Pricing Protection: Credit Scores, Disaster Risk, and Home Insurance Affordability*

Joshua Blonz†
Federal Reserve Board

Mallick Hossain‡
Federal Reserve Bank of Philadelphia

Benjamin J. Keys§
University of Pennsylvania and NBER

Philip Mulder¶
University of Wisconsin - Madison

Joakim A. Weill‖
Federal Reserve Board

September 2026

Abstract

How do insurers price risks they cannot directly observe? We use 70 million policies linked to mortgages and property-level disaster risk to show that insurers use credit scores as a proxy to price home insurance. Homeowners with lower credit scores pay 24% more for identical coverage than high-credit-score homeowners. Leveraging a natural experiment, we find that banning credit-based pricing reduces the relationship between credit score and premiums by 70%. We use novel survey data in a structural model to show that credit scores proxy for unobserved differences in the frequency and severity of losses rather than differences in claim filing behavior or financial literacy. Although discussions around credit scores and housing affordability typically focus on the mortgage market, we show that a low credit score increases premiums roughly as much as it raises the cost of mortgage interest.

*We thank Jean-Marc Bourgeon, Ben Dennis, Jen Dlugosz, Sarah Edelman, Jacob Gellman, Erik Heitfield, Ralph Blanchard III, Hugh Montag (discussant), Namloc Nguyen (discussant), Tess Scharlemann, Ishita Sen (discussant), Mike Springborn, Ana-Maria Tenekedjieva, Matt Walker, Margaret Walls, and seminar participants at the ASSA 2026 meetings, the 2026 SFS Cavalcade, the University of Wisconsin Risk & Insurance brownbag, the Wharton Real Estate brownbag, the Wisconsin Housing Demography brownbag, Oberlin College, Baruch College, the Federal Reserve Banks of Cleveland and San Francisco, the University of British Columbia, the University of Cincinnati, AgroParisTech, the University Paris-Saclay, Yale School of Management, Resources for the Future, HEC Montreal, the AERE Summer Conference and the AERE Fall Workshop, UH WEER Workshop, Clemson University, CEE-M, and Toulouse School of Economics for valuable feedback. We thank Tom Akana, Matthew Drayton, and Amber Lee for sharing results from the Federal Reserve Bank of Philadelphia insurance survey with us. We thank Jingao Jiao for outstanding research assistance. The views expressed here are those of the authors and do not necessarily reflect those of the Federal Reserve Board of Governors, the Federal Reserve Bank of Philadelphia, or of any other person associated with the Federal Reserve System. The authors declare no material or relevant financial relationships or conflicts of interest.

†Email: joshua.blonz@frb.gov.
‡Email: mallick.hossain@phil.frb.org.
§Email: benkeys@wharton.upenn.edu.
¶Email: philip.mulder@wisc.edu.
‖Email: joakim.a.weill@frb.gov.

1 Introduction

Firms increasingly set prices based on who the buyer is, in addition to what the buyer purchases. In insurance markets, this practice reflects an information problem: the cost of serving a customer often depends on characteristics that no insurer observes directly (Rothschild and Stiglitz, 1976). Insurers respond by pricing on proxies, observable traits that predict costs without revealing what generates them (Hoy, 1982). Yet how insurers balance directly pricing on observable risk against pricing on proxies is not well understood and has implications for the prices consumers pay and their incentives to reduce their risk.

In this paper, we study an important home insurance pricing proxy: credit scores. We first ask what is the relationship between credit scores and insurance premiums? Then, we examine the drivers of the credit-premium relationship and how this relationship affects the distributional costs of risk sharing and homeownership. Drawing on 70 million insurance policies linked to mortgages and a property-level disaster risk model, we show that credit scores have large effects on premiums. People with low credit scores pay as much as 24% more for the same coverage as those with high credit scores, even when conditioning on disaster risk and local geography. Using quasi-experimental evidence from a policy banning credit-based pricing in Washington state, we find that 25-30% of the credit-premium gradient is attributable to characteristics that are observable to the insurer, while the remaining three-quarters of the credit-premium gradient reflect information about home characteristics and homeowner behavior that insurers cannot directly observe.

We next ask what information credit scores provide to insurance companies. Do credit scores predict differences in actual risk, or do they proxy for differences in financial literacy or liquidity constraints that lead policyholders with lower credit scores to file more claims after small losses? These two channels have different efficiency and equity implications for credit-based pricing. Combining aggregate claims data with novel survey data on policyholders' willingness to file claims, we find that households with lower credit scores have more frequent and larger insured losses, but are only slightly more likely to file a claim conditional on having a loss. Combining our estimates in a structural model of claim filing behavior, we estimate that differences in the frequency and severity of losses explain nearly the entire credit-premium gradient, while differences in the likelihood to file a claim explain a negligible share. Finally, we compare the credit-premium gradient to the effect of credit scores on mortgage interest rates. We find that both have similar effects on monthly housing costs, highlighting

the underappreciated importance of the credit-premium gradient on home affordability.

We start our empirical analysis by quantifying the relationship between credit scores and premiums nationally. Although insurers report using credit information in their rate filings because it improves the prediction of insurance claims, the magnitude of the effect of credit score on insurance premiums is unknown (Insurance Information Institute, 2023). We show that homeowners with lower credit scores pay significantly more for their insurance policy even after conditioning on coverage, deductible, insurer, and geography, and that this relationship has slowly increased over the last decade. As of 2024, policyholders in the bottom quintile of the credit score distribution paid approximately $389 higher average annual premiums than those in the top credit score quintile—about 24% of the average premium.

We conduct an additional analysis using property fixed effects, which controls for time-invariant property-level characteristics by leveraging people with different credit scores living in the same properties over time. We find that the inclusion of property fixed effects reduces the credit-premium gradient by 26%, suggesting that insurance companies are pricing on characteristics not observed in our data. We also show that the credit-premium gradient is much flatter in the three states (CA, MA, MD) that ban the use of credit scores in pricing home insurance, suggesting that there are no other available proxies that provide the same information as the credit score.

To better understand how credit scores are used as proxies, we leverage a natural experiment in Washington state, where a ban on the use of credit scores to set insurance prices was briefly in effect before being overturned in court a year later. This unique variation in credit score-based underwriting allows us to control for unobserved individual characteristics, such as claim history or bundling of home and auto insurance, that could also affect premiums. We find that after the Washington state ban on credit-based pricing went into effect, homeowners with credit scores in the bottom quintile paid around $175 less per year, while those with high credit scores paid around $100 more per year. Overall, we find that the ban erased about 70% of the credit-premium gradient, and the gradient quickly returned when the ban was lifted. We find no effect of the credit-pricing ban on coverage decisions, mortgage delinquency, or prepayment. The finding that 70% of the credit-premium gradient attenuates with the ban confirms that credit scores are being used as a proxy to price unobservable characteristics of homeowners.

Why do insurers use credit information to set premiums? On the one hand, if credit scores predict actual losses then such proxy pricing can help insurers accurately price risk. On the other hand, if lower credit scores reflect liquidity constraints or unawareness of how claims affect premiums that make policyholders more likely to file on small claims, then distributional and fairness concerns may motivate policies restricting the use of credit scores by insurers (Kiviat, 2019). These different mechanisms could motivate different policy responses across public investments in risk reduction, financial literacy, and improving credit access. Using ZIP code-level aggregate data on homeowners claims, we find that claim filing rates and average claim amounts relative to coverage are higher in areas with lower average credit scores, demonstrating a relationship between expected incurred losses and credit scores that corresponds with the credit-premium gradient we find in the policy data.

To separately identify how liquidity, financial literacy, and risk contribute to differences in average incurred losses by credit score, we leverage novel survey data that elicits homeowners' credit scores and propensity to file insurance claims across the loss distribution. The survey finds that policyholders with lower credit scores are only slightly more likely to file small claims– they tend to be willing to pay out of pockets for small losses at a similar rate as individuals with higher credit scores, suggesting they have similar "shadow deductibles". Using the survey and claims data to calibrate a structural model of claim filing behavior, we find that almost all of the differences in expected incurred losses can be attributed to differences in the underlying frequency and severity of losses rather than the propensity to file claims. We provide supporting evidence for these findings using data on house fires, showing that census tracts with lower credit scores have more frequent fire incidents. These findings suggest that credit-based pricing reflects real differences in risk, and not simply differences in awareness that claims affect insurance premiums or the ability to absorb losses out of pocket.

Finally, we quantify the impact of the credit-premium gradient on home affordability by comparing it to the relationship between credit scores and mortgage interest rates. We use our mortgage-linked policy data to estimate a pair of relationships: first, between mortgage interest rates and credit scores conditional on loan characteristics, and, second, between homeowners insurance premiums and credit scores conditional on policy characteristics and disaster risk. Both the premium and interest rate credit relationships reflect a combination of explicit pricing on credit and correlated, unobservable factors such as claims history or

propensity to refinance.

We find that the relationships between homeowners' credit scores and (i) mortgage interest payments or (ii) home insurance premiums are similar in magnitude. In our sample of policyholders in 2024, moving from a 620 credit score to an 800 credit score is associated with a 40 basis point reduction in both interest payments and premium payments as a share of mortgage balances. This finding puts the economic significance of our results in context, showing that credit-based insurance pricing can have a large effect on housing expenses. Furthermore, unlike most mortgages, home insurance premiums change annually and are not paid off over time, thereby exposing the most liquidity-constrained homeowners to more volatile and durable increases in homeownership costs. The high and increasing cost of home insurance for people with low credit scores highlights the growing importance of insurance premiums in discussions about home affordability.

This paper advances the literature on insurance pricing by analyzing how home insurers price on credit scores as a proxy for risk. Under the canonical model in Ehrlich and Becker (1972), moral hazard can be contracted away when insurers price based on the insured's probability of loss. It matters, however, whether the insurer observes and prices the direct cause of loss or only a proxy. Crocker and Snow (1986) note the ambiguous welfare effects of costly categorization in insurance markets, while Bond and Crocker (1991) describe how agents' consumption can be used to statistically proxy for imperfectly observable risk.[1] The increasing availability of detailed customer-level information and its potential use in algorithmic pricing highlights the importance of understanding the consequences of using pricing proxies (Kleinberg et al., 2018; Rambachan et al., 2020; Calvano et al., 2020). Our paper is, to the best of our knowledge, the first to empirically use quasi-experimental evidence to show that proxy variables help insurers accurately price risk and drive substantial premium variation.

Our findings show that policyholders' credit histories are approximately as important as disaster risk in driving premiums. Many papers have studied the relationship between disaster risk and premiums, whether through the lens of reinsurance and inflation (Keys and Mulder, 2024; Solomon, 2024; Collier et al., 2026), the use of sophisticated catastrophic risk models (Boomhower et al., 2024), the interaction between private markets and last-resort

[1] In line with Bond and Crocker (1991), young smokers pay higher life insurance premiums on short duration policies even when the risk of lung cancer mortality is negligible because smoking proxies for other risky behaviors. We thank David McCarthy for discussion on this point.

insurers (Taylor, Turland and Weill, 2025), or pricing policy in the public National Flood Insurance Program (Wagner, 2022; Mulder, 2022; Mulder and Kousky, 2023; Weill, 2026). Our results show that credit scores predict a substantial amount of risk that insurers would otherwise fail to price in the absence of credit-based pricing. These findings complicate the narrative on pricing risk from Ehrlich and Becker (1972): Even though credit is a useful tool for predicting losses, it creates no direct incentives for homeowners to reduce their risk. Understanding how insurance markets actually incentivize risk reduction is increasingly important as policymakers seek to equitably promote investments in adaptation.

Second, we add novel empirical evidence on the distributional impacts of risk classification via proxy variables. While credit scores predict claims, they are also correlated with other characteristics such as race, income, and wealth (Bakker et al., 2025; Fuster et al., 2022). Blattner and Nelson (2021) find that credit scores are noisier indicators of credit risk for historically under-served groups, while Blattner, Nelson and Spiess (2021) discuss the challenges in regulating algorithmic underwriting and pricing models, and Huang and Hooker (2026) develop fairness tests for algorithmic pricing using auto insurance as a proof of concept. Credit history is also used as a screening proxy in labor markets (Ballance, Clifford and Shoag, 2020). Ex ante, restricting insurance pricing has unclear distributional effects because insurers may adjust the contract space or change their pricing of other factors (Finkelstein, Poterba and Rothschild, 2009; Pope and Sydnor, 2011; Bartlett et al., 2022). In our setting, we find that bans on credit-based pricing do significantly narrow the credit-premium gradient without evidence of short-run changes in contract features or mortgage delinquencies and prepayment.

By documenting the credit-premium gradient, we contribute to the literature on socioeconomic disparities in access to risk sharing (Blundell, Pistaferri and Preston, 2008). A growing body of research documents disparities in household exposure to disaster risks, adaptation investments, and post-disaster recovery (Bakkensen and Ma, 2020; Cain et al., 2024; Billings, Gallagher and Ricketts, 2022; Cookson, Gallagher and Mulder, 2023; Bradt and Aldy, 2025). Poorer households buy less insurance in general and are more likely to be underinsured on their home (Armantier, Foncel and Treich, 2023; Gropper and Kuhnen, 2025; Sastry et al., 2026). Related research studies how price shocks, coverage gaps, and insurer insolvencies affect housing markets through home price declines, rebuilding, and mortgage delinquencies (Sastry, 2026; Eastman, Kim and Zhou, 2024; Ge, Lam and Lewis,

2025; Cookson, Gallagher and Mulder, 2025; Biswas, Hossain and Zink, 2023; Amornsiripanitch et al., 2025; Sastry, Sen and Tenekedjieva, 2026). By making premiums more expensive for the homeowners with the least ability to pay, credit-based pricing potentially exacerbates gaps in insurance coverage and generates post-disaster fiscal and housing market spillovers.

