The Hidden Inflation in Homeowners' Insurance*

Sinjeong Kim ⓡ Mallick Hossain ⓡ
Natee Amornsiripanitch ⓡ Siddhartha Biswas†

October 2026

PRELIMINARY DRAFT.
PLEASE DO NOT CIRCULATE WITHOUT PERMISSION.

Abstract

Rising homeowners' insurance prices increase housing and debt service costs, while household coverage adjustments may increase exposure to expense shocks. Using novel data linking mortgages to insurance policies, we develop a quality-adjusted price index showing that the menu of insurance costs increased 19 percent more than premium expenditure growth from 2014-2022. We estimate low demand elasticities for insurance features. Elasticities increase significantly at home purchases and households also adjust insurance demand at refinance, especially when property valuations differ from expectation. These findings suggest inattention and information frictions substantially influence insurance decisions, and imply that behavioral nudges and regular property assessments may reduce household financial vulnerability in insurance markets. Using credit bureau data, we find that Subprime borrowers fall behind on consumer debt payments while super prime borrowers self insure when insurance costs rise.

*We are grateful for the valuable comments from Ricardo Correa, Cameron Ellis, Weiling Liu, Reid Taylor, Sisi Zhang, and participants at the System Community Development Research Conference, AEA/ASSA Annual Meetings, Federal Reserve Bank of Dallas, Consumer Finance Institute, Southwestern Finance Association, Consumer Finance Round Robin, Urban Economic Association, Brookings Institute, Hoyt Institute, and the System Applied Micro Conference. **Disclaimer:** The views expressed in this paper belong solely to the authors and do not necessarily reflect the views of the Federal Reserve Bank of Philadelphia or the Federal Reserve System. Any errors or omissions are the responsibility of the authors. No statements here should be treated as legal or investment advice.
ⓡ Author order is randomized, and is available at the AEA random author archive.

†Kim: Pennsylvania State University; Hossain, Amornsiripanitch, and Biswas: Federal Reserve Bank of Philadelphia

1 Introduction

Homeowners' insurance expenditures have risen by about 33% since 2021 (Keys and Mulder, 2024; United States Government Accountability Office, 2026). These rising insurance costs increase the total cost of homeownership and has implications for home affordability, location choice, and consumer finances. As insurance expenditures are a product of market premiums and household policy choice, expenditure growth alone likely underestimates changes in the true cost of coverage if households reduce coverage in response to rising premiums. As a result, households may pay higher premiums but hold less coverage relative to damages, exacerbating their overall financial burden. Therefore, estimating premium inflation for a fixed policy and understanding household demand for property insurance is necessary to determine household exposure to large expense shocks.

This paper studies three questions. First, how has the true cost of homeowners insurance changed? We construct a novel quality-adjusted insurance premium index that measures the counterfactual market price increase households face for the same policy from the same insurer. Second, how do households adjust their insurance coverage when facing higher prices? To understand household demand for property insurance, we estimate elasticities of insurance demand and document facts about household shopping behavior. Third, how do rising premiums affect household credit outcomes? We estimate the effect of premium increases on household credit usage and performance. To the best of our knowledge, this is the first nationwide study of homeowners insurance markets that captures important dynamics about both price and quality of coverage.

This paper makes several contributions. First, this paper helps us understand how households make insurance decisions that have implications for consumer finances and household welfare. Within monthly housing costs, insurance premiums and property taxes change over time for those with fixed rate mortgages. Insurance premium inflation therefore impacts households' debt service costs. Furthermore, we find that deductibles increase and coverage as a share of structure value decreases, which increases household exposure to expense shocks. Fulford and Low (2024) show that housing related costs are one of the three largest expense shocks. Expense shocks are more common than income shocks, which are better studied and are more likely to appear in the left *and* right tail of the damage distribution. Therefore, household exposure to expense shocks increases exactly where shocks are most prevalent, which can impact credit risks and household welfare.

Second, we document new facts about the price of insurance after holding both quantity and quality of insurance constant, therefore measuring inflation of the true cost of coverage. We do so by leveraging a novel dataset that links homeowners' insurance policies to 18 million mortgages and provides more details than existing datasets, such as deductible, premium,

coverage amount, and insurer identity. As a result, we can estimate premium shocks as the change in the local market price of a fixed policy from a fixed insurer. These estimates are especially policy relevant as these menu price changes are not well captured by common inflation statistics (Jones et al., 2026).

Third, we identify inattention and information frictions around structure value as important mechanisms that lead to lower coverage and greater financial exposure to damages. We test whether households are inattentive by comparing sensitivity of insurance decisions to insurance prices at times when households are most attentive to monthly housing costs, such as at the purchase of a house or during a refinance. To assess the prevalence of information frictions, we estimate a triple difference specification that interacts household refinancing behavior with updated structure value information presented during a refinance appraisal. Inattentiveness and information frictions playing a large role in household sensitivity to prices suggests that behavioral nudges to reevaluate current insurance contracts or frequent property assessments may be more effective at reducing household financial exposure to damages than price-based policies, such as subsidies and premium growth caps.

Specifically, this paper constructs a national quality-adjusted price index using novel mortgage and policy linked data.[1] We measure the index as the year fixed effect in a regression that controls for households' deductible choice, coverage limit, location (ZIP code), and insurer. We establish several key facts about premium inflation, describe patterns by homeowner characteristics and geography, and discuss the gap between quality-adjusted premium inflation and overall premium expenditure inflation. Then, we estimate a ZIP code-level quality-adjusted price index and interpret changes in that index as the market insurance premium shock for households to keep the same policy from the same insurer. We estimate how households change their deductible, coverage, and insurer in response to these shocks with a mortgage fixed-effects regression. Finally, we estimate the short-term impact

[1]Homeowners insurance is specifically excluded from the Consumer Price Index computed by the Bureau of Labor Statistics, but it is captured in the Producer Price Index (PPI). The PPI is "generated from policies where policy characteristics have been held constant, or 'fixed.' In particular, policy descriptions have been held constant since having first been sampled. (The only policy descriptors changed are those, such as the replacement cost of a home, that are escalated to reflect inflation.) This is done to insure a constant quality for each policy in the index, providing for price movement that is reflective of inflation only." However, homeowners insurance is included in the Bureau of Economic Analysis' Personal Consumption Expenditure measure. The index is available on FRED. This index does not measure prices as faced by consumers because it includes premiums collected (paid by consumers) plus premium supplements (investment income to the insurer) minus "normal" losses (expected claims). Our object of interest is just premiums collected. While this measure will likely be qualitatively similar to our index, they may diverge depending on the interest rate and market environment as well as modeled losses ("normal" losses are expected losses, not realized losses). Furthermore, these values are based on aggregate data sourced from A.M. Best and therefore does not control for the underlying terms and coverage of the policy. See Jones et al. (2026) for more discussion of CPI and a new discussion of PCE.

of premium changes at the time of policy renewal on credit outcomes during the year of the new policy.

We find that deductibles have increased over time and coverage limits have lagged both house price appreciation and rising construction costs. The quality-adjusted price index shows that the true cost of insurance has nearly doubled from 2014 to 2022 and has grown by 8.5 percentage points more than premium expenditure growth. In relative terms, quality-adjusted price growth is 19 percent higher than premium expenditure growth. The gap between the two inflation measures is primarily determined by households reducing coverage. Therefore, households increase their exposure and indirectly increase their costs more than what premium expenditure alone would indicate.

Demand elasticities for deductibles or insurer choice are relatively small. A premium increase of 10 percent leads to a 0.46 percent increase in deductibles, a 0.7 percentage point increase in the likelihood of switching insurers, and a 0.65 percent increase in *nominal* coverage. However, coverage as a share of structure value decreases by 5.11 percent in response to a 10 percent premium increase. These findings suggest that household insurance decisions are not very responsive to insurance prices. Therefore, we assess homeowner attentiveness and property value information mechanisms as plausible mechanisms.

We find that households are more sensitive to changes in insurance menu prices during a house purchase or a mortgage refinance than other periods of homeownership. This finding suggests that households are more attentive to housing costs at the point of purchase or refinance. Moreover, households that face larger shocks to their property appraisal value than a house price index might suggest are also more likely to adjust their coverage. Therefore, learning new information about the value of a borrower's property plays a significant role in updating their insurance coverage.

In the year after a policy renews, higher premiums result in lower monthly credit card balances for super prime borrowers and higher mortgage and credit card delinquency rates for subprime borrowers. These findings suggest that super prime households manage the increased exposure from lower coverage and higher deductibles by exercising precautionary savings, through reduced spending on credit cards. However, subprime households credit performance suffers.

This paper is related to the recent literature on property insurance markets that document new facts about growing premium expenditures and insurance pricing (Keys and Mulder, 2024; Blonz et al., 2024). Theoretical models of insurance demand predict that households should fully insure if they face actuarially fair prices (Mossin, 1968; Einav et al., 2010). However, recent empirical estimates show that household willingness to pay for property insurance is lower than expected losses, even at actuarially fair rates (Wagner, 2022; Sastry

et al., 2025). As a result, households face large protection gaps (Sastry et al., 2025; Cookson et al., 2024; Amornsiripanitch et al., 2025). Together, higher insurance premiums can affect debt service costs, and the resulting protection gaps can lead to higher default risks in the event of a loss (Biswas et al., 2023; Ge et al., 2025).

The remainder of the paper is organized as follows. Section 2 discusses the data and Section 3 presents the quality-adjusted premium index. Section 4 outlines our identification strategy and Section 5 presents our results and mechanisms. Section 6 discusses credit outcomes and Section 7 concludes.

2 Data

Our primary data source is the McDash residential mortgage service database and property insurance dataset provided by Intercontinental Exchange (ICE). The McDash mortgage data cover about two-thirds of the US mortgage market. Insurance records are collected from mortgage servicers who agreed to share insurance data with McDash and is available for around 75% of those mortgages.

For our analysis, we restrict our data to standard homeowner insurance policies that were active between 2013 and 2022. The McDash Property Insurance dataset contains information on monthly insurance premiums, coverage limits, and deductible choices for a range of homeowners insurance policies. It also includes the credit score of the homeowner at mortgage origination and the ZIP code of the property.[2] We exclude condominiums because many condos are also covered by a master condominium policy obtained by the condo association. We also exclude homes that do not escrow their insurance payments, because while servicers still monitor insurance compliance, they may not collect accurate premium or deductible information since they are not disbursing the funds for the insurance policy from an escrow account.

We use three additional datasets: Equifax Credit Risk Insight Servicing McDash (CRISM), structure value shares from FHFA, and the annual single family house construction price index (CPI) from the Census Bureau. CRISM is an anonymized match between mortgages in McDash and consumer credit bureau records. Specifically, we use CRISM to identify consumers' mortgages before and after a refinance and to study the effect of insurance premiums on household credit utilization and performance. We use the county-level home price index (HPI) from CoreLogic to inflate appraisal at origination and estimate the current house value.

After dropping observations with missing values, the final sample includes 54.1 million loan-year observations from 13.9 million loans, covering the years 2013 to 2022. Next, we

[2]References to credit scores refer to the scores recorded in the McDash data.

summarize basic features of insurance contracts and establish some important facts about deductibles and coverage limits. We provide additional descriptive statistics and stat-level comparisons of deductibles and coverage in the Appendix.

Policy Deductibles Homeowners' insurance deductibles are sticky and lumpy. Figure 1(a) shows that deductibles are often specified in round dollar figures with the most common deductible being $1,000. There are other notable masses at other round values such as $500 and $2,500. About 84% of all policies have deductibles that take one of six values: $500, $1000, $1500, $2000, $2500, and $5000.[3] Deductibles have been increasing between 2013 and 2022, as shown in Figure 1(b). While the most common deductible is still $1,000, it has fallen from 54% of policies to 48% of policies. This has been offset by a shift into higher deductibles, especially around $2,500. There has also been a sharp decline in low deductibles ($< \$1{,}000$) falling from 24% of policies to 11% of policies.

