Measuring the Impact of Property Insurance Premiums on the Mortgage Market

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Abstract

We document that increases in property insurance premiums reduce mortgage originations. The effect is strongest for the rate refinancing and cash-out refinancing segments. We show that denials associated with increased premiums are significantly more likely attributed to high debt-to-income ratios and insufficient collateral. Across the income spectrum, the effect is concentrated among highly levered borrowers. Our results suggest that increases in property insurance premiums could attenuate the refinancing channel of monetary policy as fewer borrowers are able to take advantage of lower rates.

Keywords: Property Insurance, Mortgage Market, Refinancing Channel

JEL Classification: D12, D14, G21, G52, R31

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1 Introduction

The role that property insurance plays in the housing affordability crisis has garnered new attention as premiums have surged in the U.S. over the past decade. Between 2013 and 2024, inflation-adjusted premiums grew on average by 40 percent, (Figure 1), with much of that increase taking place within the last several years. Given that insurance coverage is generally required for obtaining a mortgage, these large premiums increases could have strong implications for the mortgage market. While the effect of these premium increases on mortgage delinquencies has been documented by Ge, Johnson, and Tzur-Ilan (2025), their impact on *access* to mortgage lending—either for a new home purchase or for refinancing an existing mortgage—has not yet been explored.

Increases in property insurance premiums affect mortgage applicants in several ways. First, potential new home buyers may have less access to mortgage credit due to higher overall payments and therefore could face debt-to-income ratio constraints. Second, because insurance premiums are capitalized into house prices (Nyce et al., 2015), current homeowners could face insufficient collateral values in addition to higher debt-to-income ratios when refinancing. Finally, for those who are able to obtain a mortgage, the terms may be less favorable given the additional pressure on their budget from elevated insurance premiums.

This paper asks the question: do increases in property insurance premiums affect prospective and current homeowners' access to the mortgage market? The answer to this question is highly relevant for monetary transmission. If premium increases lower refinancing and purchase mortgage originations, then they attenuate the effectiveness of monetary policy. To answer our research question, we use detailed borrower-level property insurance from McDash and confidential mortgage application data from the Home Mortgage Disclosure Act (HMDA). These data exhibit considerable cross-sectional and time-series variation in property insurance premiums and reasons for mortgage denial. that allow us to identify the effect that changes in insurance premiums have on mortgage denials. To tightly link property insurance premiums and mortgage denials, we examine two channels. First, we examine the extent to which the effect of premiums on denials is driven by higher debt-to-income (DTI) ratios. Second, we assess whether additional denials are due to insufficient collateral.

We find that locations with higher premiums also exhibit higher mortgage denial rates. We estimate that a $1,000 increase in annual property insurance premiums increases the probability of mortgage denial by 2.3 percentage points (or 15 percent) for rate refinancing mortgages. This finding also holds for cash-out refinance mortgages (2.1 percentage points) and new purchase mortgages (0.6 percentage points). Moreover, we find that denied borrowers are not simply shifting to new lenders for approval. We show that in areas of higher premiums, mortgage originations for each of these mortgage type fall by up to 19 percent.

Second, we document a connection between location-specific premium increases and mortgage denial by examining the reasons for mortgage denial. We find that a $1,000 increase in premiums is associated with economically and statistically significant increases in denials due to DTI and collateral. By contrast, denials due to credit history have near-zero changes, and all other denial reasons also have near-zero changes. For rate and cash-out refinancing applications, DTI accounts for up to 70 percent of the denial increase and collateral for up to 40 percent. In addition, we find no clear patterns across income groups for rate and refinancing mortgages. consistent with capitalization of insurance cost into house prices, increases in denial rates due to collateral concerns are similar across all income groups. For new purchase mortgages, insufficient collateral accounts for the lion's share of denial increases. New purchase mortgage denials exhibit some heterogeneity by income. In particular, the impact of premiums on denial for collateral and DTI concerns declines with income. As expected, DTI concerns are not salient for the highest income quartile.

Third, we show that the effects of premiums on denials are larger for borrowers who are more susceptible to income shocks. Specifically, while the estimated effects of premium increases are economically and statistically significant for borrowers with low leverage, we document that the estimated effects are up to five times larger for borrowers with loan-to-value ratio above 80 for rate refinance mortgages. This finding suggests that the borrowers who could benefit most from rate refinancing are the ones most likely to be denied a lower rate mortgage after property insurance premium increases.

Finally, we show our results are robust to concerns that realized insurance premiums among existing homeowners may be a noisy measure of the actual premiums faced by borrowers. In particular, existing homeowners may be responding supply-side changes in price that would introduce error into our proxy for premiums that would be buyers face as they may have different preferences over coverage. We instrument realized premiums with the approved premium—the maximum increase in premiums allowed by the state regulator. The results remain in line with our OLS results, that higher premiums are associated with increased denials of mortgage applications. Consistent with existing homeowners purchasing cheaper insurance after a premium increase, we find somewhat larger coefficients of premium increases on mortgage denials in the IV estimation suggesting our proxy for premiums may understate the true increase holding coverage constant.

Our results contribute to two separate strands of literature. The first is a growing body of work examining the effects of property insurance on various aspects of the housing market. Keys and Mulder (2024) document that increases in property insurance premiums are tied to areas with higher extreme weather risk. Accordingly, Nyce et al. (2015) show that property insurance premiums are capitalized into house prices, focusing on Miami-Dade county—an area with substantial weather exposure. In line with Nyce et al. (2015), we find mortgage denials in areas of high premiums due to insufficient collateral, suggesting that lenders may factor in future insurance costs when making their lending decisions. Studies also find evidence that existing homeowners are impacted by premium changes: Ge, Johnson, and Tzur-Ilan (2025) show that higher premiums lead to higher prepayment and delinquency rates of current borrowers. Finally, some recent literature highlights how rising insurance costs and weather-related risks affect mortgage originations. Blickle and Santos (2022) find that the introduction of mandates for flood insurance led to reduced mortgage originations, particularly for borrowers with lower credit scores and lower incomes. Similarly, Ge, Lam, and Lewis (2025) find that rising flood insurance premiums reduce mortgage take-up. Sastry (2022) and Sastry, Sen, and Tenekedjieva (2024) show how mortgage lenders respond to increased weather risk by increasing denial rates and interest rates — but only when homes cannot be insured by subsidized government property insurance, or when loans cannot be offloaded to GSEs. We add to this literature by documenting the effect of premium increase on mortgage originations and highlight that both new home buyers and current borrowers are affected.

Second, we contribute to the literature on the refinancing channel of monetary policy. Di Maggio et al. (2017) document large effects of refinancing on durable consumption after the 2008 financial crisis. Subsequent research has highlighted the state-contingency of monetary transmission based on the distribution of mortgage rates of outstanding mortgages (Berger et al., 2021; Eichenbaum, Rebelo, and Wong, 2022). The paper closest to ours is Beraja et al. (2018) documenting that differences in home equity affect refinancing and consumer spending after interest rate cuts in the context of the 2008 financial crisis. In contrast, we document a new friction—increases in property insurance premiums—that attenuates the refinancing channel of monetary policy by increasing mortgage denials. Our findings suggest that programs mitigating this friction could stimulate consumption in the spirit of Agarwal et al. (2022) who document the consumption effects of refinancing in the context of government program insufficiently collateralized refinanced mortgages.

This paper proceeds as follows. Section 2 describes the data, and section 3 provides the summary statistics. In section 4, we develop our hypotheses and describe our empirical approach. We present the results in section 5. Section 6 concludes.

2 Data

2.1 cHMDA Mortgage Application Data

To analyze mortgage applications and denials, we use data from the Confidential Home Mortgage Disclosure Act Database (cHMDA). This loan applicant-level data contain a range of demographic and economic characteristics, as well as information on the loan itself. Unlike the public version of the HMDA database, the confidential data also include the census tract of the property that the mortgage would apply, exact dates for the application and ultimate action (e.g. denial or origination), and exact measures of credit score, debt-to-income ratio, and property value. This geographic and temporal granularity allows us to more precisely match mortgage applications to data on local insurance premiums, and other detailed information from the confidential version enriches the controls in our analysis. We also merge the cHMDA reporter file onto the applicant-level data, which contains information on the lender that reported the data.

Our cHMDA sample spans from 2018 to 2024. In 2018, cHMDA was expanded to include more detailed data on applicants, so we begin our sample here, and 2024 is the most recent year for which data is available in the confidential HMDA. This is also the period in which insurance premiums began to notably accelerate (Keys and Mulder, 2024). We restrict the sample to three types of mortgage applications: home purchase mortgages, cash-out refinances, and other refinances. We exclude loans for business or commercial purposes and reverse mortgages. Finally, we drop loans that were withdrawn before a decision was made and closed for incompleteness.

In cHMDA data, the finest level of geographic detail is the census tract, while Black Knight McDash data is available at the ZIP code level. In order to merge cHMDA applicants with data on premiums, we use census-tract-to-zip-code crosswalks from the Department of Housing and Urban Development (HUD). As the relationship between tracts and zip codes is not one-to-one – tracts may sit within multiple ZIP codes – the HUD crosswalks contain different weights. We use the residential weight, which is calculated based on the proportion of a census tract's residential units that are located in a given ZIP code. Therefore, all of our analyses apply this ZIP code residential weight.

2.2 Black Knight McDash Insurance Premium Data

Our data on insurance premiums comes from Black Knight McDash data, which tracks about two-thirds of residential mortgages in the United States using data from mortgage servicers. The McDash Residential Mortgage Servicing Database is our primary database, which reports monthly information on each mortgage. This database can be merged with the McDash Property Insurance Module. The insurance module covers about three quarters of the mortgages in McDash, reporting data on insurance premiums including coverage, deductibles, premiums, and secondary home insurance policies such as flood and earthquake insurance.

We use a sample of this data that only includes mortgages on single-family homes, and condition on the existence of data on the monthly insurance premium. Our sample spans from 2018 2023, to align with the cHMDA sample.

While a merged McDash-cHMDA dataset does exist, this dataset conditions on applicants successfully originating a loan. Thus, we cannot use it to measure the probability of denial for mortgage applicants. Instead, in order to combine the insurance premium data with cHMDA we collapse the Black Knight McDash data into a monthly panel at the 3-digit zip code level. This panel captures the average annual insurance premium for insurance policies that became effective in a given month. Prior to 2023, insurance data is only available for December of each year, but because the effective start dates of these policies vary, we are able to create a monthly panel. We drop any 3-digit zip-years of Black Knight McDash that have less than 50 insurance policies. We join this panel onto the cHMDA data using the aforementioned tract-ZIP crosswalks.

