed transactions for identical houses with the buyer and seller sharing similar attributes. To do so, we derive residualized transaction prices for each financing type through regressions that combine hedonic and repeat-sales methods. These regressions incorporate a comprehensive set of controls for property, transaction type, buyer and seller characteristics, and time and property fixed effects that account for both observed and time-invariant unobserved factors that might simultaneously influence financing choices and transaction prices. The use of nationwide housing data

[1] Appendix A provides greater detail on these motivating facts, including various robustness checks.

spanning over two decades allows for the inclusion of an extensive set of controls and fixed effects that collectively explain nearly 90% of the variation in transaction prices. This approach minimizes the risk of residualized prices misrepresenting unobserved property- and transaction-level characteristics that could influence the selection of different financing types. Finally, we calculate annual census-tract-level cash discounts by taking the difference between the average residualized mortgage purchase prices and cash purchase prices within each tract for each year.

Next, we regress the cash discount measure on the share of approved small-dollar mortgages, defined as mortgages with loan amounts less than $100,000, adjusted to 2010 dollars, while controlling for demographic characteristics and average mortgage applicant attributes.[2] The results suggest that a 1 percentage point decrease in the share of small-dollar mortgages in a census tract is associated with a 0.08 percentage point increase in cash discounts, with this increase primarily occurring in areas with low median house values.

To further account for the potential endogenous relation between small-dollar mortgages and the cash discount, we employ an IV strategy that leverages the sudden expansion in False Claim Act (FCA) enforcement actions initiated by U.S. Department of Justice (DOJ) starting in 2012 to achieve identification. The FCA actions targeted Federal Housing Administration (FHA) lenders allegedly involved in fraudulent mortgage origination practices. These litigations and lawsuits disproportionately increased regulatory burdens and financial penalty risks associated with originating smaller-sized mortgages among FCA-implicated lenders. Thus, the FCA actions reduced the incentives for small-dollar mortgage lending and thereby decreased small credit supply in regions with a higher concentration of these lenders.[3, 4]

[2] Our baseline results remain robust to alternative cutoffs of $75,000 and $125,000, adjusted to 2010 dollars, to define small-dollar mortgages.
[3] Relatedly, we observe a noticeable reduction in small-dollar mortgage approvals from these lenders after 2012, relative to other lenders.
[4] Using mortgage-related lawsuits as a shock that tightens the capital constraints of affected banks, Greg et al. (2018) study the association between a county's exposure to lawsuits and the market share of shadow banks.

Our IV strategy uses a shift-share instrument, where the shift component captures the temporal trend (or change in the share) in small-dollar mortgage approvals. The share component, which is measured as the census tract's initial share of small-dollar mortgages approved by FCA-implicated lenders, captures cross-sectional exposure to the nationwide trend in the shift component. The instrument operates on the premise that, after 2012, census tracts with a higher initial exposure to FCA-implicated lenders experienced a larger decline in small-dollar mortgage approvals due to the heightened regulatory risks faced by these lenders. Following Goldsmith-Pinkham, Sorkin and Swift (2020), our identification strategy relies on the exogeneity of the share component, with the key identifying assumption being that the initial share of small loan approved by FCA-implicated lenders, conditional on controls and fixed effects, influences cash discounts solely through its effect on the share of approved small loans in the census tract.[5]

Our main findings suggest that limiting the supply of small-dollar mortgages significantly increases price discounts associated with cash purchases. We find that a one percentage point decrease in the share of small-dollar mortgages results in an 11.43% reduction in prices paid by cash buyers (or an increase in the cash discount of 11.43%).

Additionally, we employ an alternative identification strategy using a reduced-form DD approach to confirm our results. Designating census tracts with above-median exposure to FCA-implicated lenders as the treatment group, we find that after 2012, these tracts experience a 1.1% decrease in the share of small-dollar mortgage approvals. We also find a 5.5% increase in cash discounts relative to those in census tracts with lower exposure. Further heterogeneity analyses reveal that the effects on cash discounts are more pronounced in relatively disadvantaged communities, particularly those with lower household income and higher

[5] We conduct a comprehensive set of robustness checks using a difference-in-differences (DD) approach to assess the validity of this assumption and potential endogeneity concerns.

concentrations of black residents. We also find an increase in cash discounts for properties in the 1st and 2nd price deciles after 2011 of 5.1% and 2.2%, respectively. In contrast, properties in the higher deciles show statistically insignificant changes in cash discounts.

Why does a tightening of small-dollar mortgages cause an increase in cash discounts? To address this question, we examine whether the increase in cash discounts stems from a decrease in prices for cash purchases, or alternatively, by an increase in prices for mortgaged purchases. Our empirical evidence supports the former proposition. In addition, we show that the tightening of small-dollar mortgages is associated with an increase in the volume of investor purchase and all-cash transactions, providing suggestive evidence of a mechanism for the observed effects on cash discounts.

To assess the overall impact of the declining share of small loans on the housing market, we re-estimate the IV regression using the residualized property prices as the outcome variable. Our analysis yields a positive estimate, indicating that lower shares of small loans are associated with lower property prices. Additionally, we use a DD framework to demonstrate that properties in the lowest price decile experience the greatest decline in prices, with the effect diminishing as property prices increase across deciles.

Our analysis adds to the extensive body of research on credit supply and house price growth by identifying an alternative mechanism through which the contraction of mortgage supply affects house prices.[6] This mechanism operates by disproportionately influencing price discounts associated with all-cash transactions, thereby reducing property values for low-cost housing where all-cash transactions are more prevalent. This complements existing research that focuses on channels operating through overall housing demand, particularly studies examining the role of credit in fueling the housing boom and bust cycle surrounding the GFC

[6] For example, Green and Wachter (2005) and Fetter (2013) discuss the role of liquidity in influencing homeownership, and highlight the importance of relaxing mortgage constraints to improve access to homeownership. In contrast, Vigdor (2006) finds that easing borrowing constraints can increase the market value of assets, regardless of supply elasticity, potentially reducing welfare for less-constrained households.

(Adelino, Schoar, and Severino, 2016, 2023; Albanesi, Degiorgi, and Nosal, 2022; DeFusco, Nathanson, and Zwick, 2022; Favara and Imbs, 2015; Favilukis, Ludvigson and Van Nieuwerburgh, 2017; Dong et al., 2022; and Mian and Sufi, 2022). For example, Mian and Sufi (2022) document that areas more exposed to credit expansion experienced heightened speculative activity and an amplified housing boom and bust. Our paper joins the growing literature studying the aftermath of the GFC focusing on small-dollar mortgages and their impact on the low-cost housing segment (Chen, Hanson and Stein, 2017; D'Acunto and Rossi, 2017; and Goodman, 2017). Our findings underscore the importance of analyzing the impact of credit supply separately for different housing segments and highlights the crucial role of mortgage financing in the low-cost housing market.

We also provide novel insights into the spillover effects associated with actions designed to combat mortgage fraud. In the period prior to the GFC, research documents extensive mortgage fraud involving the misrepresentation of borrower income (Ambrose, Conklin, and Yoshida, 2016; Jiang, Nelson, and Vyltacil, 2014; Mian and Sufi, 2017), the overstatement of housing appraisal values (Ben-David, 2011; Griffin and Maturana, 2016; Agarwal, Ambrose, and Yao, 2020), and the misreporting of asset values, lien status and owner-occupancy status (Garmaise, 2015; Griffin and Maturana, 2016; Piskorski et al., 2015). In response, regulators have intensified enforcement actions and legal proceedings against mortgage lenders involved in alleged fraud, while implementing comprehensive regulations to combat fraud in the mortgage market. We document that these regulatory measures adversely impact housing values in disadvantaged communities by reducing the supply of small loans due to increased regulatory burdens and for affected lenders.

Finally, our study is closely aligned with the growing literature on all-cash transactions and cash discounts in real estate (Beracha et al., 2024; Buchak et al., 2022; Han and Hong, 2024; Hansz and Hayunga, 2016; Seo, Holmes, and Lee, 2021; Reher and Valkanov, 2023;

Tidwell et al., 2018). For example, Reher and Valkanov (2023) identify substantial cash discounts of 11%, attributing them to compensations for frictions related to closing risks and seller's ambiguity aversion. Similarly, Han and Hong (2024) find smaller cash discount of 2% to 3.9%, which they attribute to both closing risks and re-listing risks. Our paper diverges from these studies by demonstrating that cash discounts vary substantially across different property price segments, which we link to changes in credit supply as the plausible causal mechanism. These findings underscore the importance of examining cash discounts and credit supply for low-cost properties, a subset often overlooked in existing research. Our study further distinguishes itself by empirically testing and quantifying the role of small-dollar mortgage supply in influencing cash discounts.

The remainder of the paper is structured as follows. Section 2 describes the data sources. Section 3 details the identification strategy and discusses the baseline results, along with the findings from robustness tests and heterogeneity analyses. Section 4 investigates potential mechanisms and presents additional results, and Section 5 concludes.

2. Data

We use two primary data sources for our empirical analysis. The first is the Consumer Financial Protection Bureau's (CFPB) Home Mortgage Disclosure Act (HMDA) data set, which contains the majority of mortgage applications spanning the years 2004 to 2020. For each application, we gather information on the loan amount, property type, application outcome, lien status, loan purpose, owner occupancy status, lender identifier, applicant's income, and applicant's gender, race, ethnicity, and census tract location. We link the lending institutions in HMDA to their parent companies using the Robert Avery lender file.[7] We restrict the sample to loan applications for owner-occupied, new purchases of single-family homes secured by a first lien,

[7] The dataset is constructed by Robert Avery and contains matching information for all lenders who have ever filed an HMDA report. It can be downloaded from Neil Bhutta's personal website at https://sites.google.com/site/neilbhutta/data.

and aggregate the loan application data to the census tract level, with tracts harmonized to the 2010 census tract boundaries following the methodology provided by the Longitudinal Tract Data Base (LTDB).[8]

Our second data source is CoreLogic, which provides transaction records for residential properties sold nationwide from 1995 to 2020. The dataset includes information on unique property and transaction identifiers, transaction price and dates, detailed geographic information, property attributes such as property type, number of bedrooms and bathrooms, property and land square footage, and effective year of construction. Additionally, it includes transaction-level details, indicating if the transaction was an all-cash deal, a resale, a corporate purchase, or investor purchase. We limit our sample to repeat sales transactions and exclude non-arm's-length transactions, such as short sales and foreclosure real estate-owned (REO) sales. For the main estimation, we use individual transaction-level data to obtain residualized prices for the years 2004 to 2020, which we then aggregate to the geographic areas defined by the 2010 census tract boundaries. To further supplement our analysis, we obtain information on economic and demographic characteristics for census tracts from the National Historical Geographical Information System (NHGIS) that combines data from each decennial census until 2020 and the American Community Survey (ACS) data from 2005 onward.

Table 1 presents the summary statistics. Panel A shows that our sample comprises approximately 40 million property transactions with a mean sales price of $281,915. Properties sold for cash represent a smaller fraction of total transactions (17.85%) and are associated with a lower average transaction price of $268,671. In contrast, purchases using mortgages have a mean transaction price of $284,793. This difference confirms our findings in Appendix A that all-cash purchases are prevalent among lower-cost housing. Appendix A also shows that homes at the lower price decile also experienced larger discounts when bought with cash.

[8] See, https://s4.ad.brown.edu/Projects/Diversity/Researcher/Bridging.htm, for more information.

Panel B reports the descriptive statistics for the variables at the census tract level. The cash discount, calculated as the difference between the average residualized mortgaged purchase price and cash purchase price, is 8%, indicating that, on average, cash purchase prices are 8% lower than their mortgaged counterparts. Approved small-dollar mortgages, defined as loans with amounts less than $100,000 in 2010 dollars, constitute 22% of the total approved loans, with those approved in the initial year of 2004 by FCA-implicated lenders accounting for 25% on average. On average, census tracts have a median home value of $249,149. The average loan applicant's income is $84,137, with 10% of applicants being black, 38% male, and 87% non-Hispanic.

3. The Effect of Access to Small-Dollar Mortgages on Cash Discounts

To investigate whether restricting small credit supply contributed to the growth in cash discounts, we estimate the following model that relates changes in the share of small-dollar mortgages to property cash discounts at the census tract level between 2004 and 2020:

$$Cash\ Discount_{ct} = \beta_1 Small\ Loan\ Share_{ct} + \beta X_{ct} + \delta_c + \theta_t + \varepsilon_{ct} \quad (1)$$

where δ_c and θ_t denote census tract and year fixed effects, respectively. X_{ct} represents a set of census tract-level controls, including aggregated borrower characteristics controls such as (log) average borrowers' income, percentage of white borrowers, percentage of black borrowers, percentage of male borrowers, percentage of joint-sex borrowers, and percentage of non-Hispanic borrowers, and demographic variables such as (log) total population, (log) total number of housing unit, (log) median household income, (log) median house value, percentage of white population, percentage of Hispanic population, percentage of population below poverty, percentage of population above 65 years old, percentage of population between 18 to 65 years old, percentage of population in the labor force, employment rate, percentage of

population with less than 9th-grade education, and percentage of population with at least a bachelor's degree. These controls account for the likelihood that changes in small mortgage share and cash discounts are correlated with local economic and housing market conditions, and for the fact that census tracts with a higher number of lower-value properties may mechanically exhibit larger average cash discounts. We cluster standard errors at the census tract level.

The outcome variable, $Cash\ Discount_{ct}$, represents the annual difference in average prices between mortgage-financed and cash-financed properties at the census tract level. Misestimation of cash discounts can occur if differences exist in transaction aspects beyond financing type, such as property, seller, and buyer attributes. For example, cash discounts may be overestimated if cash-rich investors with greater negotiation power are more likely to purchase properties with all cash, if inexperienced sellers are more inclined to expedite sales to cash buyers, or if houses with poor structural conditions, which are unobserved by the econometrician, are more likely to be purchased with cash due to ineligibility for mortgage financing (particularly relevant to borrowers using Federal Housing Administration (FHA) mortgages). To account for these non-financing factors, we derive residualized prices by estimating separate OLS regressions for cash-financed and mortgage-financed property transactions. In these regressions, the dependent variable is the property transaction price adjusted to 2010 dollars, and the explanatory variables include property fixed effects, year fixed effects, property attributes, and transaction characteristics.[9]

Specifically, we include 100 indicators for property age percentiles to control for the non-linear effect of aging on property prices, as older properties are more likely to have deteriorated structures, be sold at a discount, and face higher mortgage rejection rates (Pew,

[9] The controls include property age at the transaction and the seller's holding duration before sale, sale type, (resale or developer sale), corporate buyer involvement, the seller's financing type (cash or mortgage), the seller's purchase purpose (owner-occupation or investment), the buyer's previous location (same zip code, city, or state), and the buyer's purchase purpose (owner-occupation or investment).

2023).[10] We also account for buyer and seller characteristics, such as the buyer's purchase purpose (owner-occupation or investment), buyer's previous residence location, corporate buyer involvement, seller's previous purchase purpose, seller's previous financing type (cash or mortgage), and seller's holding duration before the sale. These factors may reflect unobserved property conditions at sale and account for the transaction parties' experience in the housing market, both of which can influence transaction price and the buyer's financing choice. Finally, similar to Reher and Valkanov (2023), we focus exclusively on repeat-sales transactions of non-distressed properties and incorporate property fixed effects to ensure our residualized prices eliminate time-invariant, property-specific characteristics that might influence buyer's selection into all-cash and mortgage-financed purchases, while also mitigating potential confounders from distressed properties.[11]

Subsequently, we compute the location-specific average residualized prices for mortgaged and cash-purchased properties for each time period, and calculate the difference between the two:

$$Cash\ Discount_{ct} = \frac{1}{N_{ct}^{M}} \sum_{i=1}^{N_{ct}^{M}} res_{price_{ict}^{M}} - \frac{1}{N_{ct}^{C}} \sum_{i=1}^{N_{ct}^{C}} res_{price_{ict}^{C}} \quad (2)$$

where N_{ct}^{M} and N_{ct}^{C} are the number of mortgaged and cash-purchased properties, respectively, in census tract c in year t.

Our variable of interest, $Small\ Loan\ Share_{ct}$, is defined as the proportion of approved small-dollar mortgages relative to the total approved mortgages in census tract c in year t. We

[10] Seo, Holmes, and Lee (2021) show that all-cash transactions are prevalent for smaller, older, and distressed properties.

[11] For example, Lambie-Hanson, Li, and Slonkosky (2022) and Ganduri, Xiao, and Xiao (2022) document a surge in investment activities by individual and institutional investors in distressed properties following the GFC.

categorize small-dollar mortgages as those with loan amounts less than $100,000, adjusted to 2010 dollars.[12, 13]

Table 2 presents the regression results. The estimated coefficient for β_1 is 0.077, indicating that a 10-percentage point decrease in the share of approved small loans corresponds to a 1.01 percent (0.077/0.076×0.01) increase in cash discounts. Since Figure 1 Panel A shows that lower-cost properties exhibit the largest cash discounts relative to higher-cost properties, we anticipate a stronger correlation in lower-cost properties. To confirm this hypothesis, we conduct analyses on subsamples of properties located in census tracts with initial median house values at the 1st and 4th quantiles, respectively, and present the results in Columns 2 and 3. As anticipated, we observe a strong and significant negative correlation in properties situated in census tracts with the lowest property values, whereas those with the highest property values exhibit a correlation that is both small in magnitude and statistically insignificant.

3.1 Instrumenting for Small Loan Share

One concern with the above analysis is that reverse causality may occur if a large number of purchases with cash discounts exert downward pressure on nearby property values, which in turn increase demand for small-dollar mortgages—leading to an underestimation of the estimated effect. Additionally, local housing and financial shocks, such as increased investments by institutional investors in the single-family home market, can impact both mortgage demand and property transaction outcomes, resulting in biased estimates.

To establish a causal relationship between supply of small credit and cash discounts, we adopt an instrumental variable (IV) approach. We propose an instrument for local changes

[12] The fixed costs associated with loan originations have increased substantially post-crisis, making mortgages with small dollar loan amounts less profitable to originate and thus reducing their availability (D'Acunto and Rossi, 2022, McCargo et al., 2020). This definition also aligns with the conventions used in several policy reports, including those by Demaria and Goldstein (2022), Goodman et al. (2022), and Ballesteros et al. (2020).

[13] In Table 6, we show that results remain robust when using alternative cut-offs for defining small-dollar mortgages, including $75,000 and $125,000. In Appendix Figure 6, we present a graph with more granular loan amount categories, further demonstrating that this redistribution predominantly affects loans smaller than $100,000, thereby justifying the use of $100,000 as the cutoff for small loans in this study.

in the supply of small-dollar mortgages by exploiting False Claims Act (FCA) litigations and investigations initiated by the Department of Justice (DOJ) beginning in 2012. These actions targeted Federal Housing Administration (FHA) mortgage lenders involved in fraudulent mortgage underwriting practices, particularly during the years leading up to the GFC.[14] A major wave of litigations gained momentum in 2012, when Deutsche Bank reached a $202.3 million settlement with the DOJ—the largest under the FCA at the time—for falsifying compliance certifications in the mortgage origination from 1999 through 2009.[15] As documented in Mayer, Xu and Zhao (2023), these litigations imposed heightened risks of financial penalties, resulting in a substantial reduction in FHA lending.[16] Using raw mortgage approval data, we also observe that the proportion of small-dollar mortgages approved by FCA-implicated lenders, relative to those approved by other lenders, decreased substantially following 2012, the year when the DOJ litigations and settlements commenced (Appendix Figure 7 Panel A). In terms of the number of small-dollar loan approvals, those by FCA-implicated lenders continued to decrease since 2012, while those by other lenders increased, albeit marginally, during the same period.

To implement the IV strategy, we employ a shift-share instrument, where the shift component represents the common shock experienced by all census tracts—the annual change in the share of small-dollar mortgage approvals across the nation. Appendix Figure 8 illustrates the shift component, showing a declining trend in the share of small loans in the years from 2012 onwards. We define the share component, which measures differential exposure to this common shock, as the census tract-level initial share of small-dollar mortgages approved by lenders implicated in FCA litigations. The intuition behind the instrument is that census tracts with a larger presence of FCA-implicated lenders are likely to face greater exposure to the

[14] See Griffin (2021) for a review of the fraudulent practices undertaken by mortgage lenders.
[15] Appendix Table 1 lists all mortgage lenders involved in the DOJ's FCA litigations for FHA-related investigations and lawsuits. See https://www.justice.gov/archives/opa/blog/false-claims-act-federal-housing-administration-lending for more details on the FCA lawsuits.
[16] Bhutta, Lauer, and Ringo (2017), in their policy note, also identify the FCA lawsuits as a possible factor contributing to the declining share of mortgage lending to low- and moderate-income households in recent years.

common shock—the redistribution of mortgage credit from small loans to large loans since the GFC—leading to a larger decrease in access to small-dollar mortgages. Appendix 7 Panel B compares the share of small loan approvals in census tracts with initially high and low concentrations of FCA-implicated lenders over time, using raw mortgage approval data. We observe that after 2012, census tracts with a higher initial presence of FCA-implicated lenders experienced a greater decline in small loan approvals.