Coverage Limits Since 2013, we find that home prices have increased by 93% while insurance coverage limits have only increased by 44% (Figure 2). However, benchmarking insurance coverage growth against home price appreciation may not be the best comparison. First, homeowners' insurance only insures the structure on the property and does not insure the land. Therefore, home price appreciation may not be an accurate measure of how structure values are changing over time. The accuracy of this assumption rests on one's priors on how property appreciation is capitalized into the structure and the land. For HPI to be a reasonable proxy for the changes in structure value, we must assume that HPI changes are similarly capitalized into structure and land. In an extreme case, if all the property value changes were capitalized into land, then the proper baseline would be for structure values to be flat or declining over time and therefore the "right" amount of insurance coverage should also be flat or declining. Therefore, if property value changes are more likely to be embodied in the land value instead of the structure value, then our comparison will be less accurate.

Another way of conceptualizing these dynamics is that insurance coverage is based on the reconstruction value of the home. Therefore, coverage growth over time should be more tightly linked to growth in construction costs. Comparing against the costs of new construction (i.e., recently built houses), we find that coverage has still lagged changes in construction costs, but not as severely. Since 2013, new construction costs have increased by 73% while coverage limits have risen by 44%. However, we should note that this gap widened substantially during the pandemic and was notably narrower before the COVID-19 pandemic.

[3]There are small spikes at other multiples of $500, so when categorizing deductibles, we formally define a dollar deductible as any multiple of $500 between $500 and $5000 and then $7500 and $10000. This expanded definition picks up an additional 0.6% of policies.

For the remainder of the paper, coverage limits enter our analysis primarily through coverage as a share of home structure value. We approximate current home structure value using ZIP code structure value share of property value from Davis et al. (2021) and current property value by inflating the appraisal value at time of mortgage origination with the county house price index:

$$\text{Structure Value}_{it} = \underbrace{\text{Property Appraisal}_{i,t_i^0} \times \frac{\text{County HPI}_{c(i),t}}{\text{County HPI}_{c(i),t_i^0}}}_{\text{Property Value}_{it}} \times \text{Structure Value Share}_{z(i),t}$$

where i indexes properties, t indexes calendar years, t_i^0 denotes the mortgage origination year for property i, and $c(i)$ and $z(i)$ denote its county and ZIP code, respectively. Notably, changes to structure value in our calculation arise from changes to property value and changes to the structure value share over time.

3 Quality-Adjusted Price Index

We construct a quality-adjusted price index for homeowners' insurance. In the spirit of the hedonic price index, we first estimate the following regression to obtain **quality-adjusted price index**, λ_t^{qa}:

$$\log(Premium_{it}) = \alpha + \beta_1 \cdot Ded_{it} + \beta_2 \cdot CovShare_{it} + \lambda_t^{qa} + \delta_{z(i)} + \gamma_{k(i,t)} + \epsilon_{it} \tag{1}$$

where $Premium_{it}$ denotes annual premium. As controls, we use deductible Ded_{it} grouped in intervals of \$500, coverage share $CovShare_{it}$, which is defined as the ratio of coverage limits to the current home structure value, grouped in intervals of 0.05, year dummies λ_t^{qa}, ZIP code fixed effects $\delta_{z(i)}$ for each ZIP code z, and insurer fixed effects $\gamma_{k(i,t)}$ for each insurer k. The estimated year fixed effect $\hat{\lambda_t^{qa}}$ becomes the quality-adjusted price index. As a comparison, we estimate the **raw price index**, λ_t^{raw}, as the year fixed effects without controlling for any policy characteristics:

$$\log(Premium_{it}) = \alpha + \lambda_t^{raw} + \epsilon_{it}. \tag{2}$$

Figure 3 plots the estimated price indices over time. Specifically, it compares $\exp(\hat{\lambda_t^{qa}})$, the quality-adjusted price index, and $\exp(\hat{\lambda_t^{raw}})$, the raw price index, where both are normalized to 100 in the base year 2014. It shows that the quality-adjusted index reveals much sharper growth than raw insurance premium. Between 2014 and 2022, quality-adjusted insurance premiums have increased by 52.4% compared to 43.9% based on unadjusted premiums. Therefore, after adjusting for quality reductions, the true cost of insurance by 8.5 percentage points, or 19 percent, more than measured by premium growth alone.

By comparing the year fixed effects from the quality-adjusted and raw regressions, $\hat{\lambda}_t^{qa}$ and $\hat{\lambda}_t^{raw}$, we can quantify the extent of observed price growth to which changes in each quality over time can be attributed. In particular, we normalize $\lambda_{2014}^{qa} = \lambda_{2014}^{raw} = \log(100)$ and define the wedge between the two measures of premium inflation by:

$$\Delta_t \equiv (\lambda_t^{qa} - \lambda_{2014}^{qa}) - (\lambda_t^{raw} - \lambda_{2014}^{raw}) = \lambda_t^{qa} - \lambda_t^{raw}.$$

We derive the following equation that decomposes the difference in the two indices

$$\begin{aligned}\Delta_t = \beta_1 \left(\overline{Ded}_{2014} - \overline{Ded}_t\right) + \beta_2 \left(\overline{CovShare}_{2014} - \overline{CovShare}_t\right) \\ + \left(\overline{\delta}_{2014} - \overline{\delta}_t\right) + (\overline{\gamma}_{2014} - \overline{\gamma}_t) + \text{Residual}_t.\end{aligned}$$

Here, $\overline{Ded}_t$ and $\overline{CovShare}_t$ denote the sample averages of the deductible and coverage share, respectively, among observations in year t. Similarly, $\overline{\delta}_t$ and $\overline{\gamma}_t$ denote the observation-weighted averages of the ZIP code and insurer fixed effects among observations in year t.

We decompose the wedge between the quality-adjusted index and the raw price index into five components. The first component, $\beta_1 \left(\overline{Ded}_{2014} - \overline{Ded}_t\right)$, reflects the effect of changes in average deductibles while the second, $\beta_2 \left(\overline{CovShare}_{2014} - \overline{CovShare}_t\right)$, captures the effect of changes in average coverage shares. The third, $\left(\overline{\delta}_{2014} - \overline{\delta}_t\right)$, represents changes in the composition of ZIP code fixed effects. The fourth, $(\overline{\gamma}_{2014} - \overline{\gamma}_t)$, represents changes in composition of insurer fixed effects. Lastly, Residual_t represents the unexplained variation, potentially due to finite sample errors.

To visualize the decomposition, Figure 4 presents a bar chart of the empirical analog of Δ_t over time. Each bar reflects the estimated contribution of quality improvements to price growth in a given year. Reductions in coverage relative to home price represent the largest contributor to the gap between quality-adjusted and raw premium growth.[4]

4 Homeowners' Insurance Demand

We estimate household demand elasticities in two steps. First, we construct a ZIP code-level quality-adjusted price index in a similar fashion as the national price index. Instead of a year and ZIP code fixed effect, we introduce a year by ZIP code fixed effect, $\lambda_{z,t}^{qa}$. Therefore, for each ZIP code, this index recovers the average market price change if residents keep fixed policy terms (deductible, coverage, and insurer).

[4]We also construct state-specific quality-adjusted price indices, and discuss the results in the Appendix (see Figures A.4 and A.5).

$$\log(Premium_{it}) = \alpha + \beta_1 Ded_{it} + \beta_2 CovShare_{it} + \lambda^{qa}_{z(i),t} + \gamma_{k(i,t)} + \epsilon_{it}.$$

Second, we use the ZIP code level quality-adjusted premium index to estimate insurance demand elasticities β

$$y_{it} = \alpha + \beta \hat{\lambda}^{qa}_{z,t} + \mu_i + \gamma_{k(i,t)} + \gamma_t + \epsilon_{it}. \tag{3}$$

The outcomes measure the insured's policy terms y_{it}, including deductible, coverage limit, coverage as share of home value, and an indicator for changing insurer. The right hand side includes a loan fixed effect μ_i, a ZIP code-level quality-adjusted price index $\hat{\lambda}^{qa}_{z,t}$, insurer fixed effect $\gamma_{k(i,t)}$, and year fixed effect γ_t.

Identification of β as a demand elasticity relies on the exogeneity of ZIP code-level insurance menu price shocks, $\hat{\lambda}^{qa}_{z,t}$. The primary threat to identification would be if the price shocks are driven by demand factors. However, $\hat{\lambda}^{qa}_{z,t}$ is estimated as part of the residual premium growth after the primary demand drivers of household deductible, coverage, and insurer choice. Therefore, the variation in the price shocks will be driven by insurance supply that shifts insurers' marginal cost of providing a specific policy, as defined by deductible and coverage. Moreover, our specification includes a loan fixed effect that accounts for unobserved homeowner types that might drive insurance demand, such as permanent risk preferences or private information about property-level risks.

We interpret β as the change in household insurance demand in response to a counterfactual change in local market prices for their current policy terms. Further understanding insurers' marginal costs is critical to the interpretation of our estimate. This marginal cost depends on two important factors: the underlying risk the contract insures and insurer mark-ups and administrative costs. Our approach captures variation in the underlying risk profile of a specific market (ZIP code) over time. This approach complements other studies that primarily estimate the impact of variation in mark-ups by utilizing instruments that depend on insurer-level shocks to pricing in other markets (Ge et al., 2025; Sastry et al., 2025).

5 Results

We find that households are more likely to increase their deductible and switch insurers in response to a price increase. As shown in the first column of Table 1, we estimate the demand elasticity for deductibles to be 0.0458 – a 10 percent increase in insurance prices results in a 0.46 percent increase in deductibles. In the third column, we estimate that a 10 percent increase in price would lead to a 0.68 percentage point increase in the likelihood of switching insurers. Household coverage limit choice does not seem to vary much with price changes. In the first column of Table 2, we find that a 10 percent increase in prices would lead to a

0.65 percent increase in the nominal coverage limit. However, households fall behind on their coverage relative to their property's structure value as a 10 percent increase in prices implies a 5.11 percent *decrease* in coverage as a share of structure value. The fourth column shows that households actual premium expenditures rise as menu prices increase. We estimate a 10 percent increase in prices passes through as a 7.4 percent increase in expenditures.

There are two potential interpretations of the counterintuitive increase in nominal coverage limit. First, automatic coverage limit increases by set percentages are common provisions in many policies. The large decrease in coverage as a share of structure value further suggests that households are following insurer automated policy limit changes as households are falling behind on coverage in response to price changes without actually decreasing their nominal limits. Second, rising insurance premiums may serve as a signal for a larger likelihood of damages. In response, households may opt to hold more coverage.

Our results show that households over time pay more for insurance, have less coverage relative to their structure value, and choose higher deductibles. As a result, households incur higher monthly housing costs and are more financially exposed to property damage. Specifically, households choose higher nominal coverage limits, but they do not keep up with growing structure values and costs of construction. This latter finding suggests potential frictions. Frictions can include homeowner inattention about insurance choices, search frictions that make it difficult to switch or constrain household choice sets, and information frictions about risks and reconstruction value of the structure. While we are unable to test all such frictions, we specifically test the validity of homeowner inattention to insurance choices and information frictions about their structure values as potential mechanisms leading to our observed results.

5.1 Homeowner Inattention

One explanation for coverage limits lagging structure values is homeowner inattention. Property insurance choices are commonly annual decisions and, as observed from our previous analysis, homeowner choices are relatively sticky. If homeowners are not attentive to these decisions and instead roll over their existing policies year to year without major changes, policies that affect insurance prices become a less effective tool to boost coverage. We consider two tests of homeowner inattention by focusing on periods when homeowners are evaluating all of their monthly housing costs: at the time of mortgage origination from a home purchase and at the time of a refinance. If homeowners are inattentive, we expect homeowners to be more sensitive to rising insurance costs and to be more willing to shop around at these two periods.

