Impact of All-Cash Home Purchases on Mortgage Lenders

PRELIMINARY DRAFT

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Abstract

We study the impact of all-cash home purchases on the performance and behavior of local mortgage lenders from 2004–2021. We link detailed residential mortgage data to the deed transaction records at the census tract level and document the competing relationship between cash buyers and local lenders. Our findings indicate that, while increased cash buyer activity is associated mechanically with lower home purchase loan growth, originations of refinance and home improvement loans are not as strongly affected. Furthermore, loans backed by properties in census tracts with a high degree of cash buyer activity are less likely to be sold by the originators, suggesting that cash-buyer activity has implications for the lenders' balance sheets. Interestingly, our analysis by lender type indicates that, facing increased cash buyer activity, commercial banks perform relatively well compared to credit unions and specialized mortgage banks. Our study has potential implications for mortgage market stability, real estate market transparency, and policies on housing affordability and households' access to credit.

Keywords: Mortgage lenders, Home purchases, Cash purchases, Mortgages

JEL-codes: G21, R30, R31

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1. Introduction

Single-family residential mortgages are a vital part for many lenders. For example, loans secured by 1-4 family homes accounted for more than one tenth of the total assets of commercial banks in the U.S at the end of 2024. The importance single family home mortgages is even higher for community banks and credit unions, for which home mortgages take approximately 17% and 32%, respectively.[1] For this reason, lenders are prominent stakeholders in housing markets, in which all-cash purchases have grown in market share considerably since the Great Financial Crisis (GFC) (Figure 1). In this project, we investigate how changes in all-cash buyer activity influence the behavior of mortgage lenders and the conditions in local credit markets.

Using data on the source of funding for individual home purchases from Core Logic, and loan originations from the Home Mortgage Disclosure Act (HMDA) we construct a data set consisting of mortgage loan volumes and the share of home purchases financed entirely with cash for each census tract during each year between 2003 and 2021. We use this data to explore the relationship between loan origination and the share of all-cash home purchases for different mortgage types.

Our OLS specifications consist of year-census tract level regressions of the total value of loan originations on the share of transactions completed entirely with cash. Besides our OLS estimations, we perform instrument variable regressions using the share of home purchases by cash buyers from outside the property's state. This way, we address potential bias caused by omitted variables that simultaneously affect the wealth of cash buyers and the dynamics of local credit markets. Our estimations suggest that home purchase loan originations are negatively correlated with cash buyer activity. This is consistent with the reduction in credit demand due to a decrease in the number of potential mortgage borrowers. Our results show, however, that the negative effects are exclusive to home purchase loans: mortgage refinances and home improvement loans are either positively correlated or uncorrelated with all-cash transaction activity at the local level.

[1]See Federal Deposit Insurance Corporation (FDIC) (2025) and National Credit Union Administration (NCUA) (2025).

To extend our analysis of local lending outcomes, we explore changes in lenders' retention of loans backed by properties in areas with high cash-buyer activity, and find that loan retentions increase across all types of mortgage loans, consistent with a reduced need by lenders to secure funds for new mortgage originations.

Finally, we study how these results vary across three broad types of lenders: commercial banks, credit unions, and independent mortgage banks. Our results suggest that the negative correlation between all-cash transactions and loan origination is fully driven by credit unions and independent mortgage banks. Indeed, commercial banks actually observe relatively high volumes of home purchase loan originations in census tracts with a high share of all-cash transactions.

1.1. Related literature

The academic literature on home purchases with cash has mainly focused on the price effects of cash purchases. Recent work includes, as referenced above, Reher and Valkanov (2024), Han and Hong (2024), and Seo et al. (2021). This last paper, besides estimating the price difference between cash and mortgaged transactions, finds that all-cash transactions are associated with properties that are smaller, older, lower-priced, and located in neighborhoods with high vacancy and relatively low shares of white residents. However, their estimation sample covers only one metropolitan area in Florida, thus limiting the study's external validity. In our paper, instead of focusing on house prices, we seek to understand the implications of cash purchases for mortgage lenders.

There is also a growing literature on the effects of the entry of different types of institutional buyers into the single-family home market. For example, Buchak et al. (2020) examines the role of online dealer companies (iBuyers), and Gorback et al. (2024), study the role of institutional investors on the housing market. These studies form our understanding of the consequences of cash purchases on homeowners and households. However, they do not address the consequences that the growth of cash purchases has for lending institutions.

The literature on the relationship between cash purchases and local credit markets is scarce. Austin (2022) finds that the entry of institutional investors to Atlanta neighborhoods led to higher home prices and quality. Importantly, she finds that the increase in quality was partially driven by a higher demand for home-improvement loans and permits from owner occupiers.

From a broader perspective, we contribute to the literature on how incumbent lenders react to changes in credit demand. For example, Chakraborty et al. (2018) find that banks that have a presence in markets with growing high prices, associated with an increased demand for mortgage credit, increase home lending at the expense of other loan types. In a different context, Cortés and Strahan (2017) show that, facing increased credit demand after natural disasters, banks reduce lending in areas not affected by natural phenomena and devote more resources to satisfy the credit demand related to reconstruction. A future goal of this research project is to examine whether lenders respond to shifts in the home purchase loan market by adjusting their behavior in other areas of lending or business operations.

Our study also relates to the literature on the relationship of incumbent lenders and new types of competitors in mortgage markets. Previous studies have explored the behavior of incumbent lenders facing the entry of new types of loan market competitors. For example, Buchak et al. (2018) study the decrease in the market share of traditional banks in mortgage origination and find that the main reason for the growth of shadow banks is regulatory arbitrage. Fuster et al. (2019) find that fintech mortgage lenders are faster in processing and particularly active in the refinance market. Law and Mislang (2022) find that the loss in traditional banks' market share comes primarily from smaller banks. Relatedly, Bushman et al. (2016) find that the entry of new competitor, among other things, drive incumbent lenders to focus on non-interest revenue, which is an example of how the lenders' decision making may be impacted by external factors. In our case, rather than entry of new competitors, incumbent lenders may face increased competition due to a shrinkage of the market stemming from cash buyers preventing potential mortgage borrowers from acquiring a home and, thus, qualifying for mortgage loans.

2. Background and hypothesis development

Many homes are bought entirely with cash. Figure 1 shows that the market share of cash buyers essentially doubled over the last two decades, reaching a peak of close to one third of all home acquisitions in the last year depicted, 2022. While there is a growing literature on the home price effects of all-cash transactions, there remain considerable information gaps regarding the repercussions of all-cash purchases for the different stakeholders in the housing market. When a housing transaction takes place entirely with cash, the most eminent parties involved are the (cash) buyer and the seller. For the buyer, the most direct consequence of buying with cash is outcompeting other bidders by securing ownership. The seller, on the other hand, receives a lower transaction price in exchange for limiting transaction risk and shortening time-to-close. There are, however, stakeholders that, while not directly involved in the final transaction, participate in the process.[2]. Notably, the occurrence of an all-cash home purchase affects other prospective buyers whose offers were rejected and were forced to continue the housing search. To the extent that some of these bidders planned to use a mortgage as financing means, the all-cash transaction also implies a *lost opportunity* for loan origination, which impacts mortgage lenders.

2.1. Local credit market outcomes

To understand the relevance of all-cash transactions for lenders, consider a highly stylized local credit market in an economy that suddenly experiences a large inflow of cash buyers. The initial equilibrium in the market for home-purchase loans is point E_0 in Figure 2. This equilibrium prior to the entry of all-cash buyers, is simply given by the intersection between supply and demand for home-purchase loans. For illustrative purposes, we assume that every qualifying borrower that demands a mortgage loan at the current rates.[3] The equilibrium quantity of home-purchase loans is denoted Q_0.