2.3 CRISM Credit Panel

In future analysis, we plan to use individual-level data on current mortgage holders using CRISM credit panel data, which contains Equifax credit data merged to McDash mortgage information. With this data, we are able to identify individual-level changes in insurance premiums. We can also track mortgage refinancing, as well as credit inquiries and other borrowing activity.

2.4 Additional data sources

Rate filings data. We also use data on home insurer's rate filings to state regulatory agencies to strengthen our analyses. In our initial analyses of the relationship between insurance premium increases and mortgage denials, we use Black Knight McDash data on newly issued insurance policies to generate monthly average premiums for each 3-digit zip code. This has a fundamental limitation: the set of newly-issued insurance policies captures both insurer-side premium increases, and consumer-side choices about how to adjust their policies in response to a changing insurance market. This mismeasurement could bias our estimates in both directions: households may reduce the quality of their insurance policies to attain lower premiums (Cookson, Gallagher, and Mulder, 2025; Sastry et al., 2025), — in fact, researchers find that households will seek lower premiums by reducing coverage below expected losses, perhaps due to a combination of irrational "coverage neglect" and financial constraints. At the same time, if they perceive that risk is increasing, households may also improve their coverage in response.

Rate filings data allow us to isolate supply-side changes in observed average premiums in the Black Knight McDash data. Insurers are required to submit rate change proposals to the state insurance regulators for information and in some states approval. To do this insurers use the System for Electronic Rates & Forms Filing (SERFF) platform, which was implemented in 2004.[1] These filings are for policies written to policyholders in the particular state (so an insurer files requests based on policyholder location, not the location of the insurer's headquarters) and the vast majority of personal homeowners policies are covered under these filings.[2]

The median insurer in the data submits one homeowners insurance rate change per year in each state, which usually covers all of their written policies in the state. In the rate filing data we observe aggregate information about each filing including the total policies affected, total premiums affected, the rate approved, and the date the rate change goes into effect.

From the insurers' rate filings we observe the average rate change for homeowners policies across the entire state, while in our primary analyses we aggregate Black Knight McDash insurance premium data to the 3-digit zip code level. In order to create a zip-code level measurement of rate filings, we use Black Knight McDash to create a monthly measure of insurer market share within a 3-digit zip code. We join each insurer's state-level rate filings onto this market share panel to create a monthly weighted average of approved premium increases (which are reported in percentage terms).

Next, we turn these 3-digit zip-level average premium increases from percentage values

[1]We obtain these filings from SNL Financial. SNL Financial LC. Contains copyrighted and trade secrete material distributed under license from SNL.

[2]FAIR Plans and residual market insurers do not file rate changes through SERFF and some smaller insurers do not file rate filings individually.

to dollar values. We do so using a monthly panel of outstanding home insurance policies from Black Knight McDash, to calculate average monthly premiums for each 3-digit zip. We multiply the average approved premium increases by the average premiums one year prior to generate, in dollar terms, a monthly measure of approved premium increases.

Secondary control variables. We also use a series of secondary variables as controls in our analyses. We use conforming loan limit values from the Federal Housing Finance Agency – defined annually by county – to indicate applications for jumbo loans. We use zip-tract crosswalks from the U.S. Department of Housing and Urban Development to connect HMDA data, which reports census tracts, to Black Knight McDash data, which we aggregate at 3-digit zip code level. To control for county economic conditions, we use Zillow's home value index and unemployment rates from the Bureau of Labor Statistics. Finally, we use annual county controls from the American Community Survey, including variables on race, income, college education, the homeownership rate, and the proportion of homeowners with outstanding mortgages.

3 Summary Statistics

Table 1 provides summary statistics, with each column representing one of three samples defined by mortgage application type: rate refinance, cash-out refinance, and new purchase. The data include the near-population of mortgage applications from January 2018 through December 2024. On average, roughly 16% of rate refinance applications, 21% of cash-out refinance applications, and 11% of new purchase applications are denied during our sample period. Across all three samples, high debt-to-income ratio was the most common reason for application denial (29-34%), followed by insufficient collateral (12-15%).

Average income ranged from \$109,500 among cash-out refinancing applicants to \$125,000 among rate refinancing applicants. Similarly, on average rate refinancing applicants had the highest average credit score (751), while cash-out refinancing applications had the lowest average credit score (721) The youngest applications comprised those buying purchasing a new home, with an average age of 41.

Across the three samples, aggregate county level demographic characteristics are relatively similar. The average share of the white population within a county is around 65%. The average share of people with a college degree ranges from 36-38%, while the share of homeowners is around 65%. The average county unemployment rate is highest among the rate refinancing applicants and lowest in among the new purchase sample.

Panel (a) of Figure 4 shows the aggregate rate refinance applications scaled by the total stock of outstanding mortgages each month. The dashed line shows the gap between the current 30-year fixed mortgage rate and average interest rate on existing mortgages. As expected, when the gap is negative, i.e. the current mortgage rate is lower than the existing stock's rate, applications to refinance mortgages for the purpose of interest restate increases. By contrast, applications for cash-out refinancing (panel b) are less sensitive to to swings in rates.

Finally, panel (c) shows applications for loans on new purchases scaled by the total stock of existing mortgages. This time the solid line shows the 30 year mortgage rate. By contrast to refinancing applications, new purchase loans declined between 2018 and 2021 and began to rise starting in January 2022.

Figure 3 shows the aggregate denial rate by mortgage loan application type over time. While denial rates for new purchases is relatively stable, denial rates for rate refinancing follows a cyclical pattern that is negatively correlated with application rates.

[Need to add map summarizing premium data by county]

4 Empirical

In this section, we first develop our testable hypothesis. We then present our baseline specification. Last, we describe our instrumental variable strategy.

4.1 Hypotheses Development

We are interested in the impact of increases to homeowners insurance premiums on the mortgage market. Higher insurance premiums should, all else equal, increase the propensity of a mortgage application denial because higher property insurance increase monthly expenditures and reduces a household's available income—that is, higher insurance premiums lower the debt-to-income ratio and reduce the value of the collateral. Since insurance premium increases similarly affect current and prospective house owners, the effect should be present in refinancing and new mortgage applications.

Hypothesis 1 Applications in locations with larger property insurance increases have higher denials rates for all application types.

Denials by themselves do not indicate lower credit supply to a location with larger property insurance increases as borrowers could simply apply at a different lenders. However, if property insurance premium increases are the cause for denial, then this should be the case for all lenders, and we expect less mortgage origination in these locations.

Hypothesis 2 Locations with larger property insurance exhibits lower mortgage origination volumes.

It also follows that if denials are driven by higher insurance premiums, then we should also observe that either debt-to-income ratio or collateral concerns are given as reasons for an application denial. Specifically, higher monthly premiums directly impact the calculation of debt-to-income ratios, as they raise the cost of debt servicing. Thus, higher premiums could push an applicant's debt-to-income ratio above a limit. Moreover, higher insurance costs could be directly capitalized into lower housing prices (Eastman, Kim, and Zhou, 2024; Keys and Mulder, 2024). Higher insurance costs could also cause lenders to update their perceptions of weather-related risk, lowering the property's value. In a study of flood insurance prices, Ge, Lam, and Lewis (2025) find that higher insurance costs lower home values through both the capitalization and risk-updating channels.

Hypothesis 3 Debt-to-income ratio and collateral concerns are more likely to be cited as reasons for denials in locations with larger property insurance premiums.

While insurance premiums increase the debt service of borrowers, borrowers' housing choices reflect their income and hence we cannot make a clear prediction with respect to income heterogeneity. However, we expect the effects to be larger for highly leveraged borrowers across the income spectrum for whom insurance increases may me most binding.

Hypothesis 4 We expect denial rates to be higher for more leveraged borrowers.

In section 5 we test these hypotheses using our data on property insurance premiums and mortgage applications.

4.2 Baseline specification

We now describe our baseline specification to test the hypotheses developed above. As described in Section 2, our premium data are derived from realized choices of homeowners. We start by running a regression of zip code level homeowners' realized insurance premiums on an indicator that takes on a value of one if a loan application is rejected, and zero otherwise.

$$Prob(Reject)_{ijt} = \beta_0 + \beta_1 P_{ijt} + \beta_3 X_{ijt} + T_t + \lambda_j + \epsilon_{ijt} \tag{1}$$

We include as controls the applicant's debt to income ratio, income, credit score, and age. We also control for loan level characteristics including an indicator for loan type (FHA, VA, FSA, jumbo loan) and an indicator for non-bank originators. Finally, we control for time-varying county level demographic characteristics such as the share of the White population, the share of the population with a bachelor's degree, the share of homeowners, the share of homeowners with a mortgage, the unemployment rate, and a home value index.

One concern is that changes in insurance premiums are due to factors like extreme weather events, that also impact the lender's decision to approve a loan. We account for these factors by including granular geographic fixed effects under the assumption that such changes develop slowly over time. Given that are data are a short-panel spanning less than 10 years, we believe this assumption is not unreasonable. That said, we note this possible omitted variable bias as a caveat when interpreting results.

4.3 Instrumental Variables Model

Given the construction of our premium data from existing homeowners, any change in the realized premium, which we measure as a 3-digit ZIP code average, reflects changes driven by both supply and demand: we are capturing both insurer-side increases in the cost of insurance, and consumer-side adjustments to their policy, including shopping for a new insurer or changing coverage levels. In particular, past literature (Cookson, Gallagher, and Mulder, 2025; Sastry et al., 2025) shows that households are more sensitive to insurance price rather than coverage amount. When premiums rise, if households respond by decreasing their coverage (and lowering their bill), then the realized price will not reflect the true price increase of a given region. In this example, our proxy would understate the price of insurance. On the other hand, if insurance prices were to rise, a household may see that as a signal of increased risk where they live and choose to purchase more coverage. In this case, the observed price could overstate the true price increase for that area.