5.1.1 Mortgage Origination

First, we estimate the following regression in the period of mortgage origination during home sales that is analogous to our main demand elasticity specification:

$$y_i = \alpha + \beta \hat{\lambda}^{qa}_{z(i),t_i^0} + \delta X_i^0 + \gamma_{k(i,t_i^0)} + \gamma_{t_i^0} + \epsilon_i. \tag{4}$$

As this regression only includes one observation per loan at the period of origination, we cannot include loan fixed effects. Instead, we include insurer and origination-year fixed effects, and control for a set of mortgage characteristics at origination, X_i^0, including property appraisal value, credit score, debt-to-income ratio (DTI), and loan-to-value ratio (LTV). This analysis therefore exploits variation in within ZIP code price changes for observationally similar homes purchased in different years.

Table 3 reports the results. The deductible elasticity of 0.0837 is almost twice as large as the elasticity from within mortgage price variation over time. The nominal coverage limit elasticity is -0.0621. The negative elasticity is more intuitive as new homeowners purchase less insurance when prices are higher. However, the coverage share elasticity is smaller in absolute terms than the within mortgage analysis. This finding shows that even though new homeowners buy less nominal coverage due to higher prices, they are less likely to be much less insured than their structure value than homeowners in the years after a purchase. We interpret these results as supporting evidence for homeowner inattentiveness.

5.1.2 Refinance Event Study

To further test homeowner inattentiveness, we conduct an event study around the timing of rate and term refinance. We compare homeowners who refinance to homeowners who refinance at least three years later. McDash allows us to identify whether a loan is prepaid due to refinance but does not link to the new loan originated after the refinance. Therefore, we use CRISM, which links both the old and new loans to the consumer to track insurance and mortgage information across a refinance for the same property and consumer. Note that our sample only includes refinances where both the old and new mortgages are included in the McDash sample.[5]

While refinance is an endogenous decision, we avoid selection into refinance by comparing within households that all refinance at some point. Therefore, our treatment group ($T_{id} = 1$) are loans that refinance in period d while our control group ($T_{id} = 0$) are all not-yet-treated loans that refinance in a period after $d + 3$. We estimate the following stacked difference-in-differences specification with fixed effects for loan by refinance cohort and year by refinance

[5]We only consider conventional loan refinances and exclude cash-out refinances.

cohort.

$$y_{itd} = \sum_{k \neq -1} \beta_k (T_{id} \times 1\{t - d = k\}) + \alpha_{id} + \gamma_{td} + \epsilon_{itd} \tag{5}$$

Similar to the mortgage origination analysis, if homeowners are inattentive, we should expect positive estimates for β_k after the refinance period d. In Figure 5, we see that all insurance choices are highly sensitive to price changes at the time of refinance, relative to those households who have yet to refinance. Specifically, deductibles and likelihood of switching insurers are higher, suggesting households' willingness to shop around or increase deductible to offset rising insurance costs. Coverage share changes are also higher than the not-yet-refinanced group, suggesting that the treatment group's coverage limit is less likely to fall behind structure values specifically due to a one-time adjustment at the time of refinance.

Notably, these results are seemingly not driven by changes to housing costs around a refinance. First, Figure 5 shows that household's insurance premium expenditures do not change after the refinance. Second, we find a similar pattern for households who faced small changes, defined as a less than 5% increase or decrease, in their mortgage principal and interest (P+I) payments (Figure A.7). These refinance results further support the prevalence of homeowner inattentiveness.

5.2 Information Frictions

Another explanation for lagging coverage is information frictions regarding property values. That is, coverage share lags because homeowners do not know the structure value to insure. We test information frictions using a triple difference version of our refinance event studies. Specifically, during a refinance, homeowners receive new information about their property value due to required property appraisals. We estimate the following triple difference specification:

$$\begin{aligned} y_{itd} = &\sum_{k \neq -1} \beta_k (T_{id} \times 1\{t - d = k\}) + \sum_{k \neq -1} \delta_k (x_{id} \times T_{id} \times 1\{t - d = k\}) \\ &+ \sum_{k \neq -1} \theta_k (x_{id} \times 1\{t - d = k\}) + \alpha_{id} + \gamma_{td} + \epsilon_{itd}. \end{aligned} \tag{6}$$

We measure x_{id} as the difference between appraisal value at the time of refinance, d, and the predicted appraisal value of the house.

$$x_{id} = \text{Property Appraisal}_{i,d} - \underbrace{\text{Property Appraisal}_{i,t_i^0} \times \frac{\text{County HPI}_{c(i),d}}{\text{County HPI}_{c(i),t_i^0}}}_{\text{Predicted Appraisal}_{i,d}}$$

We use the home's original property appraisal and county-level house price appreciation to construct a predicted appraisal value at the time of refinance. This measure captures an information shock to the borrower who may have tracked local home prices but may not be aware of the current value of their property. A nonzero estimate of δ_k at the time of refinance suggests the presence of information frictions. That is, refinancing borrowers who face larger information shocks to their property value should be more sensitive to insurance prices if information frictions are strong. The β_k coefficients capture a general refinance effect that might make all households, even those that do not face information frictions, reassess their insurance choices.

Figures 6 to 9 show estimates of β_k and δ_k for the outcomes of nominal coverage limit, coverage share, deductibles, and likelihood of switching insurers. Estimates of δ_k in panel (b) are economically and statistically significant in the period of refinance in all of these results. This finding supports that information frictions about property value play a large role in household insurance decisions. Particularly, whenever the appraisal is a shock, that is appraisal largely exceeds property value predicted by HPI, households increase coverage, deductibles, and likelihood of switching relative to those who do not face an appraisal shock. However, these households do not increase coverage limit enough as coverage share falls. We interpret this finding as households increasing their coverage because they had to update their beliefs of structure value. As this is accompanied by higher premiums, households increase deductibles and shop around insurers to offset the higher monthly housing costs.

Estimates of β_k in panel (a) for households that do not experience an appraisal shock are also significantly positive. This finding suggests that households for whom appraisal was predicted well by HPI also changed their coverage, increased their deductibles, and shopped around more. We interpret this finding as evidence supporting that both the baseline nudge from re-evaluating insurance costs at the time of refinance and the information shock are important for decisions that reduce the cost of holding the same coverage (e.g., deductible and insurer choice).

6 Credit Outcomes

In this section, we estimate the effect of insurance market price changes on household credit outcomes. Menu price changes for insurance contracts affect household balance sheets in two ways. First, household's premium expenditures rise – as shown previously, premiums increase by \$0.74 per dollar of menu price increase. Second, households may face more out of pocket costs to cover insured risks as they increase deductibles and reduce coverage share to offset rising insurance costs. Effectively, households incur higher exposure to expense shocks from property risks while paying higher premiums.

Specifically, we estimate the following regression to understand the effect of a premium change, as measured by our insurance index, on credit usage in each month, m, of the policy year, t.

$$\Delta y_{it+m} = \alpha_m + \beta_m \hat{\lambda}^{qa}_{z,t} + \mu_i + \gamma_{tm} + \gamma_{k(i,t)} + \epsilon_{it}, \quad m \in \{1, \ldots, 11\} \tag{7}$$

Outcomes Δy_{it+m} measure the annual change in credit balance in the specific month to difference out seasonality. The specification includes loan fixed effects, year-month fixed effects, and insurer fixed effects. Furthermore, we structure the data such that month $m = 0$ identifies the policy renewal month for the specific mortgage. Therefore, the coefficients β_m measure the effect of a price increase ahead of the policy renewal for year t on credit outcomes in the m months in the year after the new policy begins. This specification provides reduced form estimates of the impact of menu price changes on household finances and does not separate whether the effect is due to higher premium expenditures or greater exposure to expense shocks from lower coverage.

Figure 10 plots the β_m coefficient estimates for monthly credit card balances. After an increase in insurance premiums, credit card balances decrease every month of the year. However, this decrease is driven by superprime borrowers. Subprime borrower credit card balances initially increase slightly, and remain flat for the rest of the year after renewal. We interpret this result as evidence in support of superprime households self insuring to manage the additional exposure from higher deductibles and lower coverage share. Lower credit card balances suggest that superprime households, who are more likely to be transactors, spend less, supporting a precautionary savings motive to plan for expected higher uninsured expenses.

We then examine whether increasing premiums and exposure lead to credit distress by estimating our baseline specification, Equation 3, for credit performance outcomes. Our outcome is an indicator for an open consumer credit account in delinquency in the current year. Table 4 shows results for all types of credit, first mortgages, and credit cards. Panel A shows that higher insurance menu prices lead to slightly higher rates of mortgage and credit card delinquency. Panel B shows that this finding is primarily driven by subprime borrowers, who have significantly higher rates of delinquency associated with an insurance price increase.

7 Conclusion

We study the rise in true cost of homeowners insurance and the resulting household demand elasticities. Using a novel dataset of mortgages linked to property insurance policy details, including coverage and deductible, we construct a homeowners insurance quality-adjusted price index. This index adjusts the raw premium index by fixing policy and insurer details. We find that homeowners are paying more for less coverage. Accounting for the quality, the

true costs of insurance have grown by 19 percent more than premium expenditure. Most of this gap between quality-adjusted and raw premium growth is driven by reductions in coverage relative to home prices.

We then interpret the index as the counterfactual annual price change for the same policy contract from the same insurer. Therefore, changes in the index are driven by supply shocks to insurance price, allowing us to identify insurance demand elasticity. We find that elasticities for deductibles, coverage limits, and insurer choices are small in response to insurance menu price shocks.

Our findings shed light on a less studied topic relevant to consumer finances. As insurance is one of the few changing components of household mortgage payments, the rising premiums increase debt service costs. Furthermore, if households adjust by increasing deductibles, they become more exposed to prevalent expense shocks. Expense shocks are more common than income shocks in the left tail of the property damage distribution and can lead to negative impacts on household finance (Fulford and Low, 2024).

Our mechanism analysis suggests that homeowner inattentiveness and information frictions around property value are important factors that lead to the observed lagging coverage. These results support simple nudges and frequent property assessments as effective policies. Nudges for households to review their insurance contracts would incentivize shopping around that can lower housing costs. Frequent and accurate property assessment would relax information frictions and subsequently reduce exposure to damages as households become more likely to keep coverage up to date with structure values. Further work is necessary to understand the broader impacts of rising insurance costs and exposure to damages on economic and financial outcomes.

References

Amornsiripanitch, N., S. Biswas, J. Orellana-Li, and D. Zink (2025): "Measuring Flood Underinsurance in the USA," *Nature Climate Change*, dOI: 10.1038/s41558-025-02396-w.

Biswas, S., M. Hossain, and D. Zink (2023): "California Wildfires, Property Damage, and Mortgage Repayment," Working Paper 23-05, Federal Reserve Bank of Philadelphia, dOI: 10.2139/ssrn.4372320.

Blonz, J. A., M. Hossain, and J. Weill (2024): "Pricing Protection: Credit Scores, Disaster Risk, and Home Insurance Affordability," Working paper, SSRN, dOI: 10.2139/ssrn.5026600.

Cookson, J. A., E. Gallagher, and P. Mulder (2024): "Coverage Neglect in Homeowners Insurance," Working paper, SSRN, dOI: 10.2139/ssrn.5057551.

Davis, M. A., W. D. Larson, S. D. Oliner, and J. Shui (2021): "The price of residential land for counties, ZIP codes, and census tracts in the United States," *Journal of Monetary Economics*, 118, 413–431.

Einav, L., A. Finkelstein, and M. R. Cullen (2010): "Estimating Welfare in Insurance Markets Using Variation in Prices," *The Quarterly Journal of Economics*, 125, 877–921, dOI: 10.1162/qjec.2010.125.3.877.