[2]For example, Reher and Valkanov (2024) point out that, because of the *mortgage price premium*, U.S. taxpayers pay a larger subsidy compared to a counterfactual where mortgage market frictions are weaker and, thus, the mortgage price premium is lower

[3]The underlying assumption is that some mortgage lender will provide a loan for any qualifying borrower. This simplification is more likely to apply to the case of conforming loans with non-subprime

The demand for mortgage credit is comprised by potential mortgage issuers, i.e., qualifying borrowers. Besides satisfying the lender's requirements in terms of credit history, income, and down-payment amount, a prospective borrower must have an ownership claim (or a promise thereof) to a real estate property that will constitute the collateral for the loan. In a scenario in which the *incoming* all-cash buyers outbid several prospective mortgage-backed buyers, there are fewer individuals that are able and willing to issue a mortgage. In other words, fewer people interested in mortgage credit qualify for a mortgage because they are unable to secure ownership of the asset that would have been used as loan collateral. In the stylized depiction of the local home-purchase-loan market, the demand curve shifts to the left, leading to a drop in the equilibrium quantity from Q_0 to Q_{CB}. Put differently, from the perspective of the lenders, increased cash-buyer activity translates into a negative credit demand shock.

Hypothesis 2.1 (Home-purchase loans). *In a given census tract, there is a negative correlation between the number of all-cash home purchases and the number and value of home-purchase loan originations.*

While there is an intuitive relationship between home-purchase loans and all-cash transactions, there is no clear *ex-ante* association between cash-buyer activity and other types of loan activity. On one hand, lenders may aim, as part of their business model, for a target portfolio allocation to residential real estate loans in a specific geographic area. While cash buyers may constrain their ability to achieve that target allocation through home-purchase lending, they might instead turn to other types of residential loans, like refinancings or home improvement loans. Under this scenario, lenders could prioritize efforts to offer more attractive loan terms to potential refinance or home-improvement clients. Under this scenario, we would expect non-purchase mortgage origination to increase when all-cash home purchases grow in a given housing market, keeping all else equal. Alternatively, current market conditions may offer very limited opportunities to increase lending locally through other types of mortgages, in which case we would not expect the originations of refinance and home improvement loans to correlate with all-cash home purchases.

borrowers, for which Government Sponsored Enterprises (GSEs) satisfy essentially any credit demand.

Hypothesis 2.2 (Other types of mortgages). *In a given census tract, the number and value of refinancings and home-improvement loans are either positively correlated or uncorrelated with the number of all-cash home purchases increases.*

Beyond having repercussions related to mortgage originations, an increase in all-cash home purchases could impact the lenders' balance sheets by modifying the incentives to sell recently-originated loans. For instance, some lenders may rely on selling mortgage loans to Government Sponsored Enterprises or other investors to secure funds needed for loan originations. When such lenders face a decrease in credit demand stemming from a growth in all-cash buyer activity, their need to resort to the secondary mortgage market also decreases, leading them to keep more loans on their balance sheet.[4]

Hypothesis 2.3 (Portfolio lending). *In a given census tract, there is a positive correlation between the number and value of loans kept by mortgage originators and the number of all-cash home purchases.*

3. Data

3.1. Data sources

We use data from two main data sources. First, we identify home purchases in which the buyers paid entirely with cash using data from CoreLogic. We then construct measures related to mortgage applications and originations using publicly available data from the Home Mortgage Disclosure Act (HMDA) from 2003 to 2021. We augment these data in the case of commercial banks using the Reports of Condition and Income (Call Reports). We also include census-tract level economic characteristics from the 2010 American Community Survey (ACS).

3.2. Housing market information

Our data on the number of housing transactions in each tract classified by funding source comes from deed records collected by CoreLogic. The deed records data set

[4]Alternatively, lenders could aim to compensate the reduction in home-purchase loan origination by increasing lending efforts for housing segments with relatively less exposure to cash-buyers. To the extent that this housing segments correspond to mortgages that have less liquid secondary markets, the outcome could be an increase in portfolio lending. Examples of housing segments with less liquid secondary markets are jumbo loans or loans that do not considered *conventional* by the GSEs.

contains over 850 million real estate transactions from more than 3,000 counties in the United States, corresponding mainly to single-family homes, townhomes, and residential condominia. The information comprises transaction dates, property addresses, buyer and seller information, and, crucially, an indicator of whether a mortgage was involved in each home sale.

To construct our main measures of all-cash purchases, we sum all home purchases in the deed records that took place without a mortgage in a given tract and calendar year. We then divide this quantity by the total number of homes sold that year in the census tract to obtain the market share of cash buyers at the tract-year level, share_cp.

At the census tract level, local credit market and housing conditions determine jointly the volume of originated mortgages and the activity of all-cash buyers. Even after controlling for lending standards –e.g., using the loan denial rate–, local economic trends may affect both the wealth of potential cash buyers and the liquidity of local lenders simultaneously. To alleviate the simultaneity bias affecting both lenders and cash buyers within the local economy, we focus on home buyers whose wealth is less likely to be impacted by the economic conditions of the area where their newly acquired property is located.

Specifically, we create an indicator variable for transactions in which the buyer comes from a different state than where the property is located based on the buyer's mailing address. We deem a sale as out-of-state if the state in the mailing address differs from the state where the property is located. Using this indicator across all transactions within a census tract in a given year, we calculate the proportion of all home purchases in which the buyer came from out of state and paid with cash, share_cp^{OOS}.

3.3. Mortgage information

The main HMDA dataset is the Loan/Application Register (LAR), which contains data on individual loan applications reported by lenders that are required to file annual reports to HMDA by regulators. The data set contains, among other information, the census tract in which the property that will be used as collateral is located, the loan amount applied for, the purpose of the loan, whether the application was denied or led to a loan origination, and a lender identifier. For originated loans, lenders are also required to disclose whether they sold the loan during the calendar year of origination.

For every lender in each census tract in a given year, we calculate the total value and number of loans originated in three categories: home purchase loans, refinancing, and home improvement.[5] With the purpose of analyzing mortgage loan retention by originators, we further break down these quantities into loans that the originators sold within the calendar year of origination and loans that were kept by the initial lenders. Because we control for the loan denial rate in our empirical specifications, we also calculate, for each lender-census tract-year observation, the number of applications that were denied and the sum of loan amounts from these denied applications.

3.4. Local credit markets sample

To study lending outcomes at the local (census tract) level, we aggregate loan variables from HMDA across all lenders for a given year and census tract, and merge with the CoreLogic and ACS data by year and census tract. To properly account for the evolution of the shape and size of census tracts over time, we use the relationship files provided by the US Census Bureau.[6] To reconcile census tracts in the HMDA data with census tracts in the CoreLogic home transaction information, we crosswalk all HMDA loans to the 2020 census tract vintage. We follow the same procedure for census tract information from the American Community Survey (ACS). The resulting sample is described in Table 1.

3.5. Lender-level panel

Using our census tract-lender-year data set, we aggregate the variables at the lender level to study firm-level responses to cash buyer activity. While most of the variables we employ are directly observed at the lender level, the census-tract economic and demographic characteristics, as well as the cash buyer-related measures must be aggregated

[5]For home purchase loans, we restrict our sample to first-lien loans. In the case of refinancings and home improvement loans, we consider all liens.

[6]HMDA data from 2003-2011 onwards records census tracts using the 2000 census vintage. Records corresponding to years 2012-2021 correspond to the 2010 census tract classification.

to compute lender-level variables.

To transform measures that vary at the census-tract level into lender-specific variables, we weigh each census-tract according to a measure of the lender's exposure to that tract. While the literature has previously used physical branch locations as a measure of lender's exposure to different geographical markets, we opt for weights based on mortgage originations.[7] This is appropriate in our context because of the existence of lenders for which branch location is relatively unrelated to the areas where they perform business —e.g., online lenders—, and because mortgage lending has become less localized over the recent decades.[8]

For each lender in a given year, we calculate our tract-specific weights as the fraction of home purchase loans that, during the previous three years, were originated in each tract. We then multiply tract-specific variables by these weights and sum across all tracts to obtain lender-specific measures. That is, to obtain the lender measure of variable $y_{i,t}$ corresponding to census tract i and year t, we calculate

$$y_{l,t} = \sum_i \frac{\sum_{\tau=1}^{3} \text{purchase}_{l,i,t-\tau}}{\sum_i \sum_{\tau=1}^{3} \text{purchase}_{l,i,t-\tau}} y_{i,t}.$$

We apply this procedure to every variable in our local credit markets sample (Table 1), except for the loan-related variables, which we aggregate for each lender directly from the HMDA data.