To account for measurement error that may be correlated with the premium change itself, we rely on an instrument variables approach using temporal and geographic variation in insurance premiums generated through regulatory requests made by insurance companies. The exclusion restriction is that insurers' rate filings only affect mortgage applicants' probability of denial through their impact on realized insurance premiums. While we are unable to test this assumption directly, it is unlikely that lenders are aware of the allowable changes insurance companies can make to their premiums or that loan applicants would change their behavior based on the allowable price changes an insurer can make. On the other hand, the premiums households face is strongly related to these allowable price changes. This relationship is confirmed by the following first stage regression:

$$P_{ijt} = \alpha_0 + \alpha_1 \rho_{jt} + \alpha_3 X_{ijt} + T_t + \lambda_j + \varepsilon_{ijt}. \tag{2}$$

We use the predicted values for observed premiums to measure the impact of insurance premiums on the likelihood of mortgage application rejections:

$$Prob(Reject)_{ijt} = \beta_0 + \beta_1 \hat{P}_{ijt} + \beta_3 X_{ijt} + T_t + \lambda_j + \epsilon_{ijt} \tag{3}$$

Finally, we look at intensive margin responses by both lenders and borrowers. Conditional on having a new purchase application accepted, we also estimate the impact of (instrumented) premiums, on different measures of mortgage costs:

$$Y_{ijt} = \beta_0 + \beta_1 \hat{P}_{ijt} + \beta_3 X_{ijt} + T_t + \lambda_j + \epsilon_{ijt}. \tag{4}$$

where Y_{ijt} includes the lender outcomes of the interest rate on the loan and the LTV ratio. We also look at applicant responses to lower loan costs including the probability of paying discount points and total discount points associated with a loan. Together with the extensive margin responses, we provide a more comprehensive analysis of how insurance prices can influence the overall mortgage market.

5 Results

5.1 Baseline Specification

We start our analysis by estimating the relationship between property insurance premiums and the probability of mortgage application denial for each application type (Hypothesis 1). We conduct this analysis using the average realized premium increases at the 3-digit zip code level as our main explanatory variable.

Table 2 gives the results from estimating our baseline specification, equation 1, where each column represents the application type (rate refinance, cashout refinance, and purchase mortgage). Column (1) shows that rate refinancing mortgage applications are significantly more likely to be denied in locations with larger realized premiums. This effect is also economically large: a \$1,000 increase in observed monthly insurance premium is associated with a 2.3 percentage point increase in the denial of rate refinance applications, compared to an average denial rate of 15.7 percent. Similarly, we find significant effects for cash-out refinance applications, indicating a 2.1 percentage point increase in the probability of denial in locations with a \$1,000 increase in observed monthly insurance premiums, or a ten percent increase in the denial rate relative to the mean (Column (2)). Column (3) shows that higher premiums are also associated with increased denials of new home purchase applications, though the effect is smaller than for refinancing mortgages. For new purchase mortgages, a \$1,000 increase in observed monthly insurance premiums is associated with a 0.6 percentage point increase in the denial rate, relative to a mean of 10.6 percent.

Higher property insurance premiums are related to higher denials rates of mortgage rate refinancing and cash-out refinancing, suggesting that price increases in property insurance could attenuate a key mechanism of monetary transmission: the refinancing channel (Berger et al., 2021; Eichenbaum, Rebelo, and Wong, 2022). When the refinancing channel is restricted, households are less able to take advantage of lower interest rates, and the associated consumption effects.

Next, we turn to the aggregate effect of property insurance premiums on local mortgage markets by estimating its impact on application and origination volumes (hypothesis 2). Volumes capture the possibility that denied borrowers simply apply for another loan with a different lender. Since our data do not follow individuals across time, we instead aggregate our data to the county level to capture possible repeat applications by the same applicant. One caveat, however, is that changes in application volume also reflect changes in credit demand. In particular, an increase in loan volume driven by repeat loan applicants could be offset by a decline in applications due to anticipation of tightening credit.

Table 3 shows results from estimating equation 1 at the county-year level with total mortgage applications and originations as the outcome variable. Hence, we implement a similar style of two-way fixed effects estimate to provide evidence that counties with rising insurance premiums are also seeing a reduction in mortgage applications. Column (1) shows that for a $1,000 increase in realized premiums, the number of annual purchase applications declines by 6.4 percent relative to the mean (111 applications), though the result is only statistically significant at the 10 percent level. Annual originations also decline significantly. Column (2) shows that for the same premium increase, the number of originations falls by 113, or 7.8 percent relative to the mean. The effects are meaningfully larger for rate refinancing, with a reduction of 21 percent in the number of applications and of 19 percent in the number of originations for a $1,000 increase in the property insurance premium (columns (3) and (4)). We find similar effects for cashout refinancing with a reduction of 16.5 percent in the number of applications and of 19 percent in the number of originations for the same property insurance premium increase (columns (5) and (6)).

Overall, we find that rising insurance premiums are associated with a decrease in mortgage originations both via a decline in applications and an increased probability of denial after application. Our results complement the findings of Ge, Johnson, and Tzur-Ilan (2025), which show that increasing insurance premiums cause households to pre-pay their mortgages and move to lower-priority areas. While the Ge, Johnson, and Tzur-Ilan (2025) study focuses on existing homeowners, we show that a similar pattern exists among all new potential buyers. We additionally document that elevated homeowners insurance premiums may limit households' ability to both lower monthly mortgage payments and extract equity through refinancing.

5.2 Inspecting Reasons for Denial

To shed light on the mechanisms underlying rising denial rates and lower mortgage applications and originations, we investigate the reason for denial. The confidential HDMA data provides the lender-reported reason for denial. We focus on four categories: debt-to-income (DTI) ratio, collateral, credit history, and all other reasons.[3] Increases in property insurance premiums increase the debt-to-income ratio, as premiums are included in the debt calculation. As such, we expect that lenders in places with higher property insurance premiums cite the debt-to-income ratio more frequently as a reason for denial. Additionally, higher property insurance costs should reduce the value of a property by increasing user cost and potentially signaling higher future costs for homeowners due to more frequent insurance events and prevention. Hence, lenders in places with higher property insurance premiums may be more likely to cite insufficient collateral as a denial reason. In contrast, we would not expect property insurance to factor in if a denial is due to credit quality concerns (e.g. credit history). By assessing the relative importance of these two reasons for denial in places with larger property insurance bills, we test our third hypothesis.

Table 4 shows that across all three application types, a $1,000 increase in realized premium is associated with economically meaningful and significant increases in denials due to DTI and collateral, while denials due to credit history — one of the most common reasons for mortgage denials, but unlikely to be related to homeowners' insurance — have near-zero

[3] The full list of reasons are: debt-to-income ratio, employment history, credit history, collateral, insufficient cash, unverifiable information, credit application incomplete, mortgage insurance denied, and other.

changes, and all other denial reasons also have near-zero changes.

To gauge the relative importance of these increases, figure 4 plots the coefficients of estimating equation 1 with the respective denial reason as the explanatory variable, where the plotted coefficients sum to one to show shares. The top panel shows that for rate refinancing mortgages, almost 70 percent of the increase in denials is attributable to debt-to-income ratio concerns (the red dot) with the rest being attributed to collateral concerns (the yellow dot). Credit history and other concerns are not differentially cited as the reason for denial in places with higher premiums.

The middle panel showing the results for cash-out refinancing mortgage similarly shows that almost all of the increase in denials can be attributed to debt-to-income ratio concerns (50 percent) and collateral (40 percent).

The bottom panel of figure 4 shows the results for denial composition of mortgages used for new purchases. In this subsample, collateral accounts for much of the increase in denials. This result is to be expected since home buyers do not control appraisals that are more likely to factor in future costs and exposure to various risk. While our results suggest a higher quality pool of applicants (the negative coefficient on credit history), debt-to-income ratio concerns still account for a significant share of the denial increase, suggesting that higher insurance premiums play a role.

Taken together, this figure shows that DTI denials can explain 40-70% of the measured increase in denials documented in Table 2, and collateral denials can explain 30-80%, while all other denial reasons are marginal.

5.3 Are the effects income-dependent?

A natural question is whether the changes in mortgage denial patterns are driven by specific income groups. For instance, high income borrowers may be less likely to face binding constraints, particularly for debt-to-income ratios. On the other hand, the effect of property insurance premium increases should affect the collateral similarly for all income groups.

Figure 5 (top panel) shows the results of estimating equation 1 after splitting the sample across quartiles of applicant income for any denials reason, debt-to-income ratio denial, and collateral denials for rate refinancing mortgages. The plot shows proportional increases in denial rates, meaning that the coefficients are normalized by each denial type's average rate for each denial reason. We find that a $1,000 increase in the insurance premium is associated with increases in denial rate (shown in grey) that peaks for the middle income range.[4] Debt-to-income ratio concerns (in red) increase most for high incomes potentially because these income groups have larger, more expansive houses for which insurance is a more sizable share of income. Last, the effect on collateral as the denial reason (shown in blue) is similar across income group consistent with property insurance premium increases decreasing all property values.[5] We find similar results for cash-out refinancing mortgages shown in the middle

[4] In the appendix, table A1 shows the denial probabilities when insurance premiums rise by income bin. We find that the effect of a $1,000 increase in realized premiums decline in income but remains statistically and economically significant even for the highest income quartile.

[5] All coefficients for denial reason by income quartile are shown in the appendix table A2.

panel.

The bottom panel shows the results for new home purchase mortgages, where effects are larger for collateral denials. This is consistent with unexpected low appraisals, relative to the effects of larger insurance premium increases on debt-to-income ratio denials.

Taken together, we find evidence that mortgage denials increase across the income spectrum with the percent increases being comparable across the four quartile. However, due to lower overall denial rates though the absolute effects are smallest for high income borrower.

5.4 Do highly levered borrowers drive the results?

A second plausible mechanism that can account for our result is that property insurance premium increases are particularly problematic for highly leveraged borrowers, those with loan-to-value ratios over 80%. Being above this threshold means that lenders less likely to be sold the mortgage to government-sponsored enterprises and have to keep these mortgages on the balance sheets. Since high-leveraged borrowers are more susceptible to (income) shocks, we would expect that lenders are more likely to deny these borrowers after large increases in property insurance premiums. This is the key prediction of our fourth hypothesis: the effects of property insurance increases are larger for applicants with a higher loan-to-value ratio, as they are riskier — and perhaps more marginal — applicants.