Fulford, S. and D. Low (2024): "Expense Shocks Matter," Working Paper 24-08, Consumer Financial Protection Bureau, dOI: 10.2139/ssrn.5035531.

Ge, S., S. Johnson, and N. Tzur-Ilan (2025): "The Hidden Effects of Climate Risk: Rising Insurance Premiums Increase Mortgage Delinquency and Drive Relocation to Safer Areas," Working paper, SSRN, dOI: 10.2139/ssrn.4992281.

Jones, R. A., R. Taylor, and N. Tzur-Ilan (2026): "Measures of Inflation Misalign with Pricier Home Insurance," Dallas Fed Economics, Federal Reserve Bank of Dallas.

Keys, B. J. and P. Mulder (2024): "Property insurance and disaster risk: New evidence from mortgage escrow data," Tech. rep., National Bureau of Economic Research.

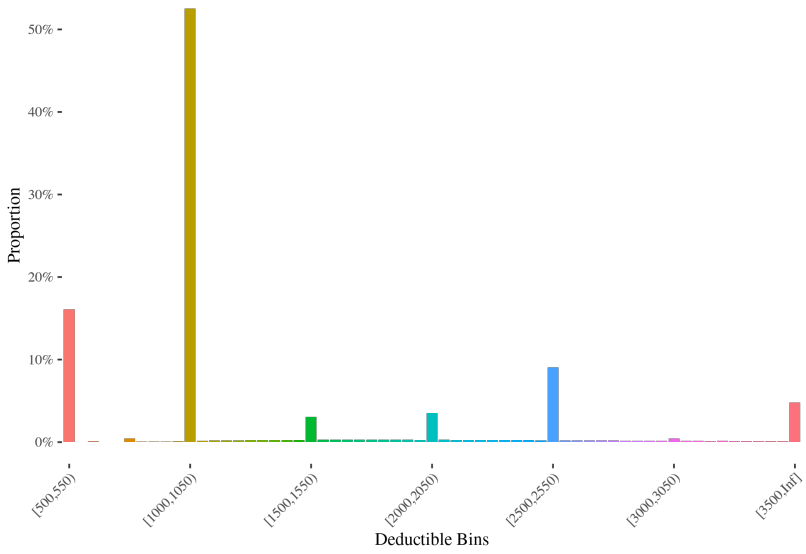
Mossin, J. (1968): "Aspects of Rational Insurance Purchasing," *Journal of Political Economy*, 76, 553–568.

Sastry, P., T. C. Scharlemann, I. Sen, and A.-M. Tenekedjieva (2025): "The Limits of Insurance Demand and the Growing Protection Gap," Working paper, SSRN, dOI: 10.2139/ssrn.4909444.

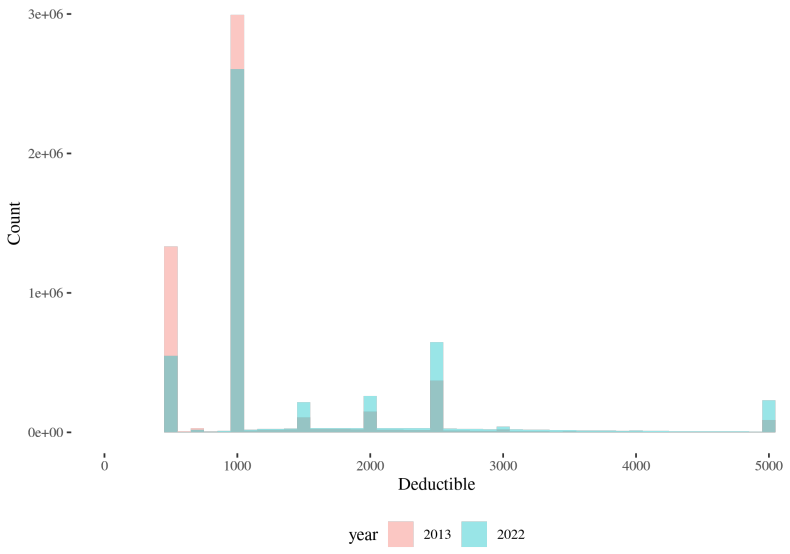
United States Government Accountability Office (2026): "Homeowners Insurance: Premiums Generally Tracked Inflation but Rose More in Disaster-Prone Areas," Tech. Rep. GAO-26-107867, United States Government Accountability Office.

Wagner, K. R. H. (2022): "Adaptation and Adverse Selection in Markets for Natural Disaster Insurance," *American Economic Journal: Economic Policy*, 14, 380–421, dOI: 10.1257/pol.20200378.

Figure 1: Distribution of Deductibles



(a) Pooled Distribution



(b) Comparison of 2013 and 2022 Distributions

Data sources: ICE McDash insurance module.

Figure 2: Coverage Limits and Related Price Indices

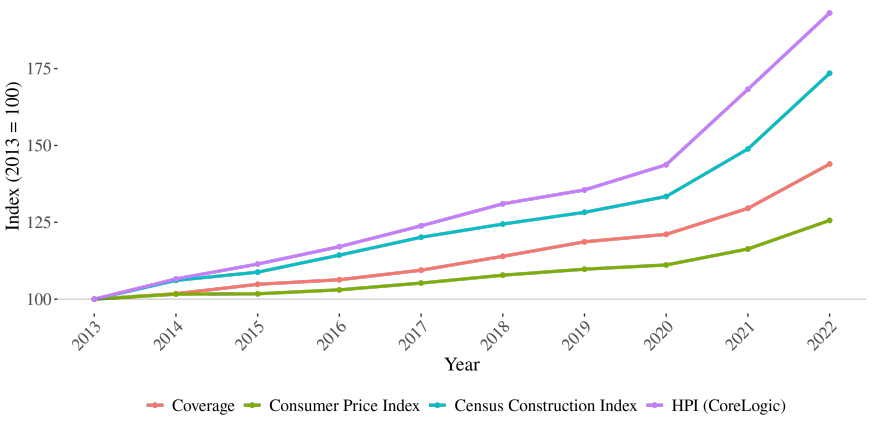
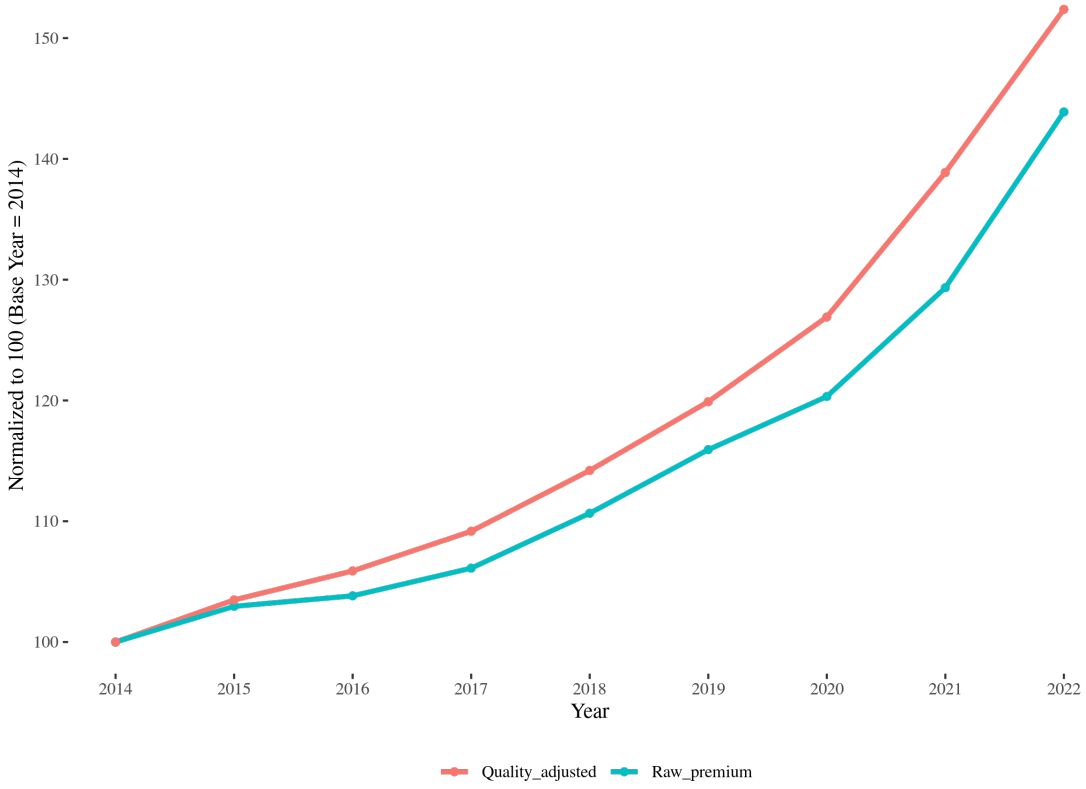
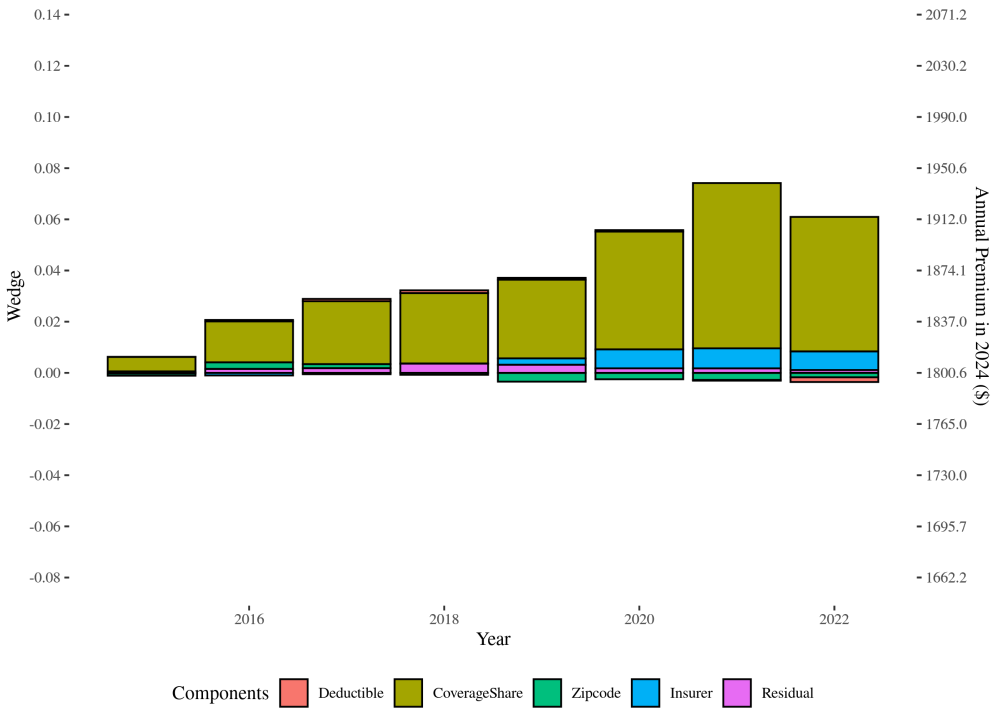


Figure 3: Quality-Adjusted Price Index



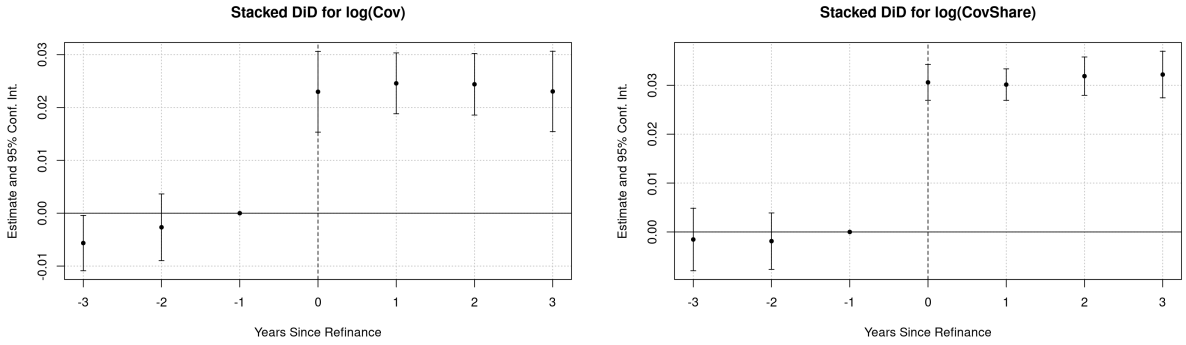
Note: This figure compares the quality adjusted insurance price index from Equation 1 to raw insurance expenditure growth from Equation 2. Data sources: ICE McDash insurance module, FHFA structure value share.