In our analysis of commercial banks, we augment our data set with financial information contained in Call Reports. For each commercial bank in our sample, we calculate the share of total assets that corresponds to residential real estate loans, commercial real estate (CRE) loans, commercial and industrial (C&I) loans, loans to individuals, and small business (SB) loans. Across our different specifications, we include other bank-specific variables as controls: bank size (total assets), equity ratio, cost of deposits, and income to assets.

[7]For example, Bassett and Marsh (2017) and Chakraborty et al. (2018) weigh local variables using the proportion of each bank's branches located in a given state in two different contexts.

[8]For instance, the evidence in Nguyen (2019) suggests that, relative to small business lending, mortgage loans are less influenced by branch location.

4. Cash buyers and local credit markets

In this section we analyze how changes in neighborhood-level activity by cash buyers relates to local mortgage market conditions. First of all, we study the relationship between mortgage originations and all-cash purchase transactions. Beyond loan originations, we explore how all-cash transactions affect the amount of home loans retained in the lenders' balance sheets. At the end of the section, we replicate these results distinguishing among loans originated by commercial banks, credit unions, and independent mortgage banks.

4.1. Loan originations

In Section 2, we lay out the conflict between home purchase loan originations and all-cash home purchases. We study this relationship empirically by regressing the yearly value of originated loans during a census tract on the proportion of home purchases that took place entirely with cash. Specifically, we estimate the following equation using OLS:

$$L_{i,t} = \beta_1 + \beta_2 share\_cb_{i,t} + \beta_3' X_{i,t} + \beta_4' \eta_i + \mathbf{c}_i + \tau_t + \varepsilon_{i,t}. \tag{1}$$

In equation 1, $L_{h,i,t}$ represents the total value of loans originated of type h in census tract i during year t. Depending on the specification, the loan type h is either home-purchase loans, refinance loans, or home improvement loans. The vector $X_{i,t}$ includes time-varying local credit and housing market conditions: the loan denial rate in tract i across all loan types, the number of loans of all types originated in tract i during the previous year, and the number of homes sold in the tract during year t. We also control for neighborhoods characteristics, η_i, and include year and county fixed effects, which we denote τ_t and $\mathbf{c}_i$, respectively. We cluster standard errors by county to allow for potential correlation in conditional outcomes among all census tracts that pertain to the same county.

In order to alleviate the potential bias caused by unobserved local economic trends simultaneously faced by all-cash buyers and mortgage lenders, we also show results of a two-stage least squares (2SLS) specification using the market share of all-cash purchases by out-of-state buyers, $share\_cb^{OOS}$. The estimation equations are as follows:

$$\begin{aligned}
&\text{First Stage:} \qquad share_cb_{i,t} = \alpha_1 + \alpha_2 share_cb^{OOS}_{i,t} + \alpha_3' X_{i,t} + \alpha_4' \eta_i + \mathbf{c}_i^1 + \tau_t^1 + \epsilon_{i,t} \\
&\text{Second Stage:} \qquad L_{i,t} = \gamma_1 + \gamma_2' \widehat{share_cb}_{i,t} + \gamma_3' X_{i,t} + \gamma_4' \eta_i + \mathbf{c}_i + \tau_t + \varepsilon_{i,t}.
\end{aligned} \tag{2}$$

The results for home originations are shown in the first two columns of Table 2. As expected, the relationship between home-purchase loan originations and the market share of cash transactions is negative, confirming hypothesis 1. It must be said, however, that, although the point estimates are negative for the both specifications, the the OLS coefficient is small and statistically insignificant. The coefficient estimated through 2SLS, on the other hand, are much larger in magnitude and statistically significant at the 10% level.

Table 2 also shows the results of estimating equations 1 and 2 using mortgage refinancings and home improvement loans as dependent variables. In contrast to the case of home purchase loans, for which all-cash transactions represent a direct competitor, mortgage refinancing are not negatively correlated to cash buyer activity. In fact, as indicated by columns 3 and 4 of Table 2, the partial correlation between mortgage refinancings and all-cash home purchases is positive.[9] As stated in Section 2, this could be explained by mortgage originators attempts to compensate lower lending opportunities in the home purchase market by approaching other mortgage sectors, like refinancings, more aggressively. The final pair of columns in Table 2 correspond to originations of home improvement loans, which, according to our results, are uncorrelated with all-cash home purchases. Overall, our results for refinancings and home improvement loans are consistent with our second hypothesis, outlined in Section 2.

4.1.1. Tract-level loan retention

The LAR data from HMDA includes a variable that indicates whether a loan was sold within the same calendar year of its origination. Mortgage lenders may rely on

[9]As in the case of purchase loans, the coefficient for share_cb is statistically significant only in the 2SLS model.

the secondary mortgage markets to different degrees. This is particularly true for mortgage banks whose main revenue source are loan fees. Fee-driven lenders hold relatively few assets and base their business model on being able to quickly sell their recently originated loans in the secondary markets and use the sale proceeds to fund new originations with the goal of maximizing revenue from origination and servicing fees. That said, even portfolio lenders – those that normally keep a considerable fraction of originated mortgages in their balance sheet– benefit from secondary markets which complement deposits and other funding sources for mortgage lending.

In this subsection, we explore how all-cash home purchases in the local market relates to how lenders interact with the secondary markets. Specifically, we estimate modified versions of equations 1 and 2 in which the dependent variables are the total value of loans retained —i.e., not sold in the secondary market— by lenders. The results are shown in Table 3. Our estimation shows that retained loans are positively correlated with all-cash home purchases across all loan types and specifications, confirming our third hypothesis. As laid out in Section 2, lenders' decreased need for funds to originate home-purchase loans may constitute a mechanism driving the positive estimated coefficients for share_cp in Table 3.

4.2. Types of lenders

While the results in Table 2 indicate there's a negative partial correlation between all-cash transactions in a census tract and the amount of originated purchase loans, it is not clear whether origination levels are lower across all lenders, or if specific types of lenders are more negatively impacted. To shed light on potential lender heterogeneity, we break down our loan variables into three broad types of lenders: commercial banks, credit unions, and independent banks.

In Tables 4 and 5, we estimate variations of equations 1 and 2 in which the dependent variables are the total value of loan originations by each different lender type. The estimated coefficients suggest that, in the case of home purchase loans (Table 4), the reduction in originations is driven entirely by credit unions and independent mortgage banks. Interestingly, the loan originations of commercial banks (columns 1 and 2) are, in fact, positively correlated with cash buyer market share. While there are multiple factors at play, a potential explanation for this effect would be that commercial banks may have other ties with the local economy that encourage them to remain actively seeking to finance home purchases and maintaining other relationships with their clients, whereas independent mortgage banks, by definition, face fewer incentives to continue lending in the area. Table 5 indicates that the positive coefficient for refinance loans in Table 2 stems entirely from refinancings by commercial banks. Similarly, Tables 6 and 7 show that the only lender type for which the total value of retained loans correlates positively with all-cash home purchases is commercial banks.

5. Conclusion

We investigate how all-cash home purchases shape local mortgage lending markets. Using a comprehensive panel of deed records and HMDA loan-level data from 2004 to 2021, we show that increased activity by cash buyers leads to a decline in home-purchase loan originations at the census tract level. This pattern is particularly pronounced for credit unions and independent mortgage banks, while commercial banks appear more resilient, or even responsive, to higher levels of cash purchases. Notably, we find that lenders compensate for reduced demand in the home-purchase market by increasing their activity in other mortgage segments — namely, refinancing and home improvement loans—and by retaining a larger share of loans on their balance sheets.