Finally, our results deepen our understanding of how credit scores affect housing affordability. This literature has focused on mortgage interest rates and credit access, for example over the housing cycle (Bhutta, 2015; Hurst et al., 2016) or as mediated by differences in shopping behavior (Keys, Pope and Pope, 2016; Bhutta, Fuster and Hizmo, 2024). In other cases, researchers have studied how credit can affect renters' housing access and the impacts of eviction and rent control policies (Humphries et al., 2024; Arefeva et al., 2024; Collinson et al., 2024). The longstanding American goal to promote homeownership have led to a number of policies to expand credit access for homeowners with weak credit (Green and Wachter, 2005). We show that the relationship between credit scores and homeowners insurance premiums is approximately as large as their relationship with interest rates, suggesting a meaningful barrier to homeownership for low-score households as premiums continue to rise.

2 Homeowners Insurance Background

Mortgage lenders usually require homeowners to purchase and maintain sufficient home insurance coverage for a range of perils (Fannie Mae, 2024; Freddie Mac, 2024). The HO-3 form is the most common insurance policy type and covers all perils except those explicitly excluded (floods, earthquakes, and wars are the most common exclusions).[2]

Originally, insurance companies did not account for credit history when setting insurance premiums. In 1993, FICO introduced credit-based "insurance scores" that were quickly adopted by insurance companies to help set insurance prices (National Association of Insurance Commissioners, 2009). By 2005, their use in the industry was widespread (Webel, 2005).[3] These credit-based insurance scores are derived from a person's credit history and

[2]Based on industry aggregates, we estimate that natural hazards account for 10–35% of collected premiums in a given year (Congressional Budget Office, 2024; AM Best, 2025). In 2023, wind and hail accounted for 42% of incurred losses, water damage (excluding flooding) and freezing for 23%, and fire and lightning for 22% (Insurance Information Institute, 2025). Wildfires represent only about 5% of fire and lightning claims, with most fires originating from cooking and other appliances (U.S. Fire Administration, 2024). Premiums finance these losses as well as other claims unrelated to disaster risk (theft, vandalism, and liability). Premiums also finance insurers' expenses and required returns on capital.

[3]See Appendix A.1 for further discussion of this history.

are very similar to the better-known FICO credit scores.[4] We refer to the use of credit-based insurance scores to price policies as "credit-based pricing." In practice, actuarial rate-setting is predictive: actuaries include variables that improve forecasts of losses, regardless of whether the economic mechanism is known.[5] Credit-based insurance scores are used because they are correlated with expected incurred losses. This correlation could reflect people with higher credit scores having lower risks of damage events, smaller amounts of damage, or a higher likelihood of paying for smaller losses out of pocket.

Concerns about unfairly discriminatory pricing led California, Massachusetts, and Maryland to ban the use of credit information in homeowners insurance ratemaking in the early 2000s, and Washington state briefly altered its policy on the use of credit scores in 2021 before reverting in 2022. We examine the Washington state policy variation in Section 5.

The following framework outlines three of the major factors that influence claims payouts that insurers consider when setting prices:

$$\mathbb{E}[\text{Claim}_{ipke}] = P(\text{Event}_{pe}) \times \mathbb{E}[\text{Damages}_{pke}|\text{Event}_{pe}] \times P(\text{File Claim}_{ike}|\text{Damages}_{pke}) \quad (1)$$

Where $\mathbb{E}[\text{Claim}_{ipke}]$ is the expected dollar value of claims filed by homeowner i living in property p, choosing insurance contract k, and for event type e leading to damages. For simplicity, we assume two types of damage events: disaster and idiosyncratic. Disaster events include hurricanes, severe convective storms, and wildfires, where many properties in a concentrated geographic area are likely affected. Idiosyncratic events include, for example, house fires started by appliances, water damage from leaking pipes, and theft or other property damage. When setting the price of insurance policies, insurance companies rely on estimates of the probability of a damage event, $P(\text{Event}_{pe})$, and the expected damages to a property conditional on an event, $\mathbb{E}[\text{Damages}_{pke}|\text{Event}_{pe}]$.

Insurers also consider how likely a homeowner is to file a claim when suffering a loss, $P(\text{File Claim}_{ike}|\text{Damages}_{pke})$.[6] Insurance companies use homeowner characteristics, including past claims behavior and credit score, to help determine the likelihood that the homeowner will file a claim given any damages. Equation 1 highlights that insurers have an

[4] While we do not directly observe credit history or the credit-based insurance scores used by insurers, these scores are very highly correlated with the credit scores that we use in our analysis (FICO, 2025*a*,*b*).

[5] Appendix A.2 provides an overview of how insurance premiums are calculated and a worked-out example based on Allstate's rate filing in Oklahoma.

[6] Some claims may be denied by the insurer, but in this simple framework we only consider successful claims. There may be additional costs to determining which claims should be paid.

incentive to charge higher rates to homeowners they think are more likely to file claims, conditional on risk frequency, severity, and the insurance contract characteristics. In the following sections, we explore the importance of these three terms and their interaction with credit scores in home insurance premiums.

3 Data

We use insurance policy data from the ICE, McDash residential mortgage servicer database and property insurance dataset (referred to as "McDash" in this paper). The McDash mortgage data cover about two-thirds of all residential mortgages in the U.S. and are frequently used in economics research (Elul et al., 2010; Foote et al., 2010; Ghent and Kudlyak, 2011; Fuster et al., 2022). The McDash insurance sample we use starts in 2015 and covers about 70% of McDash mortgages whose servicers reported data.[7]

The McDash property insurance dataset reports monthly insurance premiums, coverage limits, and deductible choices for homeowners insurance policies and any escrowed flood insurance policy.[8] The property insurance data also report the insurer for each policy, directly identifying the top 25 insurers in each state, including the Florida Citizens and California FAIR plans, with smaller insurers grouped under an "other" code. It also includes the credit score of the homeowner at mortgage origination and the ZIP code of the property. We exclude condominiums because many are also covered by a master condominium policy obtained by the condo association, and we exclude loans without escrowed insurance payments, as servicers may not capture reliable premium or deductible data when they are not disbursing funds. After cleaning the data, the dataset contains 132 million policy-year observations from 2015–2024 (see Appendix Table S3 for details).

One advantage of our policy-level data is that we can disentangle changes in insurance expenditure from changes in insurance coverage. Appendix Figure S1, panel A documents a positive correlation between home values and insurance premiums and shows that, on average, more expensive homes cost more to insure. However, panel B of Appendix Figure S1 shows that more expensive homes obtain insurance at a lower rate per dollar of coverage.

[7] Appendix Table S4 provides a balance table showing that mortgages with insurance records are similar to those without.

[8] Although the homeowners insurance premiums in our data can reflect discounts from bundling, say, home and auto policies with one carrier, we note that the observed premiums are only for the homeowners insurance portion of the bundled premium.

We merge the McDash data with CoreLogic Property Basic data using a one-to-one match on ZIP code, origination amount, and closing date (Sastry et al., 2026).[9] With this conservative method, we match about 60% of the McDash mortgages. The matched sample closely resembles the full McDash sample on observables (Appendix Table S5). We also attach CoreLogic's Resiliency data which include 2021 property-level estimates of Average Annual Losses (AAL).[10]

CoreLogic's AALs offer four advantages: (1) they include all disaster-related losses; (2) they separate floods and earthquakes from other hazards, which allows us to focus on disasters covered by homeowners insurance; (3) they incorporate property characteristics and the condition of the property; and (4) they are used by several insurers (Boomhower et al., 2024).[11] Linking policies to property-level AALs lets us analyze the pricing of disaster risk using our representative insurance sample and, because predicted losses vary sharply within small areas, mitigates spatial aggregation bias. CoreLogic's AAL estimates provide valuable information on disaster risk, complementing a range of other models available to insurers, who may also draw on tools from different vendors.

Table 1 reports summary statistics for homeowners policies in our sample. The insurance-to-loan ratio (insurance cost divided by mortgage principal and interest payments, which we call the "insurance burden") is around 15%, highlighting that even for the average homeowner, insurance costs represent a meaningful homeownership expense.

Figure 1, panel A shows the average premium per thousand dollars of coverage ("normalized premiums"), which allows us to compare premiums across areas of the country with different housing values. Premiums vary sharply across space: People living in Florida, Louisiana, Texas, and the Great Plains pay the most for insurance on a per-coverage basis, whereas individuals in the Western and Northeastern states pay the least.[12] There are two likely drivers of the differences in cost across states: differences in disaster risk and differences in state-level regulation (Oh, Sen and Tenekedjieva, 2026).

Figure 1, panel B shows the difference between the normalized premiums for individuals

[9] We thank Tess Scharlemann for sharing this approach with us.

[10] The AAL is reported by CoreLogic as a percent of total insured value. To convert this to expected losses (in dollars), we multiply the percent AAL by the imputed structure value of the property. We calculate the imputed structure value by multiplying the transaction value (or the assessed value if missing) by the structure share computed by the Federal Housing Finance Agency (FHFA) reported in 2023 dollars using the FHFA Housing Price Index (see Davis et al., 2021, for details).

[11] AALs are only calculated for natural disasters and do not include other sources of claims such as kitchen fires, burst pipes, or liability claims (e.g., dog bites).

[12] Appendix Figure S2 shows normalized premiums at the county level.

Table 1: Summary statistics

Variable	Mean	SD	Min	Max	N
Coverage (USD)	330,704.62	187,622.59	50,001.00	2,000,000	74,567,665
Annual premium (USD)	1,550.03	1,080.34	24.00	91,608	74,567,665
Prem. per 1k	5.26	3.43	0.01	359	74,567,665
Deductible (USD)	1,564.96	7,610.04	2.00	9,576,500	65,220,530
Appraisal (USD)	296,178.90	223,651.41	50,001.00	2,999,999	74,567,665
Debt-to-Income (%)	34.89	11.60	0.00	99	44,819,042
Loan-to-Value (%)	80.22	18.02	0.00	150	74,567,665
Origination (USD)	223,193.42	149,870.52	10,000.00	3,558,000	74,567,665
Average Annual Losses (%)	0.11	0.10	0.00	11	74,567,665
Average Annual Losses (USD)	339.99	463.91	0.00	89,936	70,284,727
Insurance-to-loan (%)	14.62	11.70	0.03	140	74,567,665
Annual mortgage (USD)	13,459.42	8,772.22	156.00	932,808	74,567,665

Source: ICE, McDash®; CoreLogic
Notes: Coverage is the dwelling coverage limit of the policy (Coverage A). Average Annual Losses (%) are the estimated damages as a share of the estimated total insured value.

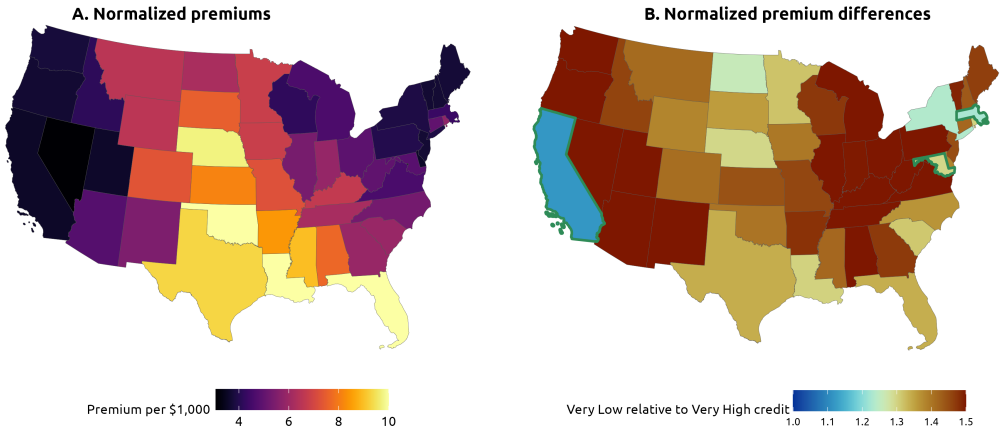
in the bottom quintile of credit score ("Very Low Credit") relative to those in the top quintile of credit scores ("Very High Credit") by state. We see that homeowners with very low credit pay about 30% to 40% more than those with very high credit in nearly every state. The main exceptions are California, Maryland, and Massachusetts (outlined in green), which limit the use of credit information in insurance pricing and have a much flatter credit-premium gradient.[13]

Figure 2 shows the insurance-to-loan ratio ("insurance burden"), by year and credit score groups. The figure depicts two trend regression lines for the 2015–2019 and the 2020–2024 periods. Between 2015 and 2019 the insurance burden was relatively flat, with homeowners with very low credit always having a higher insurance burden on average. Starting in 2020, the insurance burden begins to increase for everyone, although it increases for policyholders with very low credit at a faster rate. The average insurance burden for those with very low credit grows from around 17% in 2020 to 24% by 2024, an increase of around 1.7 percentage points per year.

There is also significant state-level heterogeneity in the insurance burden. Appendix Figure S4 shows that the 2024 insurance burden for homeowners with very low credit is

[13]Appendix Figure S3 shows trends in normalized premiums by credit score over time in the homeowners insurance market and for flood insurance. Notably, credit history is not used to price flood insurance policies provided through the public National Flood Insurance Program. In contrast to the homeowners insurance time series, there is no evidence of a clear, stable ordering by credit score of normalized flood insurance premiums.

Figure 1: Premium per $1,000 and credit differences at the state level



Source: ICE, McDash®
Notes: The figure displays state-level maps showing average premiums per thousand dollars of coverage ("normalized premiums," panel A) and average differences in normalized premiums between the top and bottom quintiles of the credit score distribution (panel B). Scale is bounded on $1 - 1.5$ for clarity. The green borders denote the three states that ban the use of credit information in homeowners insurance pricing (CA, MA, and MD).