Figure 4: Decomposition of Wedge for Nation



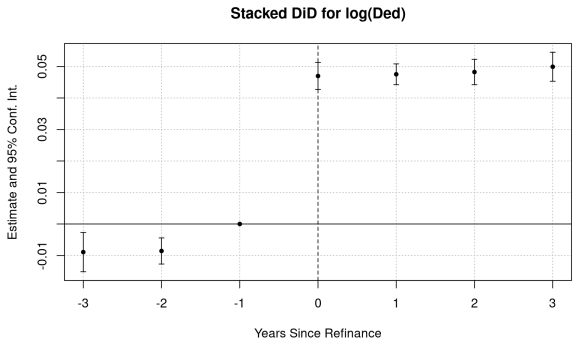
Note: This figure plots the decomposition of the difference between the quality adjusted insurance price index and the raw insurance expenditure growth. Data sources: ICE McDash insurance module, FHFA structure value share.

Figure 5: Insurance Demand at Time of Refinance

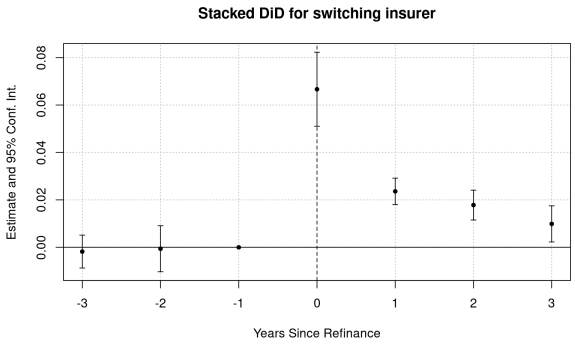


(a) Coverage

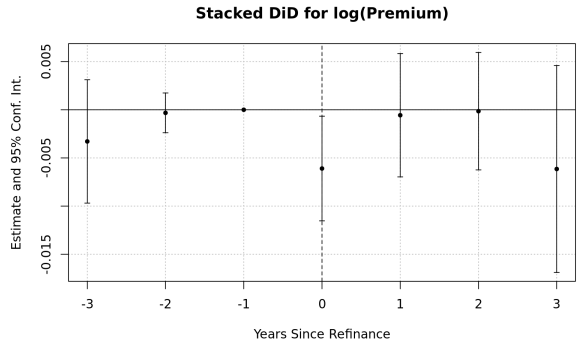
(b) Coverage Share



(c) Deductibles



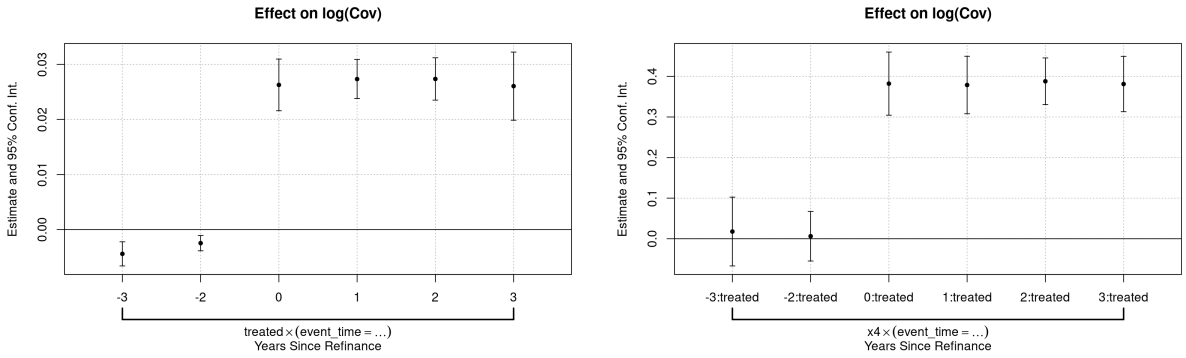
(d) Switching Insurer



(e) Premiums

Note: Figure plots coefficients from the event study regression in Equation 5. Error bars indicate 95% confidence intervals. Standard errors are clustered by zip code. Data sources: ICE McDash insurance module, Equifax CRISM, FHFA structure value share.

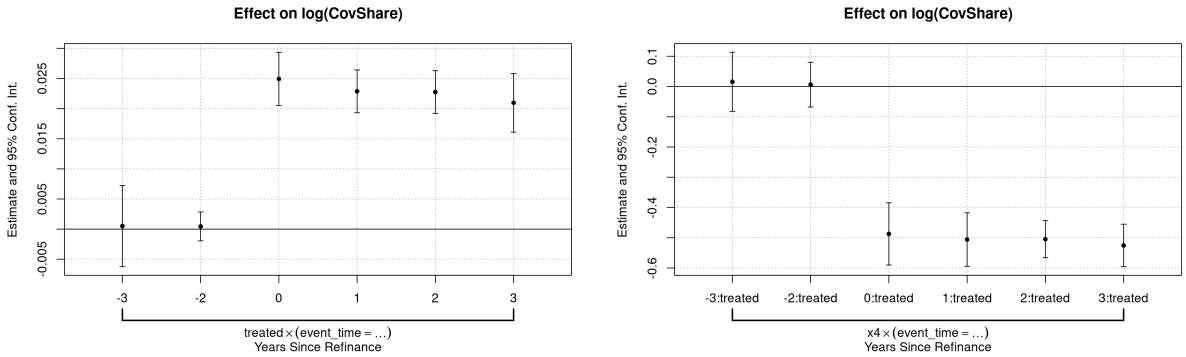
Figure 6: Triple Difference at Time of Refinance, Coverage



(a) Baseline Refinance Effect, β_k (b) Interaction with Appraisal Shock, δ_k

Note: Figure plots coefficients from the triple difference regression in Equation 6. The appraisal shock is calculated as the difference between actual appraisal value and predicted appraisal value based on county HPI growth. Error bars indicate 95% confidence intervals. Standard errors are clustered by zip code. Data sources: ICE McDash insurance module, Equifax CRISM, FHFA structure value share.

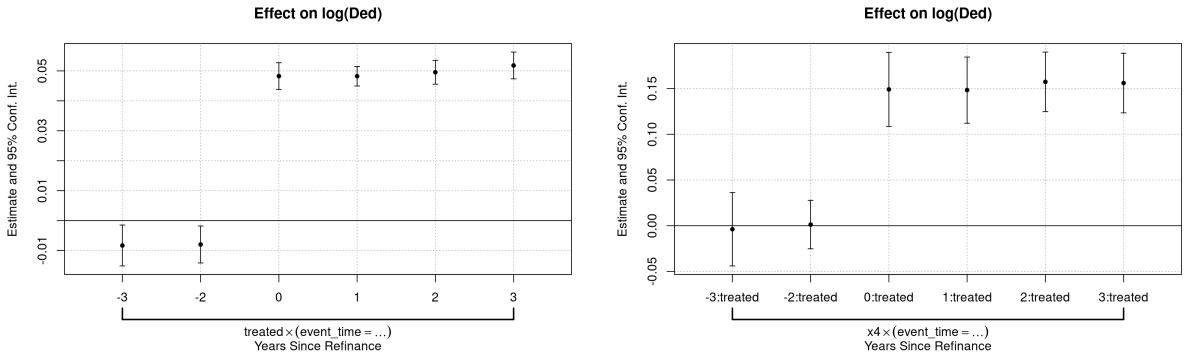
Figure 7: Triple Difference at Time of Refinance, Coverage Share



(a) Baseline Refinance Effect, β_k (b) Interaction with Appraisal Shock, δ_k

Note: Figure plots coefficients from the triple difference regression in Equation 6. The appraisal shock is calculated as the difference between actual appraisal value and predicted appraisal value based on county HPI growth. Error bars indicate 95% confidence intervals. Standard errors are clustered by zip code. Data sources: ICE McDash insurance module, Equifax CRISM, FHFA structure value share.

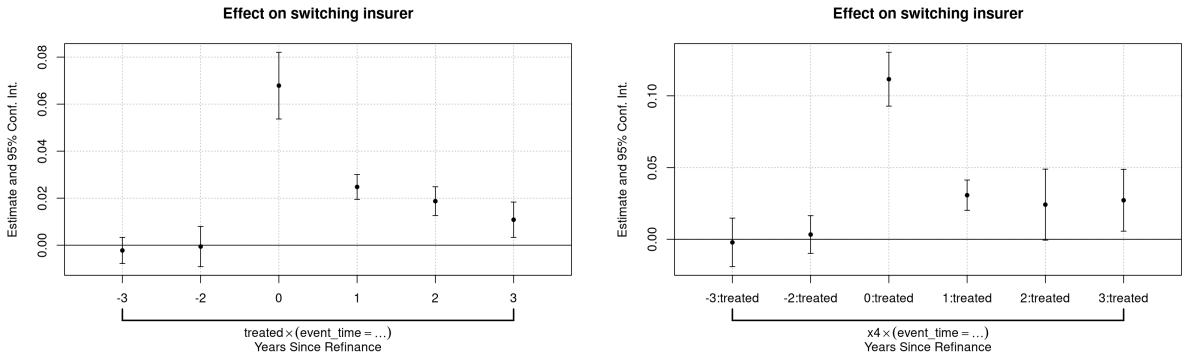
Figure 8: Triple Difference at Time of Refinance, Deductibles



(a) Baseline Refinance Effect, β_k (b) Interaction with Appraisal Shock, δ_k

Note: Figure plots coefficients from the triple difference regression in Equation 6. The appraisal shock is calculated as the difference between actual appraisal value and predicted appraisal value based on county HPI growth. Error bars indicate 95% confidence intervals. Standard errors are clustered by zip code. Data sources: ICE McDash insurance module, Equifax CRISM, FHFA structure value share.