These results suggest that cash-buyer activities have broader implications beyond individual housing transactions. By reducing mortgage loan demand, cash purchases can indirectly reshape lender behavior and local credit availability, potentially affecting the distribution of financial services across neighborhoods and altering the risk profile of lenders' portfolios.

Looking forward, we plan to explore several extensions to this work. First, we aim to examine how shifts in loan portfolio composition driven by cash buyer activity influence lenders' profitability, risk exposure, and long-term stability. Second, we are interested in whether the displacement of mortgage-financed buyers by cash buyers has heterogeneous effects on different borrower groups — particularly first-time homebuyers or historically underserved communities. Lastly, future work could also investigate how these dynamics play out in the context of regulatory changes or economic shocks, including during the COVID-19 pandemic or periods of monetary tightening.

References

Austin, N. (2022). Keeping up with the blackstones: Institutional investors and gentrification. *Available at SSRN 4269561.*

Bassett, W. F. and Marsh, W. B. (2017). Assessing targeted macroprudential financial regulation: The case of the 2006 commercial real estate guidance for banks. *Journal of Financial Stability*, 30:209–228.

Buchak, G., Matvos, G., Piskorski, T., and Seru, A. (2018). Fintech, regulatory arbitrage, and the rise of shadow banks. *Journal of financial economics*, 130(3):453–483.

Buchak, G., Matvos, G., Piskorski, T., and Seru, A. (2020). Why is intermediating houses so difficult? evidence from ibuyers. Technical report, National Bureau of Economic Research.

Bushman, R. M., Hendricks, B. E., and Williams, C. D. (2016). Bank competition: Measurement, decision-making, and risk-taking. *Journal of Accounting Research*, 54(3):777–826.

Chakraborty, I., Goldstein, I., and MacKinlay, A. (2018). Housing price booms and crowding-out effects in bank lending. *The Review of Financial Studies*, 31(7):2806–2853.

Cortés, K. R. and Strahan, P. E. (2017). Tracing out capital flows: How financially integrated banks respond to natural disasters. *Journal of Financial Economics*, 125(1):182–199.

Federal Deposit Insurance Corporation (FDIC) (2025). *FDIC Quarterly Banking Profile 2024Q4*. FDIC.

Fuster, A., Plosser, M., Schnabl, P., and Vickery, J. (2019). The role of technology in mortgage lending. *The Review of Financial Studies*, 32(5):1854–1899.

Gorback, C., Qian, F., and Zhu, Z. (2024). Impact of institutional owners on housing markets. Technical report, Working Paper, RERI.

Han, L. and Hong, S.-H. (2024). Cash is king? understanding financing risk in housing markets. *Review of Finance*, 28(6):2083–2118.

Law, K. and Mislang, N. (2022). The heterogeneity of bank responses to the fintech challenge. *Available at SSRN 4069077*.

National Credit Union Administration (NCUA) (2025). *Quarterly Credit Union Data Summary 2024Q4*. NCUA.

Nguyen, H.-L. Q. (2019). Are credit markets still local? evidence from bank branch closings. *American Economic Journal: Applied Economics*, 11(1):1–32.

Reher, M. and Valkanov, R. (2024). The mortgage-cash premium puzzle. *The Journal of Finance*, 79(5):3149–3201.

Seo, Y., Holmes, C., and Lee, M. (2021). Examining the cash-only price discount and the driving forces of cash-only transactions in the housing market. *The Journal of Real Estate Finance and Economics*, pages 1–37.

Figure 1: **All-cash market share**. The figure shows the proportion of homes that were acquired with cash in the United States.

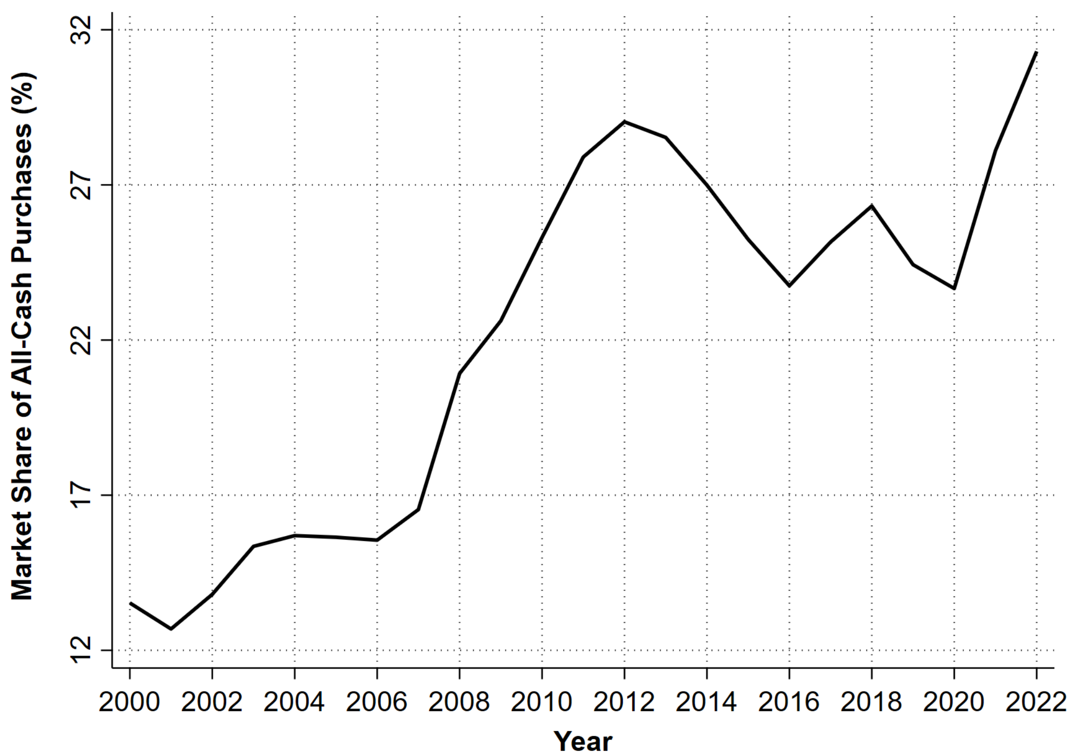

Figure 2: **Equilibrium in home-purchase loan market**. The figure depicts equilibria with and without cash buyers in a stylized model of a local home-purchase mortgage credit market.