Table 5 shows our results, split between applicants with loan-to-value ratios below 80, or 80 and above. For both rate refinance mortgages (top panel) and purchase mortgages (bottom panel) the increase in denials for a $1,000 increase in premiums is substantially larger for applicants with an loan-to-value above 80, further showing that higher-risk applicants are more affected by higher insurance costs. Hence, the results support our fourth hypothesis.

For cash-out refinances (middle panel), the results differ: among the lower half of borrower incomes, we see the opposite pattern, with lower-loan-to-value-ratio borrowers seeing denial rates rise more. One potential explanation for this pattern is that the conditional probability of denial of borrowers with high loan-to-value ratio is already very high (52 percent for borrowers with incomes under $56k). Given that these borrowers applied to extract even more equity from a highly leveraged asset, it is perhaps unsurprising that property insurance premium increase are somewhat less salient for this mortgage type.

Taken together, we find support for more leverage borrower being more likely to be denied a rate refinancing or new purchase mortgage, consistent with already constrained borrowers being more susceptible to additional income shocks.

5.5 Instrumental variable approach

Recall from Section 2, that our measure for the expected insurance premium faced by an applicant is derived from the average, realized policy decision of existing homeowners at the 3-digit ZIP code level. As such, it includes both changes made by supply side and demand side pressures. To isolate prices changes driven by insurer behavior, we instrument for household premiums using the allowable premiums facing insurers that are set by regulators.

We estimate equations 2 and 3 and present the results in Tables 6 and Tables 7, respectively.

Table 6 shows that across all three samples, the allowed premium rate derived from rate filings is a strong predictor of average realized insurance premiums. The coefficients vary modestly across the three mortgage samples. For the rate refinance, cash-out refinance, and purchase mortgage samples, respectively, a dollar increase in approved premium correlates with a 0.94, 0.69, and 0.84 dollar increase in realized premium.[6] Thus, the approved premium change seems to be a strong predictor of the realized premium.

We present the results from estimating equation 3 in Table 7, where the probability of application denial is our outcome variable. For completeness, we also include in Table 7 the reduced form results when allowable premium is directly controlled for. For rate refinance applications, a $1,000 increase in instrumented premium leads to a 2.9% increase in denials, compared to the OLS estimate of 2.3%. For cash-out refinance applications, the IV estimate is substantially larger than the OLS estimate: a $1,000 increase in premium leads to a 13.1% increase in denial rate compared to the 2.1% with OLS. Finally, for purchase applications, the IV estimate is a 1.6% increase compared to a 0.6% estimate with OLS.

5.6 Other mortgage level outcomes

Next, we study the extent to which lenders may respond to rising insurance costs on other mortgage outcomes, conditional on origination. While our previous results show how the extensive margin of mortgage origination is impacted by premium increases, these results

[6] The F-Statistics are large: 14,032, 14,276, and 26,411 respectively.

highlight other margins by which households and lenders may adjust.

We begin with OLS results on this sample of originated mortgages, with results displayed in Table 8. In Columns (1), we report that a $1,000 increase in insurance premiums is associated with a 0.36 percentage point decline in the loan-to value ratio of originated mortgages, complementing the results in Table 5 and potentially suggesting a lender-side adjustment to higher default risk (Sastry, 2022). Additionally, perhaps in response to higher payments for premiums, borrowers appear to adjust their behavior to lower their monthly mortgage payments when premiums rise. In particular, we look at the extent to which potential buyers in high premium areas are more likely to pay for discount points, and if so, how much do they pay upfront. Columns (2) and (3) of Table 8 show for $1,000 increase in insurance premium, the likelihood of purchasing discount points increases by 0.4 percentage points, while the amount spent on discount points increases by $163. In Column (4), we report that the interest rate declines slightly, by 0.04 percentage points, which may be due to the purchase of discount points.

Next, we report results for the same set of mortgage outcomes using out instrumented premium measure. Column (1) shows a substantially higher response in LTV, with LTV declining by 1.32 percentage points. Columns (2) and (3) of Table 9 show for $1,000 increase in insurance premium, the likelihood of purchasing discount points increases by 7.5 percentage points or 21%. Although potential homeowners in these high premium areas are more likely to purchase points, the amount purchased is on average $800 lower compared to areas with lower insurance premiums. This suggests a possible composition change in the pool of discount point buyers, whereby the average purchaser of discount points due to insurance premiums may be more liquidity constrained or simply demand a smaller discount.

Finally, we find that a \$1,000 dollar increase in insurance premium, is associated with 32 basis points increase to the interest rate on an originated loan. This higher interest rate could reflect a higher perceived risk in these areas even among approved loans.

6 Conclusion

We show that increases in property insurance premiums are associated with significant increases in the denial of refinancing and new purchase mortgage loan applications. Reasons given by lenders associated with these denials, DTI and collateral concerns, are consistent with insurance premiums driving the result. Specifically, insurance premiums are both incorporated into DTI calculations and have been shown to be capitalized into house prices.

Our results have implications for policymakers, suggesting that the refinancing threshold—the amount of interest savings to be "in the money"—for current homeowners may be significantly higher. Importantly, we find that the effects are significantly larger for highly leveraged borrowers who would benefit most for rate refinancing when interest rates fall. Hence, current and future increases in property insurance premium are likely to attenuate the refinancing channel of monetary policy. Moreover, the sharp increase in denials due to insufficient collateral suggests that house price growth in high premium locations may slow down as borrowers in these locations face tighter lending conditions.

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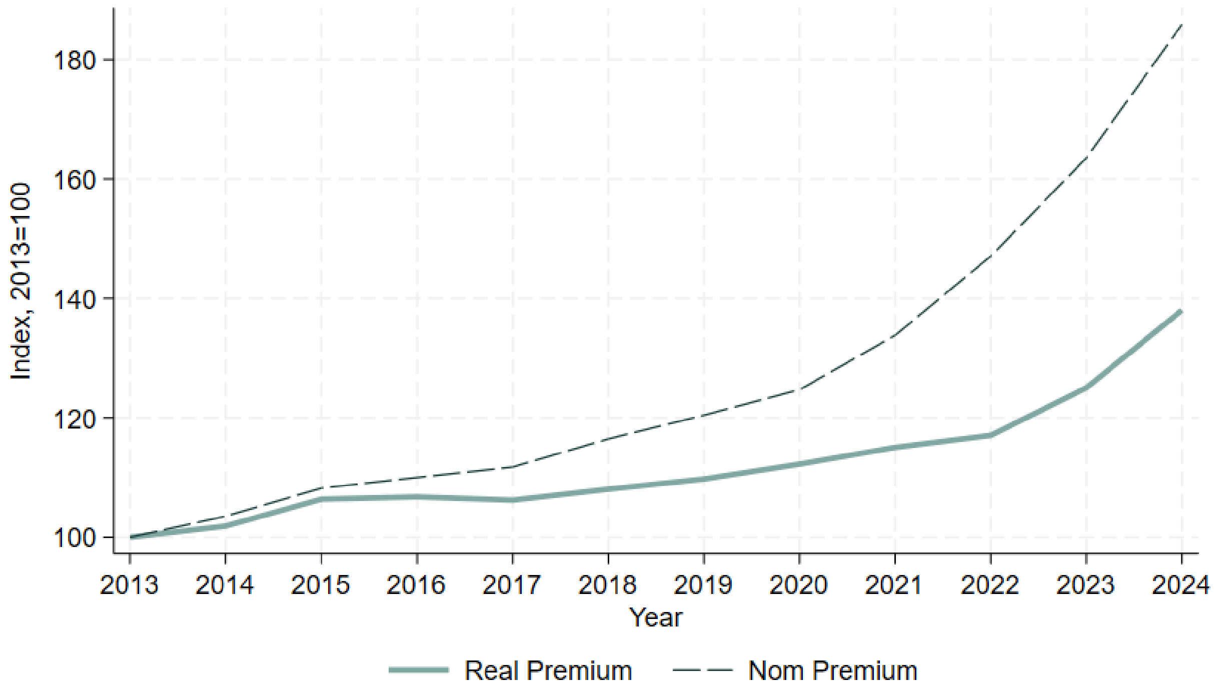
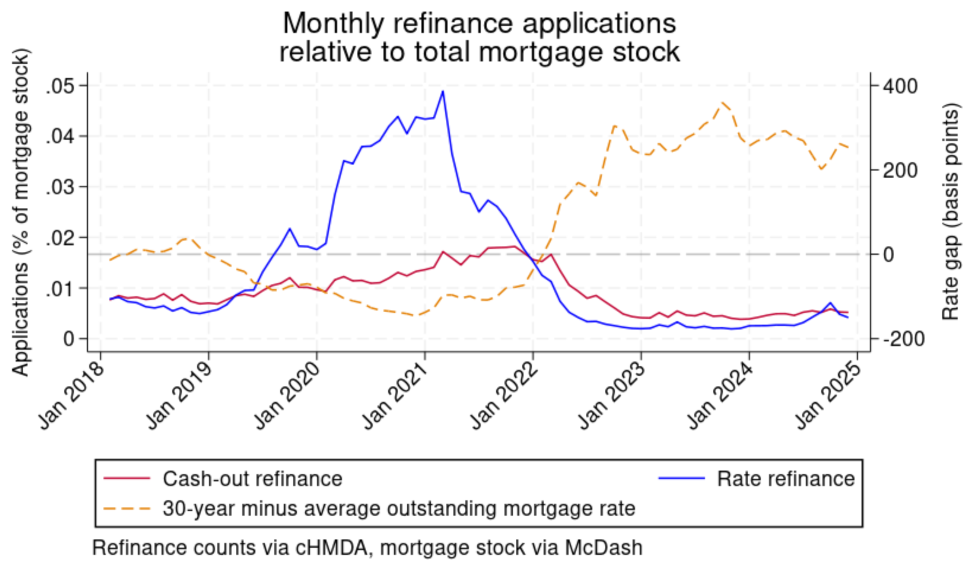
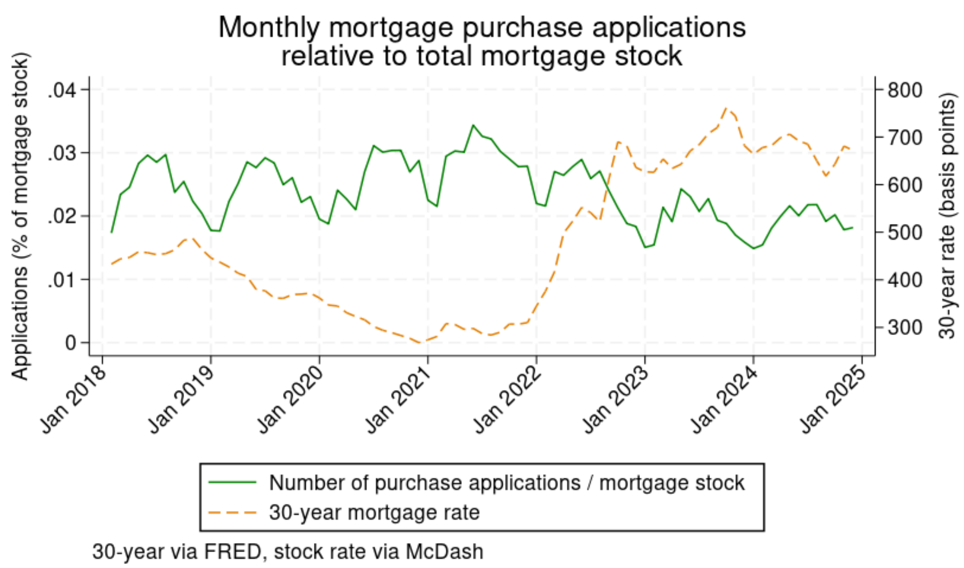
Figure 1: Annual Insurance Premiums (2013=100), 2013-2024



Notes The figure plots inflation adjusted average premiums each year from McDash against the (solid line) along with nominal average annual premiums (dashed line).