Our identification relies on the exogeneity of the share component. Conditional on controls and fixed effects, the initial shares of small-dollar mortgage approvals by FCA-implicated lenders are exogenous to changes in the error term (Goldsmith-Pinkham, Sorkin and Swift, 2020). The first and second stages of the IV are specified as follows:

$$Small\ Loan\ Share_{ct} = \gamma_1 \frac{Small\ Loan\ by\ FCA\ Lenders}{Total\ Small\ Loan}_{c,04} \times \Delta Small\ Loan\ Share_t + \gamma X_{ct} + \delta_c + \theta_t + \varepsilon_{ct} \quad (3)$$

$$Cash\ Discount_{ct} = \beta_1 \widehat{Small\ Loan\ Share}_{ct} + \beta X_{ct} + \delta_c + \theta_t + + \varepsilon_{ct} \quad (4)$$

where the first component of the instrument is the proportion of approved small-dollar mortgages by FCA-implicated lenders relative to the total approved mortgages (hereafter *FCA share*) in census tract c in the initial year of 2004, and the second component of the instrument represents the annual variation in the national share of small-dollar mortgage approvals. $\widehat{Small\ Loan\ Share}_{ct}$ is the predicted share of small-dollar mortgage approvals from the first-stage specification (3).

Validity of the Instrument

To identify causality, the instrument must satisfy the relevance and exclusion restrictions. The relevance condition requires that the instrument be correlated with the share of small-dollar mortgages. Table 3 Panel A presents the first-stage results estimated from Equation (3). The coefficient is positive and statistically significant, with an F-statistics of 61.8, which rules out concerns about a weak instrument.[17] Appendix Table 2 shows the pairwise correlations between the *FCA shares* across different years. The correlations provide assurance that the *FCA share* in the initial period is informative of the cross-sectional exposure to the common shock in later years. Interestingly, the correlations decline significantly after 2012; the correlation between the *FCA share* in 2004 and the *FCA share* in 2020 is only 0.020, providing suggestive evidence of changing lending dynamics among FCA-implicated lenders following the series of enforcement actions.

In addition, we test the monotonicity assumption by examining whether the first-stage estimates are consistent across various subsamples. Appendix Table 3 presents these first-stage results separately for groups above and below the median for certain demographic attributes including race, age groups, employment and education level. In line with the monotonicity assumption, we find that the first-stage results consistently show a positive coefficient and a similar magnitude across all subsamples.

Second, the exclusion restriction assumption requires the instrument to isolate variation in the share of small-dollar mortgages that, conditional on controls and fixed effects, is orthogonal to changes in cash discounts. Simply put, any effect that the initial *FCA share* has on the cash discounts must operate solely through its impact on small-dollar lending as a result of FCA litigations beginning in 2012. That is, if the exclusion restriction is plausible, we should

[17] The positive coefficient suggests that census tracts with a greater *FCA share* experience a larger decline in small loan approvals (tighter small credit supply) in years with negative changes in small credit supply nationwide.

not observe any differences in the cash discounts between census tracts with varying presence of FCA-implicated lenders prior to the FCA shock in 2012. This is analogous to a standard difference-in-differences design, where examining the pre-trends reveals whether any preexisting differences in cash discounts existed before the FCA shock, which, if present, may suggest alternative channels through which *FCA share* influences the cash discounts. We examine the parallel pretrends assumption using the following reduced-form equation:

$$Cash\ Discount_{ct} = \sum_{s=2004,\neq 2011}^{2020} \beta_s \frac{Small\ Loan\ by\ FCA\ Lenders}{Total\ Small\ Loan}_{c,04} \times \mathbb{I}[\text{Year} = s] + \beta X_{ct} + \delta_c + \theta_t + \varepsilon_{ct} \quad (5)$$

Figure 2 shows that the variation in the initial *FCA shares* did not statistically or economically predict changes in cash discounts from 2004 through 2011, providing evidence in support of the plausibility of the exogeneity assumption. Similar parallel trends are observed when comparing the unconditional cash discounts between census tracts with *FCA shares* at the 1st and 4th quantiles (Appendix Figure 9). Contrary to the muted pre-trends, both conditional and unconditional cash discounts increase more in census tracts with a larger initial *FCA share* than in those with a smaller initial *FCA share* after 2012, and this positive difference continues in subsequent years.

A significant threat to the validity of the instrument is that the initial *FCA shares* may predict cross-sectional foreclosure patterns, which are likely associated with cash discounts, potentially violating the exogeneity condition. According to Griffin and Maturana (2016), zip codes with higher mortgage fraud rates experienced a larger housing boom before the GFC and a more severe housing bust afterward due to the initial loosening and subsequent tightening of credit supply. Consequently, census tracts with a substantial initial presence of FCA-implicated lenders—and likely higher mortgage fraud rates—may have undergone significant housing

price increases followed by sharp declines before and after the GFC. Additionally, excess credit to risky borrowers may lead to higher mortgage defaults and foreclosures, both of which are closely associated with cash discounts.[18] If census tracts with higher initial *FCA share* are linked to higher foreclosure rates and mortgage defaults, which in turn drive higher cash discounts, this would lead to an overestimation of the IV estimate. We address these concerns in four ways.

First, the cash discount measure is derived from a sample of repeat-sale transactions that excludes all foreclosure and foreclosure-related sales, thereby limiting exposure to foreclosure events that may invalidate the instrument. Second, we calculate the pairwise correlations between the initial *FCA share* and various measures of foreclosure conditions. As shown in Appendix Table 4, we do not find a positive relationship between *FCA share* and foreclosure measures. Instead, we observe a negative relationship: census tracts with a higher initial *FCA share* exhibit lower foreclosure rates. This suggests that, in any case, our IV estimate is likely an underestimation. Third, in Section 4.3, we demonstrate robustness by using various subsamples that exclude census tracts with high foreclosure indicators.

Lastly, we assess the plausibility of the exclusion restriction by examining the correlations between the initial *FCA share* and census-tract level characteristics. Strong correlations could indicate potential violations if changes in initial *FCA share* are systematically related to local factors that may also influence cash discounts. To test this, we regress initial *FCA share* on a set of 2010 baseline variables, including housing market indicators (e.g., average annual change in house price index, number of foreclosures, transaction volume, and investor purchases), local economic activity (e.g., small business loan originations, bank branch openings and closings), and demographic characteristics (e.g.,

[18] FCA-implicated lenders were found to have committed material defects, such as failing to verify borrowers' employment, assets, or credit, overstating income or assets, understating liabilities, and failing to ensure adequate property collateral, all in violation of FHA requirements.

population, housing units, median income, house values, etc.), which are included as controls throughout the analysis.

As shown in Appendix Table 5, the regression yields a low adjusted R-squared, suggesting that local characteristics explain little of the variation in initial *FCA share*. Additionally, while a few variables—such as median income, house value, and the shares of Hispanic and college-educated residents—are statistically significant, most other characteristics are not, reinforcing the plausibility of the exclusion restriction.

Taken together, these results suggest that our estimates are unlikely to be affected by unobservable factors and reflect the causal impact of small-dollar mortgage approvals on cash discounts in property transactions.

Instrumental Variable Results

We report the two-stage least squares (2SLS) estimates in Table 3, Panel B. Column 1 presents 2SLS results without controls, while Columns 2 and 3 present results controlling for demographics and borrower characteristics, respectively. The inclusion of these controls does not materially affect the magnitude of the estimates, suggesting that our results are robust and unlikely to be influenced by unobservable confounding factors.

Our preferred specification (Column 4) includes the full set of control variables. The coefficient of -0.880 indicates that a 1 percentage point reduction in the share of small-dollar mortgage approvals increases cash discounts by 0.880 percentage points. This effect is economically significant. Given that the average cash discounts at the census tract level is approximately 7.7%, a 1 percentage point decrease in the share of small-dollar mortgage approvals leads to an 11.43% increase in cash discounts ($0.880/0.077 \times 0.01$).[19]

[19] Our results remain robust under sample restrictions that exclude census tracts outside of MSAs, or when regressions are weighted by the total population of the census tracts, or both, as suggested by Mian and Sufi (2017).

The 2SLS estimates are larger than those in the OLS regression, suggesting that unobservable factors simultaneously affect small-dollar mortgage approvals. For instance, positive shocks to the housing market may narrow the price differences between cash and mortgage purchases (Han and Hong, 2024); these shocks may also raise overall housing prices, thereby increasing the demand for larger mortgages while reducing the demand for smaller mortgages.

3.2 Robustness Checks

Endogeneity Concerns Related to the Instrument

One concern is that the exclusion restriction assumption may fail if *initial FCA share*s influence cash discounts other than through the small loan share. For example, census tracts with greater initial exposure to FCA-implicated lenders may experience higher foreclosure rates if a higher concentration of fraudulent mortgage originations by these lenders leads to increased mortgage defaults, and consequently, larger cash discounts. To address this potential endogeneity concern, Table 4 presents robustness check using various subsamples .

Our first measure utilizes the foreclosure data from the Neighborhood Stabilization Program I-III administered by the Department of Housing and Urban Development (HUD).[20] Columns 1 and 2 show the estimated coefficients for Equation (4) using a sample that excludes census tracts with average foreclosure rates, while column 2 removes total foreclosures in the top quantile. Additionally, Columns 3 and 4 exclude census tracts with an initial share of subprime mortgages and an initial share of loans originated by subprime lenders in the top quantile, respectively.[21] In Column 5, we remove census tracts with the largest increase in

[20] The NSP is a series of programs initiated since 2008 to provide grants to state and local housing agencies in areas that experienced severe foreclosures and abandonments in the neighbourhoods, with the aim to rejuvenating and stabilizing these areas. For more details about the program, refer to https://www.huduser.gov/portal/datasets/NSP.html.

[21] Following Mayer and Pence's (2008) definitions, which categorize subprime mortgages as those with high interest rates and subprime lenders as those specializing in subprime mortgages, we identify subprime mortgages

house prices from 2003 to 2006 and the largest decrease from 2007 to 2012, as these areas tend to have high concentrations of lenders involved in fraudulent mortgage misreporting (Griffin and Maturana, 2016). To mitigate potential biases arising from unobserved local shocks during the GFC, we exclude sales transactions from years 2007 and 2008 in Column 6. Lastly, Column 7 combines all sample restrictions from the preceding six columns. The estimated effect of small-dollar mortgage share on cash discounts remains negative and statistically significant across all columns, supporting the validity of the exclusion restriction for the instrument.

Another concern involves the recent trend of institutional investors purchasing single-family homes following the GFC. These activities, which are predominately all-cash transactions, tend to concentrate in suburban, lower-income neighborhoods and target lower-priced, entry-level homes—characteristics that overlap with neighborhoods with a larger *FCA share*. As a result, institutional purchases may generate spillover effects on nearby home prices, thereby potentially introducing bias into our IV estimates.[22] However, the direct effect of institutional investments is unlikely to distort our estimates, as our cash discount measure is constructed using residualized prices, with the effects of investors and corporate buyers partialed out in the hedonic regression used to generate these prices. To address potential spillover effects, we exclude MSAs with significant institutional investment activity, considering the geographical concentration of these activities (Ganduri, Xiao and Xiao, 2022). Our results remain robust to these sample restrictions, as shown in Appendix Table 6.

A related issue concerns the rise of shadow banks including FinTech institutions following the GFC, as shown in Appendix Figure 10 Panel A. Buchak et al. (2018) demonstrate that these lenders expanded significantly in areas where regulatory pressures intensified due to

as those with a reported spread in the HMDA data and subprime lenders as those appearing on the HUD's Subprime and Manufactured Home Lender List.

[22] The direction of bias from spillover effects is unclear, as the literature presents mixed evidence on the impact of institutional activities on housing prices (Billings and Soliman, 2024; Cohen, 2023; Ganduri, Xiao and Xiao, 2022). A negative relationship between institutional purchases and neighboring house prices could lead to overestimation of our IV estimate, while a positive relationship might result in underestimation.

heightened enforcements focused on banks originating loans to less creditworthy and minority borrowers. Additionally, Panel B shows that these nontraditional lenders marginally increased their presence in the small-dollar mortgage market during periods when traditional lenders scaled back their involvement. However, this increase is modest and diminishes over time, leaving the overall number of small loan approvals relatively small. This observation aligns with Jagtiani, Lambie-Hanson and Lambie-Hanson (2021), who find that FinTech lenders are not more likely to make small-dollar loans. Nevertheless, concerns arise regarding whether areas exposed to a larger presence of FCA-implicated lenders tend to experience a more significant increase in nontraditional lenders. These lenders may originate more loans to lower credit score borrowers or loans that are more likely to default, thereby increasing cash discounts and potentially invalidating the exclusion restriction assumption.

To address potential confounders associated with nontraditional lenders, we control for the market shares of total loan approvals by shadow banks and FinTech banks. As shown in Column 1 of Table 5, the estimated effect of small loan shares on cash discounts is nearly identical to the baseline effect. Our results remain robust even when excluding census tracts where shadow banks and FinTech lenders have the highest market shares (Column 2). In Column 3, we test for differential effects between census tracts with high and low market shares of nontraditional banks. The statistically insignificant coefficient on the interaction term suggests no meaningful variation in effects between these census tracts.

Alternative Definitions of Small-dollar Mortgages

Throughout the analysis, we use a static cutoff of $100,000, adjusted to 2010 dollars, to define small-dollar mortgages. To address concerns about the arbitrary nature of our cutoff, Table 6 presents the results using alternative cutoffs of $75,000 and $125,000, showing consistent estimated effects ranging from 1.193 to 1.577. However, one natural question is whether the

cutoff and the corresponding estimated effect are relevant for regions with high home prices. For example, in high-cost areas such as California, a $300,000 loan might be considered small. To assess this concern, we present descriptive evidence by reproducing Appendix Figures 1 and 2 using only the top 10 states with the highest average house prices, as shown in Appendix Figure 11.[23] The diverging trend between the number of approved small and large loans (Panel A) and the narrowing gap between cash and mortgaged purchases for houses in the lowest decile (Panel B) in these states closely follow the trends observed in the full sample. Additionally, Panel C shows that the average transaction price for properties in the lowest decile in these 10 states is approximately $96,000, with yearly averages mostly falling below the $100,000 cutoff, suggesting the validity of the cutoff even in these high-cost regions.

We also explore an alternative to the static cutoff by applying geographically and temporally varying cutoffs based on the local housing price levels and appreciation across years. While these dynamic cutoffs may reflect shifts in credit demand and thereby introduce potential endogeneity, we utilize the county-level conforming loan limit (CLL), applying a 20% margin to the maximum CLL as the new cutoff to assess the validity of spatially and temporally varying loan amount cutoff. Additionally, we consider the 20th percentile of loan amounts from all approvals within the census tract as another cutoff with spatial and temporal variation. Appendix Figure 12 Panel A plots the shift component of the instrument—the annual change in the share of approved small loans—based on these various cutoffs. We observe that the annual changes in approval share based on the dynamic cutoffs remain relatively consistent. Panel B shows that the average loan amounts at these dynamic cutoffs stay relatively small at $125,000 in the early years but increase substantially after 2011 to over $200,000 in 2019. Together, these findings suggest that the tightening of small credit impacts loans that are

[23] The 10 states include California, Colorado, Connecticut, District of Columbia, Hawaii, Massachusetts, New Jersey, Virginia, Virgin Islands, Washington.

specifically small in absolute dollar amounts, rather than those relatively small within the overall distribution, supporting our use of static cutoffs to define small-dollar mortgages.

Reduced-form Empirical Strategy

We also explore an alternative identification strategy with a reduced-form difference-in-differences approach. This involves regressing our second-stage outcome, $Cash\ Discount_{ct}$, directly on the interaction of indicators variables for years following 2012 and the share component of our instrument, $\frac{Small\ Loan\ by\ FCA\ Lenders}{Total\ Small\ Loan}_{c,04}$. The reduced-form coefficients thus capture the total effect of FCA litigation risks on cash discounts, which include both the direct effect of reduced small-dollar credit supply and indirect effects operating through other channels. For example, the positive reduced-form estimates on the DD terms, as shown in Figure 2, suggest that the FCA shock may increase cash discounts directly by limiting access to small-dollar mortgage financing, or indirectly by encouraging greater participation from experienced, cash-rich investors with stronger bargaining power.[24]

To facilitate the causal interpretation, we use a binary treatment indicator instead of a continuous treatment variable. This treatment indicator equals one if the census tract has an above-median exposure measure and zero otherwise. We estimate the following regression:

$$Cash\ Discount_{ct} = \beta_1 \mathbb{I}\left[\frac{Small\ Loan\ by\ FCA\ Lenders}{Total\ Small\ Loan}_{c,04} > Median\right] \times \mathbb{I}[\text{Year} \geq 2012] + \beta X_{ct} + \delta_c + \theta_t + \varepsilon_{ct} \quad (6)$$

[24] An alternative way that the FCA litigations can indirectly affect cash discounts is by lowering sellers' price expectations in response to perceived risks associated with the tightening of mortgage credit induced by the FCA shock.

Table 7 Column 1 shows the estimated coefficients for the DD interaction term and finds that census tracts with higher exposure to FCA-implicated lenders experience a 0.2 percentage point, or 1.11% (0.002/0.218), decrease in small loan share compared to census tracts with relatively smaller exposure after 2012. The reduced-form estimate is presented in Columns 2 and 3, indicating that cash discounts in these highly exposed census tracts increase by 1.1 percentage point or 5.5%.[25, 26] Appendix Figure 13 presents the dynamic effects of increased FCA litigation risks on cash discounts in property transactions, with the absence of pre-trends suggesting the validity of the parallel trend assumption.

Next, we explore heterogeneity in our reduced-form estimates by stratifying census tracts based on observable characteristics pre-treatment and examine triple differences that allow for all lower-order interaction terms. We categorize census tracts by whether the median value of a particular variable in 2000 is above or below the sample median. The census tract attributes include household income, percentage of the population below poverty, percentage of black residents, percentage of unemployed persons, percentage of the population with at least a bachelor degree, and median house value.

Table 8 reports the coefficients of the triple interactions. The statistically significant and positive estimates from Columns 1 through 6 indicate that the effects on cash discounts are concentrated in relatively disadvantage communities. Considering that many of these characteristics may be highly correlated with each other, in Column 7, we include all interactions in a single regression to isolate the main factors driving the heterogeneity effects. We find that disadvantaged communities, particularly those with lower household income and

[25] The number of observations in the estimation sample is larger than the baseline IV regression because there are instances of zero approved loans in certain census tracts during specific years, resulting in missing small loan share data.

[26] Before transforming the cash discounts into their natural logarithmic form, we add the minimum cash discount value in the sample to all cash discount values to obtain non-negative values.

higher percentages of black residents, are more affected by the FCA events and consequently experience larger increases in cash discounts.

Lastly, we examine whether the effects on cash discounts more pronounced in lower-cost properties using the unconditional quantile regression method proposed by Firpo, Fortin, and Lemieux (2009). We estimate a series of RIF-OLS regressions at the property transaction level for property prices across various deciles, focusing on repeat-sale transactions. Specifically, we regress the natural logarithm of property transaction prices on a triple interaction term among the treatment indicator, the post-2011 indicator, and a mortgaged purchase indicator, including their lower-order interaction terms. Additionally, we control for census tract demographics, census-tract level borrower characteristics, time-varying property and transaction attributes, year-month fixed effects, and property fixed effects.

Appendix Figure 14 Panel A plots the coefficients of the triple interaction term obtained from the nine separate regressions. The results indicate that lower-cost properties with greater exposure to FCA-implicated lenders experience a larger increase in cash discounts following heightened FCA litigation risks. Specifically, cash discounts for highly-exposed properties in the lowest price decile increase by 5.1%, and those in the second price decile increase by 2.2% following the FCA shock. Conversely, higher-priced properties, those in the 3rd decile and above, show statistically insignificant changes in cash discounts. These findings align with our expectations and highlight the significant role of small-dollar mortgage in affecting property values, particularly in the lower price segments.