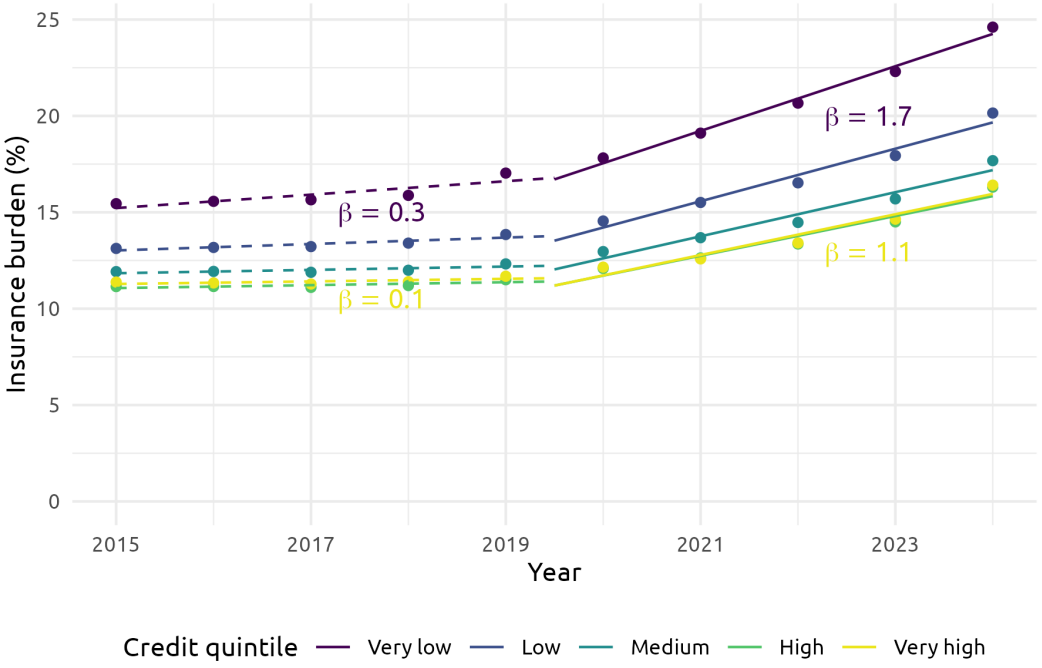
already more than 35% in states like Florida, Louisiana, Oklahoma, and Nebraska. Overall, these results highlight that insurance payments can be a substantial financial burden that has increased over the last five years, particularly for homeowners with lower credit scores.

4 Nationwide evidence on credit scores and premiums

In this section, we measure the national credit–premium gradient and compare its contribution to homeowners insurance premiums with that of property-level disaster risk. Although credit scores are widely used in rating, this does not necessarily translate into meaningful differences in paid premiums. Homeowners with low credit scores may sort into insurers that put less weight on credit scores, or credit pricing may be small relative to pricing along other dimensions. Leveraging purchased policy data, rather than insurers' quotes (Todoroff, 2024, 2025; Graetz, 2025), allows us to quantify the existing association between premiums and credit.

To decompose the relationship between premiums, credit scores, and disaster risk, we

Figure 2: Insurance burden by year and credit score bin



Source: ICE, McDash®; CoreLogic
Notes: The figure displays the insurance burden (the ratio of the monthly premium to the sum of the monthly principal and interest payments) by credit score bin between 2015 and 2024. The annual rate of increase over the two five-year segments is shown for people with very low (in purple) and very high (in yellow) credit scores as the β coefficients on the figure.

first estimate the following specification:

$$P_{igt} = \sum_{b=1}^{4} \beta_b \, Credit_{ib} + \gamma_1 AAL_i + \gamma_2 Deductible_{it} + \gamma_3 Coverage_{it} + \lambda_j + \lambda_t + \lambda_g + \epsilon_{igt}. \tag{2}$$

where P_{igt} is the annual insurance premium of homeowners insurance policy i in geography g (state or census blockgroup) during year t. The sample spans insurance policies active between 2015 and 2024. $Credit_b$ is an indicator for an individual being in a particular credit score group b at mortgage origination.[14] We define five credit groups based on the quintile of the observed distribution of credit scores: Very low (less than 671), Low (671-715), Medium

[14]Most insurance is priced based on credit information at mortgage origination. While a homeowner can request a re-pricing based on a higher credit score, such repricing is not automatic. Appendix Table S6 conducts the analysis with current credit scores and finds similar results.

(716-755), High (756-786), and Very high (greater than 786).[15] The Very high credit group is the omitted reference category. AAL_i is the predicted average annual loss for property i in dollars derived from CoreLogic. As described above, the AAL is fixed at the 2021 property-level estimate. We control flexibly for deductible choice ($Deductible_{it}$, which includes \$500 bins for deductible choice and is top-coded at \$10,000), and coverage choice ($Coverage_{it}$, which includes \$50,000 bins for coverage amount and is top-coded at \$2 million). λ_j, λ_t, and λ_g are insurer, year, and geography fixed effects, respectively, and errors are clustered at the ZIP code level. The $\{\beta_b\}$ coefficients report the conditional associations between credit score and premiums, while γ_1 measures the pass-through of predicted disaster losses to premiums.

Table 2 presents the results. Column 1, where we focus on credit while excluding AAL, shows that policyholders with lower credit scores pay more for insurance: individuals in the lowest quintile of credit scores pay \$370 higher average premiums per year than those in the highest credit score quintile, conditional on deductible, coverage limit, state, and year fixed effects. The premium surcharge shrinks monotonically as credit scores increase.

It is possible that these large credit score differences are driven to some extent by policyholders with lower credit scores living in homes with higher disaster risk, which is captured by the term $P(\text{Event}_{pe})$ in Equation 1. It is also possible that people with lower credit scores live in homes in worse condition, leading to more damages if they are hit by a disaster event ($\mathbb{E}[\text{Damages}_{pke}|\text{Event}_{pe}]$ in Equation 1). To investigate whether a correlation between expected losses and credit score might drive the credit-premium gradient observed in column 1 of Table 2, we include the AAL term in column 2. Our measure of AAL captures both the riskiness of the property to disasters covered by home insurance ($P(\text{Event}_{pe})$) and the observable condition of the property with respect to disasters $E[\text{Damages}_{pke}|\text{Event}_{pe}]$ in one annual dollar measure.[16] If the credit-premium gradient is driven by a correlation between expected losses and credit scores — whether driven by the underlying disaster risk of the property or its condition — we would expect the credit-premium gradient to be attenuated when the AAL regressor is included.

Column 2 shows that including AAL in the regression does not shrink the estimated coefficients on credit — if anything, the effect of credit scores on premiums for the two

[15] Many of the borrowers in our data in the bottom credit score quintile have FHA (45%) or VA (5%) loans.

[16] Our AAL measure does not account for idiosyncratic losses such as dog bites or losses not related to natural disasters.

Table 2: Premiums and credit scores

Dependent Variable:	Annual premium (USD)						
	Full Sample					Sales sample	
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables							
Very low	369.8***	389.1***	360.1***	348.2***	334.3***	284.4***	210.1***
	(3.489)	(3.082)	(1.432)	(1.464)	(1.523)	(1.788)	(2.085)
Low	223.7***	233.6***	213.6***	206.2***	204.1***	182.8***	135.9***
	(2.198)	(1.895)	(0.9548)	(0.9796)	(1.021)	(1.343)	(1.701)
Medium	134.3***	138.0***	126.0***	124.4***	124.7***	113.9***	86.62***
	(1.611)	(1.348)	(0.7620)	(0.7733)	(0.7716)	(1.092)	(1.487)
High	61.54***	60.60***	56.14***	58.20***	57.89***	55.12***	42.82***
	(1.115)	(0.9420)	(0.6294)	(0.6299)	(0.6125)	(0.9417)	(1.337)
AAL (USD)		0.5776***	0.3234***	0.2869***	0.2791***		
		(0.0231)	(0.0141)	(0.0133)	(0.0130)		
Fixed-effects							
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Coverage	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Deductible	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Blockgroup			Yes	Yes	Yes	Yes	Yes
Year built				Yes	Yes	Yes	Yes
Insurer					Yes	Yes	Yes
Property							Yes
Fit statistics							
Observations	53,304,488	53,304,488	53,304,488	50,008,468	50,008,468	14,617,984	14,617,984
R^2	0.46504	0.50801	0.60059	0.61564	0.63602	0.64258	0.83288
Within R^2	0.02205	0.10059	0.03755	0.03388	0.03296	0.01942	0.00650
Dep Var Mean	1,598.8	1,598.8	1,598.8	1,603.8	1,603.8	1,530.9	1,530.9

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

Source: ICE, McDash®; CoreLogic
Notes: Table reports the results of Equation 2, which regresses insurance premium on credit score quintile, disaster risk, policy characteristics, time fixed effects, and geography fixed effects. Credit score quintiles are: Very low (less than 671), Low (671-715), Medium (716-755), High (756-786), and Very high (greater than 786). The Very high credit group is the omitted reference category.

lowest bins becomes slightly larger. The small changes in the credit-premium gradient when AAL is added as a control show that, on average, the higher prices paid by homeowners with lower credit scores cannot be explained by disaster risk exposure. The coefficient estimate on AAL indicates that predicted disaster losses are passed through to premiums at about 58 cents per dollar of damages over our entire sample. The coefficients in column 2 imply that moving from the bottom to the top quintile of AAL in our estimation sample would increase premiums by approximately $389, or about the same effect as moving from the top "very high" credit quintile to the bottom "very low" credit quintile. The comparison highlights that disaster risk and credit scores have similar average effects on homeowners insurance premiums.[17]

In column 3, we include census block group fixed effects to control for local time-invariant characteristics (for example, crime rates) or other geographic risk factors. These granular geographic controls do little to change the credit coefficients, although they do substantially shrink the coefficient on AAL.[18] In column 4, we include year-built fixed effects to control for older homes potentially being more expensive to insure. We find that adding year-built controls only slightly reduces the credit-premium gradient. Column 5 adds insurer fixed effects, which help address the concern that the credit-premium gradient could be driven by selection of people with lower credit scores into specific insurers. We find that insurer choice is not meaningfully driving the credit-premium gradient and the credit-premium gradient happens within insurers.

Even though we control for a rich set of property characteristics, there may be additional characteristics that are both important for insurance pricing and unobservable to the econometrician. We next estimate a modified version of Equation 2 using property fixed effects to capture any remaining time-invariant unobservables of the property. The analysis leverages

[17] In Appendix Figure S5, we present time-varying annual credit score coefficients by estimating a modified version of the specification in column 2 of Table 2. Our estimates show an increasing cost paid by people with lower credit scores over time, with policyholders in the bottom credit score quintile paying an average $550 more in average annual premiums as of 2024. Appendix Figure S6 shows that policyholders with very low credit paid around 21% more than people with very high credit in 2015, which increased to around 24% by 2024, suggesting that the credit-premium gradient is more stable as a percentage of the rising premiums over this period.

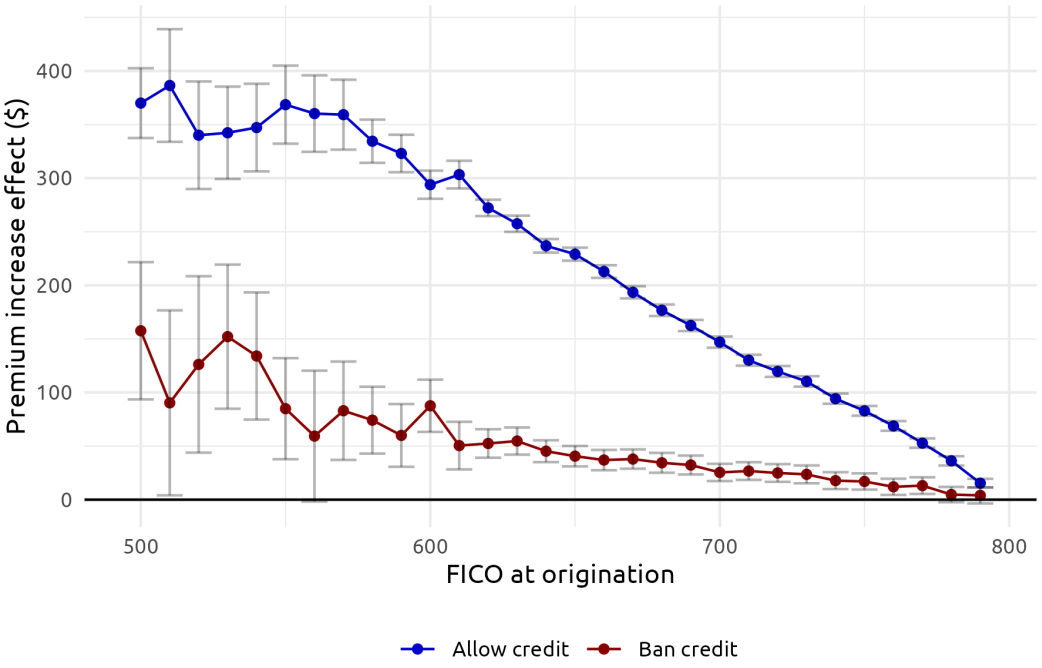
[18] For many perils, insurers set rates based on broad ZIP code factors rather than property-level risk measures. Using block group fixed effects absorbs the ZIP-level variation that drives much of the pricing on risk, explaining our attenuated coefficient in column 3 of Table 2. We further find evidence of this in Appendix Figure S12, where we see that both a property's own AAL and the average AAL of other property's in its ZIP code affect premiums. Interestingly, the relative magnitude on the property-level relative to ZIP-level risk scores is increasing over time, consistent with findings from Boomhower et al. (2024) that insurers are increasingly using property-level risk models to set premiums.

identifying variation from properties that were sold during our sample window (the "sales sample"), a necessarily smaller subset of the full dataset, and compares premiums charged to owners with different credit scores on the same property.

Column 6 of Table 2 first shows the results of estimating Equation 2 on the sales sample without using property fixed effects. Relative to the comparable full sample specification from column 5 of Table 2, the credit-premium gradient is somewhat flatter in the sales sample. Column 7 adds property fixed effects, which reduces the credit-premium gradient by around 26%. This substantial reduction suggests that some portion of the credit-premium gradient reflects housing characteristics that are priced by insurance companies but not observed in our data. However, a sizable credit-premium gradient remains even after including property fixed effects.

We next leverage state-level policy variation by studying the three states (California, Massachusetts, and Maryland) that banned the use of credit-based insurance pricing more than 20 years ago. Figure 3 shows the credit-premium gradient, estimated in 10-point bins, from these "credit ban" states separately from the other 47 states, using the property fixed effects specification from column 7 of Table 2. The figure shows that in the credit ban states, the credit-premium gradient is much flatter, suggesting that insurance companies are directly using credit scores, and are not able to use other proxies that provide information similar to credit scores.