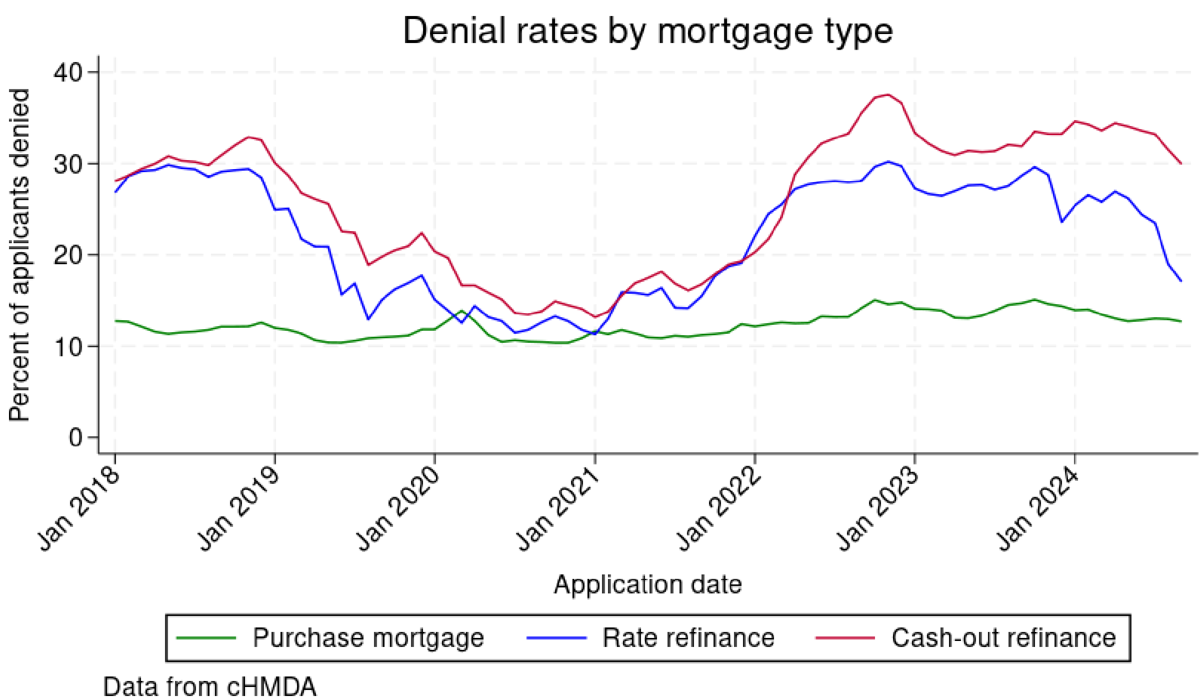
Figure 2: Refi and Purchase Applications, 2018-2024





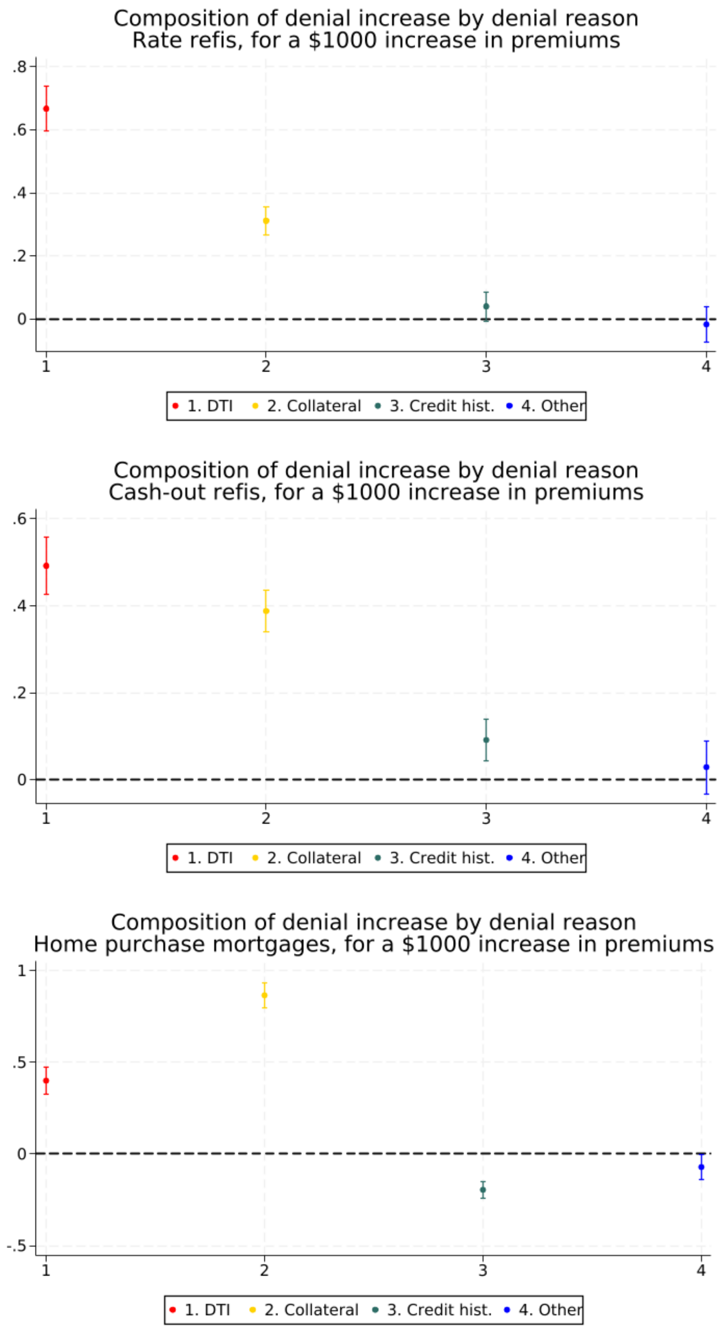
These figures depict the monthly number of applications for different types of mortgages in the HMDA from 2018 through 2024, scaled by the total stock of mortgages. HMDA counts are based on the application date and include all applications regardless of outcome. The stock of mortgages is taken from the McDash dataset, counting all outstanding mortgages each month. The outstanding mortgage rate, as depicted in the top panel, is also calculated from the stock of mortgages in McDash, while the market 30-year rate comes from FRED.

Figure 3: Refi and Purchase Denial Rates, 2018-2024



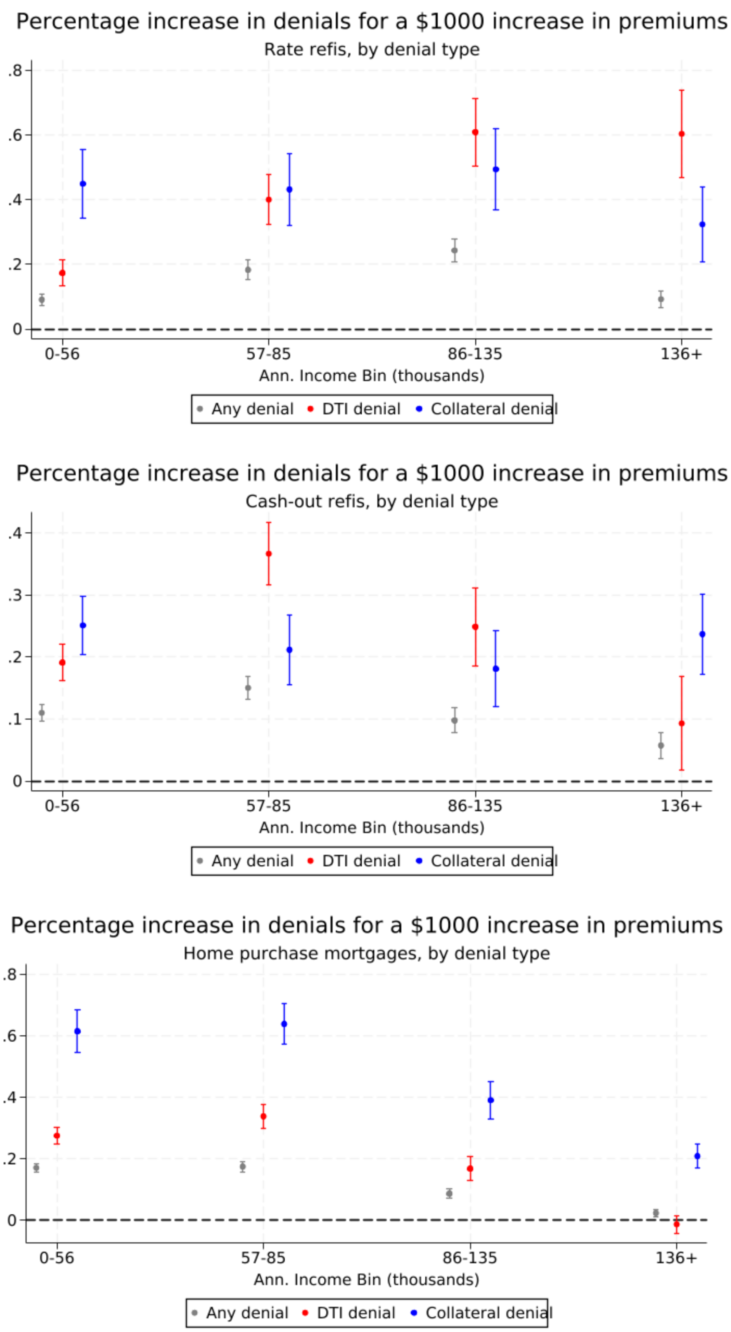
This figure uses data from the confidential HMDA to show mortgage denial rates, calculated by month, for different types of mortgages from 2018 through 2024. This subsample of the HMDA excludes mortgages that were withdrawn or closed for incompleteness, as described in Section 2.1.