4. Mechanism

In this section, we explore the potential mechanisms driving the causal relationship between small loan share and cash discounts and examine its broader impact on the housing market. First, we investigate whether the increase in cash discounts following the tightening of small-dollar mortgages results from a decrease in cash purchase prices relative to mortgage purchase

prices, or an increase in mortgage purchase prices relative to cash purchase prices. We show that our findings support the former proposition by examining the effect of small loan share on transaction prices of mortgaged and cash purchases in separate regressions. Specifically, we estimate Equation (4), replacing the outcome variable with the natural logarithm of average residualized prices for mortgaged and cash purchases. As presented in Table 9 Columns 1 and 2, a one-percentage-point decrease in the share of small loans decreases prices for mortgaged purchases by 0.21% and for cash purchases by 1.03%. The sensitivity of prices for cash purchases to changes in the small loan share is almost five times that for mortgaged purchases, suggesting that in a credit-tightening situation, prices for cash purchases experience a significantly larger decline than for mortgaged purchases. In Appendix Table 7, we further regress the residualized prices for mortgaged purchases and cash purchases separately using the reduced-form DD as specified in Equation (6). Our findings show that while prices for cash purchases decrease by 1.2% following increased FCA enforcement actions against lenders involved in fraudulent mortgage originations, prices for mortgaged purchases decline by just 0.2%.

Two potential channels explain how tightening small loan supply results in increased cash discounts. First, with limited availability of small loans, financially constrained homebuyers are forced to opt for lower-valued properties, restricted by their available cash. This selection into cheaper properties, following the tightening of small loan supply, results in lower transaction prices and thus larger cash discounts. However, our cash discount measure, by design, rules out this channel, as it accounts for most observable and unobservable property characteristics by including a comprehensive set of controls for seller, buyer, transaction, and property attributes, along with property fixed effects, in the regression used to generate residualized prices. The second channel suggests that as small-dollar mortgage approvals decline, prospective homebuyers face higher financing costs and fewer financing opportunities,

limiting their ability to purchase properties. In contrast, financially liquid investors step in to fill the gap left by these homebuyers, purchasing houses with cash. As investors typically have greater negotiation power during property transactions, combined with fewer competing homebuyers in the market, this dynamic leads to increased cash discounts.

To verify this conjecture, we analyze the relationships between small loan share and transaction volumes, investor purchases, and cash purchases, focusing on low-cost properties, where cash discounts are more prominent and the share of small loans is of greater concern. Column 3 of Table 9 shows a negative relationship between small loan share and transaction volume: a one-percentage-point decrease in the share of small loans increases the transaction volume by 5.58%. Much of this increase in transaction volume is driven by cash-rich investors, as shown in Columns 4 and 5, where investor purchases increase by 5.57% and cash purchases rise by 6.54% for every percentage point decrease in the share of small loans.

Finally, the last column examines the broader impact of small loan share on the housing market by studying its impact on residualized property prices. We find a positive relationship between the two, suggesting that a lower share of small loans leads to a reduction in property prices. However, this could also indicate that a larger share of larger loans results in increased property prices. To further investigate, we use the RIF-OLS specification outlined in the previous section, and present the coefficients on the double interaction term in Appendix Figure 14 Panel B. The coefficients capture the average effect of the tightening of small loans due to increased FCA litigation risks on property prices across different price deciles. We observe a significant reduction in prices for lower-cost properties, with those in the lowest decile experiencing a 6.65% decrease in property prices. The reduction in property prices diminishes as we move up the price deciles.

Taken together, these findings indicate that the increased transaction volumes driven by investor purchases and the corresponding rise in cash purchases potentially explain the cash

discounts in low-cost properties. The additional result on property prices provides important implications: credit-induced cash discounts may dampen housing prices in general. Thus, we present a mechanism beyond housing demand that explains the positive relationship between credit supply and housing outcomes (Favara and Imbs, 2015, Mian and Sufi, 2022). Specifically, we show that, at least for low-cost properties, investor purchases and the associated cash discounts are significant driving factors of lower property prices when the supply of small-dollar mortgages is limited.

5. Conclusion

Since 2012, there has been a noticeable decline in small-dollar mortgages, a trend that corresponds with an increasing proportion of cash purchases and a substantial cash discount among low-cost properties. Our analysis indicates that a one-percentage-point reduction in the share of small-dollar mortgages results in an 11.43% increase in cash discounts. These findings remain robust when applying alternative thresholds to define small-dollar mortgages, controlling for the market share of shadow banks or fintech lenders, and imposing various sample restrictions, such as excluding regions with high foreclosure rates, high levels of subprime loans and lenders, data from the Global Financial Crisis (GFC) years, and areas that experienced significant boom and bust cycles related to the GFC.

We also find that price sensitivity to the tightening of small-dollar mortgage supply is more pronounced for cash purchases than for mortgaged purchases. Additional heterogeneity analysis indicates that the impact on cash discounts is more pronounced in disadvantaged communities, especially those with lower household incomes and higher concentrations of Black residents. Moreover, properties in the lower price deciles exhibit a larger increase in cash discounts, whereas properties in the higher price deciles show a more muted response. Finally, we show that the effect of tightening small credit on property prices varies across deciles, with the most significant reduction occurring in the lowest price decile.

These findings highlight significant challenges for households with limited savings. First, the limited availability of small-dollar mortgages restricts the potential for lower income households to build wealth through homeownership. Secondly, for current homeowners, the ongoing scarcity of small-dollar mortgages poses a risk of property value depreciation, exacerbated by the increasing presence of cash investors, further complicating the financial stability and potential for asset appreciation among these low-income homeowners.

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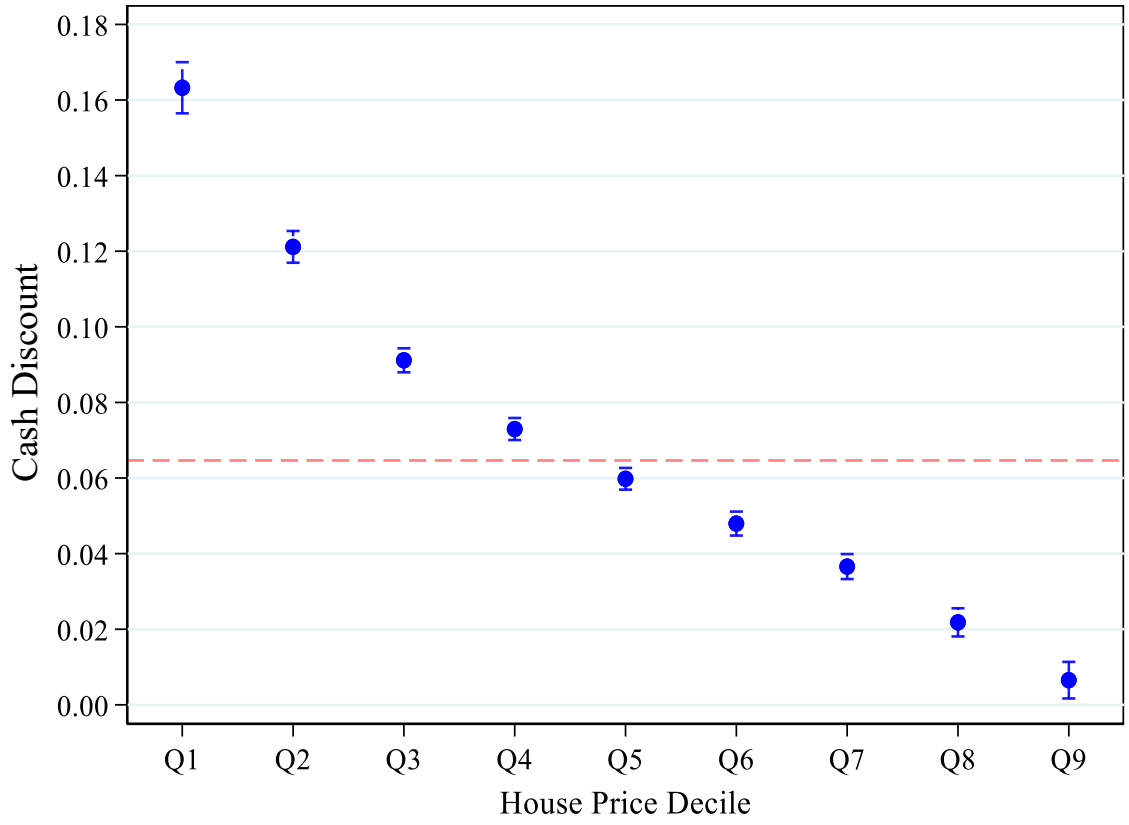
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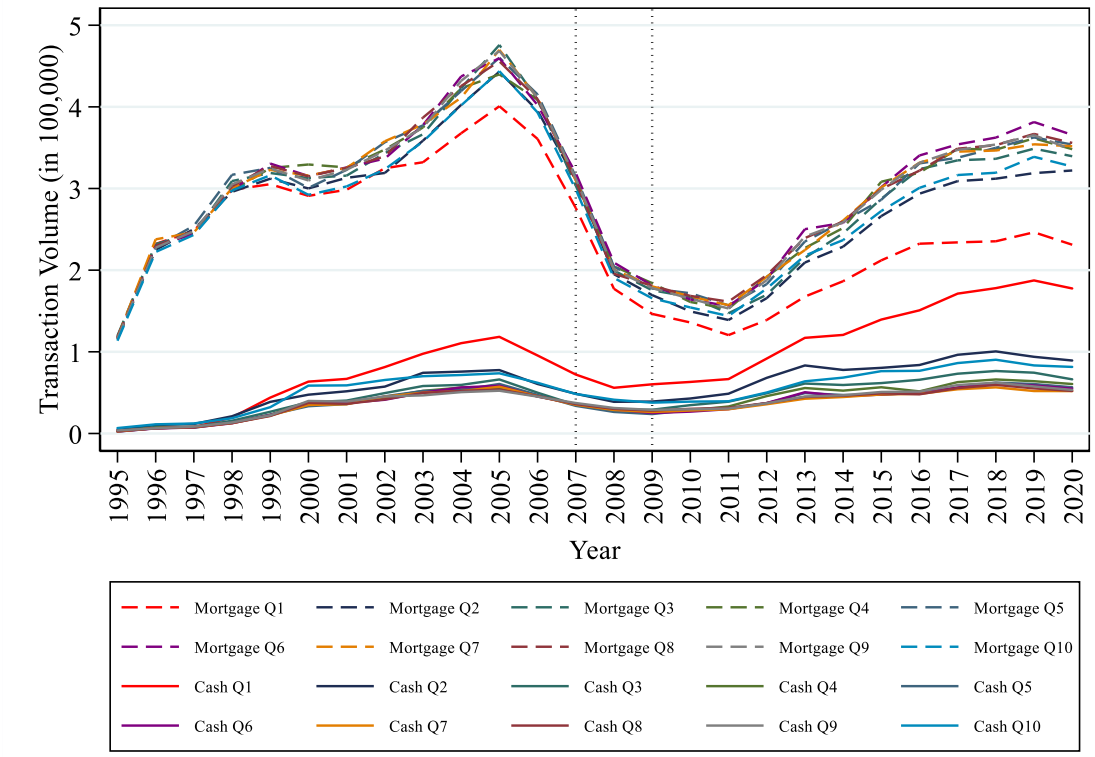
Figure 1. Total Mortgage Approvals, Property Transactions and Average Residualized Price by Year

The figure presents the total volume of mortgage approvals, property transactions, average residualized prices, and cash discounts from 2004 to 2020. Panel A presents cash discounts estimated from nine separate unconditional quantile regressions of the RIF counterpart of property transaction prices adjusted to 2010 dollars on a dummy indicating mortgage-financed purchase, along with a battery of property and transaction controls and fixed effects. The details of the regressions are provided in Appendix A3 and Appendix Figure 4. Panel B illustrates the total volume of property transactions from 1995 to 2020, divided into ten deciles based on transaction prices adjusted to 2010 dollars, separated by financing type. Panel C presents the average residualized prices for mortgage- and cash-financed property transactions in neighborhoods with above-median (higher-cost) and below-median (lower-cost) house values according to the 2000 census. The residualized price is obtained by regressing the log of transaction price on transaction, buyer and seller characteristics, property fixed effects, and year fixed effects. Panel D shows the total volume of loan approvals, separated by loan size, with loan amounts adjusted to 2010 dollars.

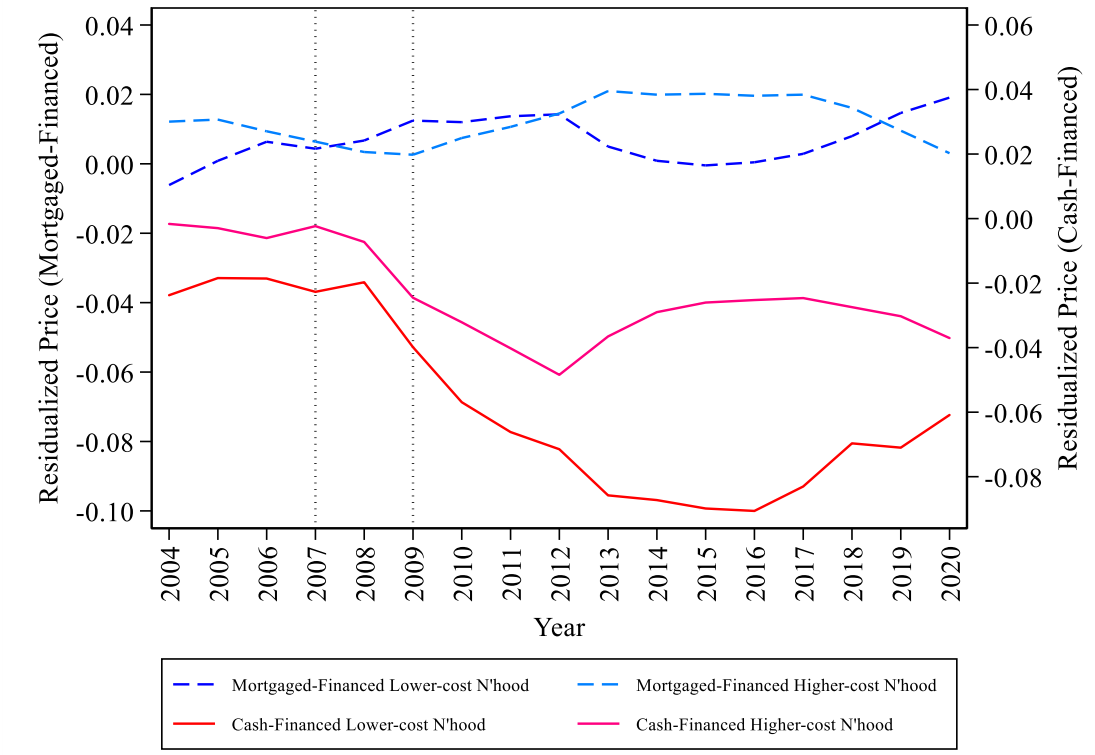
Panel A. Cash Discounts by Property Price Decile



Panel B. Transaction Volume by Property Price Decile and Financing Type



Panel C. Residualized Price by Neighborhood Type and Financing Type



Panel D. Loan Approvals by Loan Size



Figure 2. Dynamics of Cash Discount

The figure presents regression estimates of β_s from the following regression:

$$Cash\ Discount_{ct} = \sum_{s=2004,\neq 2011}^{2020} \beta_s \frac{Small\ Loan\ by\ FCA\ Lenders}{Total\ Small\ Loan}_{c,04} \times \mathbb{I}[\text{Year} = s] + \beta X_{ct} + \delta_c + \theta_t$$

where the dependent variable is $Cash\ Discount$. The variables of interest are the interactions between the initial share of small-dollar mortgage approvals in 2004 by lenders implicated in False Claims Act (FCA) litigations and year indicators, with 2011 as the omitted reference year. The regression includes census tract fixed effects (δ_c) and year fixed effects (θ_t). X_{it} is a vector of controls for census tract demographic characteristics and loan applicant characteristics. Ninety-five percent confidence intervals are displayed around each point estimate. Standard errors are clustered at the census tract level.

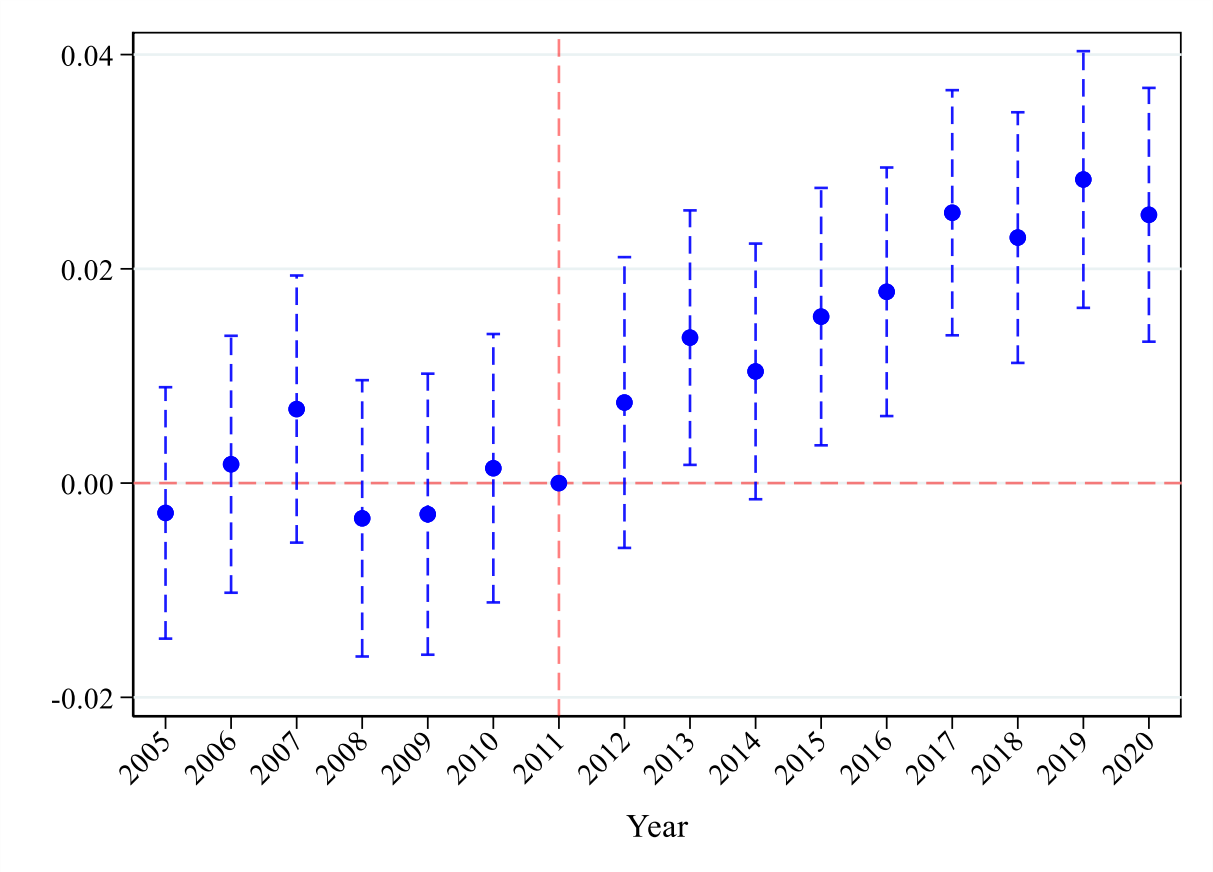


Table 1. Summary Statistics

This table presents summary statistics for the key control variables and variables of interest in our baseline analysis covering the years 2004 to 2020. Panel A presents summary statistics for property transaction prices, adjusted to 2010 dollar, at the transaction level. Panel B summarizes statistics for variables aggregated at the census tract level. $Cash\ Discount$ is defined as the difference between the average residualized prices for mortgaged purchases and the average residualized prices for cash purchases. Residualized prices are obtained by estimating the residuals from an OLS regression of the (log) transaction price on property fixed effects and year month fixed effects, and a set of control variables for property, transaction, seller and buyer characteristics, separately for mortgage purchases and cash purchases. $Small\ Loan\ Share$ represents the fraction of approved small-dollar mortgages (loan amount below $100,000 adjusted to 2010 dollars) out of the total approved mortgages. The $Small\ Loan\ Share_{FCA04}$ is the initial fraction of small-dollar mortgages approved in 2004 by lenders implicated in False Claims Act (FCA) litigations out of the total approved small-dollar mortgages. All demographic controls are sourced from the NHGIS, and loan applicant controls are obtained from HMDA.