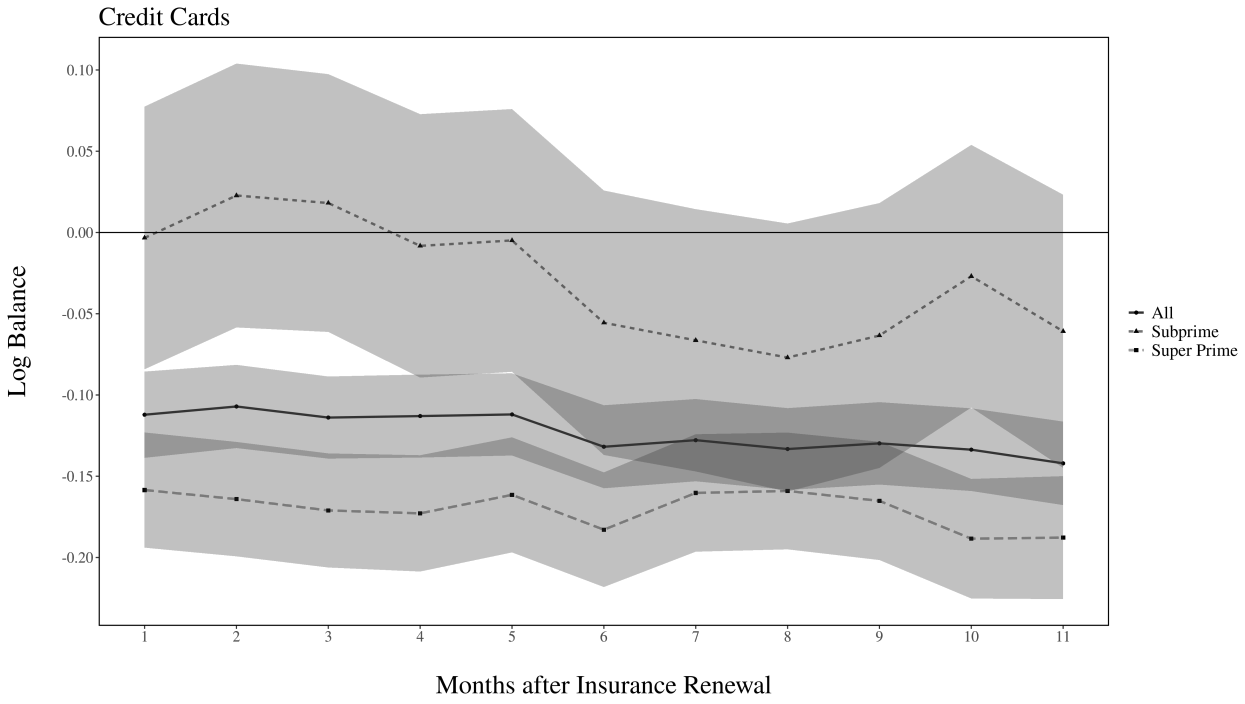
Figure 9: Triple Difference at Time of Refinance, Switching Insurers



(a) Baseline Refinance Effect, β_k (b) Interaction with Appraisal Shock, δ_k

Note: Figure plots coefficients from the triple difference regression in Equation 6. The appraisal shock is calculated as the difference between actual appraisal value and predicted appraisal value based on county HPI growth. Error bars indicate 95% confidence intervals. Standard errors are clustered by zip code. Data sources: ICE McDash insurance module, Equifax CRISM, FHFA structure value share.

Figure 10: Credit Card Balances During the Year after Insurance Price Change



Note: Figure plots coefficients β_m from Equation 7. Each of the eleven coefficients is estimated from a separate regression of the credit card balance in the m-th month after the policy renewal associated with the menu price increase. Subprime borrowers have credit scores below 620 and super prime borrowers have credit scores of 720 or greater. Shaded region indicates 95% confidence intervals. Standard errors are clustered by zip code. Data sources: ICE McDash insurance module, Equifax CRISM, FHFA structure value share.

Table 1: Price Elasticity of Deductibles and Insurer Choice

Y	$\log(Ded)$	Changed Deductibles	Switched Insurer
$\hat{\lambda}_{zt}^{qa}$	0.0458***	0.0158***	0.0683***
	(0.0037)	(0.0036)	(0.0031)
Loan FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Insurer FE	Yes	Yes	Yes
Observations	39,513,717	39,513,717	39,513,717
R2	0.92509	0.51000	0.30121
Adj. R2	0.90371	0.37018	0.10180
Mean(Y)	7.0568	0.09146	0.07013

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered by zip code.

Table 2: Price Elasticity of Coverage

Y	$\log(Cov)$	$CovShare$	$\log(CovShare)$	$\log(Premium)$
$\hat{\lambda}_{zt}^{qa}$	0.0650***	-0.6264***	-0.5106***	0.7401***
	(0.0029)	(0.0143)	(0.0095)	(0.0063)
Loan FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Insurer FE	Yes	Yes	Yes	Yes
Observations	39,513,717	39,513,717	39,513,717	39,513,717
R2	0.98380	0.93834	0.94296	0.94111
Adj. R2	0.97918	0.92075	0.92668	0.92430
Mean(Y)	12.566	1.4021	0.29679	7.0987

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered by zip code.

Table 3: Price Elasticity in First Year of Mortgage

Y	$\log(Ded)$	$\log(Cov)$	$\log(CovShare)$
$\hat{\lambda}_{zt}^{qa}$	0.0837***	-0.0621***	-0.2603***
	(0.0084)	(0.0075)	(0.0099)
Credit Score, DTI, LTV	Yes	Yes	Yes
Zip FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Insurer FE	Yes	Yes	Yes
Observations	8,652,455	8,652,455	8,652,445
R2	0.35067	0.73696	0.40148
Adj. R2	0.35002	0.73670	0.40088
Mean(Y)	7.0741	12.472	0.33692

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered by zip code.

Table 4: Insurance Prices and Financial Distress

Panel A: Not current on open accounts				
	Any Account (1)	First Mortgage (2)	HELOC (3)	Cards (4)
$\hat{\lambda}_{zt}^{qa}$	0.0128***	0.0092***	-0.0048**	0.0097***
	(0.0019)	(0.0016)	(0.0019)	(0.0015)
Observations	56,877,625	51,966,514	7,858,067	53,698,494
R^2	0.6261	0.6345	0.7116	0.6045
Adjusted R^2	0.4973	0.5025	0.5748	0.4637
Mean(Y)	0.1594	0.0554	0.0400	0.1089
Panel B: Not current on open accounts, Subprime borrowers (FICO $<$ 620)				
	Any Account (1)	First Mortgage (2)	HELOC (3)	Cards (4)
$\hat{\lambda}_{zt}^{qa}$	0.0441***	0.0159	0.0379	0.0361***
	(0.0079)	(0.0092)	(0.0275)	(0.0094)
Observations	3,424,867	3,041,908	278,875	2,882,905
R^2	0.7187	0.7144	0.8051	0.7366
Adjusted R^2	0.5361	0.5151	0.6140	0.5424
Mean(Y)	0.7518	0.3801	0.3373	0.6140
Panel C: Not current on open accounts, Super-prime borrowers (FICO $\geq$ 720)				
	Any Account (1)	First Mortgage (2)	HELOC (3)	Cards (4)
$\hat{\lambda}_{zt}^{qa}$	0.0016	0.0012	0.0015	0.0037**
	(0.0013)	(0.0006)	(0.0015)	(0.0011)
Observations	29,784,747	29,039,364	4,609,752	28,580,234
R^2	0.5368	0.5605	0.5993	0.5276
Adjusted R^2	0.3320	0.3634	0.3952	0.3150
Mean(Y)	0.0607	0.0131	0.0109	0.0392

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors are clustered by zip code. All specifications include loan, year, and insurer fixed-effects.

Appendix

Deductibles and Coverage

Insurance policies across the country most commonly have a similar deductible structure of flat dollar deductibles. However, there is a range of intermediate values. These intermediate values tend to be clustered at flat percentages of the insurance coverage. For policies that do not have level deductibles, we show that the majority of them have percent deductibles of 0.5%, 1%, or 2% of their coverage limit.

Texas is the most prominent exception to flat dollar deductibles, as deductibles are specified as a percentage of the coverage limit and this is often massed at 2%. The fact that deductibles are fixed in levels and do not vary over time does have important implications for insurance pricing. Notably, as construction costs increase, insurer exposures also increase since homeowner exposures are fixed over time. Furthermore, if damages are smoothly distributed as a percent of structure value across properties then over time, insurers are not just bearing more risk as construction costs increase, but are also insuring a larger share of the distribution as the tail below the deductible shrinks as property values increase.

Overall, we find that nationwide, the share of homeowners that have changed (and usually increased) their deductible has almost doubled from 8.5% in 2013 to nearly 13.8% in 2022. While this share has increased over time, we find substantial inertia within deductibles. As shown by the concentration in the diagonal of the transition matrix in Figure A.1, nearly 95% of policies keep the same deductible from year to year (pooled from 2013 to 2022).

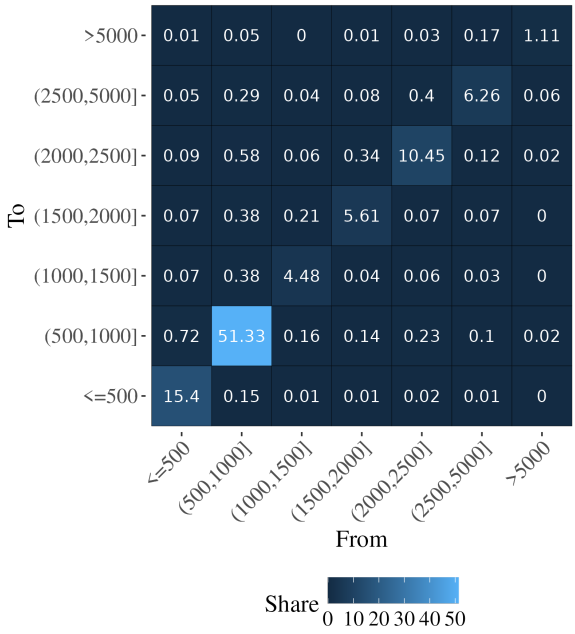
Coverage limit dynamics are further illustrated in Figure A.2. Panel (a) shows that coverage limit as a share of home price has declined from 2013 to 2022 - the distribution has shifted to the left. Panel (b) shows the distribution of annual changes in the nominal coverage limits, showing a large mass of small (<5%) coverage limit changes. As seen in Figure A.3, coverage share changes are also persistent year to year, although less so than deductibles. Nearly 60 percent of policies make the same change to coverage as the previous year.

State-Level Comparison

We construct state-specific quality-adjusted price indices to capture regional variation. Figure A.4 shows the wedge, Δ_t, between the quality-adjusted and raw price index across states.

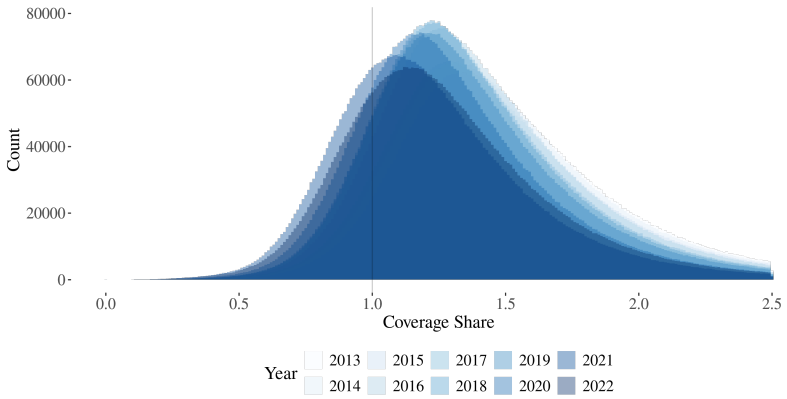
In Figure A.5, we compare the wedge decomposition across select states. Florida, California, and Louisiana all face high natural disaster risks, yet display largely different wedges. Quality-adjusted premium inflation has been high for both California and Florida, primarily due to lagging coverage share, but Florida's raw premium expenditures have been deflated more than California due to residential sorting to lower price zip codes. On the other hand, Louisiana's premium expenditures exceed the quality-adjusted prices due to households

Figure A.1: One-Year Transition Matrix of Deductibles

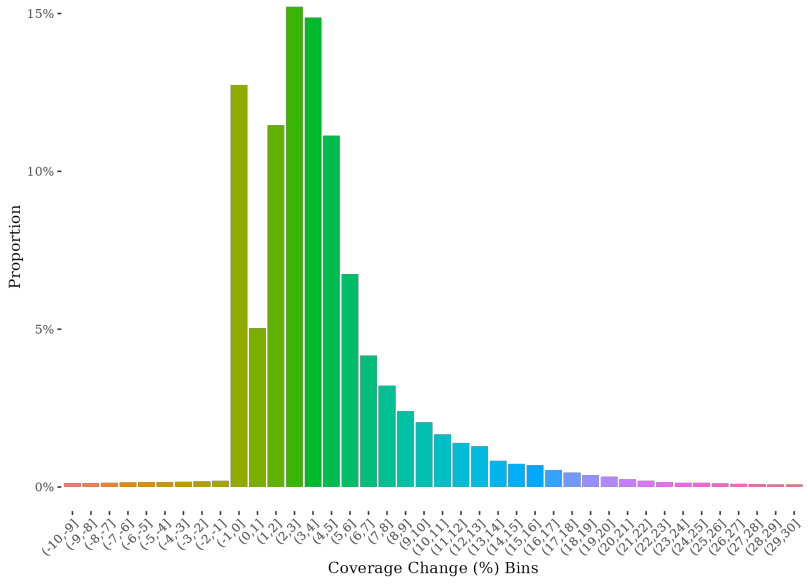


moving to more expensive zip codes and choosing lower deductibles that raise the premium. Texas represents a state where the quality-adjusted price index does not deviate greatly from the raw prices. However, the decomposition shows two competing underlying effects: households are reducing coverage and reducing deductibles. This suggests that households are trading off insuring specific parts of the damage distribution in response to premium increases.