Figure 4: Reasons For Denial, by Application Type



From the increase in mortgage application denials documented in Table 2, this figure plots the composition of denial reasons. The plotted coefficients are created by first running a version of 1, our baseline regression showing the relationship between zip3-level premium increases and the probability of application denial. In this case, the outcome is application denials for a particular reason (debt-to-income ratio, insufficient collateral, etc.). For each denial reason, the coefficient on realized premiums is then scaled by the coefficient on realized premiums for all denials. Thus, the results sum to 1, giving the "composition" of reasons for increasing denial rates.

Figure 5: Reasons For Denial, by Income



This figure plots the percentage increase in mortgage denials for each of the four income bins. The coefficients come from first running versions of 1 with each denial reason as the outcome variable, separately for each income subsample. To turn these baseline regressions into percentage increases, they are scaled by the average denial rate for each type of denial within each income group.

Table 1: Summary Statistics, 2018-2023

	Rate Refi (1)	Cash-out Refi (2)	New Purchase (3)
Application Denied	0.157	0.211	0.105
Reason for Denial			
High Debt-To-Income	0.325	0.289	0.343
Insufficient Collateral	0.121	0.152	0.133
Other	0.561	0.559	0.524
Preapproval	.	.	0.056
Non-Bank Loan	0.593	0.663	0.655
Debt-to-Income	35.49	38.86	39.30
Income (1000's $)	126.5	109.5	118.3
Credit Score	750.8	721.2	729.3
Age	48.96	52.75	41.53
Annual Premium ($)	1,504	1,565	1,639
Δ Annual Premium ($)	86	109	118
Share White in County	0.641	0.643	0.654
Share Bachelors in County	0.383	0.369	0.363
Share Homeowners in County	0.649	0.650	0.655
County Unemployment Rate	6.187	5.131	4.863
Observations	26,906,593	19,125,262	44,037,086

Notes: Column (1) gives summary statistics on the population of individual applicants refinancing their mortgage rate between 2018-2024. Column (2) gives summary statistics on the population of individual applying to extract equity from their mortgage loan between 2018-2024. Column (3) gives summary statistics on the population of individuals applying for a new home purchase. All three samples are restricted to have non-missing observations for all sample characteristics.

Table 2: Probability of Application Rejection, OLS

	Rate Refi (1)	Cash-Out Refi (2)	New Purchase (3)
Realized Premium	0.023***	0.021***	0.006***
	(0.001)	(0.001)	(0.000)
Avg Denial Rate	0.157	0.211	0.105
Controls	Y	Y	Y
Month-Year FE	Y	Y	Y
Zip Code FE	Y	Y	Y
Observations	26,906,593	19,125,262	44,037,086

Notes: Table presents results from estimating equation 1. Each regression includes controls the variables listed in Table 1, as well as month by year fixed effects, and zip code fixed effects. The average mean outcome for each regression is also provided for reference.
*, **, and *** reflect statistical significance at the 10, 5, and 1% level.

Table 3: County Level Results on number of originations, 2018-2024

	Purchases		Rate Refis		Cash-out Refis	
	Applications	Originations	Applications	Originations	Applications	Originations
	(1)	(2)	(3)	(4)	(5)	(6)
Realized Premium	-110.658*	-113.455**	-295.596**	-213.255**	-155.841**	-131.517**
	(56.625)	(52.222)	(133.795)	(105.700)	(64.975)	(56.954)
Mean value	1723.81	1454.72	1399.96	1114.17	936.35	694.34
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y
Observations	19765	19765	15102	15102	14581	14581

Notes: This table reports results from a modified version of 1, where results are instead reported at the county-year level. The regressions include county-level averages of the individual-level controls listed in Table 1, as well as county and year fixed effects. For each of the purchase, rate refinance, and cash-out refinance samples, we test the total number of applications and originations as the outcome. The mean values are reported for reference. *, **, and *** reflect statistical significance at the 10, 5, and 1% level.

Table 4: Probability of Application Rejection, OLS by denial reason

	Denial Rate			
	DTI	Collateral	Credit Hist.	Other
	(1)	(2)	(3)	(4)
	Panel A. Rate Refinance			
Realized Premium	0.015***	0.007***	0.001*	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	26906593	26906593	26906593	26906593
Proportion of denials	0.28	0.11	0.21	0.4
Year-month FE	Y	Y	Y	Y
Zip3 FE	Y	Y	Y	Y
R^2	0.05	0.01	0.11	0.01
	Panel B. Cash-out Refinance			
Realized Premium	0.010***	0.008***	0.002***	0.001
	(0.001)	(0.000)	(0.000)	(0.001)
Observations	19125262	19125262	19125262	19125262
Proportion of denials	0.27	0.15	0.24	0.34
Year-month FE	Y	Y	Y	Y
Zip3 FE	Y	Y	Y	Y
R^2	0.02	0.02	0.14	0.02
	Panel C. Purchase			
Realized Premium	0.002***	0.005***	-0.001***	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	44037086	44037086	44037086	44037086
Proportion of denials	0.32	0.13	0.24	0.32
Year-month FE	Y	Y	Y	Y
Zip3 FE	Y	Y	Y	Y
R^2	0.03	0	0.1	0.01

Notes: This table reports results from a version of 1, where we separately test different reasons for denial of a mortgage application. The first three columns report results for three specific denial reasons: Debt-to-income ratio, collateral, and credit history. The fourth column reports results for the other five denial reasons (employment history, credit history, collateral, insufficient cash, unverifiable information, credit application incomplete, mortgage insurance denied, and other). The regressions include applicant-level controls, county controls, 3-digit zip code fixed effects, and year-month fixed effects. For context, in each sample we report the proportion of total denials that each reason represents. *, **, and *** reflect statistical significance at the 10, 5, and 1% level.

Table 5: Probability of Application Rejection, OLS by income bin and LTV ratio

	Denial Rate							
	Panel A. Rate Refinance							
Realized Premium	0.011***	0.025***	0.025***	0.053***	0.024***	0.060***	0.008***	0.043***
	(0.003)	(0.007)	(0.003)	(0.007)	(0.003)	(0.006)	(0.002)	(0.005)
Observations	3800419	1345765	4384646	1235808	5973279	1598175	7236669	1331823
Income group	$0-56	$0-56	$57-85	$57-85	$86-135	$86-135	$136+	$136+
LTV split	Up to 80	Over 80	Up to 80	Over 80	Up to 80	Over 80	Up to 80	Over 80
Mean denial rate	0.284	0.311	0.153	0.261	0.111	0.203	0.096	0.148
Year-month FE	Y	Y	Y	Y	Y	Y	Y	Y
Zip3 FE	Y	Y	Y	Y	Y	Y	Y	Y
R^2	0.17	0.21	0.11	0.15	0.08	0.12	0.06	0.1
	Panel B. Cash-out Refinance							
Realized Premium	0.036***	0.019***	0.034***	0.014***	0.014***	0.025***	0.008***	0.018***
	(0.003)	(0.006)	(0.002)	(0.005)	(0.002)	(0.005)	(0.002)	(0.005)
Observations	3834078	677572	3822302	716694	4445317	767786	4071287	543101
Income group	$0-56	$0-56	$57-85	$57-85	$86-135	$86-135	$136+	$136+
LTV split	Up to 80	Over 80	Up to 80	Over 80	Up to 80	Over 80	Up to 80	Over 80
Mean denial rate	0.313	0.519	0.187	0.384	0.142	0.321	0.121	0.31
Year-month FE	Y	Y	Y	Y	Y	Y	Y	Y
Zip3 FE	Y	Y	Y	Y	Y	Y	Y	Y
R^2	0.15	0.15	0.11	0.16	0.09	0.15	0.07	0.13
	Panel C. Purchase							
Realized Premium	0.026***	0.048***	0.017***	0.021***	0.009***	0.006***	0.003***	-0.002*
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	2363142	7795395	2769320	8123606	3859528	7590879	6332362	5202848
Income group	$0-56	$0-56	$57-85	$57-85	$86-135	$86-135	$136+	$136+
LTV split	Up to 80	Over 80	Up to 80	Over 80	Up to 80	Over 80	Up to 80	Over 80
Mean denial rate	0.139	0.231	0.076	0.122	0.062	0.093	0.059	0.087
Year-month FE	Y	Y	Y	Y	Y	Y	Y	Y
Zip3 FE	Y	Y	Y	Y	Y	Y	Y	Y
R^2	0.11	0.2	0.05	0.08	0.04	0.05	0.02	0.04

Notes: This table reports results from a version of 1, where we separately test the probability of mortgage application denial by subgroups of income, split by whether their loan-to-value ratio is below 80. Columns (1) and (2) report results for low-LTV, low-income applicants and high-LTV, low-income applicants respectively. The remaining columns report the equivalent regressions for each income group. The regressions include applicant-level controls, county controls, 3-digit zip code fixed effects, and year-month fixed effects. For context, in each sample we report the mean denial rate for each subgroup. *, **, and *** reflect statistical significance at the 10, 5, and 1% level.

Table 6: First Stage Regression (Impact of Rate Filing on Realized Premiums)

	Realized Premium		
	(1)	(2)	(3)
Approved Premium	0.9397***	0.6907***	0.8448***
	(0.002)	(0.003)	(0.008)
Sample	Rate Refi	Cash-out Refi	New Purchase
Controls	Y	Y	Y
Month-Year FE	Y	Y	Y
Zip Code FE	Y	Y	Y
F-Stat	14,032	14,276	26,411
Observations	26,627,421	18,866,656	43,234,190

Notes: The table represents the results from estimating equation 2. The outcome variable include premiums derived from McDash property insurance data. The independent variable is a constructed level of allowable premium based on rate filings to insurance regulators within a state and weighted by insurer market share within a zip code.