	(1) N	(2) Mean	(3) Sd	(4) P25	(5) P50	(6) P75
Panel A. Transaction-level Variables						
Transaction Price	39,681,099	281,914.87	237,167.17	138,506.31	215,357.95	344,080.56
Cash Purchase Price	7,083,557	268,670.90	279,130.58	101,320.29	182,359.56	322,000.53
Mortgaged Purchase Price	32,597,542	284,792.83	226,922.58	145,757.67	221,507.61	347,122.31
Panel B. Census Tract Level						
Main Variables						
Cash Discount	585,088	0.08	0.21	-0.03	0.04	0.14
Small Loan Share	585,088	0.22	0.27	0.02	0.10	0.33
Small Loan Share$_{FCA04}$	585,088	0.25	0.23	0.00	0.24	0.38
Demographic Controls						
Total Population	585,088	4,723.21	2,173.86	3,263.00	4,423.65	5,815.00
Total No. of Housing Unit	585,088	2,006.97	878.94	1,415.00	1,882.00	2,448.00
Median Home Value	585,088	249,149.28	173,660.69	133,900.00	200,800.00	314,700.00
Median Household Income	585,088	62,955.73	32,757.54	41,897.00	58,107.00	79,500.00
% of White	585,088	0.73	0.24	0.61	0.80	0.91
% of Hispanic	585,088	0.14	0.19	0.03	0.07	0.18
% of Population below Poverty Line	585,088	0.13	0.11	0.05	0.10	0.18
% of Age Above 65	585,088	0.16	0.08	0.11	0.15	0.19
% of Age 18-65	585,088	0.62	0.07	0.58	0.62	0.65
% of Population in Labor Force	585,088	0.51	0.08	0.46	0.51	0.56
% of Employed Person	585,088	0.47	0.08	0.42	0.48	0.52
% of Population below 9th Grade	585,088	0.03	0.04	0.01	0.02	0.04
% of Population with Bachelor Degree	585,088	0.21	0.13	0.11	0.18	0.29
Loan Applicants Controls						
Borrower Income	585,088	84,136.92	77,985.85	54,927.74	71,736.12	97,319.53
% of White Borrowers	585,088	0.81	0.21	0.76	0.89	0.96
% of Black Borrowers	585,088	0.10	0.19	0.00	0.03	0.10
% of Male Borrowers	585,088	0.38	0.12	0.30	0.37	0.44
% of Joint-Sex Borrowers	585,088	0.36	0.16	0.25	0.36	0.47
% of non-Hispanic Borrowers	585,088	0.87	0.19	0.85	0.94	0.98

Table 2. Small-dollar Mortgage and Cash Discount: OLS Results

This table presents ordinary least squares regression estimates of β_1 from the following model:

$$Cash\ Discount_{ct} = \beta_1 Small\ Loan\ Share_{ct} + \beta X_{ct} + \delta_c + \theta_t$$

where the dependent variable is $Cash\ Discount$, and the variable of interest is $Small\ Loan\ Share$, which represents the fraction of small-dollar mortgage (loan amount below $100,000 standardized to 2010 dollars) approvals out of the total mortgage approvals. The regression includes census tract fixed effects (δ_c) and year fixed effects (θ_t). X_{it} is a vector of controls for census tract demographic characteristics and loan applicant characteristics. Column 1 displays regression results using the full baseline sample, while Columns 2 and 3 use samples restricted to census tracts with median house values in 2000 in the bottom and top quantiles, respectively. The standard errors are clustered at the census tract level and presented in parenthesis below the coefficients. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
Small Loan Share	-0.077***	-0.088***	0.003
	(0.003)	(0.006)	(0.013)
Observations	734,050	143,758	204,113
Adjusted R-squared	0.149	0.144	0.108
CTract Controls	Y	Y	Y
Borrower Controls	Y	Y	Y
CTract FE	Y	Y	Y
Year FE	Y	Y	Y
Sample	Full	1st Quantile Median House Value$_{2000}$	4th Quantile Median House Value$_{2000}$

Table 3. Small-dollar Mortgage and Cash Discount: IV Results

This table presents estimates from the first stage (Panel A) and second stage (Panel B) of the Instrumental Variable (IV) regressions:

$$Small\ Loan\ Share_{ct} = \gamma_1 \frac{Small\ Loan\ by\ FCA\ Lenders}{Total\ Small\ Loan}_{c,04} \times \Delta Small\ Loan\ Share_t + \gamma X_{ct} + \delta_c + \theta_t$$

and

$$Cash\ Discount_{ct} = \beta_1 \widehat{Small\ Loan\ Share}_{ct} + \beta X_{ct} + \delta_c + \theta_t$$

where the variable of interest, $Small\ Loan\ Share$, represents the fraction of small-dollar mortgage (loan amount below $100,000 standardized to 2010 dollars) approvals out of the total mortgage approvals. It is instrumented using the interaction between the initial share of small-dollar mortgage approvals in 2004 by lenders implicated in False Claims Act (FCA) litigations and the annual change in the share of small-dollar mortgage approvals. The regressions include census tract fixed effects (δ_c) and year fixed effects (θ_t). X_{it} is a vector of controls for census tract demographic characteristics and loan applicant characteristics. The standard errors are clustered at the census tract level and presented in parenthesis below the coefficients. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Panel A. First Stage				
Instrument	0.052***	0.062***	0.064***	0.070***
	(0.007)	(0.006)	(0.007)	(0.006)
Panel B. Second Stage				
Small Loan Share	-1.175***	-0.993***	-0.961***	-0.880***
	(0.237)	(0.187)	(0.179)	(0.160)
Observations	585,273	585,268	585,093	585,088
CTract Controls	N	Y	N	Y
Borrower Controls	N	N	Y	Y
CTract FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
CTract Time Trend	N	N	N	N
Kleibergen-Paap F-stat	61.78	90.70	96.42	116.13

Table 4. Robustness to Sample Restrictions

This table presents estimates from the second stage of the Instrumental Variable (IV) regression:

$$Cash\ Discount_{ct} = \beta_1 Small\ \widehat{Loan}\ Share_{ct} + \beta X_{ct} + \delta_c + \theta_t$$

where the variable of interest, $Small\ Loan\ Share$, represents the fraction of small-dollar mortgage (loan amount below $100,000 standardized to 2010 dollars) approvals out of the total mortgage approvals. It is instrumented using the interaction between the initial share of small-dollar mortgage approvals in 2004 by lenders implicated in False Claims Act (FCA) litigations and the annual change in the share of small-dollar mortgage approvals. The regressions include census tract fixed effects (δ_c) and year fixed effects (θ_t). X_{it} is a vector of controls for census tract demographic characteristics and loan applicant characteristics. Column 1 excludes census tracts with average foreclosure rates across NSP I-III in the top quantile. Column 2 excludes census tracts with the total number of foreclosures across NSP I-III in the top quantile. Column 3 excludes census tracts with a share of subprime loans, defined as mortgages with a reported rate spread in the HMDA data, in the top quantile. Column 4 excludes census tracts with a share of loans originated by lenders listed in the HUD's Subprime and Manufactured Home Lender List in the top quantile. Column 5 excludes census tracts with changes in average house prices between 2003 and 2006 in the top quantile, and changes in average house prices between 2007 and 2012 in the bottom quantile. Column 6 excludes observations from the years 2007 and 2008. Column 7 applies all sample restrictions from Columns 1 to 6. The standard errors are clustered at the census tract level and presented in parenthesis below the coefficients. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Small Loan Share	-0.802***	-1.016***	-0.782***	-0.643***	-0.990***	-0.737***	-0.626***
	(0.163)	(0.197)	(0.164)	(0.145)	(0.195)	(0.144)	(0.203)
Observations	432,777	402,545	453,051	453,691	420,154	516,539	210,527
CTract Controls	Y	Y	Y	Y	Y	Y	Y
Borrower Controls	Y	Y	Y	Y	Y	Y	Y
CTract FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Kleibergen-Paap F-stat	149.41	103.60	120.60	141.27	128.65	128.59	102.73
Sample (Remove)	CTs W/ High Foreclosure % (NSPs)	CTs W/ High No. of Foreclosures (NSPs)	CTs W/ High Subprime Loans	CTs W/ High Subprime Lenders	CTs W/ High $\Delta Price_{0306}$ & Low $\Delta Price_{0712}$	2007 & 2008	(1) – (6)

Table 5. Small-dollar Mortgage, Cash Discount, and Shadow Banks

This table presents estimates from the second stage of the Instrumental Variable (IV) regression:

$$Cash\ Discount_{ct} = \beta_1 Small\ \widehat{Loan}\ Share_{ct} + \beta X_{ct} + \delta_c + \theta_t$$

where the variable of interest, $Small\ Loan\ Share$, represents the fraction of small-dollar mortgage (loan amount below $100,000 standardized to 2010 dollars) approvals out of the total mortgage approvals. It is instrumented using the interaction between the initial share of small-dollar mortgage approvals in 2004 by lenders implicated in False Claims Act (FCA) litigations and the annual change in the share of small-dollar mortgage approvals. The regressions include census tract fixed effects (δ_c) and year fixed effects (θ_t). X_{it} is a vector of controls for census tract demographic characteristics and loan applicant characteristics. Column 1 controls for the market shares of total loan approvals by shadow banks and FinTech banks. Column 2 further excludes census tracts where the market share of total loan approvals by shadow banks (or Fintech lenders) falls in the top quantile. Lender classification follows Buchak et al. (2018). The standard errors are clustered at the census tract level and presented in parenthesis below the coefficients. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
Small Loan Share	-0.881***	-1.178***	-0.763***
	(0.160)	(0.327)	(0.257)
Small Loan Share × Large Market Share of Shadow/Fintech Bank			0.346
			(0.605)
Observations	585,088	364,128	585,088
CTract Controls	Y	Y	Y
Borrower Controls	Y	Y	Y
Market Share Controls	Y	Y	Y
CTract FE	Y	Y	Y
Year FE	Y	Y	Y
Kleibergen-Paap F-stat	115.236	38.16	2.51
Sample (Remove)	-	CTs W/ High Market Share of Shadow or Fintech Lenders	-

Table 6. Robustness to Alternative Definitions of Small-dollar Mortgage

This table presents estimates from the Ordinary Least Squares regression, and the first stage (Panel A) and second stage (Panel B) of the Instrumental Variable (IV) regressions:

$$Small\ Loan\ Share_{ct} = \gamma_1 \frac{Small\ Loan\ by\ FCA\ Lenders}{Total\ Small\ Loan}_{c,04} \times \Delta Small\ Loan\ Share_t + \gamma X_{ct} + \delta_c + \theta_t$$

and

$$Cash\ Discount_{ct} = \beta_1 \widehat{Small\ Loan\ Share}_{ct} + \beta X_{ct} + \delta_c + \theta_t$$

where the variable of interest, $Small\ Loan\ Share$, represents the fraction of small-dollar mortgage (loan amount below \$75,000 for Columns 1 and 2, and below \$125,000 for Columns 3 and 4, standardized to 2010 dollars) approvals out of the total mortgage approvals. It is instrumented using the interaction between the initial share of small-dollar mortgage approvals in 2004 by lenders implicated in False Claims Act (FCA) litigations and the annual change in the share of small-dollar mortgage approvals. The regressions include census tract fixed effects (δ_c) and year fixed effects (θ_t). X_{it} is a vector of controls for census tract demographic characteristics and loan applicant characteristics. The standard errors are clustered at the census tract level and presented in parenthesis below the coefficients. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
	< 75K		< 125K	
	OLS	IV	OLS	IV
Panel A. First Stage				
Instrument		0.038***		0.054***
		(0.004)		(0.010)
Panel B. Second Stage				
Small Loan Share	-0.107***	-1.193***	-0.044***	-1.577***
	(0.004)	(0.246)	(0.003)	(0.381)
Observations	734,050	511,127	734,050	626,363
CTract Controls	Y	Y	Y	Y
Borrower Controls	Y	Y	Y	Y
CTract FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Adjusted R-squared	0.149		0.148	
Kleibergen-Paap F-stat		76.40		29.21

Table 7. Small-dollar Mortgage and Cash Discount: Reduced-form Difference-in-Differences

This table presents ordinary least squares estimates of β_1 from the following model:

$$Cash\ Discount_{ct} = \beta_1 \mathbb{I}\left[\frac{Small\ Loan\ by\ FCA\ Lenders}{Total\ Small\ Loan}_{c,04} > Median\right] \times \mathbb{I}[\text{Year} \geq 2012] + \beta X_{ct} + \delta_c + \theta_t$$

where the variable of interest is the interaction between the indicator for census tracts with an above-median initial share of small-dollar mortgage (loan amount below $100,000 standardized to 2010 dollars) approvals in 2004 by lenders implicated in False Claims Act (FCA) litigations and an indicator for years 2012 and after. The regression includes census tract fixed effects (δ_c) and year fixed effects (θ_t). X_{it} is a vector of controls for census tract demographic characteristics and loan applicant characteristics. The dependent variable in Column 1 is the share of small-dollar mortgage approvals; in Column 2, the dependent variable is $Cash\ Discount$, as used throughout the paper; in Column 3, the dependent variable is the natural logarithm of 0.414 plus $Cash\ Discount$, where -0.414 is the minimum cash discount value in the sample. The standard errors are clustered at the census tract level and presented in parenthesis below the coefficients. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1) Small Loan Share OLS	(2) Cash Discount OLS	(3) Log(Cash Discount) OLS
Highly Exposed × Post 2011	-0.002***	0.011***	0.055***
	(0.001)	(0.001)	(0.010)
Observations	585,088	586,789	586,789
Adjusted R-squared	0.845	0.148	0.057
CTract Controls	Y	Y	Y
Borrower Controls	Y	Y	Y
CTract FE	Y	Y	Y
Year FE	Y	Y	Y

Table 8. Heterogeneity by Census Tracts Characteristics

This table presents ordinary least squares estimates of β_1 from the following model:

$$Cash\ Discount_{ct} = \beta_1 \text{Highly Exposed}_c \times Post2011_t \times \mathbb{I}[\text{Characteristic}]_c + \beta_2 \text{Highly Exposed}_c \times Post2011_t + \beta_3 Post2011_t \times \mathbb{I}[\text{Characteristic}]_c + \beta X_{ct} + \delta_c + \theta_t$$

where the dependent variable is $Cash\ Discount$. The variable of interest is the interaction between Highly Exposed, $Post$, and $\mathbb{I}[\text{Characteristic}]$. Highly Exposed is defined as $\left[\frac{Small\ Loan\ by\ FCA\ Lenders}{Total\ Small\ Loan}_{c,04} > Median\right]$, an indicator for census tracts with an above-median initial share of small-dollar mortgage (loan amount below $100,000) approvals in 2004 by lenders implicated in False Claims Act (FCA) litigations. $Post$ is an indicator for years 2012 and after. $\mathbb{I}[\text{Characteristic}]$ is an indicator for census tracts with an above-median (or below-median) value of the particular characteristic in 2000. The regression includes census tract fixed effects (δ_c) and year fixed effects (θ_t). X_{it} is a vector of controls for census tract demographic characteristics and loan applicant characteristics. The standard errors are clustered at the census tract level and presented in parenthesis below the coefficients. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Highly Exposed × Post 2011	0.009***						0.007**
× 𝟙[Low Household Income]	(0.002)						(0.003)
Highly Exposed × Post 2011		0.008***					-0.000
× 𝟙[High % Below Poverty]		(0.002)					(0.003)
Highly Exposed × Post 2011			0.007***				0.005**
× 𝟙[High % Black]			(0.002)				(0.002)
Highly Exposed × Post 2011				0.007***			0.003
× 𝟙[High % Unemployed]				(0.002)			(0.003)
Highly Exposed × Post 2011					0.007***		0.003
× 𝟙Low % Bachelor]					(0.002)		(0.003)
Highly Exposed × Post 2011						0.005**	-0.002
× 𝟙[Low House Value]						(0.002)	(0.003)
Observations	586,789	586,789	586,789	586,789	586,789	586,789	586,789
Adjusted R-squared	0.148	0.148	0.148	0.148	0.148	0.148	0.148
CTract Controls	Y	Y	Y	Y	Y	Y	Y
Borrower Controls	Y	Y	Y	Y	Y	Y	Y
CTract FE	Y	Y	Y	Y	Y	Y	Y

Year FE	Y	Y	Y	Y	Y	Y	Y

Table 9. Small-dollar Mortgage and Other Outcome Variables

This table presents estimates from the second stage of the Instrumental Variable (IV) regression:

$$y_{ct} = \beta_1 Small\ \widehat{Loan}\ Share_{ct} + \beta X_{ct} + \delta_c + \theta_t$$

where the variable of interest, $Small\ Loan\ Share$, represents the fraction of small-dollar mortgage (loan amount below $100,000 standardized to 2010 dollars) approvals out of the total mortgage approvals. It is instrumented using the interaction between the initial share of small-dollar mortgage approvals in 2004 by lenders implicated in False Claims Act (FCA) litigations and the annual change in the share of small-dollar mortgage approvals. The dependent variables are the natural logarithm of the average residualized prices for mortgage-financed transactions (Column 1), the natural logarithm of the average residualized prices for cash-financed transactions (Column 2), the natural logarithm of the volume of investor purchase (Column 3), the natural logarithm of the volume of investor purchase of properties in the bottom price quantile (Column 4), the natural logarithm of the volume of cash purchase (Column 5), the natural logarithm of the volume of cash purchase of properties in the bottom price quantile (Column 6), and the residualized property prices averaged at the census tract level (Column 7). The regressions include census tract fixed effects (δ_c) and year fixed effects (θ_t). X_{it} is a vector of controls for census tract demographic characteristics and loan applicant characteristics. The standard errors are clustered at the census tract level and presented in parenthesis below the coefficients. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1) Log(Mortgaged Purchase Price)	(2) Log(Cash Purchase Price)	(3) Log(Transaction Volume in Q1)	(4) Log(Investor Purchase in Q1)	(5) Log(Cash Purchase in Q1)	(6) Log(Price)
Small Loan Share	0.208**	1.032***	-5.575***	-5.567***	-6.540***	0.457***
	(0.088)	(0.167)	(0.660)	(0.624)	(0.689)	(0.092)
Observations	585,088	585,088	585,088	585,088	585,088	585,088
CTract Controls	Y	Y	Y	Y	Y	Y
Borrower Controls	Y	Y	Y	Y	Y	Y
CTract FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Kleibergen-Paap F-stat	116.128	116.128	116.128	116.128	116.128	116.128

Appendix

Appendix A. Three Observations about the Mortgage and Housing Markets

In this section, we present three observations concerning the U.S. mortgage and housing markets as motivating evidence for our empirical analysis to follow.

A.1 The share of approved small loans has decreased since 2011

Appendix Figure 1 Panel A presents the trends in mortgage approvals by loan size from 2004 to 2020. We calculate the total number of approved loans with amounts larger and smaller than $100,000, in real dollars adjusted to 2010 dollars. While the number of approved loans decreased following the peak of the housing market in 2005, the number of approved large loans has seen an increasing trend since the end of the Global Financial Crisis (GFC), reaching nearly 4 million loans in 2020, similar to pre-GFC levels. In contrast, the number of small loans did not follow this recovery pattern and has remained low. From 2004 to 2020, the number (share) of approved loans with amounts smaller than $100,000 decreased by 70.8% (65.8%) in nominal terms and 38.7% (28.3%).

Several factors can explain this observation. First, much of the decline in small-dollar loans can be attributed to home price appreciation, particularly in the years subsequent to the GFC. As house prices escalate over time, the availability of low-cost housing stocks at which small mortgages could finance diminishes, leading to a lower demand for small-dollar loans and consequently, a decrease in the number of approved small loans. Appendix Figure 1 Panel B documents the volume of housing transactions for houses transacted at prices below $100,000, between $100,000 and $200,000, and above $200,000. In contrast to higher-cost houses, which have experienced an increasing trend in transaction volume since the GFC, the volume of transactions of houses priced below $100,000 and between $100,000 and $200,000 saw declines of 27.3% and 19.3%, respectively. Nonetheless, this reduction falls short of the 38.7% decrease in small mortgage volume. Furthermore, considering that housing transactions

do not encompass all available low-cost housing stocks for sale, additional factors beyond this demand-side mechanism likely contribute to this trend.

The second explanation pertains to the credit supply side, where lenders have increasingly approved larger loans while reducing smaller loans since 2011, as documented by D'Acunto and Rossi (2022). This shift is primarily due to the passage of the Dodd-Frank Wall Street Reform and Consumer Protection Act (Dodd-Frank Act), which has increased both the expected fixed and per-loan costs of mortgage origination. For example, the Act mandates specialized training for all loan officers and imposes a complex and costly income verification procedure at the time of loan application. These increases in fixed costs, combined with the price caps on closing costs, reduce the per-loan profit for small loan originations greater than for larger loans, thereby diminishing the incentive for lenders to originate small loans.