Figure A.2: Coverage Limit Changes

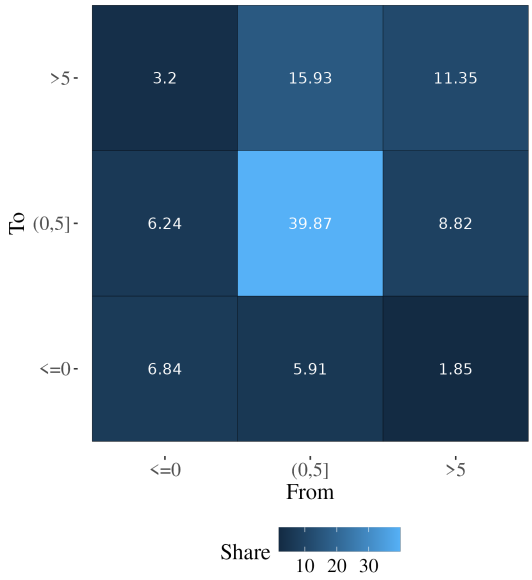


(a) Distribution of Coverage Share, 2013 to 2022

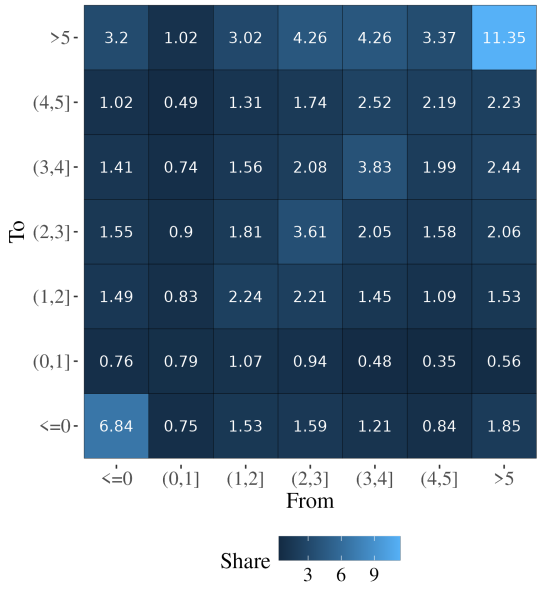


(b) Annual Changes in Coverage Limit

Figure A.3: One-Year Transition Matrix of Annual Coverage Changes



(a) Three Bins of Coverage Share Percentage Point Change



(b) Seven Bins of Coverage Share Percentage Point Change

Table A.1: Deductible Changes over Time

Year	Keep Deductible Type (%)	Type of Deductible	Direction of Deductible Change (%)		
			Increase	Decrease	Same
2014	95.7	$	4.6	0.9	94.5
		%	3.4	36.9	59.7
		others	16.5	4.0	79.5
2015	95.2	$	3.8	0.8	95.4
		%	3.4	44.0	52.6
		others	16.2	3.7	80.1
2016	95.3	$	3.5	0.8	95.7
		%	3.3	42.6	54.1
		others	14.6	3.8	81.5
2017	95.1	$	3.3	0.9	95.8
		%	2.7	48.7	48.6
		others	11.8	4.6	83.6
2018	95.5	$	3.4	1.1	95.5
		%	3.3	43.4	53.3
		others	16.2	6.0	77.8
2019	95.6	$	3.2	1.1	95.7
		%	4.2	35.0	60.8
		others	19.6	5.3	75.1
2020	95.1	$	3.2	1.1	95.7
		%	7.2	30.7	62.1
		others	24.9	5.2	70.0
2021	95.0	$	3.2	1.0	95.8
		%	9.8	22.7	67.5
		others	31.6	3.2	65.2
2022	94.8	$	3.6	1.0	95.4
		%	10.3	26.1	63.6
		others	31.7	2.5	65.8

Figure A.4: Wedge Map for 2022

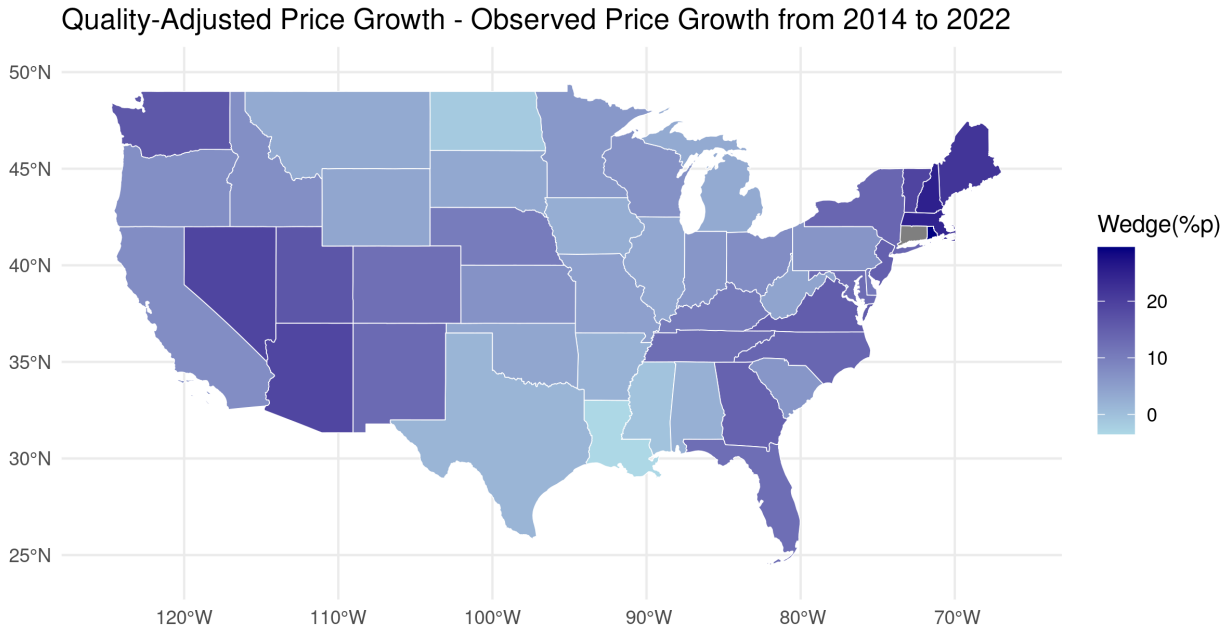
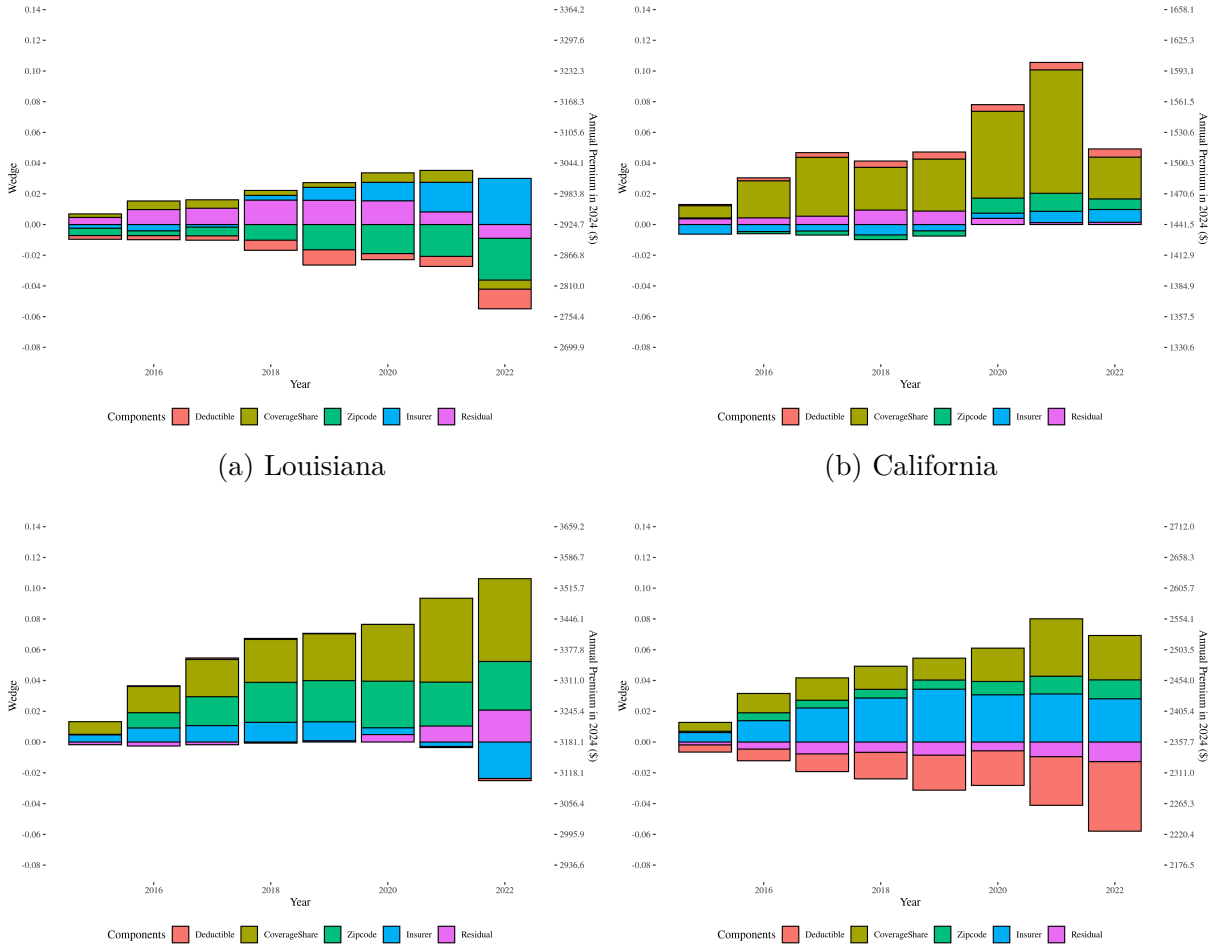