Figure 3: Credit-premium gradient by credit score bin by ability to use credit-scoring



Source: ICE, McDash®; CoreLogic
Notes: The figure displays estimates of Equation 2 with credit score bins that are divided into increments of 10 points. All estimates are relative to the omitted bin (having a credit score of 800 and above). Standard errors are clustered at the ZIP code level; the figure shows 95% confidence intervals around the point estimates. States that ban credit in insurance pricing (in red) are CA, MA, and MD. All the other states allow the use of credit information in insurance pricing. The sample is restricted to 2024 insurance policies.

Our results in this section establish novel evidence that homeowners with lower credit scores pay substantially higher average premiums than those with higher scores, even after conditioning on disaster risk, deductible choice, coverage limits, geographic fixed effects, year built, and insurer fixed effects. Property fixed effects can explain about a quarter of the credit-premium gradient, which is similar in magnitude to the premium difference between the states that ban versus permit credit-based pricing. Overall, these descriptive analyses suggest that 25% of the credit-premium gradient can be explained by non-credit factors that are correlated with credit scores being priced by the insurer while the other 75% is attributable to insurers directly pricing on credit as a proxy variable.

However, we caveat that these results are a correlational decomposition of actual premiums based on observable characteristics and cross-sectional policy differences across states. There are many factors that could produce the credit-premium gradient that we cannot

fully account for. For example, the credit-premium gradient could be an artifact of how people shop for insurance, with higher credit score homeowners having better information or spending more time searching for the lowest-cost policy.[19] Homeowners with higher credit scores may also be more likely to receive bundling discounts from buying auto insurance policies with the same company.[20] To rule out these possibilities, in the next section, we turn to a natural experiment in Washington state.

5 Credit as a Pricing Proxy: Evidence from Washington State's Natural Experiment

To isolate the causal effect of credit-based insurance pricing on the credit-premium gradient, we examine exogenous policy variation from a natural experiment in Washington state. In March 2021, the Washington Insurance Commissioner issued an emergency rule that would require insurers to stop using credit information in setting auto, homeowner, and renter insurance rates starting in June 2021. The rule was set to remain in effect for three years after the federal COVID-19 national emergency was declared, based on the argument that the pandemic's economic fallout and the mortgage forbearance granted under the federal CARES Act legislation made credit histories unreliable for insurance pricing. To comply with the rule, insurers were allowed to make new rate filings that substituted any credit-based factors with a "neutral factor" that would keep premiums constant across the insurer's entire book of business. Insurers were also allowed to make more comprehensive rate revisions as long as they did not use credit-based factors.

Once proposed, the rule faced immediate legal challenges from insurers. Although the rule was allowed to go into effect in June 2021, it was overturned in October 2021 on the grounds that the Commissioner did not have a justification to implement the rule on an emergency basis (Rosanes, 2021). This judgment led the Commissioner to adopt the rule again through the normal process in February 2022 to take effect in March 2022, but the implementation was paused through ongoing legal proceedings (La Corte, 2022). The rule was finally overturned in court in August 2022 without further appeal from the Commis-

[19] We note, however, that any differences in search intensity are unlikely to result in price discrimination because rates are generally heavily regulated and must reflect expected losses.

[20] We note, however, that according to the five-year 2022 American Community Survey estimates, approximately 95% of homeowners own at least one car, which limits the scope for bundling discounts to contribute to the credit-premium gradient.

sioner (American Property Casualty Insurance Association, 2022). The upshot of this series of rules and court decisions was that credit-based insurance pricing was officially banned between June and October of 2021, while the possibility of a renewed ban remained in effect until August 2022.[21] Between the first and final court decisions, insurers were free to reintroduce credit-based factors into their pricing, although some continued to use their neutral factors until the final decision (Washington Office of the Insurance Commissioner, 2022).

Our null hypothesis is that Washington state's ban had no impact on relative premiums across the credit distribution. The causal effects of a credit-pricing ban on the distribution of premiums are not ex ante obvious. First, despite the evidence in Section 4, it remains possible that the observed credit-premium gradient reflects homeowner characteristics correlated with credit scores, in which case prohibiting the use of credit scores would not meaningfully reduce the credit-premium gradient. Second, even conditional on the fact that insurers use credit history in their pricing, insurers may still be able to replicate credit-based prices using other correlated factors or by changing the set of contracts offered under a ban (Finkelstein, Poterba and Rothschild, 2009; Pope and Sydnor, 2011).

To study how these policy changes affected the credit-premium gradient, we construct a panel of Washington state policyholders, where the time dimension records the *renewal month* of each policy. The panel is therefore unbalanced, as most policies are only renewed once per year. We estimate the following event-study specification over renewal month τ:

$$Premium_{it} = \sum_{\tau=Jan2018, \tau \neq June2021}^{Jan2024} \beta_{\tau b} CreditBin_{ib} \times \mathbf{1}\{t = \tau\} + \lambda_i + \lambda_t + \epsilon_{it} \quad (3)$$

The key benefit of leveraging the Washington state policy variation is that it allows us to estimate the effect of credit score on premiums while controlling for loan fixed effects (λ_i), which capture any time-invariant unobserved characteristics such as the condition of a home, an individual's claims history, or any bundling with car or other insurance products. We focus only on policies that renew in a given month τ to isolate the effect of the credit score ban on premiums. We estimate the treatment coefficient $\beta_{\tau b}$ for each month of sample τ and for each credit score quintile b, using the medium quintile as the omitted group. Our treatment effects can thus be interpreted as the relative change in premiums for a

[21] Appendix Figure S7 illustrates the timeline of ban proposals and court rulings.

credit score group compared to the medium credit score group. Our identification strategy assumes that, conditional on fixed effects, premiums for each credit score group were moving in parallel and would have continued to do so in the absence of the credit pricing ban. It also leverages the quasi-random timing of policy renewals, with similar homeowners having policies that renewed just before and after the ban went into effect.

Figure 4 shows the results of estimating Equation 3. Prior to the June 2021 decision, there is no evidence of a pre-trend in premiums across any credit score group, supporting the parallel trends assumption. Between June 2021, when the emergency rule first went into effect, and October 2021 when the court order overturned the first emergency ruling, we see a sharp relative decrease in premiums for the lowest credit group by $175 and an increase for the highest credit score group of $100. From October 2021 to August 2022, when the final ruling on the ban was pending, we see the treatment effects shrink, likely reflecting some insurers amending their rate filings to once again incorporate credit-based pricing. By September 2022, the Washington state credit-premium gradient had returned to its pre-ruling baseline. These results show that banning the use of credit pricing caused meaningful changes in policyholders' premiums when their policy renewed, even when controlling for individual loan fixed effects.

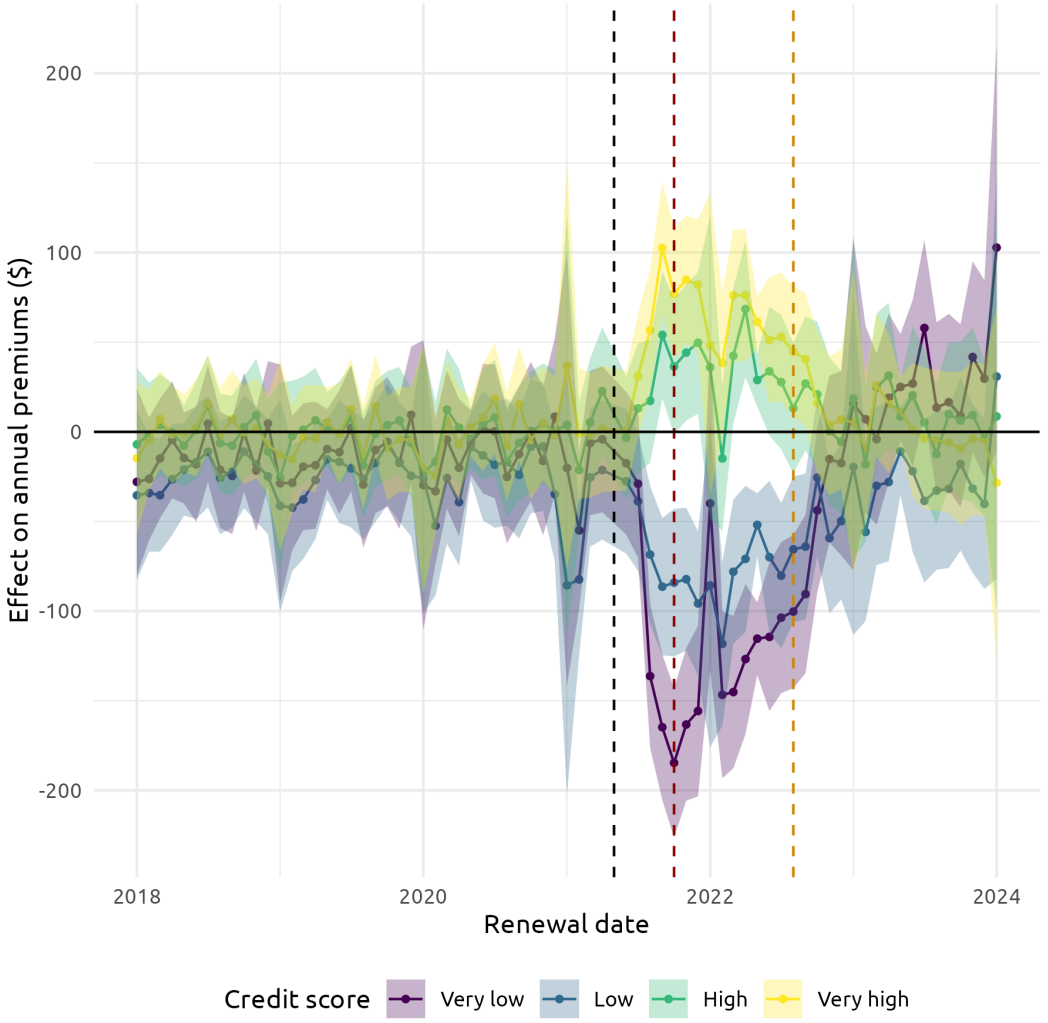
Figure 5 shows how the absolute credit-premium gradient changed in Washington state by estimating Equation 2 by year, i.e., without the mortgage fixed effects in Equation 3.[22] The figure shows that the ban compressed the credit-premium gradient by around 70% in October 2021.[23]

The remaining credit-premium gradient could be the result of insurers pricing on other factors that are correlated with credit score or some insurers having not fully adopted the ban by October 2021. While we caution that our quasi-experimental evidence only applies to Washington state, these results suggest that credit pricing itself causally contributes significantly to the observed credit-premium gradient, and that insurers cannot easily reproduce credit-based predictors by pricing on other correlated factors. Supporting the external va-

[22] We use the Medium credit score as the omitted category to facilitate the comparison with Figure 4. Due to the short-term nature of the ban, we focus on policies that renewed in October of each year. We use October because it was the final month the credit ban was in effect, and expect this cohort of policies to experience the largest adjustments by insurers in 2021. Figure 4 also shows that October 2021 has the largest treatment effect. It is possible that, absent the court ruling, the credit-premium gradient would have continued to shrink.

[23] In Appendix Figure S8, we show similar results using Idaho and Oregon as a control group, rather than using the Washington state median credit score bin as an omitted group.

Figure 4: The effects of Washington state's ban on the credit-premium gradient

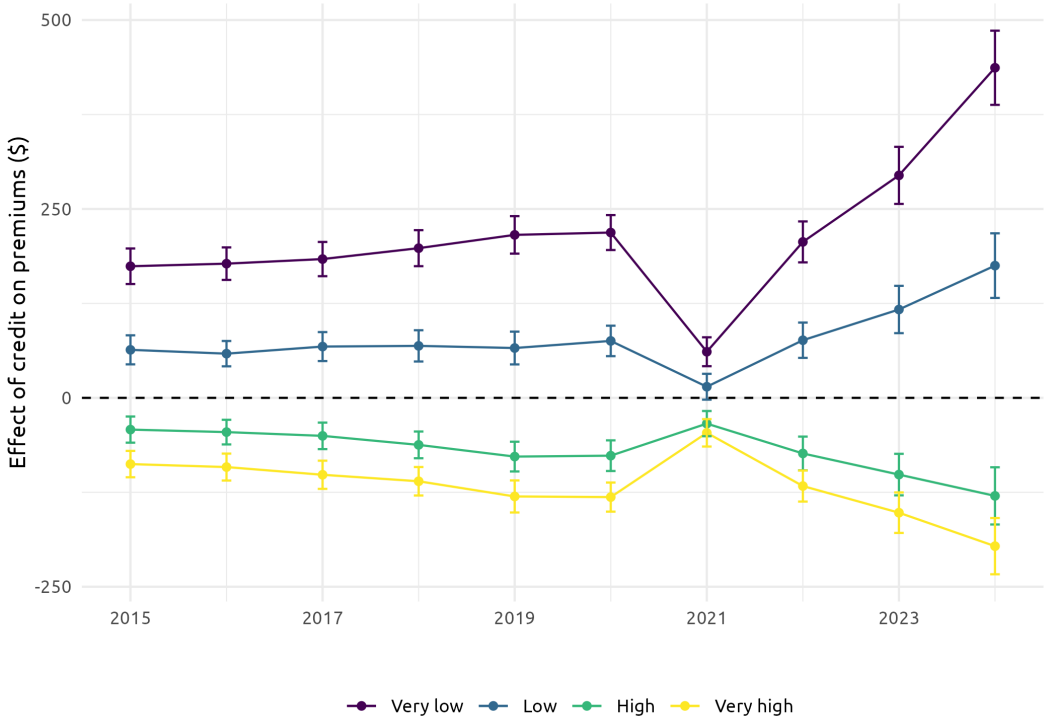


Source: ICE, McDash®; CoreLogic;
Notes: Figure plots the time-varying credit quintile coefficients from Equation 3, which regresses insurance premium on credit score quintile, loan fixed effects, and a renewal month fixed effect and allows for time-varying coefficients. Credit score quintiles are: Very low (less than 671), Low (671-715), Medium (716-755), High (756-786), and Very high (greater than 786). The Medium credit group is the omitted reference category. Dashed lines indicate the effective date of the emergency rule (June 2021, black dashed line), its initial pause (Oct 2021, red dashed line), and final overturning (August 2022, orange dashed line). 95% confidence intervals with standard errors clustered at the ZIP code level are shaded.

lidity of our Washington state findings, it is notable that the relationship between credit and premiums in Washington state during the ban is comparable to the credit-premium gradient in the three states that have long banned credit-based pricing (CA, MA, MD; see

Figure **??**).