A.2 The share of all-cash purchases among lowest-cost housing has increased

We now turn to assess the dynamics in the housing market. All-cash purchases have experienced an unprecedented increase since the GFC, driven not only by institutional investors, who predominantly opt for all-cash transactions, but also by a growing number of individual buyers engaging in such transactions.[30] Here, we document that the surge in all-cash purchases is primarily concentrated within the lowest-priced housing segment.

Appendix Figure 2 Panel A plots the volume of arm's length transactions of residential properties by mortgage versus cash transactions, after categorizing property transactions into deciles based on transaction price. Mortgage transactions have consistently dominated the property transaction market, although there is a slight increasing trend in cash transactions overall. Contrary to trends observed in properties within other deciles, those in the lowest decile exhibit a significant narrowing gap between mortgage transactions and cash transactions since

[30] "Share of Homes Bought With All Cash Hits 30% for First Time Since 2014" (Redfin News, July 15 2021).

2011. Relatedly, there is a notable surge in the number of investor purchases of these lowest-decile properties during the same period (Appendix Figure 2 Panel B).

These trends, including the significant increase in cash transactions along with the surge in investor purchases for properties within the lowest decile, seem to imply the predominant role of large-scale real estate investors making substantial investments to acquire distressed houses and those in markets particularly affected by the housing recession (Allen et al., 2017, Lambie-Hanson et al., 2022). However, this may not be the sole explanation. First, the transactions only include arm's-length transactions and exclude short sales, foreclosure sales, and real estate-owned (REO) sales. Second, similar trends can also be observed in Appendix Figure 3, which replicates Appendix Figure 2 using a sample of transactions that exclude regions with high foreclosure rates during the housing recession period and regions with a large presence of institutional investors. Taken together, these findings suggest that other factors, such as the tightening access to small-sized credit as illustrated in Appendix Figure 1, may also account for these trends.

A.3 The cash discount on the lowest-cost housing has been the largest

In this section, we document that cash discounts, which are transaction price reductions associated with cash transactions relative to mortgage transactions, are largest for properties in the lowest prices segment. Han and Hong (2024) and Reher and Valkanov (2023) find average cash discounts of 3% and 11%, respectively, and attribute these discounts to sellers' financing risks, including closing risk and re-listing risk, as well as sellers' subjective beliefs and aversion to uncertainty. Considering the diverging patterns of mortgage and cash transactions for properties in the lowest price segment as presented in Appendix Figure 2, one may expect the price dynamics between mortgage and cash transactions to also vary across different price deciles. For example, sellers of low-cost housing may exhibit stronger uncertainty aversion compared to sellers of higher-cost housing, who may be more financially liquid. Thus, sellers of low-cost houses may demand greater compensation for risks associated with mortgage

transactions. Alternatively, low-cost housing may face a higher likelihood of mortgage rejection, particularly after the GFC due to tightened borrowing standards, thus reducing the pool of prospective financing contingent buyers and strengthening negotiation power for cash buyers.

To examine cash discounts in properties across price deciles, we employ the following unconditional quantile regression, specifically the RIF-OLS regression proposed by Firpo, Fortin and Lemieux (2009), and estimate a series of regressions for alternative deciles q_τ:

$$\widehat{RIF}(y_{ict}; \widehat{q_\tau}) = \beta_1 mortgage_{it} + \beta X_{it} + \delta_i + \theta_{ct} + \varepsilon_{ict} \quad \text{(A1)}$$

where y_{ict} is the natural logarithm of property i's transaction price in year-month t; $mortgage_{it}$ is a dummy for a mortgage purchase in the property transaction; δ_i and θ_{ct} denote property fixed effects and census tract-by-year month fixed effects, respectively; X_{it} is a vector of property- and transaction-level controls.

The primary coefficient of interest is β_1, which, if positive, indicates a price premium associated with mortgage purchases or a price discount associated with cash purchases (henceforth referred to as the cash discount for consistency). The estimated cash discount may be biased if the cash purchase decision is correlated with the error term. For example, institutional investors who tend to make cash purchases may have greater negotiation power , leading to an upward bias in the estimated cash discount. Similarly, an upward bias may occur if poor-quality houses are more likely to be rejected for mortgage applications.

To alleviate these concerns, first, we limit the estimation to a sample of repeat-sales transactions. Additionally, we include property fixed effects, denoted as δ_i, which capture all time-invariant property-level attributes. This approach helps control for selection bias where

properties with specific characteristics are more likely to be chosen for cash transactions, thus mitigating the potential confounding of the estimated cash discount.

Second, to account for hedonic attributes that may change over time, we include 100 indicators for the percentiles of property age at transaction to control for the ageing effects that may be non-linear and correlated with both the cash purchase decision and the transaction price. We include census tract-by-year month fixed effects to absorb time-varying conditions at the neighborhood level. We also include indicators for the percentiles of sellers' duration of holding onto the property before sale, as this variable may provide some insight into the condition of the property. For instance, a property held for only one year may be in a newer condition than one held for ten years. In addition, we control for additional sellers' characteristics, including indicators for whether the seller bought the property in cash or through a mortgage, and whether the seller acquired the property for owner-occupation or investment purposes. Lastly, we control for buyer's and transaction-level characteristics, including the sale type (resale or developer sale), indicators for corporate buyer, whether the buyer's previous residence is located in the same zip code, city, or state, and whether the purchase is for investment or owner-occupation purposes.

We first estimate a standard Ordinary Least Squares (OLS) regression counterpart of Equation (A1) and find that, on average, cash transactions are associated with a price discount of 6.47%.[31] Appendix Figure 4 presents nine separate regression estimates of β_1 from Equation (A1), where the dependent variable is replaced with the RIF counterpart for each price quantile, providing a visual summary of cash discounts across different quantiles of the unconditional distribution of transacted prices. The estimates reveal a striking variation in cash discounts

[31] Our estimated cash discount is smaller than that reported in Reher and Valkanov (2023) due to our inclusion of more stringent neighborhood fixed effects, census tract-by-year month fixed effects, and additional controls for buyer and seller characteristics. Specifically, we find a cash discount of 10.4%, which is comparable to Reher and Valkanov (2023)'s 11.7% when we replicate their baseline regression by excluding additional controls and replacing the fixed effects with zip code-year month and hedonic-year month fixed effect.

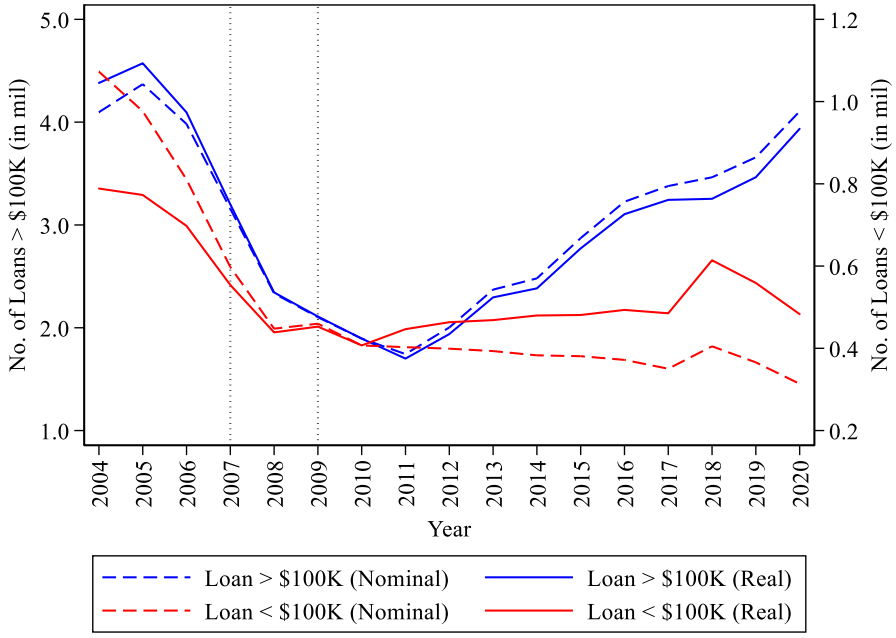
across price segments, with the largest cash discounts (16.3%) observed in the lowest-price segment, followed by 12.1% among properties in the 2nd price decile, while properties in the 8th and 9th deciles exhibit negligible discounts of just 2.2% and 0.7%, respectively.[32] This pattern of variation in cash discounts across price deciles remains strongly consistent when we use alternative specifications and subsamples (Appendix Figure 5).

[32] UQR analyses the marginal effect of small location shifts in the distribution of independent variables on any unconditional quantile. Since our variable of interest, $mortgage_{it}$, is binary, we can interpret the coefficient as follows: the 1st decile of transaction prices would decrease by 1.63% if the share of mortgage purchases in the sample decreased by 10 percentage points.

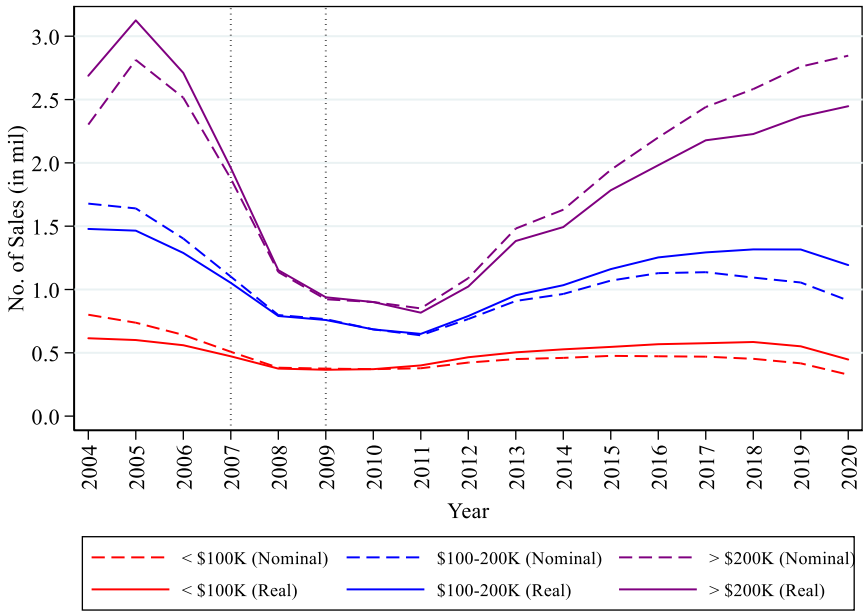
Appendix Figure 1. Total Mortgage Approvals and Property Transactions by Year

The figure presents the total volume of mortgage approvals and property transactions from 2004 to 2020. Panel A shows the total volume of loan approvals, separated by loan size, with the left y-axis displaying results for larger mortgages (loan amount above $100,000) and the right y-axis displaying results for small-dollar mortgages (loan amount below $100,000). Panel B illustrates the total volume of property transactions over the years, separated by transaction price: below $100,000, $100,000-$200,000, and above $200,000. The dotted lines indicate the total volumes by loan amount or transaction price in nominal terms, while the solid lines represent these values in real terms, adjusted to 2010 dollars.

Panel A. Total Mortgage Approvals by Year



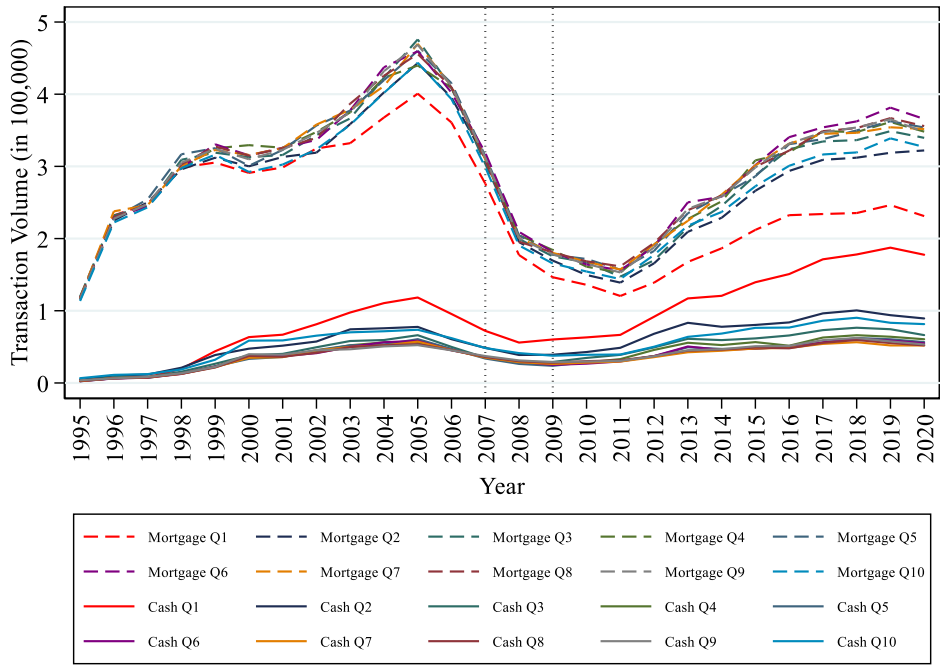
Panel B. Total Property Transactions by Year



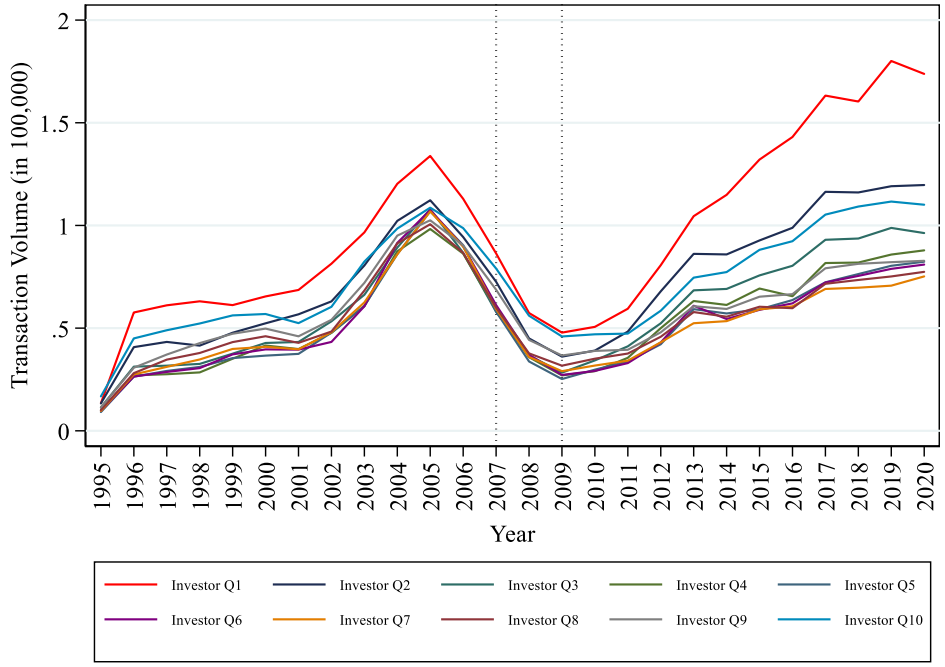
Appendix Figure 2. Total Property Transactions by Price Decile and Year

The figure presents the total volume of property transactions from 1995 to 2020, divided into ten deciles based on transaction prices adjusted to 2010 dollars. Panel A shows the transaction volume separately for all-cash transactions and mortgage-financed transactions, with the solid line representing all-cash transactions and the dotted line representing mortgage-financed transactions. Panel B illustrates the transaction volume of investor purchases separated into ten price deciles.

Panel A. Total Property Transactions by Price Decile and Financing Type



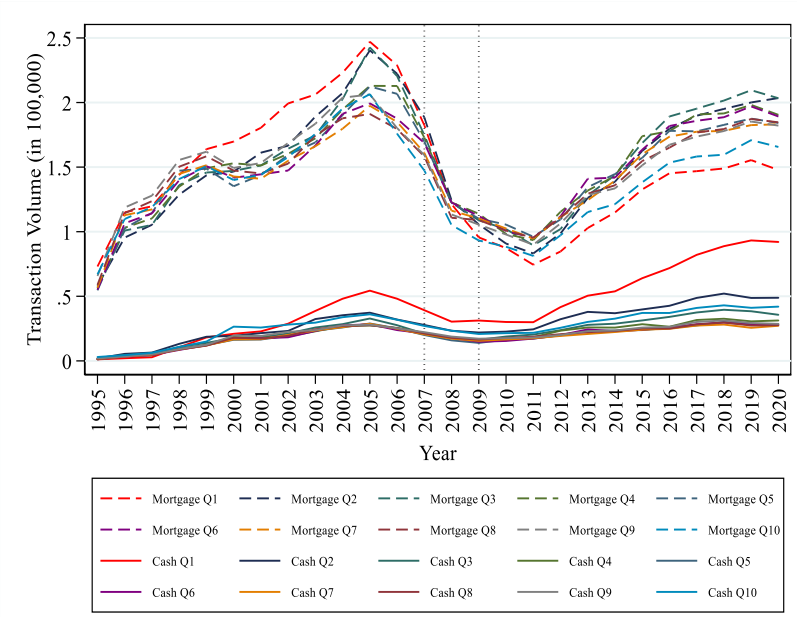
Panel B. Total Investor Purchases by Price Decile



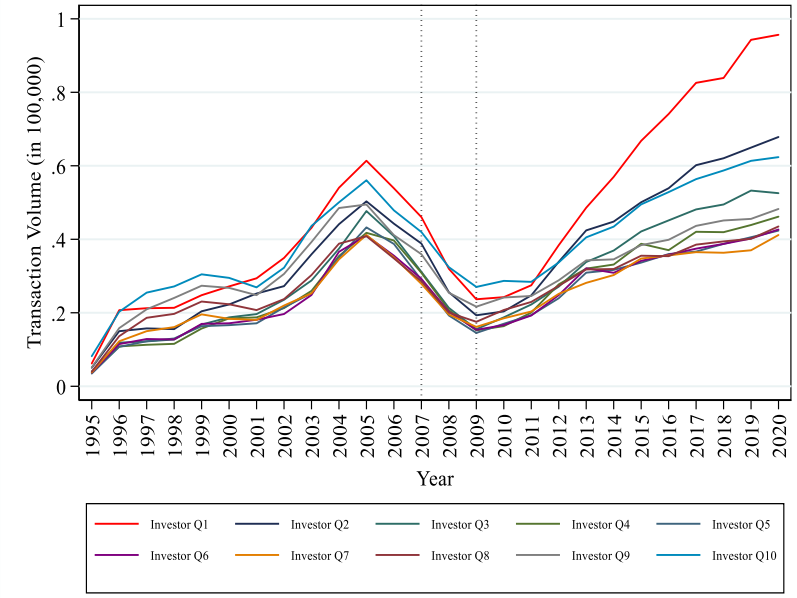
Appendix Figure 3. Total Property Transactions by Price Decile and Year in a Restricted Sample

The figure presents the total volume of property transactions from 1995 to 2020, divided into ten deciles based on transaction prices adjusted to 2010 dollars. Property transactions in census tracts with high average foreclosure rates (Neighborhood Stabilization Program) at the top quantile and in MSAs with a high concentration of single-family rental properties owned by institutional investors (Ganduri, Xiao, and Xiao, 2022) are excluded from the sample. Panel A shows the transaction volume separately for all-cash and mortgage-financed transactions, with the solid line representing all-cash transactions and the dotted line representing mortgage-financed transactions. Panel B illustrates the transaction volume of investor purchases, separated into ten price deciles.