Figure A.5: Quality-Adjusted Price Wedge Decomposition, Select States



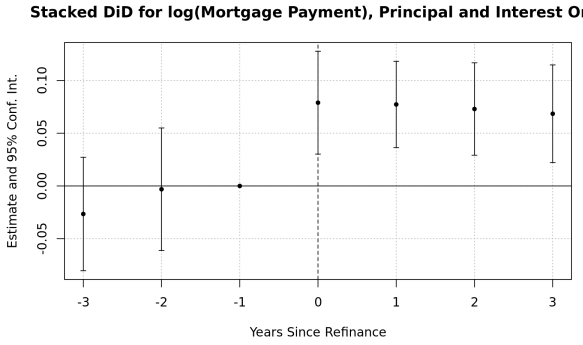
(a) Louisiana

(b) California

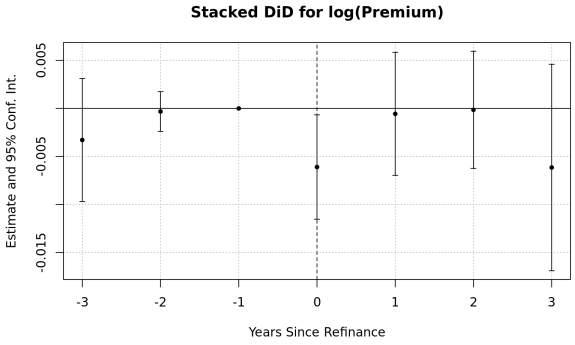
(c) Florida

(d) Texas

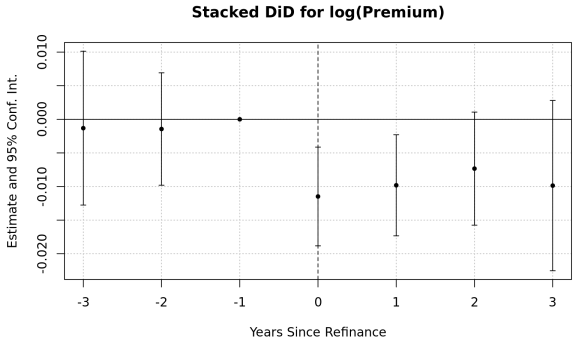
Figure A.6: Payment Changes at Time of Refinance



(a) Principal and Interest



(b) Premiums

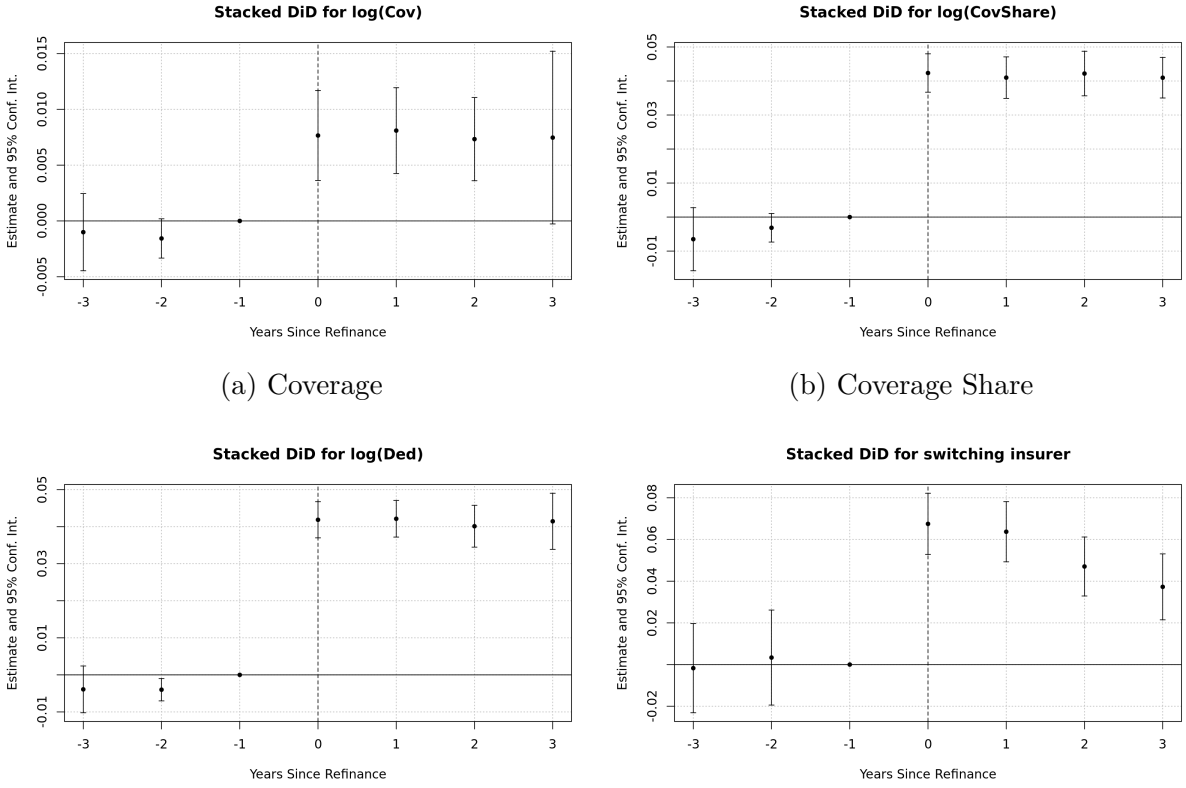


(c) Premiums, for Small P+I Changes

Note: Error bars indicate 95% confidence intervals. Standard errors are clustered by zip code.

Refi Payment Changes

Figure A.7: Price Elasticity at Time of Refinance, Small P+I Change



(a) Coverage

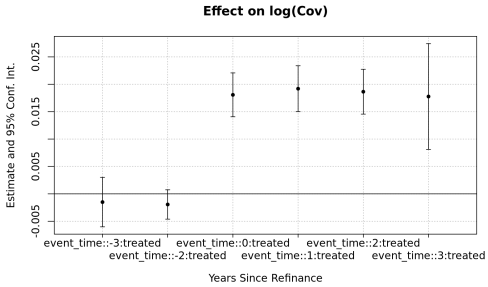
(b) Coverage Share

(c) Deductibles

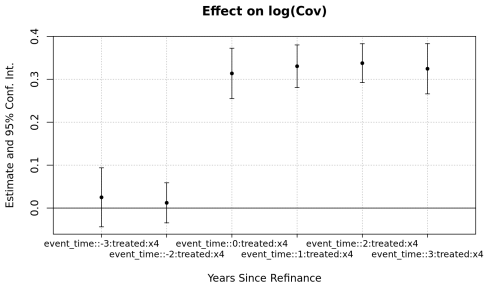
(d) Switching Insurer

Note: Error bars indicate 95% confidence intervals. Standard errors are clustered by zip code.

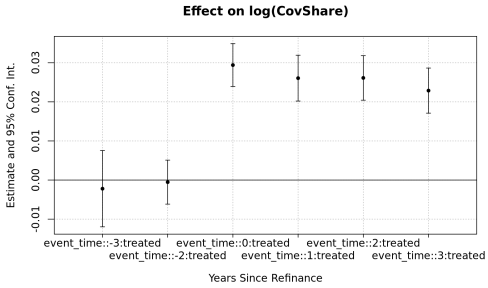
Figure A.8: Triple Difference at Time of Refinance, Coverage, Small P+I Change



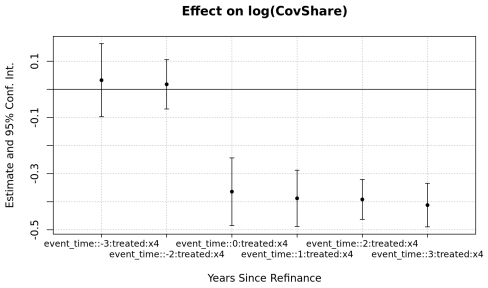
(a) Baseline Refinance Effect, β_k



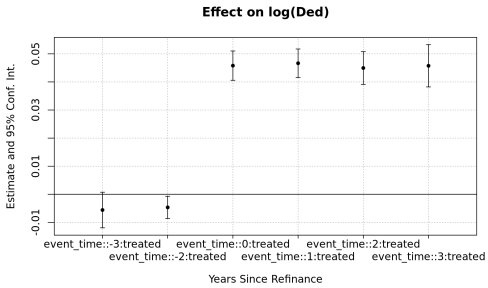
(b) Interaction with Appraisal Shock, δ_k



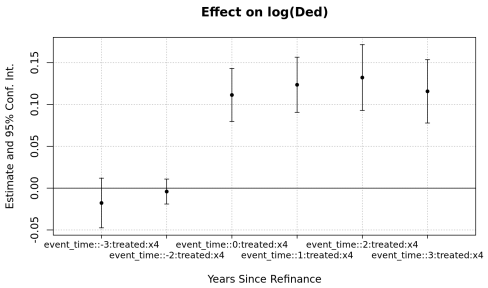
(c) Baseline Refinance Effect, β_k



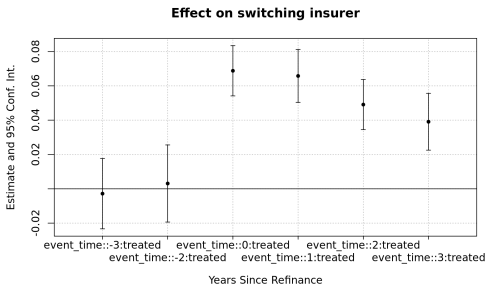
(d) Interaction with Appraisal Shock, δ_k



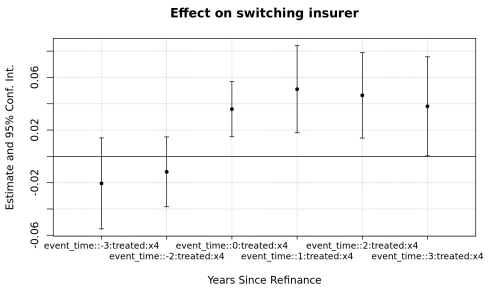
(e) Baseline Refinance Effect, β_k



(f) Interaction with Appraisal Shock, δ_k



(g) Baseline Refinance Effect, β_k



(h) Interaction with Appraisal Shock, δ_k

Note: Error bars indicate 95% confidence intervals. Standard errors are clustered by zip code.

Table A.2: Insurance Prices and New Financial Distress

Panel A: Not current on existing current accounts				
	Any Account (1)	First Mortgage (2)	HELOC (3)	Cards (4)
$\hat{\lambda}_{zt}^{qa}$	0.0035**	-0.0017*	-0.0024	0.0045***
	(0.0013)	(0.0008)	(0.0015)	(0.0012)
Observations	35,475,995	38,629,595	5,779,803	35,622,999
R^2	0.5045	0.4963	0.5120	0.4991
Adjusted R^2	0.2899	0.2936	0.2869	0.2844
Mean(Y)	0.0641	0.0216	0.0150	0.0484
Panel B: Not current on existing current accounts, Subprime borrowers (FICO $<$ 620)				
	Any Account (1)	First Mortgage (2)	HELOC (3)	Cards (4)
$\hat{\lambda}_{zt}^{qa}$	-0.0004	-0.0112	0.0296	0.0194
	(0.0169)	(0.0083)	(0.0248)	(0.0138)
Observations	635,369	1,785,291	184,738	1,012,184
R^2	0.7818	0.6817	0.7297	0.7445
Adjusted R^2	0.4583	0.3479	0.3988	0.3893
Mean(Y)	0.2039	0.1217	0.1041	0.1963
Panel C: Not current on existing current accounts, Super-prime borrowers (FICO $\geq$ 720)				
	Any Account (1)	First Mortgage (2)	HELOC (3)	Cards (4)
$\hat{\lambda}_{zt}^{qa}$	0.0024*	0.0009	0.0004	0.0036***
	(0.0012)	(0.0006)	(0.0012)	(0.0010)
Observations	28,387,548	28,793,506	4,577,720	27,730,783
R^2	0.5040	0.5164	0.5325	0.5033
Adjusted R^2	0.2770	0.2984	0.2935	0.2747
Mean(Y)	0.0432	0.0095	0.0075	0.0290

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors are clustered by zip code. All specifications include loan, year, and insurer fixed-effects.