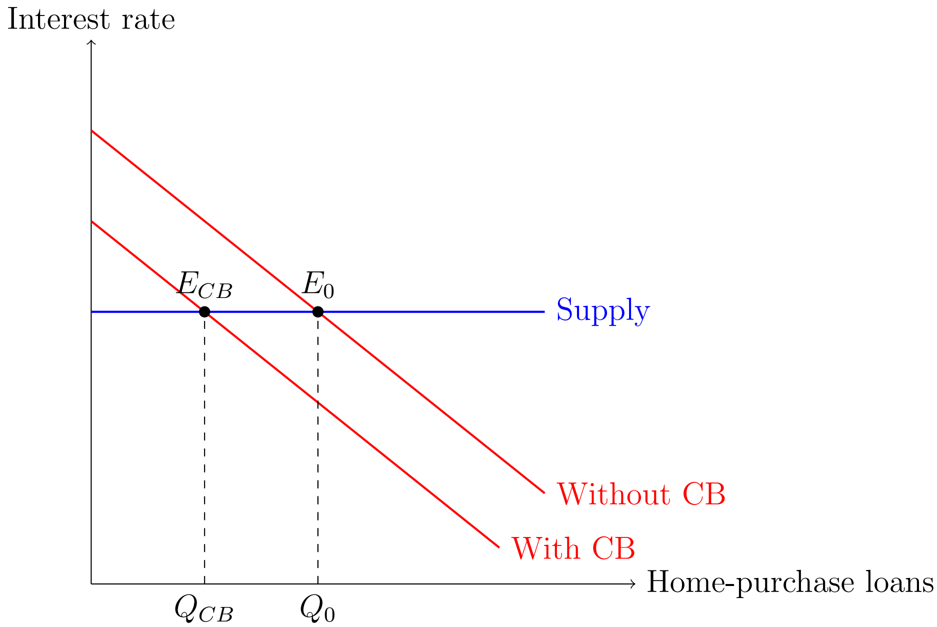

Table 1: **Summary statistics**. The table shows descriptive statistics of the variables in our census-tract year data set. The variable share_cp corresponds to the share house purchases in which the buyer paid entirely with cash in a given year and census tracts. Similarly, share_cp^{OOS} represents the ratio of all-cash purchases by buyers from out of state to total home purchases in a given tract and year. The variables purchase, refinance, and improve, correspond to the the sum of loan amounts, in thousands of dollars, of the home-purchase loans, refinancings, and home improvement loans that were originated in a given year backed by properties located in the corresponding census tract. The suffix "_kept" attached to a variable signifies that the loan was not sold by the originating institution within the calendar year of origination. The measure denial_all captures the ratio of denied applications to total applications across all three types of loans. l_loan_tot_unit represents the total number of loans of all types originated in a given tract during the previous year, whereas num_tx stands for the yearly number of homes sold in a given census tract. The variables labeled *static census tract characteristics* are taken from the 2010 American Community Survey (ACS) and measure demographic, economic, and dwelling-specific characteristics at the census-tract level. We provide a description of ACS variables in the appendix.

Variable	Mean	SD	p.25.	p.50.	p.75.	N
All-cash transactions						
share_cp	23.32	17.94	10.42	20.62	33.04	1,498,304
share_cp^{OOS}	1.891	4.094	0	0	2.083	1,498,304
Loan originations						
purchase	11,095	15,978	2,387	6,247	13,954	1,615,835
refinance	14,259	24,193	2,297	6,388	16,209	1,615,835
improve	619.7	1,093	81	277	706	1,615,835
purchase_kept	2,969	6,979	447	1,199	2,865	1,615,835
refinance_kept	3,683	9,153	544	1,508	3,645	1,615,835
improve_kept	368.3	726	37	153	411	1,615,835
Local credit and housing conditions						
denial_all	28.76	13.48	19.02	26.32	36	1,608,190
l_loan_tot_unit	113.1	108.3	42	86	151	1,528,685
num_tx	119.2	92.83	59	99	155	1,498,304
Static census tract characteristics						
p1detached	62.27	26.36	47.16	68.45	82.34	1,607,992
p3bed	40.11	15.17	30.2	41.15	50.85	1,607,992
p4bedup	20.52	15.16	10.18	16.73	26.63	1,607,992
pbs1_10	14.72	16.94	3.308	9.275	19.05	1,607,992
pbs11_20	13.68	12.32	4.034	10.97	19.99	1,607,992
pbs21_40	29.18	18.14	15.62	27.69	39.22	1,607,992
p1room	1.965	4.114	0	0.5845	2.276	1,607,992
p2_5room	48.21	19.25	35.06	48.25	61.38	1,607,992
pvac	12.21	10.61	5.435	9.462	15.56	1,603,558
pcol	27.71	18.29	13.72	22.77	38.01	1,605,738
punemp	9.855	6.022	5.813	8.555	12.44	1,604,183
ppov	16.08	12.88	6.685	12.57	21.93	1,604,030
pnhblk	13.72	21.49	1.352	4.462	15.01	1,608,476
pasian	5.139	9.364	0.6917	1.948	5.241	1,608,476
phisp	16.28	22.67	2.168	6.59	19.42	1,605,977
mrent_log	6.437	0.8854	6.191	6.507	6.84	1,612,794
mhmval_log	11.86	1.571	11.53	11.97	12.48	1,612,794
hinc_log	10.71	0.9788	10.48	10.78	11.09	1,612,794

Table 2: **Estimation results: loan origination**.

	Purchase		Refinance		Improvement	
	OLS	IV	OLS	IV	OLS	IV
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
share_cp	-0.3002	-14.65*	8.794	36.36***	-0.0719	0.5716
	(3.067)	(7.866)	(5.366)	(12.06)	(0.4765)	(0.6125)
denial_all	0.3948	3.716	47.48***	41.10***	1.197	1.048
	(7.946)	(8.692)	(15.74)	(15.62)	(0.7966)	(0.7392)
l_loan_tot_unit	90.92***	90.68***	113.6***	114.1***	3.356***	3.367***
	(2.897)	(2.887)	(4.337)	(4.434)	(0.1368)	(0.1437)
p1detached	-41.10***	-41.06***	-9.919	-10.01	1.546***	1.544***
	(3.842)	(3.849)	(8.804)	(8.784)	(0.4208)	(0.4211)
p3bed	-17.13***	-17.94***	-26.55**	-25.00**	-0.2241	-0.1879
	(5.289)	(5.379)	(11.71)	(11.78)	(0.5063)	(0.5179)
p4bedup	102.2***	101.3***	211.6***	213.3***	7.657***	7.696***
	(10.49)	(10.57)	(24.49)	(24.76)	(1.008)	(1.025)
pbs1_10	25.89***	25.52***	-110.4***	-109.7***	-7.642***	-7.625***
	(5.403)	(5.439)	(17.76)	(17.73)	(0.8523)	(0.8453)
pbs11_20	-27.67***	-27.95***	1.593	2.126	-2.166***	-2.153***
	(5.746)	(5.775)	(15.66)	(15.62)	(0.7120)	(0.7070)
pbs21_40	-40.60***	-40.81***	-28.73**	-28.34**	-1.638***	-1.628***
	(3.329)	(3.330)	(11.57)	(11.60)	(0.5984)	(0.5967)
p1room	-13.03	-13.11	-163.8***	-163.6***	-9.151***	-9.147***
	(16.21)	(16.20)	(44.19)	(44.26)	(2.454)	(2.455)
p2_5room	8.242	8.295	-7.876	-7.978	-0.9287*	-0.9311*
	(7.177)	(7.180)	(11.64)	(11.58)	(0.4938)	(0.4935)
pvac	101.3***	103.0***	90.02***	86.68***	3.998***	3.920***
	(9.233)	(9.144)	(11.59)	(11.91)	(0.8340)	(0.8521)
pcol	120.7***	120.6***	176.1***	176.3***	7.201***	7.205***
	(8.188)	(8.200)	(19.07)	(19.08)	(0.8411)	(0.8423)
punemp	25.76***	26.93***	21.22**	18.98*	0.6068	0.5543
	(6.169)	(6.142)	(10.47)	(10.30)	(0.4693)	(0.4548)
ppov	73.24***	74.17***	139.5***	137.7***	4.925***	4.884***
	(8.424)	(8.600)	(18.79)	(18.75)	(0.6574)	(0.6574)
pnhblk	-19.82***	-19.55***	-21.60**	-22.11**	-1.078***	-1.090***
	(4.037)	(4.024)	(8.805)	(8.825)	(0.2735)	(0.2698)
pasian	-79.22***	-79.28***	-90.24***	-90.13***	-7.879***	-7.876***
	(12.10)	(12.17)	(24.95)	(24.95)	(1.014)	(1.011)
phisp	-19.18**	-19.24**	-74.58***	-74.46***	-3.192***	-3.189***
	(8.586)	(8.630)	(25.48)	(25.38)	(1.137)	(1.135)
mrent_log	-186.5***	-186.3***	-1.297	-1.549	5.558	5.552
	(58.62)	(58.69)	(77.93)	(77.84)	(3.683)	(3.681)
mhmval_log	355.3***	347.0***	526.5***	542.3***	33.41***	33.78***
	(55.19)	(55.30)	(87.55)	(89.61)	(4.659)	(4.670)
hinc_log	1,306.7***	1,304.0***	1,974.3***	1,979.6***	88.94***	89.07***
	(275.2)	(274.5)	(492.5)	(493.8)	(23.21)	(23.28)
num_tx	21.28***	21.62***	12.28**	11.62**	0.6012***	0.5859***
	(2.390)	(2.397)	(5.227)	(5.203)	(0.2008)	(0.1970)
Fixed-effects						
county	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	1,413,343	1,413,343	1,413,343	1,413,343	1,413,343	1,413,343
R^2	0.70926	0.70911	0.64009	0.63985	0.41538	0.41533
Within R^2	0.61843	0.61823	0.47005	0.46969	0.22235	0.22227

Clustered (county) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 3: **Estimation results: loan retention**.