Panel A. Total Property Transactions by Price Decile and Financing Type



Panel B. Total Investor Purchases by Price Decile

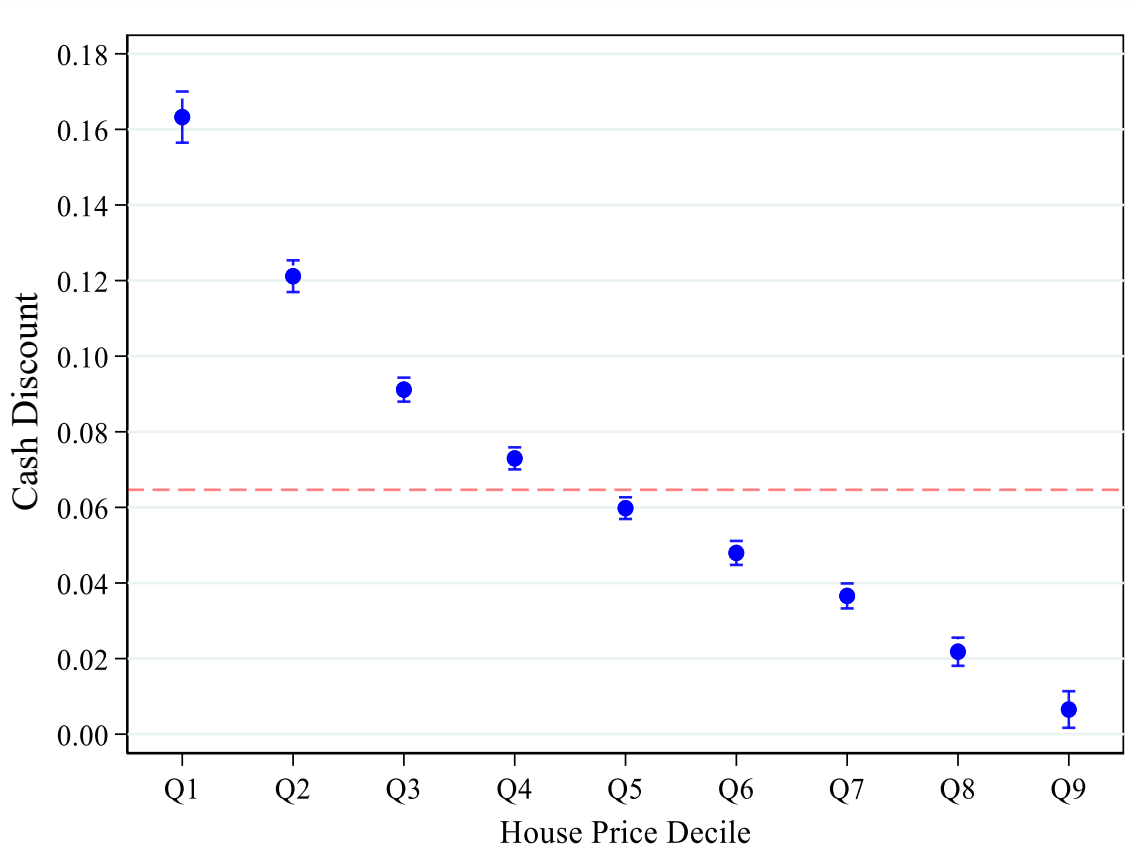


Appendix Figure 4. Estimate Cash Discounts by Property Price Decile

The figure presents regression estimates of β_1 from nine separate regressions of:

$$\widehat{RIF}(y_{ict};\hat{q}_\tau) = \beta_1 mortgage_{it} + \beta X_{it} + \delta_i + \theta_{ct} + \varepsilon_{ict}$$

where the dependent variable is the RIF counterpart for the 1st to the 9th decile of property transaction prices, respectively. $mortgage_{it}$ is an indicator for a mortgage-financed purchase. The sample is restricted to repeat-sales transactions and includes property fixed effects (δ_i) and census tract-by-year month fixed effects (θ_{ct}). X_{it} is a vector of controls for property, transaction, seller and buyer characteristics. The red dotted line represents the estimated average cash discount obtained from estimating the OLS counterpart of the above regression. For computational convenience, we draw a 25% random sample of repeat sales from 1995 to 2020. Ninety-five percent confidence intervals are displayed around each point estimate. Standard errors are clustered at the census tract level.

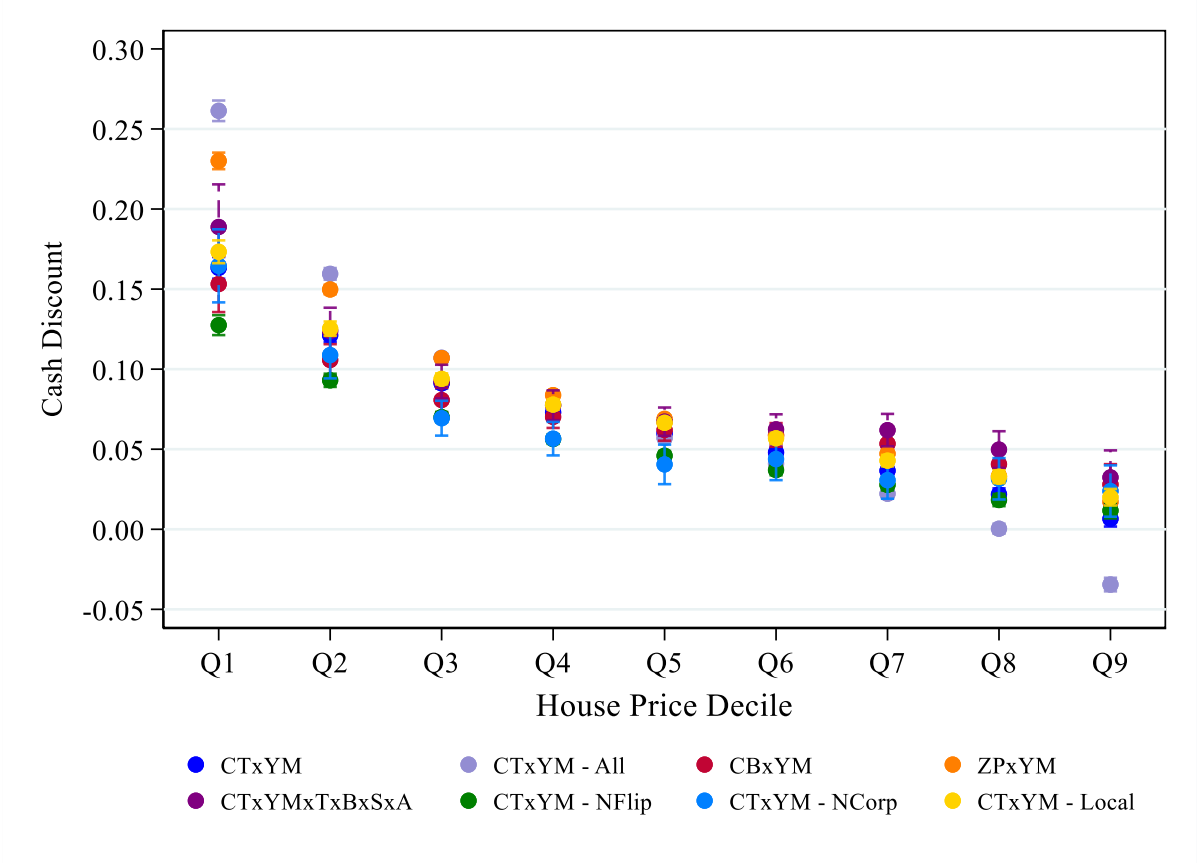


Appendix Figure 5. Estimate Cash Discounts by Property Price Decile using Alternative Specifications

The figure presents regression estimates of β_1 from eight sets of nine separate regressions (in total 72 estimates) of the following regression or its variations:

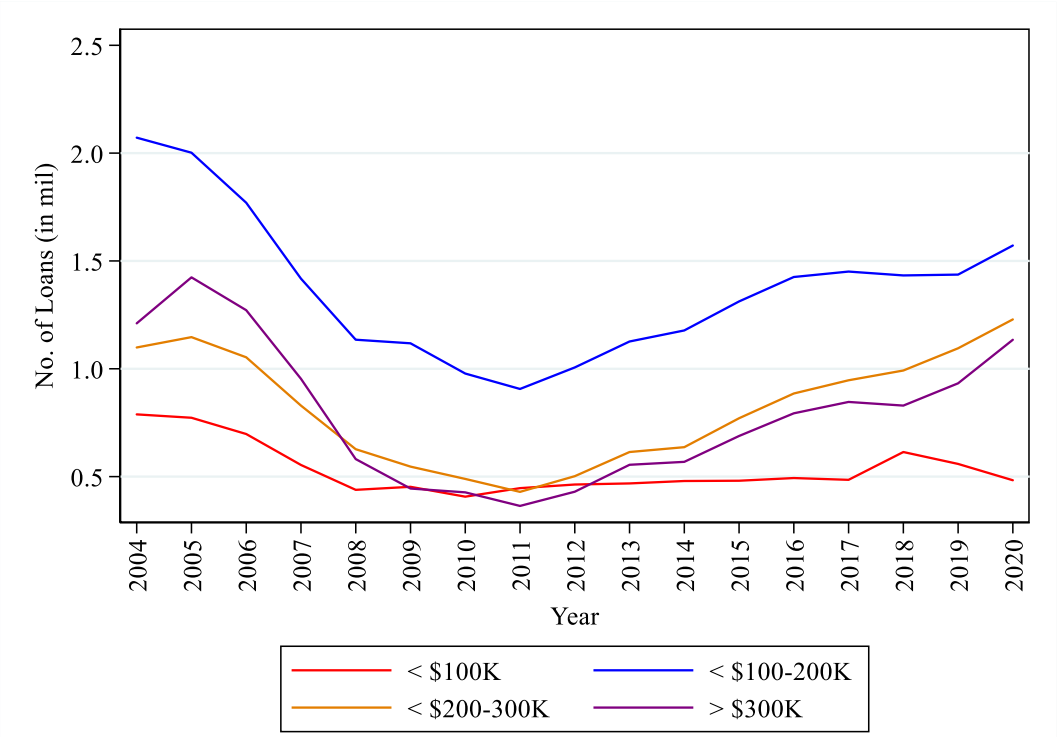
$$\widehat{RIF}(y_{ict};\widehat{q_\tau}) = \beta_1 mortgage_{it} + \alpha X_{it} + \delta_i + \theta_{ct} + \varepsilon_{ict}$$

where the dependent variable is the RIF counterpart for the 1st to the 9th decile of property transaction prices, respectively. $mortgage_{it}$ is an indicator for a mortgage-financed purchase. The baseline regression ($CT \times YM$) includes property fixed effects (δ_i) and census tract-by-year month fixed effects (θ_{ct}). $CT \times YM - All$ modifies the baseline regression by replacing property fixed effects with a comprehensive set of control variables for property characteristics, including indicators for the number of bathrooms, number of bedrooms, property type, building size, mobile home, and pool. $CB \times YM$ and $ZP \times YM$ replace census tract-by-year month fixed effects with census block-by-year month fixed effects and zip code-by-year month fixed effects, respectively. $CT \times YM \times T \times B \times S \times A$ further modifies the baseline regression by interacting census tract (CT), year month (YM), property type (T), number of bedroom (B), building size indicators (S), and property age indicators (A). Lastly, $CT \times YM - NFlip$, $CT \times YM - NCorp$, and $CT \times YM - Local$ restrict the baseline regression to repeat-sales transaction samples for non-flippers (buyers who hold the property for more than one year), non-corporate buyers, and local buyers (buyers in the same state as the property location), respectively. For computational convenience, we draw a 25% random sample of repeat sales from 1995 to 2020. Ninety-five percent confidence intervals are displayed around each point estimate. Standard errors are clustered at the census tract level.



Appendix Figure 6. Total Mortgage Approvals by Loan Size and Year

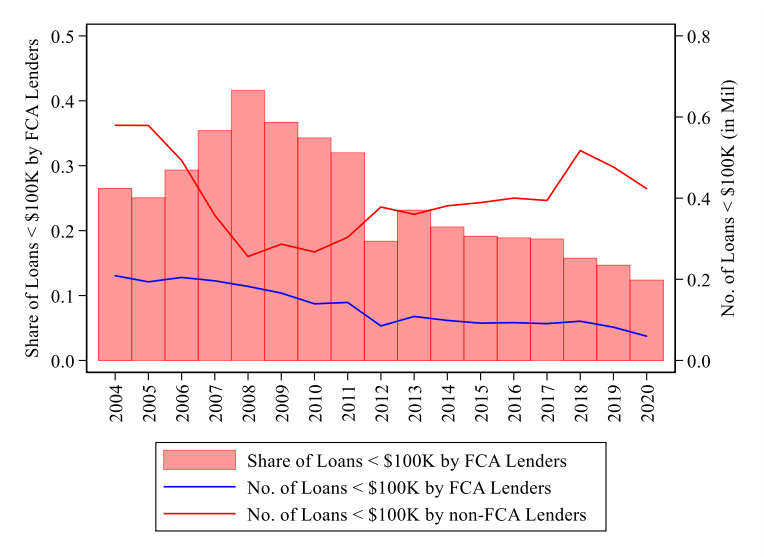
The figure illustrates the total volume of mortgage approvals, categorized by loan size: below $100,000, $100,000-$200,000, $200,000-$300,000, and above $300,000. Loan amounts are expressed in real terms, adjusted to 2010 dollars.



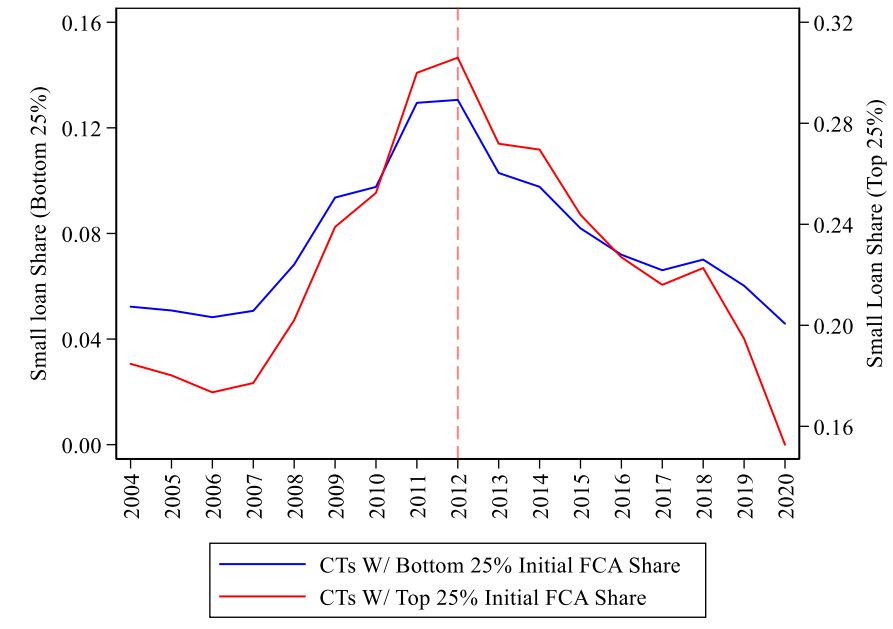
Appendix Figure 7. Small-dollar Mortgage Approvals by FCA-implicated Lenders

Panel A presents the total volume and the share of approved small-dollar mortgages (loan amount below $100,000, adjusted to 2010 dollars) by lenders implicated in False Claims Act (FCA) investigations or litigations, as listed in Appendix Table 1. The left y-axis and the bar graph display the fraction of small-dollar mortgages approved by FCA lenders out of the total small-dollar mortgage approvals. The right y-axis and the line graph illustrate the number of approved small-dollar mortgages by these FCA lenders (in blue) and other lenders not implicated in FCA investigations (in red). Panel B presents the share of approved small-dollar mortgages in census tracts with FCA share in the top quantile (red) and bottom quantile (blue) from 2004 to 2020. The FCA share, also referred to as the $\frac{Small\ Loan\ by\ FCA\ Lenders}{Total\ Small\ Loan}$ in the first-stage regression, is defined as the initial share of small-dollar mortgage approvals in 2004 by lenders implicated in False Claims Act (FCA) litigations.

Panel A. Total Share and Volume of Small-dollar Mortgage Approvals by FCA-implicated Lenders

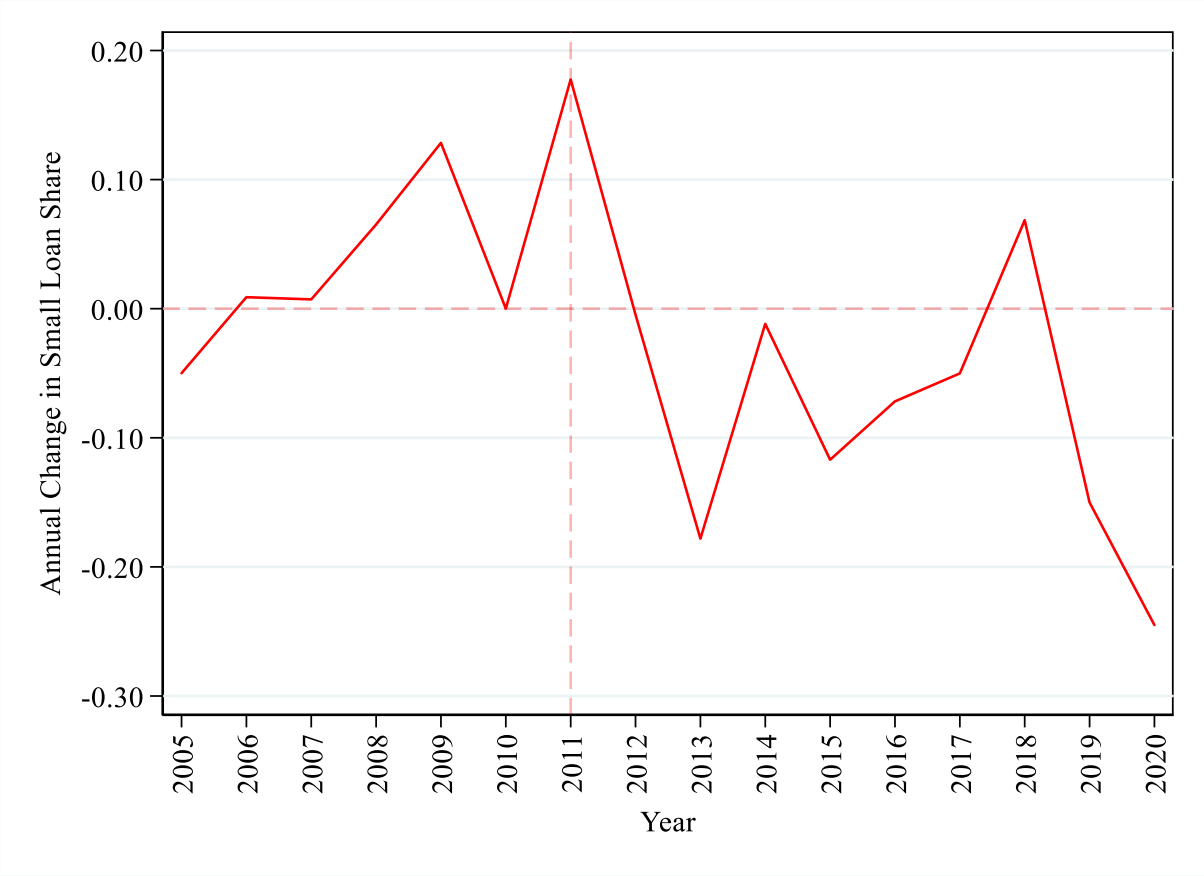


Panel B. Share of Small-dollar Mortgages by Initial Exposure to FCA-implicated Lenders



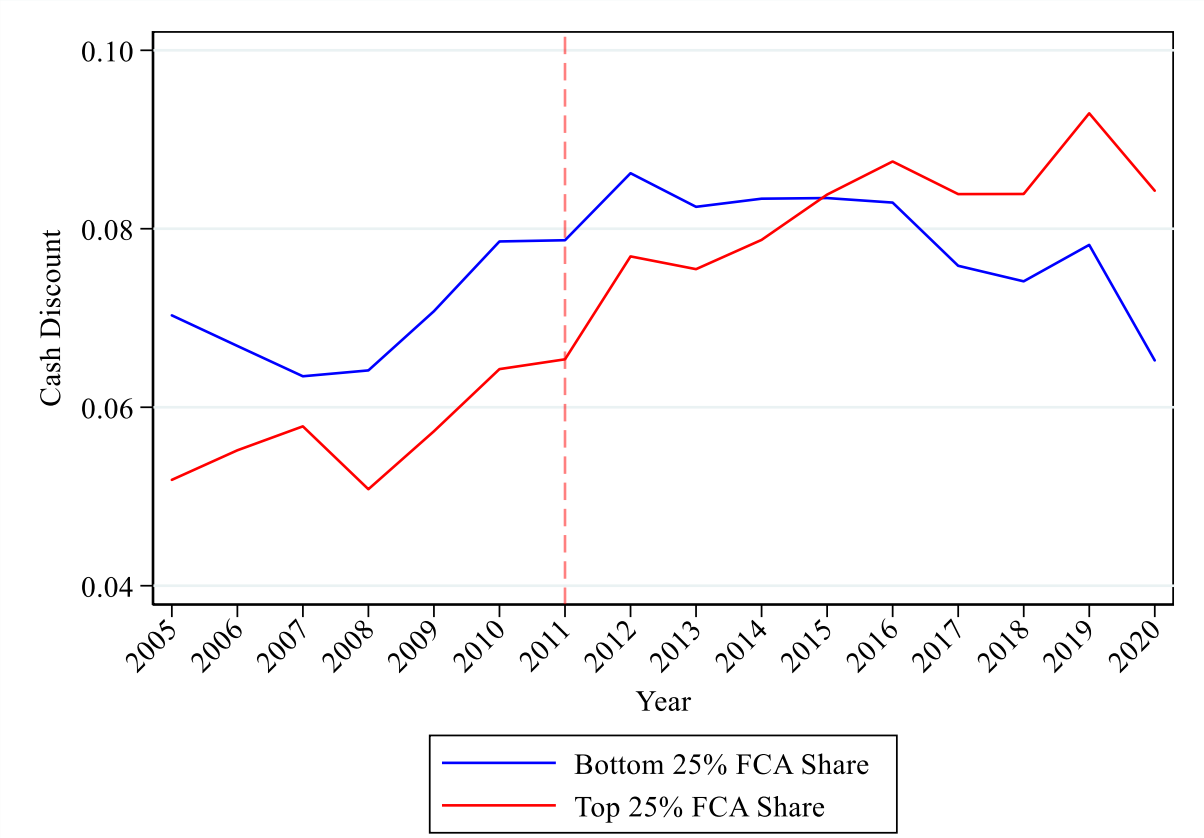
Appendix Figure 8. Annual Change in the Number of Small-dollar Mortgage Approvals by Year

The figure presents the $\Delta Small\ Loan\ Share_t$, defined as the annual change in the total number of small-dollar mortgages (loan amount below $100,000, adjusted to 2010 dollars) from 2005 to 2020. The values are calculated using the formula $\frac{Small\ Loan\ Share_t - Small\ Loan\ Share_{t-1}}{Small\ Loan\ Share_{t-1}}$.