*, **, and *** reflect statistical significance at the 10, 5, and 1% level.

Table 7: Probability of Application Rejection, IV Results

	Rate Refi (1)	Cash-Out Refi (2)	New Purchase (3)
Panel A. Reduced Form			
Allowed Premium	0.0271***	0.0902***	0.0133***
	(0.010)	(0.009)	(0.004)
Panel B.IV results			
$\widehat{\text{Realized Premium}}$	0.0288***	0.1305***	0.0157***
	(0.007)	(0.009)	(0.003)
Avg Denial Rate	0.157	0.211	0.105
Controls	Y	Y	Y
Month-Year FE	Y	Y	Y
Zip Code FE	Y	Y	Y
Observations	26,627,421	18,866,656	43,234,190

Notes: Panel A gives results reduced form results from estimating equation 1 with allowed premiums as the independent variable. Panel B the results from estimating equation 3 where realized premiums derived from McDash property insurance data are instrumented using allowable premiums as designated by a state's insurance regulator. The outcome is an indicator for denial of the respective type of loan application.
*, **, and *** reflect statistical significance at the 10, 5, and 1% level.

Table 8: Mortgage Market Outcomes for Successful Purchase Originations, OLS

	LTV (1)	Has Discount Points (2)	Discount Points (3)	Interest Rate (4)
Realized Premium	-0.362***	0.004***	163.154***	-0.040***
	(0.017)	(0.001)	(3.960)	(0.001)
Avg Outcome	85.73	0.36	920.3	4.41
Controls	Y	Y	Y	Y
Month-Year FE	Y	Y	Y	Y
Zip Code FE	Y	Y	Y	Y
Observations	36543608	37867453	37867453	37867453

Notes: This table reports results from a modified version of Equation 1, restricted to a sample of successfully originated purchase mortgages. On the right hand side, we examine how rising insurance prices relate to various mortgage market outcomes. Column (1) reports the interest rate of the mortgage, Column (2) reports whether the borrower purchased discount points, Column (3) reports the average number of discount points on the loan, and Column (4) reports the loan-to-value ratio of the loan. All regressions include the same set of individual-level and county-level controls as the primary specification, with an added control for loan amount. The regression also include 3-digit ZIP code and year-month fixed effects. For context, we report the average value of each outcome in the sample.

Table 9: Mortgage Market Outcomes for Successful Purchase Originations, IV Results

	LTV	Has Discount Points	Discount Points	Interest Rate
	(1)	(2)	(3)	(4)
Panel A. Reduced Form				
Allowed Premium	-1.3243***	0.0448***	-844.1014***	0.3509***
	(0.192)	(0.006)	(39.436)	(0.014)
Panel B. IV results				
Realized $\widehat{\text{Premium}}$	-0.2745*	0.0748***	-800.4448***	0.3598***
	(-0.150)	(-0.005)	(-22.138)	(-0.008)
Avg Outcome	85.73	0.36	920.3	4.41
Controls	Y	Y	Y	Y
Month-Year FE	Y	Y	Y	Y
Zip Code FE	Y	Y	Y	Y
Observations	35,903,728	37,199,443	37,199,443	37,013,640

Notes: Panel A gives results reduced form results from estimating equation 1 with allowed premiums as the independent variable. The CHMDA sample consists of purchase mortgage applications which were successfully originated. Panel B the results from estimating equation 3 where realized premiums derived from McDash property insurance data are instrumented using allowable premiums as designated by a state's insurance regulator.

*, **, and *** reflect statistical significance at the 10, 5, and 1% level.

Appendix

Table A1: Probability of Application Rejection, OLS by income bin

	Denial Rate			
	Panel A. Purchase			
Realized Premium	0.036***	0.019***	0.007***	0.002***
	(0.001)	(0.001)	(0.001)	(0.000)
Observations	10158537	10892928	11450408	11535212
Income group	$0-56	$57-85	$86-135	$136+
Mean denial rate	0.21	0.11	0.08	0.07
Year-month FE	Y	Y	Y	Y
Zip3 FE	Y	Y	Y	Y
\R^2$	0.17	0.07	0.04	0.03
	Panel B. Rate Refinance			
Realized Premium	0.027***	0.033***	0.032***	0.011***
	(0.003)	(0.003)	(0.002)	(0.002)
Observations	5146186	5620459	7571455	8568492
Income group	$0-56	$57-85	$86-135	$136+
Mean denial rate	0.29	0.18	0.13	0.12
Year-month FE	Y	Y	Y	Y
Zip3 FE	Y	Y	Y	Y
\R^2$	0.14	0.12	0.10	0.07
	Panel C. Cash-out Refinance			
Realized Premium	0.039***	0.034***	0.017***	0.009***
	(0.002)	(0.002)	(0.002)	(0.002)
Observations	4511654	4538998	5213105	4614396
Income group	$0-56	$57-85	$86-135	$136+
Mean denial rate	0.35	0.22	0.17	0.15
Year-month FE	Y	Y	Y	Y
Zip3 FE	Y	Y	Y	Y
\R^2$	0.15	0.13	0.11	0.09

Notes: This table gives results from estimating equation 1, estimated on separate income subgroups. Column (1) reports results for applicants with annual incomes from $0-$56,000, column (2) for incomes from $57,000-$85,000, column (3) for incomes from $86,000-$135,000, and column (4) for incomes $136,000 or higher. The regressions include individual-level controls, county-level controls, 3-digit ZIP fixed effects, and year-month fixed effects. *, **, and *** reflect statistical significance at the 10, 5, and 1% level.

Table A2: Probability of Application Rejection, OLS by income bin and denial reason

	Denial Rate											
	Any reason (1)	DTI (2)	Collaterial (3)	Any reason (4)	DTI (5)	Collaterial (6)	Any reason (7)	DTI (8)	Collaterial (9)	Any reason (10)	DTI (11)	Collaterial (12)
	Panel A. Purchase											
Realized Premium	0.036***	0.024***	0.011***	0.019***	0.011***	0.009***	0.007***	0.003***	0.005***	0.002***	0.000	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.00)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	10158537	10158537	10158537	10892928	10892928	10892928	11450408	11450408	11450408	11535212	11535212	11535212
Income group	$0-56	$0-56	$0-56	$57-85	$57-85	$57-85	$86-135	$86-135	$86-135	$136+	$136+	$136+
Mean denial rate	0.21	0.09	0.02	0.11	0.03	0.01	0.08	0.02	0.01	0.07	0.01	0.01
Year-month FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Zip3 FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
\Rˆ2$	0.17	0.08	0.01	0.07	0.02	0.01	0.04	0.02	0	0.03	0.01	0.01
	Panel B. Rate Refinance											
Realized Premium	0.027***	0.022***	0.010***	0.033***	0.022***	0.009***	0.032***	0.020***	0.009***	0.011***	0.009***	0.004***
	-(0.003)	(0.003)	(0.001)	(0.003)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
Observations	5146186	5146186	5146186	5620459	5620459	5620459	7571455	7571455	7571455	8568492	8568492	8568492
Income group	$0-56	$0-56	$0-56	$57-85	$57-85	$57-85	$86-135	$86-135	$86-135	$136+	$136+	$136+
Mean denial rate	0.29	0.13	0.02	0.18	0.05	0.02	0.13	0.03	0.02	0.12	0.01	0.01
Year-month FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Zip3 FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
\Rˆ2$	0.14	0.08	0.01	0.12	0.04	0.01	0.1	0.04	0.01	0.07	0.02	0.01
	Panel C. Cash-out Refinance											
Realized Premium	0.039***	0.026***	0.011***	0.034***	0.020***	0.008***	0.017***	0.008***	0.006***	0.009***	0.002**	0.007***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Observations	4511654	4511654	4511654	4538998	4538998	4538998	5213105	5213105	5213105	4614396	4614396	4614396
Income group	$0-56	$0-56	$0-56	$57-85	$57-85	$57-85	$86-135	$86-135	$86-135	$136+	$136+	$136+
Mean denial rate	0.35	0.13	0.04	0.22	0.05	0.04	0.17	0.03	0.03	0.15	0.02	0.03
Year-month FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Zip3 FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
\Rˆ2$	0.15	0.06	0.02	0.13	0.03	0.02	0.11	0.03	0.01	0.09	0.02	0.01

Notes: This table gives results from a modified version of estimating equation 1, where the right-hand side has denials separated by denial reason. The three outcome variables tested are (1) a denial for any reason, (2) a denial due to DTI, and (3) a denial due to collateral. The three denial types are estimated on separate income subgroups. Columns (1-3) reports results for applicants with annual incomes from \$0-\$56,000, columns (4-6) for incomes from \$57,000-\$85,000, columns (7-9) for incomes from \$86,000-\$135,000, and columns (10-12) for incomes \$136,000 or higher. The regressions include individual-level controls, county-level controls, 3-digit ZIP fixed effects, and year-month fixed effects. *, **, and *** reflect statistical significance at the 10, 5, and 1% level.