Figure 5: Washington state credit-premium gradient over time



Source: ICE, McDash®; CoreLogic;
Notes: Figure plots the time-varying credit quintile coefficients from Equation 2 (restricted to WA state policies renewing in October), which regresses insurance premium on credit score quintile, disaster risk, policy characteristics, time fixed effects, and ZIP code fixed effects and allows for time-varying coefficients on credit. Credit score quintiles are: Very low (less than 671), Low (671-715), Medium (716-755), High (756-786), and Very high (greater than 786). The Medium credit group is the omitted reference category.

Finally, in Appendix Figure S9, we examine how the credit pricing ban impacted a broader set of insurance and mortgage market outcomes, such as coverage choices and mortgage performance. We plot the credit bin event study coefficients on log coverage limit (panel a), deductible (panel b), 90-day mortgage delinquency (panel c), and mortgage prepayment (panel d). We see little change in coverage choices, potentially reflecting inertia in insurance choices that has been documented in health insurance settings (Handel, 2013). More broadly, the null results in panels (a) and (b) suggest that policyholders did not shop for different coverage in response to the ban, and that insurers did not substantially change the set of contracts they were willing to offer.

There is a large increase in mortgage delinquencies in 2020 among the lower credit score groups followed by a level shift downwards starting in 2021 before the credit pricing ban went into effect (panel c). These dynamics are most likely driven by the COVID pandemic and the implementation of the CARES Act legislation, which incorporated generous mortgage forbearance provisions. Given that the credit pricing ban changed annual premiums by at most $175, the effect on household disposable income was likely too small to translate to mortgage performance effects. In sum, the credit pricing ban induced sharp changes in how premiums were determined in Washington state, thereby allowing for the identification of the causal effect of scores on premiums, but did little to affect broader housing market outcomes.

Our findings in Washington state are also useful when considering the underlying mechanisms causing the credit-premium gradient. The use of loan fixed effects combined with no changes in coverage shown in Appendix Figure S9 suggests that explanations such as claims history, shopping behavior, bundling discounts, or underinsurance, all of which are unchanged before and after the ban, are unlikely to be driving factors of the credit-premium gradient. The Washington policy change provides an independent quasi-experimental estimate that supports our descriptive findings that only about 25 to 30% of the credit-premium gradient can be attributed to factors that the insurer can observe.

6 What Does Credit Proxy For?

The insurance industry's most common justification for using credit scores is that they are predictive of insured losses beyond what insurers can readily observe (NAIC, 2008). However, the policy and economic implications of the credit-premium gradient depend on what unobservable characteristics are proxied by credit score. On the one hand, if lower credit scores capture that a policyholder is more likely to file a claim after experiencing a small loss due to liquidity constraints, then credit-based pricing may exacerbate credit market frictions and raise fairness concerns (Kiviat, 2019). On the other hand, if people with lower credit scores have more frequent or more expensive losses, then credit scores may be a useful signal of differences in property characteristics that are unobservable to the insurance company.

In this section, we develop a structural model of the claims decision, disciplining the

model with the only publicly available data on homeowners insurance claims combined with a novel survey of claim filing behavior to explore the factors behind the credit-premium gradient. Motivated by Equation 1, we decompose differences in expected incurred losses across credit scores into the product of three terms: the probability of loss $P(Event)$, damages conditional on loss $E(Damages|Event)$, and the policyholder's propensity to file conditional on damages $P(FileClaim|Damages)$, which we refer to as the "shadow deductible."[24]

We calibrate the shadow deductible across credit score groups from direct survey elicitation of the losses at which policyholders report being willing to file a claim. Conditional on these differences in claim filing rates, we fit the differences in risk — $P(Event)$ and $E(Damages|Event)$ — across credit score groups to match claim frequency and claim severity moments from aggregate homeowners insurance claim data. The resulting model estimates distinguish how much of the relationship between credit and incurred losses is driven by differences in shadow deductibles versus actual risk.[25]

6.1 Data Overview

To decompose the relationship between credit and incurred losses, we leverage two new data sources. First, we use new publicly available ZIP code-level data on homeowners claims rates from 2018 to 2022, collected by the National Association of Insurance Commissioners and shared with the U.S. Treasury's Federal Insurance Office (U.S. Department of the Treasury, 2025). Second, we use novel survey data of 2,000 U.S. homeowners collected by the Federal Reserve Bank of Philadelphia to study the relationship between credit, insurance knowledgeability, and claim filing behavior. The survey data provide insight into policyholder decision-making beyond what could be gleaned even from detailed individual-level claims data.

6.1.1 Treasury Insurance Data

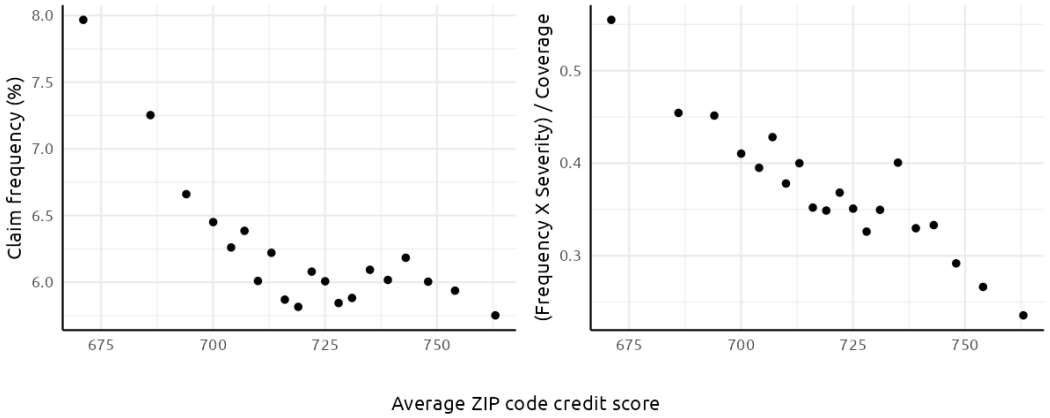
The Treasury data provide annual information on insurance claim frequency and severity by ZIP code. To create a normalized measure of expected loss rates, we multiply the claim frequency by average claim severity and divide by the corresponding average ZIP

[24] Braun et al. (2006) refer to this region above the deductible as the "pseudodeductible."

[25] In Appendix Section A.7, we examine a range of further mechanisms that could contribute to the credit-premium gradient such as home age and maintenance, differential risk passthrough by insurers, and fraud/litigation costs. Overall, we find that these are less important factors and, in some cases, substantially overlap with the fundamental loss and claims filing mechanisms that we explore.

code coverage limit in our McDash data. To compare these outcomes to credit score, we aggregate our McDash data to the ZIP code level to measure average credit scores.

Figure 6: Claims analysis using U.S. Treasury ZIP code data



Source: ICE, McDash®; U.S. Treasury;
Notes: Figure shows plots of claim frequency (left panel) and average incurred losses divided by coverage (right) from U.S. Treasury 2018–2022 ZIP code-level homeowners insurance data. ZIP code observations are aggregated into vigintiles by average credit score as measured in the McDash data. The right panel uses average ZIP code coverage limits from the McDash data in the denominator.

Figure 6 shows binscatters of average ZIP code claim frequency (left panel) and normalized expected incurred losses (right panel) against ZIP code average credit score across 20 credit score bins. The left panel shows that ZIP codes with lower average credit scores file claims more frequently, while the relationship flattens out for ZIP codes with average credit scores above 725. When claim frequency and severity are combined and normalized by coverage (right panel), we find an overall negative relationship: per dollar of coverage, expected incurred losses are higher in ZIP codes with lower average credit scores.

These aggregated data offer the first evidence based on publicly available data that credit scores are an informative proxy for expected home insurance claims. Using ZIP code averages is an indirect measure of the relationship between individual incurred losses and credit scores, and individual-level claims data, if available to researchers, could help to more precisely estimate this relationship. However, even individual-level claims data could not distinguish whether the relationship between credit scores and incurred losses is driven by differences in risk or differences in claim filing behavior. This limitation motivates the use of the novel survey data described below.

6.1.2 Insurance Survey Data

The second dataset we leverage to study the determinants of claims is a novel survey of 2,000 U.S. homeowners collected by the Federal Reserve Bank of Philadelphia in 2026 to study homeowner attitudes and knowledge of homeowners insurance. We leverage two questions that assess (i) awareness that claims affect insurance premiums and (ii) willingness to pay for expenses above the deductible.[26] The survey results summarized in Table 3 establish two facts. First, the vast majority of respondents know that filing raises future premiums, and the difference is relatively small by credit group (90–92% in the top two credit groups versus 83–87% in the bottom two credit groups). Second, most policyholders have a shadow deductible greater than their policy deductible; that is, they would rather pay for small losses out of pocket than file a claim. Somewhat more homeowners with poor or fair credit report that they would file on any loss exceeding their deductible than do those with higher credit scores (33% versus 28%). However, a similarly sized majority across both groups say that they would absorb damages up to roughly 1.5 times their deductible before filing, and only 14–15% in each group would not file on losses that are over 1.5 times their deductible. Overall, the survey results suggest that there are not large differences in awareness that claims affect insurance premiums or willingness to pay above their deductible by credit score group.

Table 3: Homeowner Survey Summary Results

	Poor/Fair	Good	Very Good	Excellent
Claims raise premiums	87%	83%	90%	92%
File claims at:				
Deductible	33%	29%	27%	28%
Up to 1.5x deductible	53%	57%	58%	58%
Pay > 1.5x deductible	15%	14%	15%	14%

Source: Federal Reserve Bank of Philadelphia
Notes: Credit score groups are: Poor/Fair (less than 670), Good (670-739), Very Good (740-799), Excellent (800+).

[26] The exact survey questions are: (1) If a homeowner files an insurance claim, how likely do you think their policy premium will increase next year? and (2) A deductible is the amount a homeowner pays out-of-pocket before their insurance begins to pay. If your home was damaged by a peril (such as a fire, wind, hail, or lightning) that was covered by your homeowners insurance, how much above your current deductible would you be willing to pay before you consider filing a claim?

6.2 Model Overview and Results

In this section, we use a structural model of claim filing behavior to better understand if people with lower credit scores are more expensive to insure because they are more likely to file a claim when they experience damage or because they are more likely to experience loss events. The full model details can be found in Appendix A.6. We calibrate differences in shadow deductibles across credit scores from the Federal Reserve Bank of Philadelphia survey data, and fit differences in the probability and severity of loss to match the corresponding moments from the Treasury data. Intuitively, the model separates how much of the relationship between credit and incurred losses is due to shadow deductibles versus risk.

The model considers representative policyholders that belong to one of four credit types (Poor/Fair, Good, Very Good, and Excellent) and one of three shadow deductible types (low, medium, high). Each agent has a probability of loss that depends on their credit type and a loss threshold above which they file a claim that depends on their shadow deductible type corresponding to the survey cutoffs in Table 3.[27] We assume that loss amounts conditional on experiencing a loss are lognormally distributed with a location parameter that allows for a linear trend in credit score. The model directly calibrates the distribution of shadow deductible types from the survey shares in Table 3, which reports each of the four credit groups separately.

Next, we fit the remaining parameters to match the claim frequency moments and average claim severity moments from the claims data, aggregated into the same four credit types. This approach provides eight moments to fit the four credit-group loss probabilities, the credit-group loss severity trend, and the common loss location parameter. Because each credit group has its own loss probability, the model matches the four claim frequency moments exactly, and it matches the severity moments to within 2.4% (Table 4, panel A).

The goal of the model is to decompose the risk and shadow deductible factors that drive the differences in incurred losses relative to coverage across credit score groups. To do so, we first make the same normalization as in the right panel of Figure 6, dividing the model-predicted incurred losses for each credit group by its average coverage limit in the policy data, to create a measure of coverage-adjusted incurred losses. The model matches 97%

[27] The low type files at the deductible. The middle survey category is "up to 1.5 times the deductible," and we place the middle type at the upper end of that range. The top category is open: respondents there would absorb more than 1.5 times the deductible before filing, and we set the filing threshold to 3 times the deductible. Our results are insensitive to setting the top threshold to 2 or 4 times the deductible, or to letting it rise to ten times the deductible for the three upper credit groups (Appendix Table S9).

Table 4: Model fit and decomposition of coverage-adjusted incurred losses

Panel A: Model fit

	Claim frequency (%, annual)		Claim severity ($1,000 per claim)		Incurred losses per $1,000 of coverage ($)	
Credit group	Model	Target	Model	Target	Model	Data
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Poor/Fair	7.08	7.08	14.8	15.1	4.52	4.63
Good	6.11	6.11	16.4	16.1	3.78	3.70
Very Good	5.98	5.98	18.3	17.9	3.19	3.11
Excellent	5.85	5.85	20.3	20.8	2.34	2.40
Poor/Fair − Excellent	1.22	1.22	−5.5	−5.7	2.18	2.24

Panel B: Decomposition of the credit gap in incurred losses per dollar of coverage

Channel	Share of gap (%)
P(File Claim | Damages)	0
P(Loss)	41
E(Damages | Loss) per dollar of coverage	59

Notes: Panel A compares the model with the data by credit group. Claim frequency and claim severity are the targeted moments (Appendix Figure S13); frequency is matched exactly because each group has its own loss probability. Incurred losses per $1,000 of coverage, claim frequency times claim severity divided by the group's average coverage limit, are not targeted. Panel B reports the share of the Poor/Fair to Excellent log difference in incurred losses per dollar of coverage that is removed by equalizing each channel across credit groups: the loss probabilities (P(Loss)), the coverage limits and credit trend in loss severity (E(Damages | Loss) per dollar of coverage), and the shadow deductible type shares (P(File Claim | Damages)). Each share is the average of the channel's contribution over the orders in which the channels are equalized, so that the shares sum to 100.

of the difference in coverage-adjusted incurred losses between the top and bottom credit groups (Table 4, panel A, columns 6 and 7). Next, we measure how much these gaps change when we eliminate credit-group differences along each channel: (1) equal shadow deductible type shares, (2) equal loss probabilities, and (3) equal average coverage limits and no credit group trend in loss severity. These three restrictions correspond to testing the $P(FileClaim|Damages)$, $P(Loss)$, and $E(Damages|Loss)$ components from our motivating model, respectively, with the last measured per dollar of coverage, since coverage limits and loss sizes both scale with home value.