	Purchase		Refinance		Improvement	
	OLS	IV	OLS	IV	OLS	IV
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
share_cp	10.01***	24.44***	14.29***	32.21***	0.4379**	0.7785*
	(2.266)	(5.267)	(2.029)	(5.010)	(0.1837)	(0.4077)
denial_all	27.69***	24.35***	48.92***	44.78***	2.651***	2.573***
	(8.434)	(8.667)	(15.11)	(15.20)	(0.7822)	(0.7862)
l_loan_tot_unit	18.96***	19.20***	23.65***	23.95***	1.906***	1.912***
	(0.8908)	(0.9080)	(1.366)	(1.391)	(0.0551)	(0.0557)
p1detached	-16.33***	-16.38***	-8.537*	-8.596*	0.9242***	0.9231***
	(2.680)	(2.647)	(4.937)	(4.899)	(0.3112)	(0.3108)
p3bed	1.377	2.189	-0.9446	0.0635	-0.6021**	-0.5829**
	(3.537)	(3.604)	(4.193)	(4.198)	(0.2383)	(0.2400)
p4bedup	58.57***	59.45***	90.75***	91.83***	4.426***	4.447***
	(8.451)	(8.469)	(13.74)	(13.75)	(0.6749)	(0.6765)
pbs1_10	-18.39***	-18.02***	-52.36***	-51.90***	-4.474***	-4.465***
	(4.113)	(4.117)	(8.592)	(8.605)	(0.4649)	(0.4653)
pbs11_20	-19.08***	-18.80***	-18.54**	-18.20**	-1.856***	-1.850***
	(3.735)	(3.743)	(7.611)	(7.616)	(0.4433)	(0.4433)
pbs21_40	-19.58***	-19.37***	-17.58***	-17.33***	-1.077***	-1.073***
	(3.104)	(3.151)	(6.128)	(6.167)	(0.3754)	(0.3765)
p1room	-14.00	-13.91	-65.43***	-65.32***	-5.454***	-5.452***
	(13.32)	(13.34)	(21.69)	(21.74)	(1.268)	(1.270)
p2_5room	12.73**	12.68**	7.151	7.084	-0.6739	-0.6752
	(5.585)	(5.558)	(7.685)	(7.655)	(0.4348)	(0.4347)
pvac	77.36***	75.61***	63.41***	61.24***	3.262***	3.220***
	(9.154)	(9.007)	(8.923)	(8.890)	(0.6942)	(0.6950)
pcol	93.40***	93.51***	105.5***	105.6***	6.141***	6.143***
	(8.390)	(8.370)	(14.49)	(14.49)	(0.7350)	(0.7353)
punemp	18.12***	16.94***	10.35**	8.886*	0.5166	0.4889
	(4.708)	(4.590)	(5.248)	(5.189)	(0.3317)	(0.3297)
ppov	49.19***	48.26***	72.76***	71.60***	3.950***	3.928***
	(7.709)	(7.744)	(14.57)	(14.58)	(0.6476)	(0.6476)
pnhblk	-18.99***	-19.26***	-22.30***	-22.63***	-1.640***	-1.646***
	(3.075)	(3.053)	(5.537)	(5.522)	(0.2544)	(0.2537)
pasian	-57.07***	-57.01***	-86.26***	-86.18***	-6.495***	-6.494***
	(9.752)	(9.690)	(19.03)	(19.03)	(0.7955)	(0.7944)
phisp	-19.27**	-19.21**	-39.61**	-39.53**	-2.539***	-2.537***
	(7.955)	(7.910)	(16.17)	(16.11)	(0.8696)	(0.8684)
mrent_log	-59.12	-59.25	28.11	27.95	1.116	1.113
	(40.36)	(40.28)	(47.62)	(47.54)	(2.815)	(2.814)
mhmval_log	307.8***	316.1***	310.3***	320.6***	23.78***	23.98***
	(45.24)	(46.34)	(50.96)	(52.29)	(3.404)	(3.424)
hinc_log	1,235.8***	1,238.5***	1,472.9***	1,476.3***	84.83***	84.89***
	(241.4)	(241.9)	(367.0)	(367.7)	(20.08)	(20.10)
num_tx	7.911***	7.569***	6.521***	6.095***	0.2234**	0.2153**
	(1.288)	(1.267)	(2.224)	(2.222)	(0.0872)	(0.0864)
Fixed-effects						
county	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	1,413,343	1,413,343	1,413,343	1,413,343	1,413,343	1,413,343
R^2	0.39561	0.39478	0.37231	0.37161	0.31311	0.31307
Within R^2	0.26913	0.26813	0.22764	0.22677	0.17406	0.17401

Clustered (county) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 4: **Estimation results by lender type: home purchase loan origination**.

	Banks		Credit Unions		Mortgage Banks	
	OLS	IV	OLS	IV	OLS	IV
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
share_cp	17.71***	25.49***	-0.9685***	-3.002***	-20.46***	-40.51***
	(2.348)	(5.860)	(0.3585)	(0.6151)	(1.773)	(4.430)
denial_all	-34.89***	-35.76***	-3.022***	-2.962***	-3.439**	-1.936
	(3.560)	(3.728)	(0.1342)	(0.1360)	(1.678)	(1.767)
l_loan_tot_unit	31.09***	31.23***	3.156***	3.118***	47.00***	46.62***
	(1.160)	(1.186)	(0.1748)	(0.1733)	(2.034)	(2.003)
p1detached	-22.89***	-22.91***	-0.6515**	-0.6480**	-15.02***	-14.96***
	(2.614)	(2.595)	(0.3167)	(0.3180)	(2.143)	(2.086)
p3bed	-3.225	-2.814	-1.309***	-1.395***	-6.523***	-7.471***
	(3.716)	(3.779)	(0.3538)	(0.3517)	(2.193)	(2.179)
p4bedup	59.49***	59.92***	0.2555	0.1744	32.36***	31.40***
	(8.018)	(8.049)	(0.5999)	(0.5979)	(3.370)	(3.357)
pbs1_10	-10.95**	-10.72**	2.349***	2.283***	35.81***	35.19***
	(4.393)	(4.406)	(0.3191)	(0.3226)	(2.427)	(2.417)
pbs11_20	-11.48***	-11.33***	0.8981***	0.8575***	-18.72***	-19.14***
	(3.794)	(3.806)	(0.2668)	(0.2668)	(3.219)	(3.281)
pbs21_40	-22.39***	-22.25***	0.6175**	0.5796*	-17.22***	-17.59***
	(3.009)	(3.054)	(0.2969)	(0.2966)	(2.045)	(2.082)
p1room	-7.984	-7.962	-0.8562	-0.8452	2.999	3.032
	(13.31)	(13.33)	(0.9282)	(0.9237)	(5.721)	(5.675)
p2_5room	5.898	5.850	-1.422***	-1.398***	5.378*	5.561*
	(5.482)	(5.463)	(0.3765)	(0.3790)	(3.069)	(3.023)
pvac	83.08***	82.03***	0.3241	0.6085*	5.680***	8.405***
	(8.280)	(8.096)	(0.3511)	(0.3638)	(1.977)	(2.147)
pcol	98.65***	98.82***	3.616***	3.539***	-9.179***	-9.788***
	(7.252)	(7.224)	(0.3943)	(0.3908)	(2.605)	(2.656)
punemp	29.39***	28.63***	0.4574	0.6770	-2.421	-0.3104
	(4.756)	(4.676)	(0.5047)	(0.5179)	(2.530)	(2.533)
ppov	48.63***	48.09***	1.339***	1.487***	11.80***	13.16***
	(7.526)	(7.611)	(0.4103)	(0.4113)	(2.172)	(2.192)
pnhblk	-15.73***	-16.03***	0.2094	0.3193	5.661***	6.609***
	(2.584)	(2.557)	(0.2836)	(0.2906)	(1.391)	(1.413)
pasian	-50.87***	-50.88***	-3.279***	-3.278***	-15.37***	-15.36***
	(9.198)	(9.142)	(0.6122)	(0.6188)	(4.999)	(4.962)
phisp	-9.067	-9.053	-0.1027	-0.0949	-4.495**	-4.354**
	(7.372)	(7.337)	(0.4214)	(0.4304)	(2.116)	(2.072)
mrent_log	-100.9**	-100.8**	-10.47***	-10.50***	-55.35**	-55.57**
	(40.19)	(40.13)	(3.003)	(3.001)	(24.09)	(24.20)
mhmval_log	312.3***	318.0***	5.610*	3.254	-45.41***	-62.54***
	(44.94)	(45.84)	(3.407)	(3.317)	(14.27)	(14.27)
hinc_log	1,228.1***	1,231.0***	57.37***	56.57***	-255.9***	-264.3***
	(242.0)	(242.2)	(9.336)	(9.212)	(75.53)	(76.81)
num_tx	9.992***	9.811***	0.7868***	0.8327***	7.264***	7.736***
	(1.323)	(1.313)	(0.0619)	(0.0642)	(0.9064)	(0.8876)
Fixed-effects						
county	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	1,412,367	1,412,367	1,330,868	1,330,868	1,407,908	1,407,908
R^2	0.51802	0.51784	0.43880	0.43812	0.67608	0.67489
Within R^2	0.40648	0.40626	0.21740	0.21645	0.55605	0.55441