Table A3: Probability of Application Rejection, OLS by income bin and DTI ratio

	Denial Rate							
	Panel A. Purchase							
Realized Premium	0.032***	0.030***	0.017***	0.018***	0.009***	0.005***	0.002***	0.00
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	3580731	6337234	4560318	6039891	5606638	5352526	6587461	3621826
Income group	$0-56	$0-56	$57-85	$57-85	$86-135	$86-135	$136+	$136+
DTI split	20-40	40+	20-40	40+	20-40	40+	20-40	40+
Mean denial rate	0.113	0.258	0.077	0.132	0.058	0.105	0.05	0.103
Year-month FE	Y	Y	Y	Y	Y	Y	Y	Y
Zip3 FE	Y	Y	Y	Y	Y	Y	Y	Y
\Rˆ2$	0.11	0.19	0.06	0.06	0.04	0.04	0.02	0.03
	Panel B. Rate Refinance							
Realized Premium	0.017***	0.021***	0.021***	0.032***	0.015***	0.036***	0.006***	0.017***
	(0.005)	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)	(0.002)	(0.003)
Observations	1763460	3072936	2934656	2381173	4534419	2326938	5070323	1614174
Income group	$0-56	$0-56	$57-85	$57-85	$86-135	$86-135	$136+	$136+
DTI split	20-40	40+	20-40	40+	20-40	40+	20-40	40+
Mean denial rate	0.145	0.367	0.108	0.26	0.087	0.217	0.081	0.153
Year-month FE	Y	Y	Y	Y	Y	Y	Y	Y
Zip3 FE	Y	Y	Y	Y	Y	Y	Y	Y
\Rˆ2$	0.12	0.15	0.09	0.12	0.07	0.1	0.05	0.08
	Panel C. Cash-out Refinance							
Realized Premium	0.042***	0.031***	0.028***	0.030***	0.018***	0.008***	0.010***	0.004
	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)
Observations	1488542	2897200	2036710	2344940	2802644	2101320	2719170	1189099
Income group	$0-56	$0-56	$57-85	$57-85	$86-135	$86-135	$136+	$136+
DTI split	20-40	40+	20-40	40+	20-40	40+	20-40	40+
Mean denial rate	0.204	0.415	0.154	0.28	0.124	0.233	0.107	0.235
Year-month FE	Y	Y	Y	Y	Y	Y	Y	Y
Zip3 FE	Y	Y	Y	Y	Y	Y	Y	Y
\Rˆ2$	0.15	0.14	0.12	0.11	0.1	0.09	0.07	0.07

Notes: This table reports results from a version of 1, where we separately test the probability of mortgage application denial by subgroups of income, split by whether their DTI ratio is either between 20 and 40, or above 40. Columns (1) and (2) report results for low-DTI, low-income applicants and high-DTI, low-income applicants respectively. The remaining columns report the equivalent regressions for each income group. The regressions include applicant-level controls, county controls, 3-digit zip code fixed effects, and year-month fixed effects. For context, in each sample we report the mean denial rate for each subgroup. *, **, and *** reflect statistical significance at the 10, 5, and 1% level.

Table A4: Probability of Application Rejection, OLS by year

	Denial Rate						
	Panel A. Purchase						
Realized Premium	-0.003	0.000	0.013***	0.003	0.007	0.004	0.009***
	(0.006)	(0.006)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)
Observations	6856142	6729422	10411425	8585895	4223122	3690636	3540444
Year	2018	2019	2020	2021	2022	2023	2024
Mean denial rate	0.12	0.11	0.11	0.11	0.12	0.14	0.13
Year-month FE	Y	Y	Y	Y	Y	Y	Y
Zip3 FE	Y	Y	Y	Y	Y	Y	Y
\Rˆ2$	0.06	0.06	0.1	0.07	0.08	0.1	0.1
	Panel B. Rate Refinance						
Realized Premium	0.045***	-0.004	0.010**	0.012***	0.036***	-0.007	-0.001
	(0.016)	(0.011)	(0.004)	(0.005)	(0.012)	(0.016)	(0.011)
Observations	1942780	3163626	11341184	8195437	1102924	520449	640192
Year	2018	2019	2020	2021	2022	2023	2024
Mean denial rate	0.28	0.18	0.13	0.14	0.23	0.28	0.23
Year-month FE	Y	Y	Y	Y	Y	Y	Y
Zip3 FE	Y	Y	Y	Y	Y	Y	Y
\Rˆ2$	0.11	0.12	0.08	0.08	0.13	0.14	0.15
	Panel C. Cash-out Refinance						
Realized Premium	0.031**	-0.006	0.019***	-0.002	0.024***	0.003	0.007
	(0.014)	(0.012)	(0.007)	(0.006)	(0.009)	(0.012)	(0.009)
Observations	2409163	2724039	4710335	5355093	1948694	928841	1049096
Year	2018	2019	2020	2021	2022	2023	2024
Mean denial rate	0.3	0.24	0.16	0.16	0.26	0.32	0.33
Year-month FE	Y	Y	Y	Y	Y	Y	Y
Zip3 FE	Y	Y	Y	Y	Y	Y	Y
\Rˆ2$	0.12	0.13	0.1	0.1	0.13	0.11	0.1

Notes: This table reports the results from running Equation 1 separately by application year, from 2018 to 2024. All regressions include the same set of individual-level and county-level controls as the primary specification, as well as 3-digit ZIP code and year-month fixed effects. For context, we report the mean denial rate for each subsample.

Table A5: Probability of Application Rejection, OLS by income bin and lender type

	Denial Rate							
	Panel A. Purchase							
Realized Premium	0.047***	0.031***	0.017***	0.021***	0.007***	0.009***	0.001**	0.001*
	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	3349083	6809453	3448295	7444632	3828467	7621941	5025841	6509371
Lender type	Bank	Non-bank	Bank	Non-bank	Bank	Non-bank	Bank	Non-bank
Income group	$0-56	$0-56	$57-85	$57-85	$86-135	$86-135	$136+	$136+
Mean denial rate	0.2 0	0.22	0.11	0.11	0.09	0.08	0.07	0.07
Year-month FE	Y	Y	Y	Y	Y	Y	Y	Y
Zip3 FE	Y	Y	Y	Y	Y	Y	Y	Y
\R^2$	0.16	0.19	0.07	0.07	0.05	0.04	0.03	0.03
	Panel B. Rate Refinance							
Realized Premium	0.017***	0.016***	0.042***	0.015***	0.036***	0.022***	0.014***	0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.002)	(0.002)
Observations	2324966	2821220	2356891	3263567	2990579	4580876	3825595	4742897
Lender type	Bank	Non-bank	Bank	Non-bank	Bank	Non-bank	Bank	Non-bank
Income group	$0-56	$0-56	$57-85	$57-85	$86-135	$86-135	$136+	$136+
Mean denial rate	0.34	0.25	0.19	0.16	0.15	0.12	0.13	0.11
Year-month FE	Y	Y	Y	Y	Y	Y	Y	Y
Zip3 FE	Y	Y	Y	Y	Y	Y	Y	Y
\R^2$	0.21	0.1	0.16	0.1	0.13	0.08	0.09	0.06
	Panel C. Cash-out Refinance							
Realized Premium	0.027***	0.045***	0.042***	0.034***	0.029***	0.015***	0.016***	0.003
	(0.004)	(0.003)	(0.004)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
Observations	1470267	3041386	1469027	3069971	1800709	3412395	1945729	2668663
Lender type	Bank	Non-bank	Bank	Non-bank	Bank	Non-bank	Bank	Non-bank
Income group	$0-56	$0-56	$57-85	$57-85	$86-135	$86-135	$136+	$136+
Mean denial rate	0.34	0.36	0.21	0.24	0.16	0.18	0.14	0.16
Year-month FE	Y	Y	Y	Y	Y	Y	Y	Y
Zip3 FE	Y	Y	Y	Y	Y	Y	Y	Y
\R^2$	0.18	0.15	0.16	0.12	0.14	0.1	0.1	0.08

Notes: This table reports the results from running Equation 1 separately by income bin and whether a lender is a bank or non-bank. Non-bank lenders are defined from the HMDA, where non-banks are defined as an "independent mortgage banking subsidiary". Columns (1) and (2) include the subsamples of applicants with incomes between $0 and $56,000 to bank and non-bank lenders, respectively. The successive columns include subsamples for bank and non-bank lenders for the other three income groups. All regressions include the same set of individual-level and county-level controls as the primary specification, as well as 3-digit ZIP code and year-month fixed effects. For context, we report the mean denial rate for each subsample.

Table A6: Probability of Application Rejection, OLS by income bin and FHA status

	Denial Rate							
				Panel A. Purchase				
Realized Premium	0.035***	0.041***	0.019***	0.014***	0.010***	0.000	0.002***	-0.005*
	(0.002)	(0.003)	(0.001)	(0.002)	(0.001)	(0.002)	(0.000)	(0.003)
Observations	7555778	2602755	8332269	2560657	9496821	1953585	10912157	623035
Loan type	Not FHA	FHA	Not FHA	FHA	Not FHA	FHA	Not FHA	FHA
Mean denial rate	0.22	0.17	0.11	0.11	0.08	0.1	0.07	0.11
Year-month FE	Y	Y	Y	Y	Y	Y	Y	Y
Zip3 FE	Y	Y	Y	Y	Y	Y	Y	Y
\R^2$	0.2	0.08	0.09	0.03	0.05	0.02	0.03	0.03
				Panel B. Rate Refinance				
Realized Premium	0.022***	0.044***	0.031***	0.061***	0.032***	0.041***	0.011***	0.021
	(0.003)	(0.011)	(0.003)	(0.011)	(0.002)	(0.011)	(0.002)	(0.015)
Observations	4786559	359622	5382002	238452	7369874	201575	8490497	77970
Loan type	Not FHA	FHA	Not FHA	FHA	Not FHA	FHA	Not FHA	FHA
Mean denial rate	0.29	0.34	0.17	0.38	0.13	0.33	0.11	0.17
Year-month FE	Y	Y	Y	Y	Y	Y	Y	Y
Zip3 FE	Y	Y	Y	Y	Y	Y	Y	Y
\R^2$	0.16	0.15	0.11	0.09	0.09	0.08	0.06	0.1
				Panel C. Cash-out Refinance				
Realized Premium	0.033***	0.051***	0.032***	0.038***	0.018***	0.010**	0.009***	-0.008
	(0.003)	(0.004)	(0.002)	(0.005)	(0.002)	(0.005)	(0.002)	(0.008)
Observations	3741003	770645	3934409	604580	4722761	490337	4426275	188093
Loan type	Not FHA	FHA	Not FHA	FHA	Not FHA	FHA	Not FHA	FHA
Mean denial rate	0.32	0.48	0.2	0.36	0.16	0.31	0.14	0.34
Year-month FE	Y	Y	Y	Y	Y	Y	Y	Y
Zip3 FE	Y	Y	Y	Y	Y	Y	Y	Y
\R^2$	0.16	0.09	0.13	0.06	0.1	0.05	0.08	0.06

Notes: This table reports the results from running Equation 1 separately by income bin and whether the loan is covered by the FHA. Columns (1) and (2) include the subsamples of applicants with incomes between $0 and $56,000 for non-FHA and FHA loans, respectively. The successive columns include subsamples for non-FHA and FHA loans for the other three income groups. All regressions include the same set of individual-level and county-level controls as the primary specification, as well as 3-digit ZIP code and year-month fixed effects. For context, we report the mean denial rate for each subsample.