Our model suggests that differences in P(File Claim | Damages), P(Loss), and E(Damages | Loss) per dollar of coverage can explain (approximately) 0%, 41%, and 59% of the relationship between expected coverage-adjusted incurred losses and credit scores, respectively (Table 4, panel B). Homeowners with low credit scores appear to incur more insured losses because they are more likely to experience a loss event, and the loss event will be more expensive per dollar of coverage than for homeowners with higher credit scores. In contrast,

differences in shadow deductibles — whether driven by liquidity constraints or misperceptions about how claim filing affects premiums — explain very little of the differences in incurred losses by credit score.

The finding in our model, that people with lower credit scores are more likely to experience losses in ways that are difficult for insurers to directly predict based on observables behaviors or home characteristics, is consistent with real-world outcomes. While insurers can use increasingly sophisticated catastrophic risk models to account for differences in exposure to natural hazards, a large share of homeowners insurance claims are driven by idiosyncratic accidents.[28] As one example of idiosyncratic losses, we show the correlation between the rate of home fires (excluding wildfires) measured in the National Fire Incident Reporting System (NFIRS) and mean census tract credit score as measured in our sample of homeowners insurance policies in Figure 7.[29] Census tracts with higher average credit scores have substantially fewer house fires than census tracts with lower credit scores. While the aggregate pattern cannot definitively show that house fires are more likely for people with lower credit scores at the individual level, they provide strong supporting evidence that households with lower credit scores are more likely to experience house fires, and, more broadly, may be more prone to such idiosyncratic losses.[30]

In the model, the contribution of the pure claim filing channel is negligible because of two reinforcing empirical findings. First, the differences in shadow deductibles are small across credit score groups (Table 3). Second, the claim severity data suggest that most claims are far above the stated shadow deductibles (Figure 6). As a result, most households file a claim when experiencing a loss.[31]

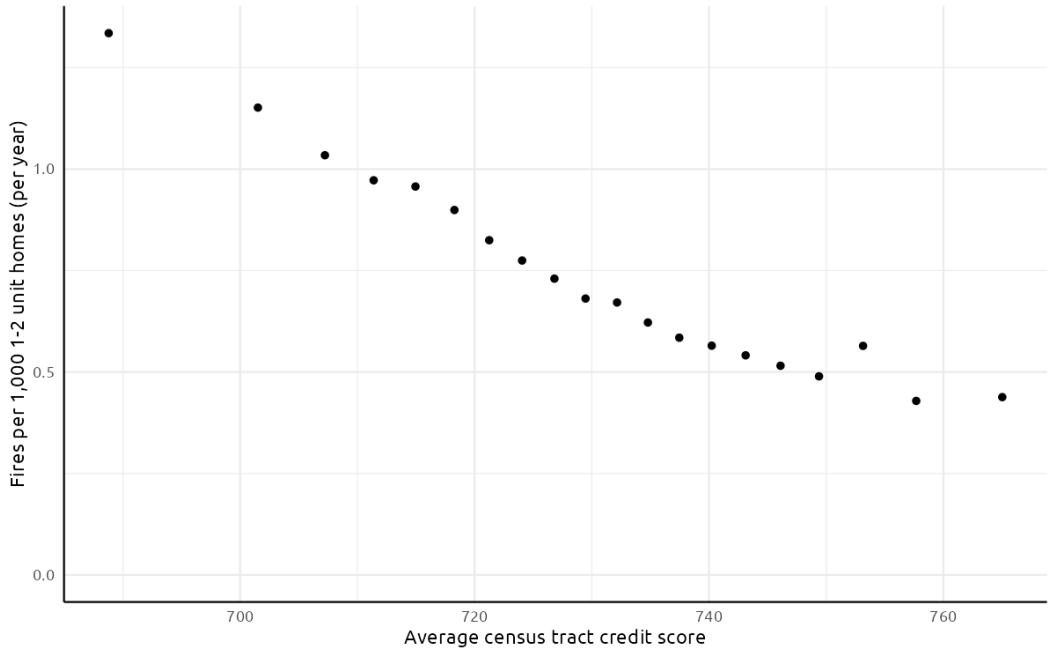
[28] In 2023, fire and lightning accounted for 22% of home insurance losses and water damage and freezing another 23% (Insurance Information Institute, 2025). Only 5% of house fires are attributable to wildfires (U.S. Fire Administration, 2024), and homeowners insurance primarily covers water damage caused by burst pipes, clogged drains, or sudden appliance failures but excludes flooding. These statistics show that a large share of homeowners insurance claims are mediated by policyholder behavior that is difficult to observe directly.

[29] We measure the rate of non-wildfire home fires from the NFIRS data as building fires (i.e. excluding fires that are only outdoors on the property or those that are confined to a cooking container) in one- or two-family dwellings excluding any incidents marked as occurring in vacant buildings or that are labeled as acts of nature. We exclude duplicate or multiple reports relating to the same incident at the same address, and geocode and aggregate annual incidents to the census tract level. Because not all fire departments report to the NFIRS every year, we exclude census tract observations where no incidents of any type were reported and subset to a balanced panel between 2014–2024. The denominator to determine the annual rate of fires is the count of occupied one- or two-family dwellings according to the 2014–2019 American Community Survey estimates.

[30] While insurers could adjust for the rate of such idiosyncratic losses by census tract, the strength of the relationship between credit and idiosyncratic fires that we document suggests that the same pattern exists at the individual level, which would make credit history a useful proxy for capturing within-tract variation.

[31] More complicated loss processes, such as mixed processes that combine small "maintenance" losses and

Figure 7: House fire frequency and census tract credit score



Source: ICE, McDash®; U.S. Fire Administration.;
Notes: Figure shows fires per 1000 homes per year for one and two unit homes at the census tract level. Census tract observations are aggregated into vigintiles by average credit score as measured in the McDash data.

Similar shadow deductibles across credit score groups suggest that liquidity constraints do not meaningfully affect the decision to file a claim. However, this does not rule out the possibility that liquidity constraints may be driving the gap in incurred losses conditional on coverage, and therefore the credit-premium gradient. Individuals with lower credit scores are likely less able to invest in home maintenance and disaster adaptation, which would imply higher likelihood of experiencing a loss and higher damages.

Although a full efficiency assessment of credit-based pricing requires further research, our results speak to both sides of the debate. In favor of using credit scores for more efficient pricing, our results do suggest that credit-based pricing picks up real differences in expected losses rather than simply exacerbating liquidity constraints. Restricting credit-based pricing could therefore induce adverse selection, distort entry into homeownership, or curtail insurance supply in vulnerable communities (Powell, 2020).

large "disaster" losses, provide similar findings.

There are also potential benefits to banning credit-based pricing. Less wealthy homeowners are more likely to be underinsured, and the resulting disaster aid externalities could justify subsidizing insurance for policyholders with lower credit scores (Armantier, Foncel and Treich, 2023; Gropper and Kuhnen, 2025; Sastry et al., 2026; Gruber and Solomon, 2026).[32] Furthermore, pricing on credit as a proxy reduces homeowners' incentive to reduce risks, while crowding out resources that could fund risk-reducing investments. For example, Bellon et al. (2024) show that a lending program for adaptation investments in Florida leads to higher delinquency rates, demonstrating one instance where credit-based pricing could actually offset the incentive to adapt. Finally, banning credit-based pricing could also incentivize insurers to invest in collecting more direct information about underlying risk and mitigation behavior, which would in turn give homeowners a financial incentive to reduce that risk (Boomhower et al., 2024).

7 The Impact of Credit on Housing Affordability

As a final exercise, we examine the impact of credit-based pricing on the distribution of homeownership costs. Homeownership affordability is a longstanding, albeit controversial, U.S. policy goal, especially for first-time and lower income buyers who typically have weaker credit (Retsinas and Belsky, 2004; Bostic and Lee, 2008). A large literature examines the additional homeownership cost of credit score through the mortgage channel (e.g., Quercia, McCarthy and Wachter, 2003; Bayer, Ferreira and Ross, 2018). By estimating the impact of credit scores on insurance premiums, our results highlight a "second credit channel" through which lower credit score borrowers face higher homeownership costs. This section compares the extra burdens of higher interest rates and higher premiums for homeowners with poor credit.

We begin by quantifying the relationship between credit scores and mortgage interest rates. We estimate the following regression on our sample of loans active in 2024:

$$r_{ibs} = \alpha_0 + \beta_1 X_i + \gamma_b Credit_{ib} + \lambda_s + \epsilon_{is}. \tag{4}$$

where r_{ibs} is the current interest rate on loan i in credit score bin b in state s, and the

[32] The costs of cross-subsidization are minimized in home insurance markets because the insurance mandate for mortgage holders prevents people with higher credit scores from exiting the market.

controls X_i include the debt-to-income ratio and loan-to-value ratio at origination, as well as binned loan origination fixed effects. $Credit_b$ include 10-point bins of the credit score at origination.

Our coefficients of interest are the γ_b, which quantify the interest rate gap between homeowners with different credit scores. These estimates cannot be interpreted as entirely causal; rather, much like the credit-premium gradient, they may reflect a mixture of both explicit pricing on credit and more subtle drivers of differences in costs, such as shopping and refinance behavior, or existing policy interventions such as access to subsidized loans. Nonetheless, our estimates capture the general sense in which it is more expensive for borrowers with poor credit to finance home purchases, making it comparable to our credit-premium gradient.

We estimate a slightly different version of Equation (2) above to quantify the credit-premium gradient over the same sample of loans active in 2024:

$$P_{is} = \alpha_0 + \alpha_1 X_i + \beta_b Credit_{ib} + \beta_2 AAL_i + \beta_3 Deductible_i + \beta_4 Coverage_i + \lambda_s + \epsilon_{is}. \quad (5)$$

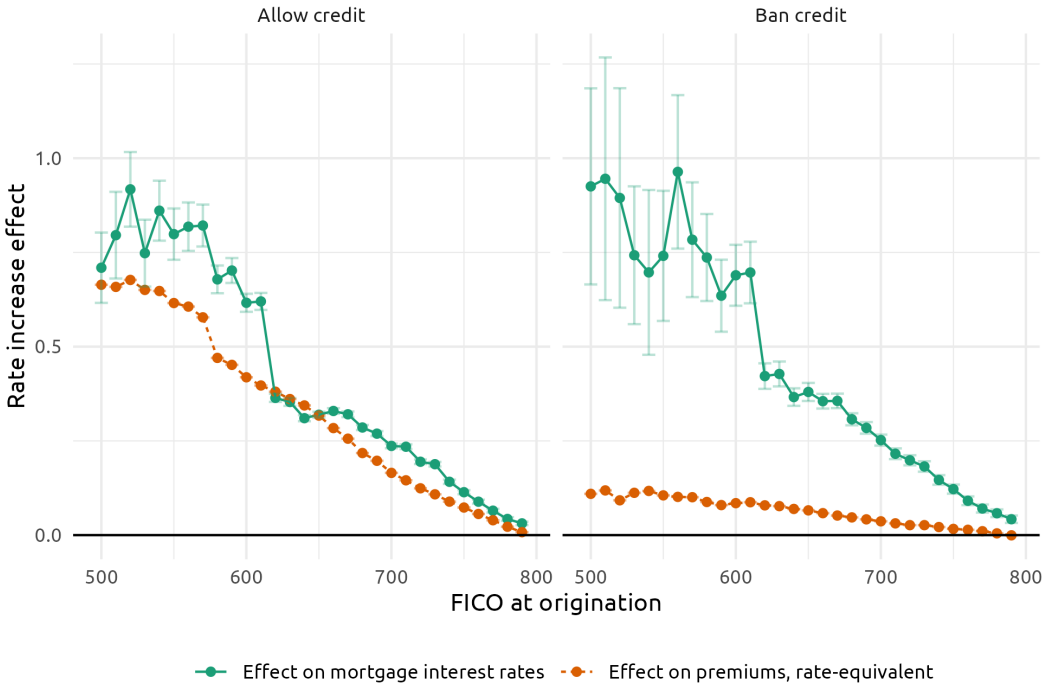
The two sets of coefficients γ_b and β_b from the regressions above capture the effects of credit scores on two channels of homeownership costs. However, the coefficient estimates are expressed in different units. For comparability, we divide the estimates and standard errors in Equation (5) by the remaining outstanding mortgage balance: $\hat{\beta}_b^{scaled} = \frac{\hat{\beta}_b}{\hat{Principal}_b}$, where $\hat{Principal}_b$ is the average principal balance of 2024 loans in credit bin b. This scaling implies that our $\hat{\beta}_b^{scaled}$ can be interpreted as a rate.[33]

Figure 8 plots the results of the above regressions on two sets of states: those that allow credit-based pricing in homeowners insurance (left); and California, Maryland, and Massachusetts, which ban it (right). The effect of credit scores on interest rates is in green, while the effect of credit scores on rate-equivalent premiums is in orange. We note two striking results.

First, the effects of credit score on rate-equivalent premiums are very similar to the effects of credit score on current interest rates — but only in states that allow credit-based

[33]Note that the relative importance of interest rates and homeowners premiums will mechanically vary with loan balance, and thus change over the life of the loan. Homeowners insurance premiums are a permanent cost of homeownership, whereas interest payments only extend through the life of a loan. Appendix Figure S10 presents the unscaled $\hat{\beta}_b$ coefficients.