Clustered (county) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 5: **Estimation results by lender type: refinance loan origination**.

	Banks		Credit Unions		Mortgage Banks	
	OLS	IV	OLS	IV	OLS	IV
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
share_cp	22.05***	42.35***	-1.549***	-1.875***	-21.72***	-22.24***
	(2.819)	(6.135)	(0.5276)	(0.7207)	(5.556)	(5.802)
denial_all	-17.36***	-19.61***	-4.190***	-4.180***	17.33***	17.37***
	(5.948)	(6.038)	(0.2135)	(0.2203)	(3.391)	(3.356)
l_loan_tot_unit	41.04***	41.41***	5.366***	5.359***	52.57***	52.56***
	(1.978)	(2.013)	(0.2875)	(0.2894)	(2.119)	(2.167)
p1detached	-9.719*	-9.782*	1.859***	1.859***	-4.980*	-4.978*
	(5.358)	(5.310)	(0.6909)	(0.6916)	(2.916)	(2.922)
p3bed	-11.38**	-10.31**	-1.955**	-1.969**	-5.968	-5.992
	(5.044)	(5.043)	(0.8176)	(0.8166)	(6.084)	(6.100)
p4bedup	107.0***	108.1***	4.472***	4.459***	65.25***	65.23***
	(13.64)	(13.69)	(1.570)	(1.578)	(7.538)	(7.633)
pbs1_10	-59.25***	-58.64***	-1.883***	-1.894***	-27.26***	-27.27***
	(10.07)	(10.07)	(0.6273)	(0.6259)	(4.882)	(4.851)
pbs11_20	-1.802	-1.403	2.133***	2.126***	-2.655	-2.666
	(8.791)	(8.782)	(0.6290)	(0.6274)	(4.303)	(4.298)
pbs21_40	-16.70**	-16.34**	1.498**	1.492**	-13.77***	-13.78***
	(7.125)	(7.166)	(0.5980)	(0.5971)	(3.099)	(3.087)
p1room	-88.05***	-88.00***	-5.607***	-5.605***	-45.07***	-45.07***
	(23.13)	(23.18)	(2.033)	(2.032)	(14.98)	(14.98)
p2_5room	-7.956	-8.084	-3.042***	-3.039***	1.354	1.358
	(7.394)	(7.343)	(0.7891)	(0.7898)	(4.452)	(4.454)
pvac	71.59***	68.84***	-0.4347	-0.3891	5.371	5.441
	(7.504)	(7.597)	(0.5983)	(0.6278)	(3.778)	(3.970)
pcol	120.3***	120.7***	3.334***	3.321***	11.97***	11.96***
	(13.69)	(13.70)	(0.6414)	(0.6390)	(3.592)	(3.574)
punemp	21.93***	19.94***	0.7215	0.7567	0.7893	0.8435
	(6.033)	(5.995)	(0.7579)	(0.7393)	(4.112)	(4.085)
ppov	82.60***	81.19***	3.568***	3.592***	29.61***	29.64***
	(14.77)	(14.76)	(0.7359)	(0.7230)	(3.792)	(3.771)
pnhblk	-19.37***	-20.15***	0.3749	0.3925	8.294***	8.318***
	(5.547)	(5.573)	(0.4861)	(0.4900)	(2.933)	(2.904)
pasian	-74.68***	-74.69***	-4.829***	-4.828***	4.235	4.235
	(16.85)	(16.82)	(1.287)	(1.288)	(6.414)	(6.414)
phisp	-36.77**	-36.73**	-3.219***	-3.218***	-23.51***	-23.51***
	(16.42)	(16.32)	(1.198)	(1.201)	(5.651)	(5.660)
mrent_log	-33.98	-33.81	-3.833	-3.838	53.60**	53.59**
	(50.84)	(50.75)	(4.486)	(4.486)	(23.80)	(23.81)
mhmval_log	354.2***	369.0***	11.88**	11.51**	76.35***	75.91***
	(54.93)	(56.42)	(6.029)	(5.841)	(22.25)	(22.55)
hinc_log	1,512.6***	1,520.1***	65.72***	65.59***	-29.81	-30.02
	(364.7)	(365.7)	(17.16)	(17.18)	(66.24)	(66.03)
num_tx	5.684**	5.212**	0.0424	0.0498	2.631*	2.643*
	(2.433)	(2.433)	(0.1344)	(0.1326)	(1.419)	(1.401)
Fixed-effects						
county	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	1,412,367	1,412,367	1,330,868	1,330,868	1,407,908	1,407,908
R^2	0.50565	0.50509	0.49126	0.49126	0.58991	0.58991
Within R^2	0.34370	0.34296	0.26446	0.26445	0.38147	0.38147

Clustered (county) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 6: **Estimation results by lender type: home purchase loan retention**.