Appendix Figure 9. Dynamics of Cash Discount using Raw Data

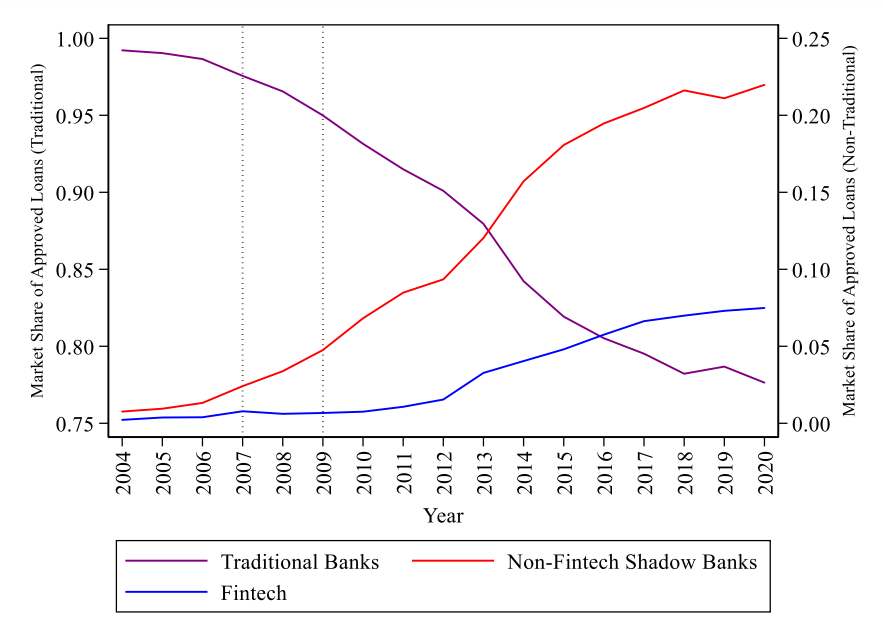
The figure presents the average cash discounts in census tracts with FCA share in the top quantile (red) and bottom quantile (blue) from 2005 to 2020. The FCA share , also referred to as the $\frac{Small\ Loan\ by\ FCA\ Lenders}{Total\ Small\ Loan}$ in the first-stage regression, is defined as the initial share of small-dollar mortgage approvals in 2004 by lenders implicated in False Claims Act (FCA) litigations.



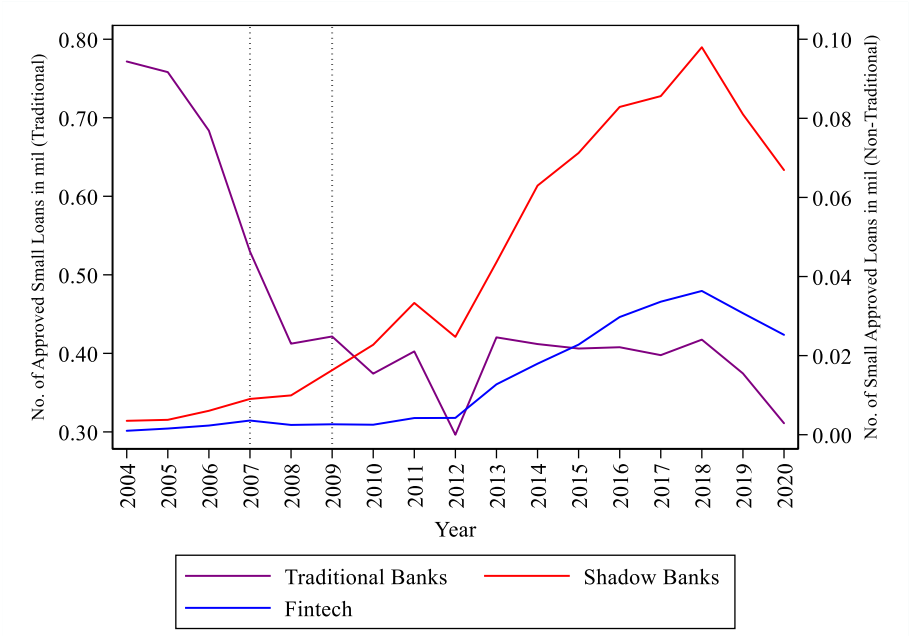
Appendix Figure 10. Market Share by Bank Type and Year

The figure presents the market share of mortgage approvals by traditional banks, shadow banks (inclusive of FinTech), and Fintech lenders over the years, classified according to Buchak et al. (2018). Panel A shows the average market share of approved mortgages by each bank type, defined as the ratio between the number of mortgage approvals by the respective bank type to the total mortgage approvals, across census tracts. The left y-axis displays results for traditional banks, while the right y-axis shows results for shadow banks and FinTech lenders. Panel B focuses exclusively on small-dollar mortgages (loan amount less than $100,000, adjusted to 2010 dollars) and presents the total number of small-dollar mortgage approvals by traditional banks on the left y-axis, and by shadow banks and Fintech lenders on the right y-axis.

Panel A. Market Share of Approved Loans by Bank Type



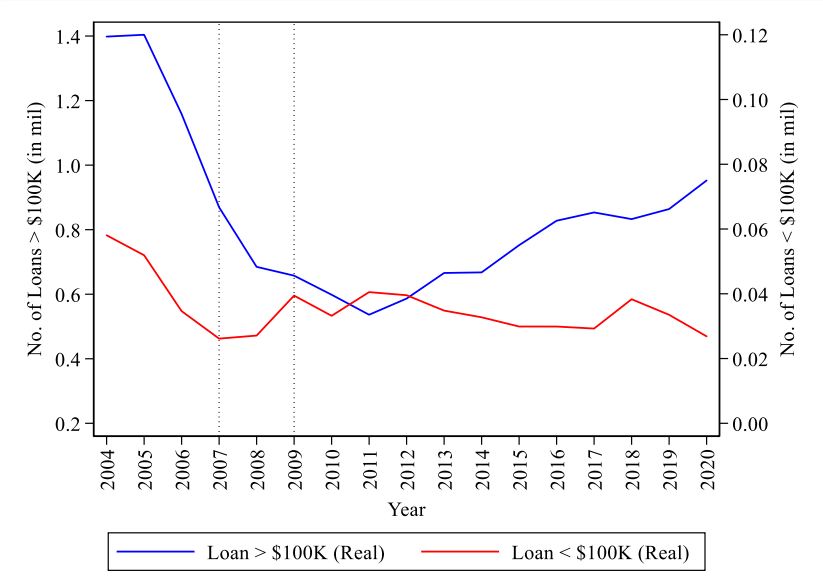
Panel B. Number of Approved Small Loans by Bank Type



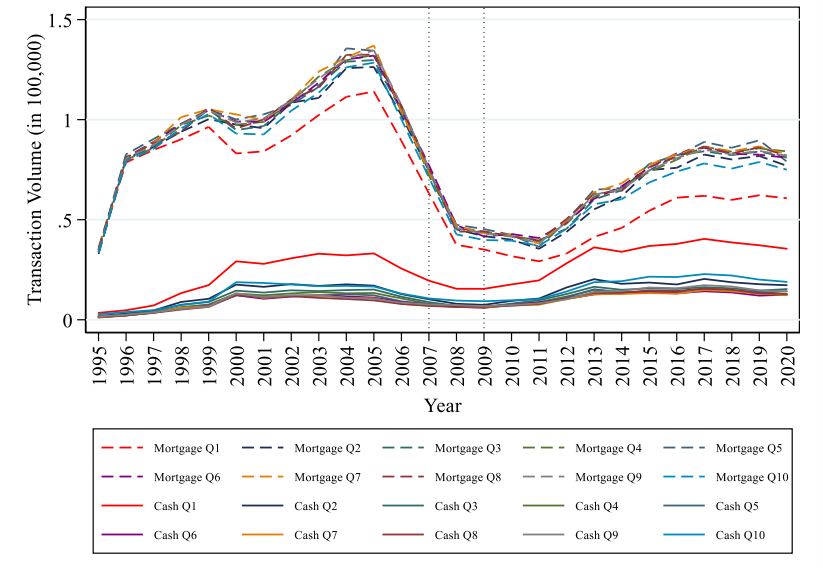
Appendix Figure 11. Total Mortgage Approvals and Property Transactions by Financing Type in the Top 10 Most Expensive States

The figure presents the total volume of mortgage approvals and property transactions from 2004 to 2020, focusing on the top 10 states with the highest average house prices. Panel A shows the total volume of loan approvals, categorized by loan size, with the left y-axis displaying results for larger mortgages (loan amount above $100,000, adjusted to 2010 dollars) and the right y-axis displaying results for small-dollar mortgages (loan amount below $100,000, adjusted to 2010 dollars). Panel B illustrates the total volume of property transactions, divided into ten deciles based on transaction prices adjusted to 2010 dollars, separately for all-cash transactions and mortgage-financed transactions. The solid line represents all-cash transactions, while the dotted line represents mortgage-financed transactions. Panel C tabulates the average transacted prices (in 2010 dollars) for houses in the 1st price decile in the 10 states.

Panel A. Total Mortgage Approvals by Year



Panel B. Total Property Transactions by Price Decile and Financing Type



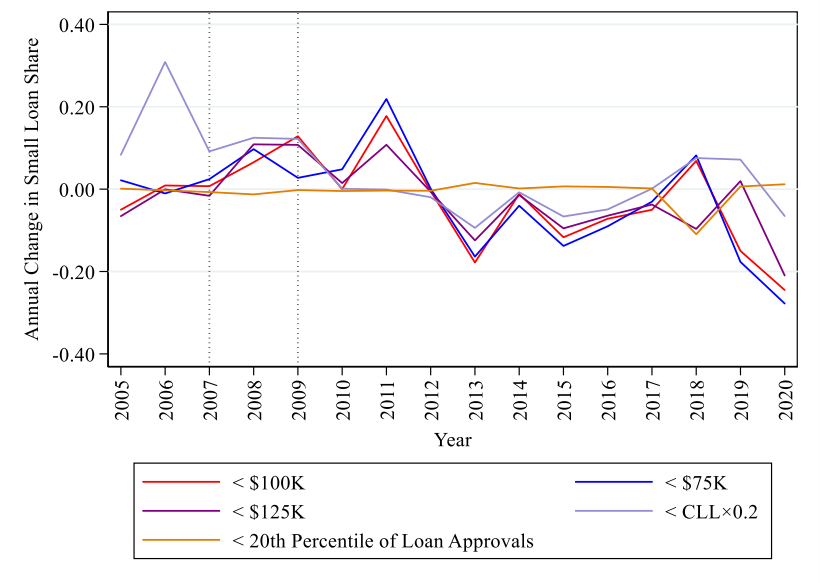
Panel C. Average Transaction Price for Houses in the 1st Price Decile

Year	Average Price for Houses in the 1st Decile
1995	$61,563
1996	$63,005
1997	$65,201
1998	$70,096
1999	$72,661
2000	$76,136
2001	$83,493
2002	$89,663
2003	$101,067
2004	$111,383
2005	$123,107
2006	$125,389
2007	$120,546
2008	$105,403
2009	$97,435
2010	$91,813
2011	$85,137
2012	$83,556
2013	$89,094
2014	$92,231
2015	$98,484
2016	$104,025
2017	$104,069
2018	$105,654
2019	$108,713
2020	$120,574
Average	$96,137

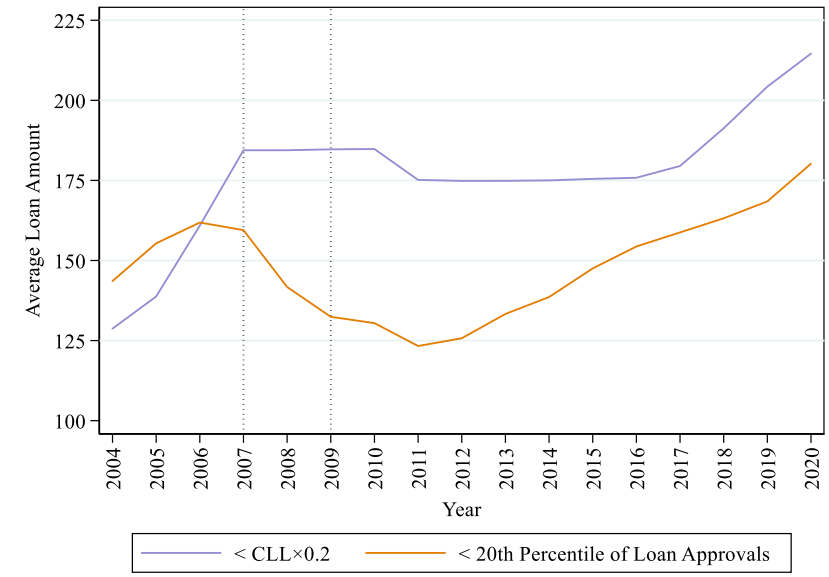
Appendix Figure 12. Annual Change in the Share of Small-dollar Mortgage Approvals and Average Loan Amount by Various Definitions of Small-dollar mortgage

Panel A presents the $\Delta Small\ Loan\ Share_t$, defined as the annual change in the share of small-dollar mortgages, based on various definitions. The values are calculated using the formula $\frac{Small\ Loan\ Share_t - Small\ Loan\ Share_{t-1}}{Small\ Loan\ Share_{t-1}}$. The red line represent values based on the primary definition, which defines small-dollar mortgages as those with a loan amount below $100,000. The blue and purple lines represent values based on defining small-dollar mortgages as those with loan amounts below $75,000 and $150,000, respectively. The light purple line shows values based on defining small-dollar mortgages as those with loan amount below the county- and year-specific conforming loan limit, with a 20% margin applied. The yellow line plots values for small-dollar mortgages defined as loans with amount below the 20th percentile of all loan approvals in the census tract for the respective year. Panel B plots the average loan amount at the dynamic cutoffs, calculated by averaging across all census tracts by year. All loan amounts are adjusted to 2011 dollars.

Panel A. Annual Change in the Share of Small Loan Approvals by Various Definitions



Panel B. Average Loan Amount at the Dynamic Cutoffs

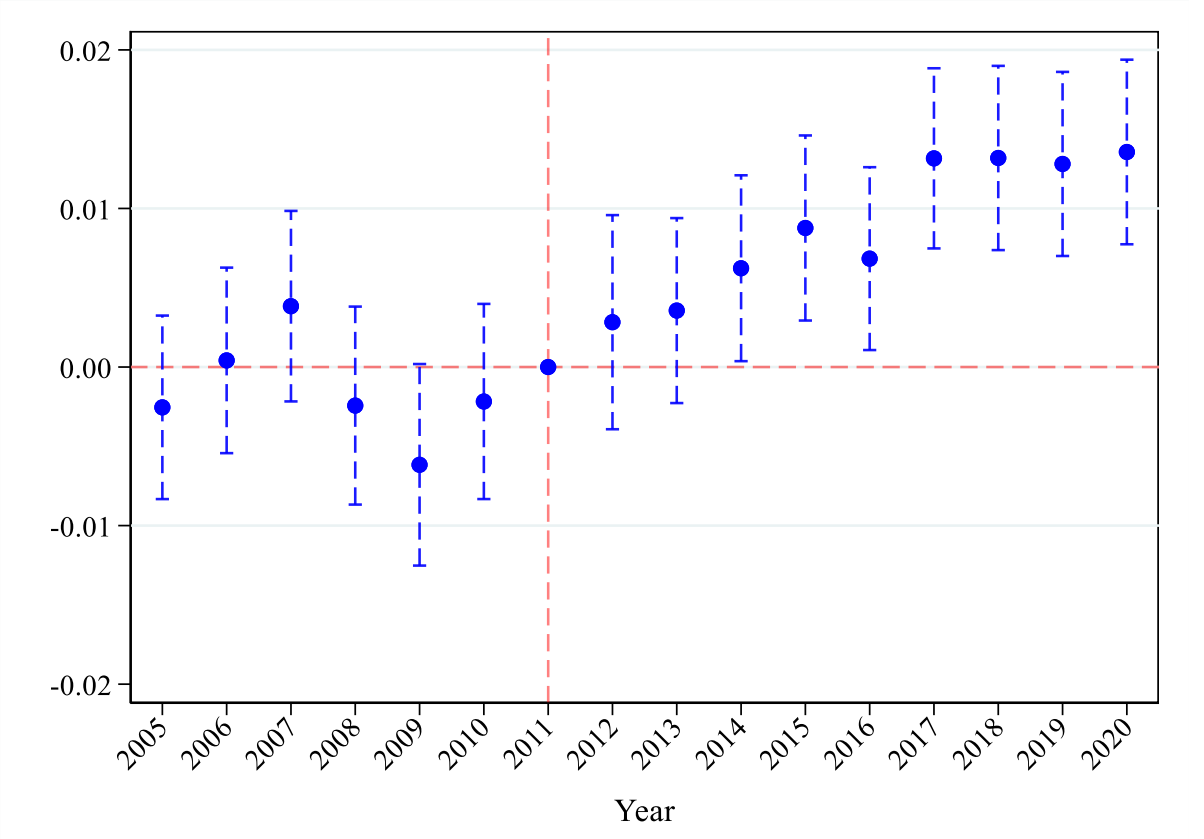


Appendix Figure 13. Dynamic Effects of FCA Litigations on Cash Discounts

The figure presents regression estimates of β_s from the following regression:

$$Cash\ Discount_{ct} = \sum_{s=2004,\neq 2011}^{2020} \beta_s \mathbb{I}\left[\frac{Small\ Loan\ by\ FCA\ Lenders}{Total\ Small\ Loan}_{c,04} > Median\right] \times \mathbb{I}[\text{Year} = s] + \beta X_{ct} + \delta_c + \theta_t$$

where the dependent variable is $Cash\ Discount$. The variables of interest are the interactions between the indicator for census tracts with an above-median initial share of small-dollar mortgage (loan amount below $100,000, adjusted to 2010 dollars) approvals in 2004 by lenders implicated in False Claims Act (FCA) litigations and year indicators, with 2011 as the omitted reference year. The regression includes census tract fixed effects (δ_c) and year fixed effects (θ_t). X_{it} is a vector of controls for census tract demographic characteristics and loan applicant characteristics. Ninety-five percent confidence intervals are displayed around each point estimate. Standard errors are clustered at the census tract level.