Figure 8: Credit scores and housing affordability: interest rates and premiums



Source: ICE, McDash®; CoreLogic;
Notes: Figure plots the credit bin coefficients from Equation 4 (green dots) which regresses the mortgage rate on origination variables, credit score bin, and a state fixed effect. Figure plots the credit bin coefficients from Equation 5 (orange dots) which regresses the insurance premium (as a share of the mortgage balance) on origination variables, credit score bin, and a state fixed effect. Results are split by whether or not a state allows for the use of credit scores. Standard errors are clustered at the ZIP-code level. The sample is restricted to 2024 insurance policies.

pricing. In the three states that ban credit-based pricing, the effect is substantially more muted (around 20% of the size). Second, the figure shows, as expected, that the effect of origination credit scores on interest rates is similar in states that ban or do not ban credit-based pricing.

Overall, our results suggest that, in 2024, the increase in homeownership costs related to one's credit score is comparable through the mortgage cost channel and the insurance pricing channel: A borrower with a credit score of 620 pays roughly 40 more basis points per year in *both* interest and insurance premium relative to one with a score of 800. The comparable effects of credit scores on mortgage rates and home insurance premiums highlight the large but underexplored role that credit-based pricing of home insurance can play in

home affordability.

8 Conclusion

How do insurers balance observable risk against risk proxies? This paper uses a panel of homeowners insurance policies linked to contract characteristics, mortgage data, and property-level disaster risk to explore the distributional consequences and drivers of the credit-premium gradient. We find that policyholders with lower credit scores pay substantially higher premiums conditional on coverage limits and deductibles, expected disaster damages, and census block. Leveraging exogenous variation from Washington state, we show that banning credit-based pricing compressed the credit-premium gradient and shifted costs across the credit score distribution, while leaving contract choices and mortgage outcomes essentially unchanged. Together, our findings show that credit-based pricing is a first-order driver of what households pay for homeowners insurance, above and beyond disaster risk and observable home characteristics. Both our descriptive and quasi-experimental analyses find that only about 25-30% of the credit-premium gradient can be attributed to risk factors that an insurer could observe.

We investigate several mechanisms that might explain why credit score is such a powerful predictor of claims. Analyzing aggregate claims data, we find that ZIP codes with lower average credit scores show higher rates of claim filing and expected costs relative to coverage limits. Through the lens of a structural model of claim filing behavior, we estimate that the vast majority of these differences are due to underlying differences in the frequency and severity of losses between credit score groups, and not due to claims decisions influenced by liquidity constraints or different understandings about the consequences of filing claims on future premiums. We support our model findings using data on house fires, showing that census tracts with lower credit scores experience more fires than census tracts with higher credit scores.

Finally, we benchmark the importance of the credit-premium gradient as a driver of housing costs. We find that in 2024, as a percentage of mortgage balances, having a lower credit score adds as much to mortgage costs through homeowners insurance premiums as it does through more expensive mortgage terms. These findings show that households with weaker credit face substantial barriers to homeownership from both mortgage and insurance

markets.

Credit-based pricing creates competing incentives that have not previously been appreciated. Traditional intuition suggests that insurance premiums provide a clear incentive for homeowners to invest in reducing the riskiness of their property (e.g., smoke detectors, upgraded wiring, or disaster resilience). However, the influence of credit scores means that homeowners are also incentivized to improve their credit score. The credit score impact could even reduce homeowners' incentives to invest in risk-reducing property improvements because they could lower a homeowner's credit score (e.g., extracting home equity to fund rewiring or electrical panel upgrades). Further research is needed to understand the full consequences of credit-based pricing on housing markets and homeowner incentives.

The use of credit information in insurance pricing raises difficult policy trade-offs. First, allowing insurers to use credit information to set prices could allow for more accurate pricing and reduce adverse selection. However, the credit-premium gradient may also be identifying differences in the budget constraints of homeowners, rather than reflecting only a homeowner's "responsibility," as the insurance industry asserts (NAIC, 2008). That is, low credit score homeowners may face higher expected losses because they do not have the funds to invest in improving their property. Policymakers should consider the tradeoffs between accuracy and distributional considerations that make homeownership less affordable for those with lower credit scores.

References

110th Congress. 2007. "Credit-based Insurance Scores: Are They Fair?; Hearing Before the Subcommittee on Oversight and Investigations of the Committee on Financial Services." U.S. House of Representatives.

AM Best. 2025. "Best's Special Report: U.S. Property/Casualty Industry Swings to Underwriting Profit of $22.9 Billion in 2024; Marks First Gain in Four Years."

American Property Casualty Insurance Association. 2022. "Washington Judge Enters Order Declaring that Insurance Commissioner Kreidler Exceeded his Authority by Banning Credit-Based Insurance Scoring." *APCIA News Releases*. Available at https://www.apci.org/media/news-releases/release/72956/ Accessed: September 25, 2026.

Amornsiripanitch, Natee, Siddhartha Biswas, John Orellana-Li, and David Zink. 2025. "Measuring flood underinsurance in the USA." *Nature Climate Change*, 1–7.

Arefeva, Alina, Kay Jowers, Qihui Hu, and Christopher Timmins. 2024. "Discrimination during eviction moratoria." National Bureau of Economic Research.

Armantier, Olivier, Jérôme Foncel, and Nicolas Treich. 2023. "Insurance and portfolio decisions: Two sides of the same coin?" *Journal of Financial Economics*, 148(3): 201–219.

Bakkensen, Laura, and Lala Ma. 2020. "Sorting over flood risk and implications for policy reform." *Journal of Environmental Economics and Management*, 104: 22.

Bakker, Trevor J, Stefanie DeLuca, Eric A English, James S Fogel, Nathaniel Hendren, and Daniel Herbst. 2025. "Credit access in the United States." National Bureau of Economic Research.

Ballance, Joshua, Robert Clifford, and Daniel Shoag. 2020. ""No more credit score": Employer credit check bans and signal substitution." *Labour Economics*, 63: 101769.

Bartlett, Robert, Adair Morse, Richard Stanton, and Nancy Wallace. 2022. "Consumer-lending discrimination in the FinTech Era." *Journal of Financial Economics*, 143(1): 30–56.

Bayer, Patrick, Fernando Ferreira, and Stephen L Ross. 2018. "What drives racial and ethnic differences in high-cost mortgages? The role of high-risk lenders." *The Review of Financial Studies*, 31(1): 175–205.

Bellon, Aymeric, Cameron LaPoint, Francesco Mazzola, and Guosong Xu. 2024. "Picking Up the PACE: Loans for Residential Climate-Proofing." *SSRN Working Paper*.

Bhutta, Neil. 2015. "The ins and outs of mortgage debt during the housing boom and bust." *Journal of Monetary Economics*, 76: 284–298.

Bhutta, Neil, Andreas Fuster, and Aurel Hizmo. 2024. "Paying too much? Borrower sophistication and overpayment in the US mortgage market."

Billings, Stephen B, Emily A Gallagher, and Lowell Ricketts. 2022. "Let the rich be flooded: the distribution of financial aid and distress after Hurricane Harvey." *Journal of Financial Economics*, 146(2): 797–819.

Biswas, Siddhartha, Mallick Hossain, and David Zink. 2023. "California wildfires, property damage, and mortgage repayment." *Federal Reserve Bank of Philadelphia Working Paper*, , (23-05).

Blattner, Laura, and Scott Nelson. 2021. "How costly is noise? Data and disparities in consumer credit." *arXiv preprint arXiv:2105.07554*.

Blattner, Laura, Scott Nelson, and Jann Spiess. 2021. "Unpacking the black box: Regulating algorithmic decisions." *arXiv preprint arXiv:2110.03443*.

Blundell, Richard, Luigi Pistaferri, and Ian Preston. 2008. "Consumption inequality and partial insurance." *American Economic Review*, 98(5): 1887–1921.

Bond, Eric W, and Keith J Crocker. 1991. "Smoking, skydiving, and knitting: The endogenous categorization of risks in insurance markets with asymmetric information." *Journal of Political Economy*, 99(1): 177–200.

Boomhower, Judson, Meredith Fowlie, Jacob Gellman, and Andrew Plantinga. 2024. "How are insurance markets adapting to climate change? risk selection and regulation in the market for homeowners insurance." *NBER Working Paper*, , (32625).

Bostic, Raphael W, and Kwan Ok Lee. 2008. "Mortgages, risk, and homeownership among low- and moderate-income families." *American Economic Review*, 98(2): 310–314.

Bradt, Jacob T., and Joseph E. Aldy. 2025. "Private Benefits from Public Investment in Climate Adaptation and Resilience." *NBER Working Paper*.

Braun, Michael, Peter S Fader, Eric T Bradlow, and Howard Kunreuther. 2006. "Modeling the "pseudodeductible" in insurance claims decisions." *Management Science*, 52(8): 1258–1272.

Cain, Lucas, Danae Hernandez-Cortes, Christopher Timmins, and Paige Weber. 2024. "Recent Findings and Methodologies in Economics Research in Environmental Justice." *Review of Environmental Economics and Policy*, 18(1): 116–142.

Calvano, Emilio, Giacomo Calzolari, Vincenzo Denicolò, and Sergio Pastorello. 2020. "Artificial Intelligence, Algorithmic Pricing, and Collusion." *American Economic Review*, 110(10): 3267–97.

Collier, Benjamin, Cameron Ellis, Anran Li, and Adam Solomon. 2026. "Capital Costs, Reinsurance, and the Price of Climate Risk." *SSRN Working Paper*.

Collinson, Robert, Anthony A DeFusco, John Eric Humphries, Benjamin J Keys, David C Phillips, Vincent Reina, Patrick S Turner, and Winnie Van Dijk. 2024. "The effects of emergency rental assistance during the pandemic: Evidence from four cities." National Bureau of Economic Research.

Colorado Division of Insurance. 2010. "Credit-Based Insurance Scoring Studies." Colorado Division of Insurance.

Congressional Budget Office. 2024. "Climate Change, Disaster Risk, and Homeowner's Insurance."

Cookson, J Anthony, Emily Gallagher, and Philip Mulder. 2023. "Money to burn: Crowdfunding wildfire recovery." *Available at SSRN 4535190*.

Cookson, J Anthony, Emily Gallagher, and Philip Mulder. 2025. "Coverage Neglect in Homeowner's Insurance."

Crocker, Keith J, and Arthur Snow. 1986. "The efficiency effects of categorical discrimination in the insurance industry." *Journal of Political Economy*, 94(2): 321–344.

Davis, Morris A., William D. Larson, Stephen D. Oliner, and Jessica 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.

DeNicola, Louis. 2024. "Which States Restrict the Use of Credit Scores in Determining Insurance Rates?" Experian.

Eastman, Evan, Kyeonghee Kim, and Tingyu Zhou. 2024. "Homeowners insurance and housing prices." *SSRN Working Paper*.

Ehrlich, Isaac, and Gary S. Becker. 1972. "Market Insurance, Self-Insurance, and Self-Protection." *Journal of Political Economy*, 80(4): 623–648.

Elul, Ronel, Nicholas S Souleles, Souphala Chomsisengphet, Dennis Glennon, and Robert Hunt. 2010. "What "triggers" mortgage default?" *American Economic Review*, 100(2): 490–494.

Fannie Mae. 2024. "Selling Guide: Fannie Mae Single Family."

Federal Trade Commission. 2007. "Credit-Based Insurance Scores: Impacts on Consumers of Automobile Insurance." Federal Trade Commission.

FICO. 2025*a*. "What's in my FICO Scores?" FICO.

FICO. 2025*b*. "What's in Your Score." FICO.

Finkelstein, Amy, James Poterba, and Casey Rothschild. 2009. "Redistribution by insurance market regulation: Analyzing a ban on gender-based retirement annuities." *Journal of Financial Economics*, 91(1): 38–58.

Foote, Christopher, Kristopher Gerardi, Lorenz Goette, and Paul Willen. 2010. "Reducing foreclosures: No easy answers." *NBER Macroeconomics Annual*, 24(1): 89–138.

Freddie Mac. 2024. "Single-Family Seller/Servicer Guide."

Fuster, Andreas, Paul Goldsmith-Pinkham, Tarun Ramadorai, and Ansgar Walther. 2022. "Predictably unequal? The effects of machine learning on credit markets." *The Journal of Finance*, 77(1): 5–47.

Ge, Shan, Ammon Lam, and Ryan Lewis. 2025. "The Effect of Insurance Premiums on the Housing Market and Climate Risk Expectations." *SSRN Working Paper*.

Ghent, Andra C, and Marianna Kudlyak. 2011. "Recourse and residential mortgage default: evidence from US states." *The Review of Financial Studies*, 24(9): 3139–3186.

Graetz, Nick. 2025. "Price signals and credit penalties in the home insurance market."

Green, Richard K, and Susan M Wachter. 2005. "The American mortgage in historical and international context." *Journal of Economic Perspectives*, 19(4): 93–114.

Gropper, Michael J, and Camelia M Kuhnen. 2025. "Wealth and insurance choices: Evidence from US households." *The Journal of Finance*, 80(2): 1127–1170.

Gruber, Jonathan, and Adam Solomon. 2026. "Optimal Flood Insurance in a Second-Best World: Fiscal Spillovers, Reclassification Risk and Moral Hazard." *NBER Working Paper*.

Handel, Benjamin R. 2013. "Adverse selection and inertia in health insurance markets: When nudging hurts." *American Economic Review*, 103(7): 2643–2682.

Hoy, Michael. 1982. "Categorizing risks in the insurance industry." *The Quarterly Journal of Economics*, 97(2): 321–336.

Huang, Fei, and Giles Hooker. 2026. "Fairness Testing for Algorithmic Pricing." *arXiv preprint arXiv:2605.11614*.

Humphries, John Eric, Scott T Nelson, Dam Linh Nguyen, Winnie van Dijk, and Daniel C Waldinger. 2024. "Nonpayment and eviction in the rental housing market." National Bureau of Economic Research.

Hurst, Erik, Benjamin J Keys, Amit Seru, and Joseph Vavra. 2016. "Regional redistribution through the US mortgage market." *American Economic Review*, 106(10): 2982–3028.

Insurance Information Institute. 2022. "Trends and Insights: Florida Homeowners' Insurance Crisis." © Insurance Information Institute, August 2022.