	Banks		Credit Unions		Mortgage Banks	
	OLS	IV	OLS	IV	OLS	IV
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
share_cp	9.257***	23.57***	-0.2371	-1.005**	-0.3978**	-2.006***
	(2.546)	(4.582)	(0.2431)	(0.4019)	(0.1756)	(0.4294)
denial_all	-3.963	-5.551*	-1.684***	-1.661***	-0.9125***	-0.7920***
	(3.204)	(3.280)	(0.0726)	(0.0742)	(0.1766)	(0.1846)
l_loan_tot_unit	9.843***	10.10***	1.732***	1.718***	3.800***	3.770***
	(0.6728)	(0.6953)	(0.1091)	(0.1081)	(0.2076)	(0.2051)
p1detached	-13.06***	-13.11***	-0.5113***	-0.5100***	-1.874***	-1.869***
	(2.203)	(2.156)	(0.1919)	(0.1926)	(0.2291)	(0.2251)
p3bed	4.344	5.100*	-0.8328***	-0.8653***	0.5301**	0.4540*
	(2.811)	(2.841)	(0.2300)	(0.2287)	(0.2540)	(0.2511)
p4bedup	46.81***	47.58***	0.8674**	0.8367*	3.775***	3.698***
	(6.577)	(6.561)	(0.4312)	(0.4292)	(0.3846)	(0.3860)
pbs1_10	-19.36***	-18.93***	1.066***	1.041***	2.270***	2.220***
	(3.495)	(3.507)	(0.2052)	(0.2067)	(0.2900)	(0.2890)
pbs11_20	-17.01***	-16.72***	0.2883	0.2730	-1.698***	-1.732***
	(3.177)	(3.186)	(0.1821)	(0.1826)	(0.3392)	(0.3462)
pbs21_40	-17.42***	-17.16***	0.1037	0.0893	-1.607***	-1.637***
	(2.755)	(2.805)	(0.1984)	(0.1988)	(0.1787)	(0.1816)
p1room	-10.30	-10.26	-0.3135	-0.3093	0.9468	0.9495
	(11.49)	(11.50)	(0.5669)	(0.5648)	(0.7088)	(0.7106)
p2_5room	11.28**	11.19**	-0.8008***	-0.7918***	1.175***	1.190***
	(4.495)	(4.464)	(0.2551)	(0.2563)	(0.3243)	(0.3230)
pvac	64.99***	63.05***	1.228***	1.335***	1.460***	1.678***
	(7.812)	(7.666)	(0.1971)	(0.2045)	(0.2313)	(0.2477)
pcol	72.88***	73.20***	3.181***	3.151***	-1.979***	-2.028***
	(6.821)	(6.792)	(0.3409)	(0.3393)	(0.2670)	(0.2729)
punemp	18.64***	17.23***	0.7585**	0.8414**	0.2743	0.4436
	(4.052)	(3.958)	(0.3302)	(0.3377)	(0.3065)	(0.2995)
ppov	39.37***	38.37***	1.457***	1.513***	0.8100***	0.9193***
	(6.737)	(6.754)	(0.2791)	(0.2803)	(0.2233)	(0.2283)
pnhblk	-11.76***	-12.31***	-0.1130	-0.0715	0.7578***	0.8339***
	(2.089)	(2.063)	(0.1803)	(0.1845)	(0.2016)	(0.1978)
pasian	-44.90***	-44.91***	-2.303***	-2.302***	-1.236***	-1.235***
	(8.452)	(8.373)	(0.4936)	(0.4948)	(0.3729)	(0.3707)
phisp	-15.17**	-15.14**	-0.3637	-0.3607	0.1315	0.1428
	(6.782)	(6.719)	(0.3357)	(0.3392)	(0.2370)	(0.2359)
mrent_log	-31.48	-31.36	-4.193**	-4.205**	-13.34***	-13.36***
	(32.40)	(32.28)	(1.972)	(1.973)	(3.072)	(3.080)
mhmval_log	241.9***	252.4***	5.892***	5.002**	-2.816*	-4.189***
	(37.05)	(38.28)	(2.233)	(2.182)	(1.468)	(1.472)
hinc_log	999.9***	1,005.1***	44.74***	44.43***	-14.48**	-15.15***
	(201.0)	(201.7)	(7.407)	(7.338)	(5.744)	(5.822)
num_tx	5.204***	4.871***	0.4423***	0.4596***	0.5612***	0.5990***
	(0.9191)	(0.8895)	(0.0336)	(0.0344)	(0.0986)	(0.0972)
Fixed-effects						
county	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	1,412,367	1,412,367	1,330,868	1,330,868	1,407,908	1,407,908
R^2	0.31041	0.30912	0.33957	0.33933	0.35694	0.35631
Within R^2	0.19109	0.18959	0.16067	0.16037	0.24110	0.24036

Clustered (county) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 7: **Estimation results by lender type: refinance loan retention**.

	Banks		Credit Unions		Mortgage Banks	
	OLS	IV	OLS	IV	OLS	IV
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
share_cp	10.89***	23.02***	-0.5355	-0.2915	-0.0704	0.2898
	(2.673)	(3.889)	(0.3971)	(0.5066)	(0.2328)	(0.4101)
denial_all	11.73**	10.38*	-2.426***	-2.433***	0.1240	0.0970
	(5.804)	(5.867)	(0.1131)	(0.1182)	(0.2369)	(0.2371)
l_loan_tot_unit	11.72***	11.94***	3.220***	3.224***	3.938***	3.944***
	(0.9153)	(0.9310)	(0.1952)	(0.1964)	(0.1651)	(0.1699)
p1detached	-10.58***	-10.62***	1.233**	1.232**	-0.1090	-0.1101
	(4.005)	(3.968)	(0.4836)	(0.4832)	(0.2213)	(0.2225)
p3bed	1.800	2.441	-1.255**	-1.244**	0.4433	0.4603
	(3.348)	(3.305)	(0.4966)	(0.4936)	(0.3596)	(0.3626)
p4bedup	62.74***	63.40***	3.483***	3.492***	5.277***	5.294***
	(10.22)	(10.16)	(1.130)	(1.135)	(0.5524)	(0.5611)
pbs1_10	-37.68***	-37.31***	-1.650***	-1.642***	-3.133***	-3.122***
	(6.768)	(6.796)	(0.4054)	(0.4048)	(0.3817)	(0.3780)
pbs11_20	-18.07***	-17.83***	1.028***	1.033***	-0.3858	-0.3782
	(5.980)	(5.994)	(0.3988)	(0.3980)	(0.2876)	(0.2847)
pbs21_40	-16.61***	-16.39***	0.7383*	0.7428*	-1.150***	-1.143***
	(4.980)	(5.015)	(0.4125)	(0.4130)	(0.2356)	(0.2335)
p1room	-50.01***	-49.97***	-3.324**	-3.325**	-1.654	-1.654
	(16.84)	(16.87)	(1.430)	(1.430)	(1.133)	(1.133)
p2_5room	4.199	4.123	-1.620***	-1.623***	1.006***	1.002***
	(5.898)	(5.875)	(0.5684)	(0.5680)	(0.3408)	(0.3405)
pvac	52.29***	50.65***	0.1571	0.1230	1.328***	1.279***
	(7.089)	(7.077)	(0.3480)	(0.3582)	(0.3089)	(0.3270)
pcol	78.83***	79.09***	2.871***	2.880***	-0.0333	-0.0223
	(11.40)	(11.40)	(0.5067)	(0.5080)	(0.3335)	(0.3317)
punemp	11.54***	10.35**	0.8506*	0.8243*	-0.3272	-0.3651
	(4.118)	(4.122)	(0.4860)	(0.4729)	(0.2823)	(0.2816)
ppov	55.60***	54.76***	3.048***	3.031***	1.739***	1.715***
	(12.73)	(12.74)	(0.5547)	(0.5453)	(0.2569)	(0.2616)
pnhblk	-14.50***	-14.97***	-0.1708	-0.1839	1.128***	1.111***
	(3.926)	(3.906)	(0.3291)	(0.3288)	(0.2699)	(0.2648)
pasian	-66.38***	-66.38***	-3.267***	-3.267***	-0.7162	-0.7163
	(15.17)	(15.16)	(0.9553)	(0.9551)	(0.6058)	(0.6065)
phisp	-30.47**	-30.45**	-2.666***	-2.667***	-0.7707**	-0.7732**
	(13.31)	(13.25)	(0.8081)	(0.8073)	(0.3450)	(0.3436)
mrent_log	21.11	21.21	0.0378	0.0414	3.856*	3.860*
	(36.63)	(36.55)	(2.978)	(2.977)	(2.094)	(2.093)
mhmval_log	219.4***	228.2***	8.673**	8.955**	10.09***	10.39***
	(38.74)	(40.03)	(3.783)	(3.700)	(1.818)	(1.877)
hinc_log	1,152.2***	1,156.6***	56.19***	56.28***	-4.385	-4.234
	(295.1)	(295.5)	(11.80)	(11.84)	(5.808)	(5.822)
num_tx	4.248***	3.966***	0.0069	0.0014	0.1466	0.1382
	(1.430)	(1.426)	(0.0861)	(0.0838)	(0.1096)	(0.1085)
Fixed-effects						
county	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	1,412,367	1,412,367	1,330,868	1,330,868	1,407,908	1,407,908
R^2	0.26233	0.26177	0.44084	0.44083	0.44890	0.44887
Within R^2	0.15221	0.15157	0.23986	0.23984	0.25406	0.25402

Clustered (county) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*