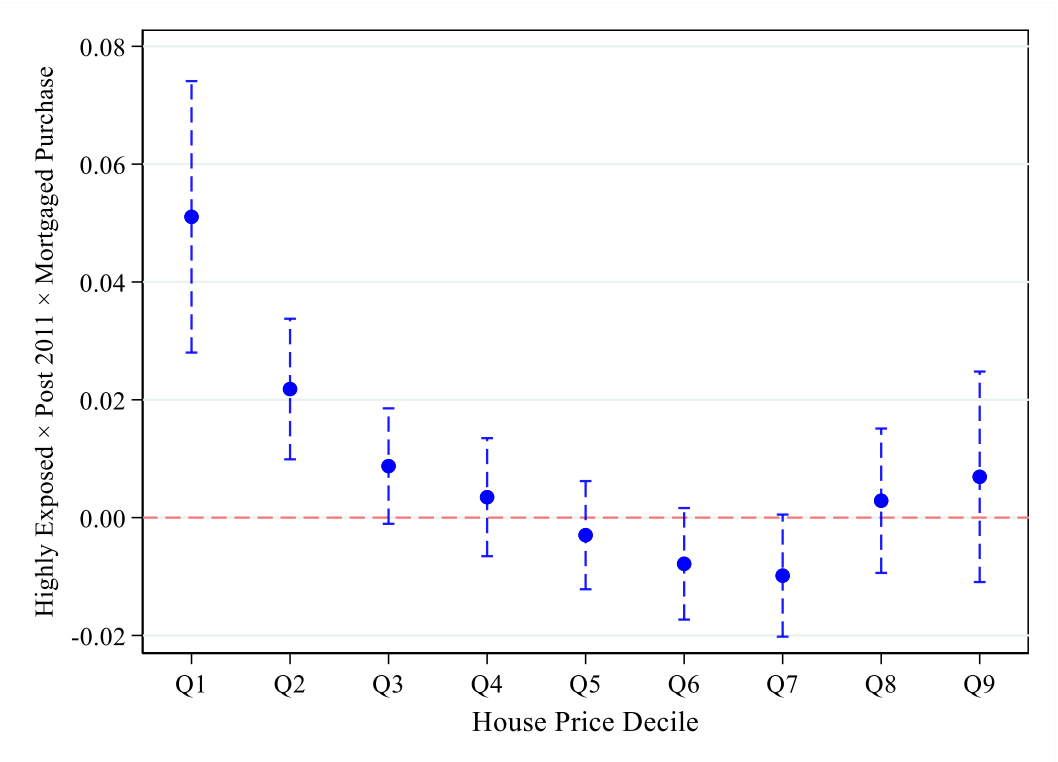
Appendix Figure 14. Effects on Cash Discounts and Property prices by Property Price Deciles

The figure presents regression estimates of β_1 (Panel A) and β_2 (Panel B) from nine separate regressions of:

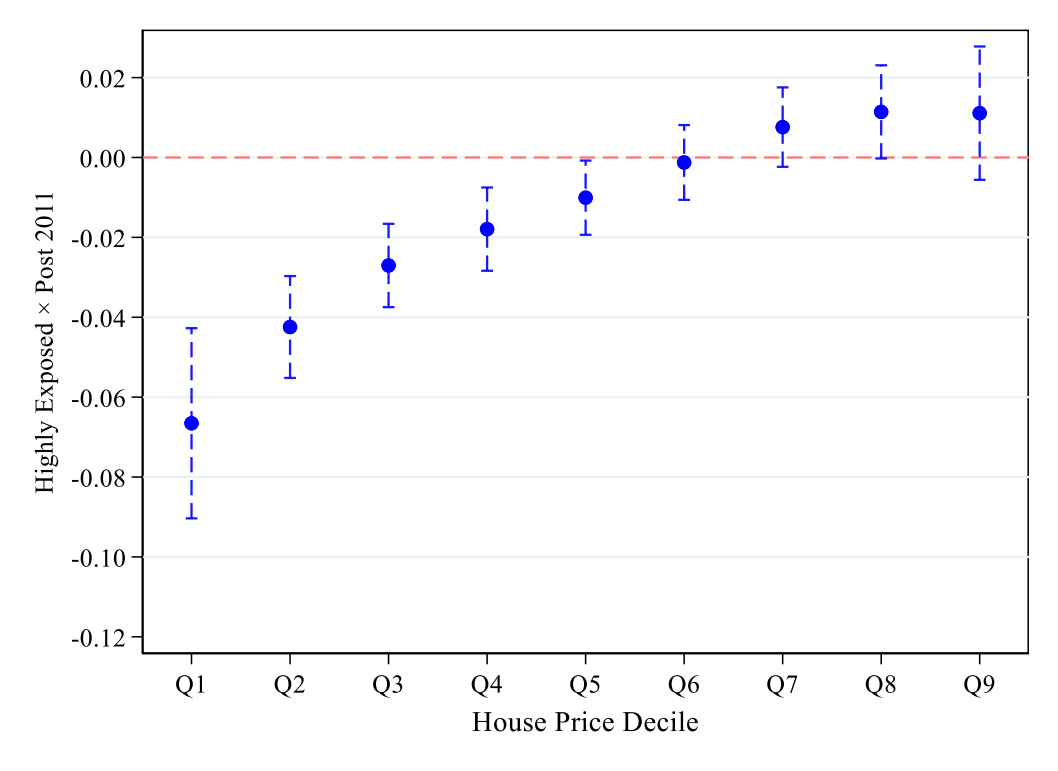
$$\widehat{RIF}(y_{ict};\hat{q_\tau}) = \beta_1 \text{Highly Exposed}_c \times Post2011_t \times mortgage_{it} + \beta_2 \text{Highly Exposed}_c \times Post2011_t + \beta_3 Post2011_t \times mortgage_{it} + \beta_4 \text{Highly Exposed}_c \times mortgage_{it} + \beta_5 mortgage_{it} + \beta X_{ict} + \delta_i + \theta_{ct} + \varepsilon_{ict}$$

where the dependent variable is the RIF counterpart for the 1st to the 9th decile of property transaction prices, respectively. Highly Exposed is defined as $\left[\frac{Small\ Loan\ by\ FCA\ Lenders}{Total\ Small\ Loan}_{c,04} > Median\right]$, an indicator for census tracts with an above-median initial share of small-dollar mortgage (loan amount below $100,000, adjusted to 2010 dollars) approvals in 2004 by lenders implicated in False Claims Act (FCA) litigations. $Post2011$ is an indicator for years 2012 and after. $mortgage_{it}$ is an indicator for a mortgage-financed purchase. The sample is restricted to repeat-sales transactions and includes property fixed effects (δ_i) and census tract-by-year month fixed effects (θ_{ct}). X_{it} is a vector of controls for property, transaction, seller and buyer characteristics. The red dotted line represents the estimated average cash discount obtained from estimating the OLS counterpart of the above regression. For computational convenience, we draw a 25% random sample of repeat sales. Ninety-five percent confidence intervals are displayed around each point estimate. Standard errors are clustered at the census tract level.

Panel A. Effect of Tightening Small Credit on Cash Discounts



Panel B. Effect of Tightening Small Credit on Property Prices



Appendix Table 1. List of Lenders Implicated in FCA Litigations

This table lists all mortgage lenders investigated or litigated by the Department of Justice (DOJ) under the False Claims Act (FCA) for alleged fraudulent mortgage lending practices from 2008 to 2020. The sources for this list include the DOJ News Archive, Buckley Sandler LLP's compilation of FCA-implicated lenders, and Mayer, Xu, and Zhao (2023).

Date Settled	Bank	Settlement Amount in mil
20080522	National City Mortgage Inc (NCM)	4.600
20081125	RBC Mortgage Company (RBC)	10.710
20090701	Beazer Homes USA Inc	53.000
20120215	CitiMortgage Inc	158.300
20120224	Flagstar Bank	132.800
20120510	Deutsche Bank AG	202.300
20140204	JPMorgan Chase Bank	614.000
20140630	US Bank National Association	200.000
20140820	Bank of America Corporation	16650.000
20140929	SunTrust Mortgage Inc	968.000
20141231	Golden First Mortgage Corporation	36.300
20141223	GTL Invesments Inc	4.200
20150225	Metlife Home Loans, LLC	123.500
20150601	First Tennessee Bank	212.500
20150930	Fifth Third Bancorp	85.000
20151202	Franklin American Mortgage Co	70.000
20160415	Freedom Mortgage Corp	113.000
20160913	Regions Bank	52.400
20160929	Branch Banking and Trust Company	83.000
20160930	Primary Residential Mortgage Inc	5.000
20160930	SecurityNational Mortgage Company	4.250
20161019	First American Mortgage Trust	1.025
20161228	United Shore Financial Services LLC	48.000
20181016	Universal American Mortgage Company LLC	13.200
20181207	Gateway Funding Diversified Mortgage Services LP	14.500
20190614	Quicken Loans Inc	32.500
20190117	Sierra Pacific Mortgage Company Inc	3.670
20200331	Finance of America Reverse (FAR)	2.470
20200429	Guaranteed Rate Inc	15.060
20201028	Guild Mortgage Company	24.900
20231204	Reunion Mortgage Inc	1.040
20240923	Nutter Home Loans	2.400

Appendix Table 2. Pairwise Correlations between the FCA Shares over the Years

The table presents pairwise correlations between the FCA shares over the years. FCA shares, also referred to as the $\frac{Small\ Loan\ by\ FCA\ Lenders}{Total\ Small\ Loan}$ in the first-stage regression, are defined as the share of small-dollar mortgage approvals by lenders implicated in False Claims Act (FCA) litigations.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
(1) FCAShare2004	1.000																
(2) FCAShare2005	0.233	1.000															
(3) FCAShare2006	0.191	0.214	1.000														
(4) FCAShare2007	0.179	0.183	0.213	1.000													
(5) FCAShare2008	0.145	0.139	0.169	0.223	1.000												
(6) FCAShare2009	0.143	0.115	0.140	0.188	0.266	1.000											
(7) FCAShare2010	0.123	0.125	0.133	0.172	0.237	0.281	1.000										
(8) FCAShare2011	0.133	0.113	0.123	0.154	0.217	0.263	0.279	1.000									
(9) FCAShare2012	0.089	0.080	0.097	0.130	0.170	0.208	0.212	0.247	1.000								
(10) FCAShare2013	0.053	0.056	0.069	0.101	0.149	0.185	0.191	0.223	0.229	1.000							
(11) FCAShare2014	0.052	0.055	0.056	0.074	0.125	0.147	0.158	0.168	0.195	0.222	1.000						
(12) FCAShare2015	0.052	0.047	0.054	0.090	0.105	0.134	0.141	0.157	0.164	0.208	0.205	1.000					
(13) FCAShare2016	0.039	0.037	0.045	0.074	0.105	0.117	0.120	0.144	0.157	0.180	0.172	0.194	1.000				
(14) FCAShare2017	0.037	0.038	0.044	0.072	0.094	0.111	0.105	0.127	0.136	0.164	0.155	0.176	0.164	1.000			
(15) FCAShare2018	0.039	0.034	0.046	0.073	0.084	0.099	0.102	0.112	0.136	0.156	0.158	0.163	0.153	0.164	1.000		
(16) FCAShare2019	0.024	0.024	0.033	0.060	0.086	0.092	0.092	0.116	0.121	0.142	0.143	0.154	0.141	0.148	0.161	1.000	
(17) FCAShare2020	0.020	0.022	0.030	0.056	0.076	0.077	0.080	0.097	0.098	0.134	0.120	0.125	0.144	0.135	0.152	0.160	1.000

Appendix Table 3. Results from First-stage Regressions using Various Subsamples

This table presents estimates from the first stage of the Instrumental Variable (IV) regression:

$$Small\ Loan\ Share_{ct} = \gamma_1 \frac{Small\ Loan\ by\ FCA\ Lenders}{Total\ Small\ Loan}_{c,04} \times \Delta Small\ Loan\ Share_t + \gamma X_{ct} + \delta_c + \theta_t$$

where the variable of interest, $Small\ Loan\ Share$, represents the fraction of small-dollar mortgage (loan amount below $100,000, adjusted to 2010 dollars) approvals out of the total mortgage approvals. The instrument is the interaction between the initial share of small-dollar mortgage approvals in 2004 by lenders implicated in False Claims Act (FCA) litigations and the annual change in the share of small-dollar mortgage approvals. For each column, the sample is divided into an above-median subsample (Panel A) and a below-median subsample (Panel B) based on the value of the demographic attribute of the census tract in 2000, as indicated in the column title. These attributes include the percentage of Black residents, the percentage of White residents, the percentage of Hispanic residents, the percentage of the population above 65 years old, the percentage of the population between 18 to 65 years old, the percentage of the population in the labor force, the employment rate, the percentage of the population with less than a 9th grade education, and the percentage of the population with a least a bachelor degree. The standard errors are clustered at the census tract level and presented in parenthesis below the coefficients. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	% Black	% White	% Hispanic	% Age > 65	% Age 18-65	% Labor Force	% Employed	% < 9 Grade	% Bachelor
Panel A: Above Median									
Instrument	0.065***	0.061***	0.075***	0.066***	0.062***	0.067***	0.066***	0.075***	0.079***
	(0.011)	(0.009)	(0.010)	(0.009)	(0.008)	(0.007)	(0.007)	(0.011)	(0.012)
Observations	292,768	245,137	256,472	303,037	295,365	313,911	313,785	273,403	269,343
Adjusted R-squared	0.837	0.865	0.807	0.855	0.814	0.839	0.839	0.840	0.825
Panel B: Below Median									
Instrument	0.074***	0.074***	0.060***	0.066***	0.074***	0.071***	0.074***	0.069***	0.061***
	(0.008)	(0.009)	(0.008)	(0.009)	(0.010)	(0.011)	(0.012)	(0.007)	(0.007)
Observations	292,320	337,070	328,616	282,051	289,723	271,177	271,303	311,685	315,745
Adjusted R-squared	0.854	0.839	0.866	0.823	0.851	0.837	0.836	0.836	0.856
CTract Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Borrower Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
CTract FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Appendix Table 4. Pairwise Correlations between the FCA Shares and Foreclosure Measures

The table presents pairwise correlations between the FCA shares and various foreclosure measures. FCA share, also referred to as the $\frac{Small\ Loan\ by\ FCA\ Lenders}{Total\ Small\ Loan}$ in the first-stage regression, is defined as the initial share of small-dollar mortgage approvals in 2004 by lenders implicated in False Claims Act (FCA) litigations. The foreclosure measures in Rows 1 and 2 represent the sum and average, respectively, of the number of foreclosures at the census tract level across all three series of data from Neighborhood Stabilization Program (I-III). Rows 3 to 5 and Rows 6 to 8 calculate the foreclosure measures using individual series data from the Neighborhood Stabilization Program I to III. Row 9 defines subprime loans as mortgages with a reported spread in the HMDA data and calculates the share as the fraction of the volume of approved subprime loans out of the total mortgage approvals at the census tract level. Row 10 defines subprime loans as loans approved by lenders listed in the HUD's Subprime and Manufactured Home Lender List.

	FCA Share
(1) Total Number of Foreclosures (NSP 1 – NSP 3)	-0.027
(2) Average Foreclosure Rate (NSP 1 – NSP 3)	-0.023
(3) Total Number of Foreclosures (NSP 1)	-0.026
(4) Total Number of Foreclosures (NSP 2)	-0.029
(5) Total Number of Foreclosures (NSP 3)	-0.022
(6) Average Foreclosure Rate (NSP 1)	-0.020
(7) Average Foreclosure Rate (NSP 2)	-0.029
(8) Average Foreclosure Rate (NSP 3)	-0.013
(9) Share of Subprime Loans (APR)	-0.022
(10) Share of Subprime Loans (Lenders)	-0.124

Appendix Table 5. Correlations between the Initial FCA Shares and Local Characteristics

This table presents ordinary least squares regression estimates from regressing initial FCA share, $\frac{Small\ Loan\ by\ FCA\ Lenders}{Total\ Small\ Loan}_{c,04}$,on census-tract level characteristics in 2010 including average annual change in house price index from 2004 to 2010, (log) number of foreclosures, (log) number of property transaction volume, (log) number of investor property purchase, (log) amount of small business loan originations, (log) number of small business loan originations, (log) number of bank branch openings, (log) number of bank branch closings, demographic variables such as (log) total population, (log) total number of housing unit, (log) median household income, (log) median house value, percentage of white population, percentage of Hispanic population, percentage of population below poverty, percentage of population above 65 years old, percentage of population between 18 to 65 years old, percentage of population in the labor force, employment rate, percentage of population with less than 9th-grade education, and percentage of population with at least a bachelor's degree, and borrower characteristics such as (log) average borrowers' income, percentage of white borrowers, percentage of black borrowers, percentage of male borrowers, percentage of joint-sex borrowers, and percentage of non-Hispanic borrowers. Robust standard errors are presented in parenthesis below the coefficients. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable = Initial *FCA Share*					
Annual HPI Growth$_{04\text{-}10}$	-0.001	Total Housing Unit	-0.012	% Employed	-0.030
	(0.001)		(0.017)		(0.094)
Total Foreclosures	-0.002	Med. Household Income	-0.044***	% Less than 9th Grade	-0.006
	(0.004)		(0.014)		(0.092)
Total Trans. Volume	0.008*	Med. House Value	-0.048***	% Bachelor	0.079**
	(0.004)		(0.008)		(0.032)
Total Investor Purchase	-0.001	% White	0.017	Borrower Income	0.002
	(0.002)		(0.018)		(0.009)
Total Small Biz Loans (Amt)	0.000	% Hispanic	-0.092***	% White Borrower	-0.002
	(0.003)		(0.026)		(0.025)
Total Small Biz Loans (No.)	0.006	% Below Poverty	-0.023	% Black Borrower	-0.027
	(0.005)		(0.039)		(0.026)
Total Bank Branch Closure	-0.002	% Above 65	0.005	% Male Borrower	-0.004
	(0.015)		(0.053)		(0.019)
Total Bank Branch Opening	-0.007	% 18-65	-0.030	% Joint-Sex Borrower	-0.019
	(0.020)		(0.055)		(0.020)
Total Population	-0.008	% Labor Force	-0.026	% non-Hispanic	0.004
	(0.017)		(0.099)		(0.023)
Observations			17,952		
Adjusted R-squared			0.024		

Appendix Table 6. Robustness to Alternative Sample Restrictions

This table presents estimates from the second stage of the Instrumental Variable (IV) regression:

$$Cash\ Discount_{ct} = \beta_1 \widehat{Small\ Loan\ Share}_{ct} + \beta X_{ct} + \delta_c + \theta_t$$

where the variable of interest, $Small\ Loan\ Share$, represents the fraction of small-dollar mortgage (loan amount below $100,000, adjusted to 2010 dollars) approvals out of the total mortgage approvals. It is instrumented using the interaction between the initial share of small-dollar mortgage approvals in 2004 by lenders implicated in False Claims Act (FCA) litigations and the annual change in the share of small-dollar mortgage approvals. The regressions include census tract fixed effects (δ_c) and year fixed effects (θ_t). X_{it} is a vector of controls for census tract demographic characteristics and loan applicant characteristics. Based on the number of single-family rental (SFR) properties owned by institutional investors in MSAs as compiled by Ganduri, Xiao, and Xiao (2022), Columns 1 and 2 exclude the top 5 and top 10 MSAs with the largest number of SFR properties owned by institutional investors, respectively. Column 3 excludes all MSAs with reported SFR properties. Column 4 applies all sample restrictions from Table 4 Columns 1 to 6, in addition to excluding all MSAs with reported SFR properties. The standard errors are clustered at the census tract level and presented in parenthesis below the coefficients. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Small Loan Share	-0.814***	-0.804***	-1.203***	-0.702**
	(0.145)	(0.139)	(0.273)	(0.288)
Observations	533,648	511,634	394,306	170,413
CTract Controls	Y	Y	Y	Y
Borrower Controls	Y	Y	Y	Y
CTract FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Kleibergen-Paap F-stat	145.262	164.368	57.982	56.228
Sample (Remove)	Top 5 MSAs with SFR owned by Inst. Investors	Top 10 MSAs with SFR owned by Inst. Investors	All MSAs with SFR owned by Inst. Investors	(3) + Table 4's (1) - (6)

Appendix Table 7. Small-dollar Mortgage and Prices for Mortgage- and Cash-financed Transactions

This table presents ordinary least squares estimates of β_1 from the following model:

$$y_{ct} = \beta_1 \mathbb{I}\left[\frac{Small\ Loan\ by\ FCA\ Lenders}{Total\ Small\ Loan}_{c,04} > Median\right] \times \mathbb{I}[\text{Year} \geq 2012] + \beta X_{ct} + \delta_c + \theta_t$$

where the variable of interest is the interaction between the indicator for census tracts with an above-median initial share of small-dollar mortgage (loan amount below $100,000, adjusted to 2010 dollars) approvals in 2004 by lenders implicated in False Claims Act (FCA) litigations and an indicator for years 2012 and after. The regression includes census tract fixed effects (δ_c) and year fixed effects (θ_t). X_{it} is a vector of controls for census tract demographic characteristics and loan applicant characteristics. The dependent variables in Columns 1 and 2 are the natural logarithm of residualized prices for mortgage-financed transactions and cash-financed transactions, respectively. The standard errors are clustered at the census tract level and presented in parenthesis below the coefficients. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1) Log(Mortgaged Purchase Price)	(2) Log(Cash Purchase Price)
Highly Exposed × Post 2011	-0.002***	-0.012***
	(0.001)	(0.001)
Observations	586,789	586,789
Adjusted R-squared	0.296	0.156
CTract Controls	Y	Y
Borrower Controls	Y	Y
CTract FE	Y	Y
Year FE	Y	Y