Insurance Information Institute. 2023. "Background on: Insurance scoring." Accessed 2025-10-06.

Insurance Information Institute. 2025. "Facts + Statistics: Homeowners and Renters Insurance." *https://www.iii.org/fact-statistic/facts-statistics-homeowners-and-renters-insurance*, Accessed October 6, 2026.

Johnson, Erik, Adam Nowak, Lars Powell, and Amanda Ross. 2023. "Asymmetric Information in the Florida Homeowners Insurance Market."

Kellison, J Bruce, Patrick Brockett, Seon-Hi Shin, and Shihong Li. 2003. "A statistical analysis of the relationship between credit history and insurance losses." Bureau of Business Research, The University of Texas at Austin.

Keys, Benjamin J, and Philip Mulder. 2024. "Property Insurance and Disaster Risk: New Evidence from Mortgage Escrow Data." NBER Discussion paper No. 32579.

Keys, Benjamin J, Devin G Pope, and Jaren C Pope. 2016. "Failure to refinance." *Journal of Financial Economics*, 122(3): 482–499.

Kiviat, Barbara. 2019. "The moral limits of predictive practices: The case of credit-based insurance scores." *American Sociological Review*, 84(6): 1134–1158.

Kleinberg, Jon, Jens Ludwig, Sendhil Mullainathan, and Ashesh Rambachan. 2018. "Algorithmic Fairness." *AEA Papers and Proceedings*, 108: 22–27.

Kousky, Carolyn, Howard Kunreuther, Brett Lingle, and Leonard Shabman. 2018. "The emerging private residential flood insurance market in the United States." *Wharton Risk Management and Decision Processes Center*.

La Corte, Rachel. 2022. "Washington judge overturns insurance rate credit scoring ban." *AP News*. Available at https://apnews.com/article/legal-proceedings-washington-olympia-f5b54526201d94abebca0c0734db4047 Accessed: September 25, 2026.

Lacy, William. 2017. "A Report to the Legislative Council and the Senate and House Committees on Insurance and Commerce of the Arkansas General Assembly (as Required by Act 1452 of 2003): Use and Impact of Credit in Personal Lines Insurance Premiums Pursuant to Ark. Code Ann. §23-67-415." Arkansas Insurance Department.

Miller, Michael J, Richard A Smith, and Klayton N Southwood. 2003. "The relationship of credit-based insurance scores to private passenger automobile insurance loss propensity." *Actuarial Study, Epic Actuaries online at http://www. epicactuaries. com*.

Monaghan, James E. 2000. "The impact of personal credit history on loss performance in personal lines." 79–105, Citeseer.

Mulder, Philip. 2022. "Mismeasuring risk: The welfare effects of flood risk information."

Mulder, Philip, and Carolyn Kousky. 2023. "Risk rating without information provision." Vol. 113, 299–303, American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203.

NAIC. 2008. "Review of the Use of Credit-Based Insurance Scoring by Insurers." National Association of Insurance Commissioners (NAIC) Report to the Market Regulation and Consumer Affairs (D) Committee, Kansas City, MO. DRAFT as of Aug. 26, 2008.

National Association of Insurance Commissioners. 2009. "Committee-Related Documents (Hearing Materials)." *https://content.naic.org/sites/default/files/committee_related_documents/committees_c_090430_hearing_materials.pdf*, Accessed online Nov 20, 2025.

Oh, Sangmin S, Ishita Sen, and Ana-Maria Tenekedjieva. 2026. "Pricing of climate risk insurance: Regulation and cross-subsidies." *The Journal of Finance*, 81(3): 1161–1215.

Pope, Devin G, and Justin R Sydnor. 2011. "Implementing anti-discrimination policies in statistical profiling models." *American Economic Journal: Economic Policy*, 3(3): 206–231.

Powell, Lars. 2020. "Risk-based pricing of property and liability insurance." *Journal of Insurance Regulation*, 1.

Quercia, Roberto G, George W McCarthy, and Susan M Wachter. 2003. "The impacts of affordable lending efforts on homeownership rates." *Journal of Housing Economics*, 12(1): 29–59.

Rambachan, Ashesh, Jon Kleinberg, Jens Ludwig, and Sendhil Mullainathan. 2020. "An Economic Perspective on Algorithmic Fairness." *AEA Papers and Proceedings*, 110: 91–95.

Retsinas, Nicolas P, and Eric S Belsky. 2004. *Low-income homeownership: Examining the unexamined goal*. Bloomsbury Publishing PLC.

Rosanes, Mark. 2021. "Judge Overturns Credit Score Ban for Calculating Premiums." *Insurance Business*. Available at https://www.insurancebusinessmag.com/us/news/breaking-news/judge-overturns-credit-score-ban-for-calculating-premiums-312729.aspx Accessed: September 25, 2026.

Rothschild, Michael, and Joseph Stiglitz. 1976. "Equilibrium in competitive insurance markets: An essay on the economics of imperfect information." In . Vol. 90, 629–649.

Sastry, Parinitha. 2026. "Who bears flood risk? Evidence from Mortgage Markets in Florida." *Review of Financial Studies (Accepted)*.

Sastry, Parinitha, Ishita Sen, Ana-Maria Tenekedjieva, and Therese C Scharlemann. 2026. "The Insurance Protection Gap." *SSRN Working Paper*.

Sastry, Parinitha, Ishita Sen, and Ana-Maria Tenekedjieva. 2026. "When insurers exit: Climate losses, fragile insurers, and mortgage markets." *SSRN Working Paper*.

Solomon, Adam. 2024. "When Insurance Markets Fail: Catastrophe-Risk Frictions and Public Reinsurance." *SSRN Working Paper*.

Taylor, Reid, Madeline Turland, and Joakim A. Weill. 2025. "Last Resort Insurance: Wildfires and the Regulation of a Crashing Market."

Texas Department of Insurance. 2004. "Report to the 79th Legislature: Use of Credit Information by Insurers in Texas." Texas Department of Insurance.

Texas Department of Insurance. 2005. "Supplemental Report to the 79th Legislature: Use of Credit Information by Insurers in Texas: The Multivariate Analysis." Texas Department of Insurance.

Todoroff, Natalie. 2024. "Factors that impact your cost of homeowners insurance." Bankrate.

Todoroff, Natalie. 2025. "Does credit score affect homeowners insurance?" Bankrate.

U.S. Department of the Treasury. 2025. "U.S. Department of the Treasury Report: Homeowners Insurance Costs Rising, Availability Declining as Climate-Related Events Take Their Toll." *https://home.treasury.gov/news/press-releases/jy2791*, Press Release.

U.S. Fire Administration. 2024. "Residential and nonresidential building fire and fire loss estimates by property use and cause (2003-2022)."

Wagner, Katherine RH. 2022. "Adaptation and adverse selection in markets for natural disaster insurance." *American Economic Journal: Economic Policy*, 14(3): 380–421.

Washington Office of the Insurance Commissioner. 2022. "Kreidler acted in good faith, followed steps, but exceeds authority on credit score ban, court rules." *Washington State Office of the Insurance Commissioner News*. Available at https://www.insurance.wa.gov/about-us/news/2022/kreidler-acted-good-faith-followed-steps-exceeds-authority-credit-score-ban-court-rules Accessed: September 25, 2026.

Webel, Baird. 2005. "Credit Scores: Credit-Based Insurance Scores." Congressional Research Service CRS Report RS21341, Washington, DC. January 19, 2005.

Weill, Joakim A. 2026. "Flood risk mapping and the distributional impacts of climate information." *American Economic Journal: Economic Policy*, 18(3): 275–305.

A Online Appendix

A.1 Additional Insurance Background

After insurance companies began using credit information in underwriting, many states began passing laws and regulations to restrict the usage of credit information when determining premiums. Most of these laws prohibit using credit scores as the "sole basis" for denying, canceling, or not renewing a policy without prohibiting their use in setting premiums. Only California, Massachusetts, and Maryland limit the use of credit scores when setting premiums (Colorado Division of Insurance, 2010; Powell, 2020; Federal Trade Commission, 2007; DeNicola, 2024). This topic has also been debated in Congress (110th Congress, 2007).

Previous industry reports found that even after adjusting for other covariates, credit score predicts the probability of filing a claim (Monaghan, 2000; Miller, Smith and Southwood, 2003; Kellison et al., 2003; Texas Department of Insurance, 2004, 2005). However, most of the work on the use of credit in insurance pricing has focused on auto insurance, except for one study of 800,000 homeowners policies active in 2001 (Texas Department of Insurance, 2005). There has been limited work on the effect of credit-based pricing on premiums, with two studies finding that credit-based pricing impacts the allocation of premium changes without changing aggregate premiums (Lacy, 2017; Federal Trade Commission, 2007).

A.2 Insurance ratemaking example

Insurers incorporate a range of home and homeowner characteristics when pricing insurance policies. In many states, insurers have to file these details with the state regulator. For expository purposes, we outline an example of the rate-making process in Oklahoma for Allstate North American Insurance Company (Allstate; NAIC# 11110). This is based off of a recent rate filing from March 2025 (SERFF#: ALSE-134292934). Based on their filing, Allstate has 97 distinct steps to calculate a premium. Furthermore, for 58 of these steps, they have to be calculated across 18 different premium components (corresponding to different perils and hazards the insurance policy covers). Table S1 summarizes the assumptions we make about the property, policy, and the homeowner:

With these property, policy, and homeowner characteristics, the insurance premium is $5775. However, since we have all of the rating factors, we can trace out the premium as we

Table S1: List of Characteristics Input into Allstate Oklahoma Ratemaking Manual

Property	**Policy**	**Homeowner**
Property at 35° 33' 50.0" N and 97° 33' 50" W	$240k coverage limit	No auto accidents
Default Z-Fire score	$1k deductible	0 years with previous auto carrier
Home built in 1995 (30-year-old house)	Escrowed premiums, good payer	Primary residence
1 story house	No multi-policy	54 years old
1500 sq ft	New home insurance policy	250 insurance score
Frame construction	Purchased with Allstate agent	No fire claims
Siding (exterior walls)	No claim forgiveness add-on	No weather water claims
No fireplace	No personal property reimbursement	No non-weather water claims
2 bathrooms	No functional replacement	No wind claims
Finished basement	No additional building code factor	No hail claims
Roof index 22	Default Coverage B (10% Cov A)	No lightning claims
Composition shingle	Default Coverage C (40% Cov A)	No theft and vandalism claims
Gable roof	Default Coverage D (20% Cov A)	No liability claims
No hail resistant roof	Default Coverage X ($100k limit)	No other claims
No roof condition group	Default Coverage Y ($1k limit)	5+ years claim free
Unavailable tree overhang	No water backup coverage	
No parcel perimeter grouping	No service lines coverage	
No parcel area data		
No parcel max footprint		

Source: Allstate
Notes: Characteristics are based on authors' selections from characteristics that are priced from Allstate's March 2025 ratemaking filing available from SERFF#: ALSE-134292934.

vary the insurance score of the homeowner (but keep property, policy, and other homeowner characteristics fixed). As the insurance score increases (in this case, we believe the scale is inverted in Allstate's handbook), premiums increase substantially. Table S2 summarizes the scores and associated premiums (all other characteristics are fixed).

Other insurers also may use credit history, but are not as transparent in their filings. For example, State Farm's 2025 ratemaking manual has a Consumer Rating Index, but neither the scores are disclosed, nor their quantitative impact on premiums. One nice feature of Oklahoma's rate filings is that each insurer must fill out a standardized "Premium Worksheet" of estimated premiums for a range of scenarios and insurers are explicitly asked "Are credit scores a determinant in the above premiums?". Filings from State Farm, Allstate, Travelers, and USAA have all indicated "yes."

Table S2: Calculated premiums for Allstate (March 2025)

Insurance Score	Premium
Unscored	$7504
250	$5775
350	$6790
450	$7961
550	$9334

Source: Allstate
Notes: Table reports the estimate premiums for a standard homeowner in Oklahoma. Each row reports the estimated premium when only the credit score of the homeowner is changed.

Insurers may also update the credit-based insurance scores they use, but there are not standardized rules regarding updates. As an example, Allstate's Oklahoma manual (referenced above) clearly states that previous credit score group assignments will persist unless the insured requests that a new credit report be pulled.[34] Oklahoma statutes do not require that credit information be updated any more frequently than 36 months (36 OK Stat § 953 (2024)). Other states have similar statutes where credit reports are updated infrequently, updated at the request of the insured, or updated in accordance with the insurer's policies.

A.3 Data cleaning

The McDash mortgage and insurance dataset includes around 215 million unique mortgage-year observations in 2015–2024. We restrict our sample to observations to first-lien, single-family homes with escrowed premiums, which reduces our sample to 153 million mortgage-year observations. After applying additional data quality cleaning we reach our final sample size of about 132 million mortgage-year observations. Data cleaning steps are summarized in Table S3.

[34]Per Allstate's Rule 35 of their March 2025 rate filing, "At each renewal, the same Policy Group will continue to apply unless at renewal the following applies: At the named insured's request, a new credit report will be obtained for the named insured. The reorder will be allowed once annually and will follow the procedure regarding ordering of credit reports that is in effect for Allstate at the time of the reorder and the applicable Policy Group will be assigned as determined in Section A."

Table S3: Cleaning steps

Step	Count
All loans	215,540,776
SF loans	182,763,361
First lien	175,868,957
Escrowed premiums	152,932,894
Coverage in [50K,2M]	151,899,244
Premiums below 10K	151,899,229
Appraisal in [50K, 3M]	149,628,867
Nonmissing FICO	133,762,884
LTV < 150	131,836,668

Source: ICE, McDash®
Notes: Table reports observations remaining after each step of data cleaning.

Insurance data is only available from servicers that have agreed to share insurance data with ICE/McDash. Table S4 compares the approximately 176 million single-family, first-lien observations we have with insurance data ("Insurance sample" column) to the 73.5 million single-family, first-lien observations that do not have insurance data ("No insurance data" column). Overall, the two samples are broadly comparable, with the most notable difference being that the insurance sample has mortgages with lower loan-to-value (LTV) ratios. Importantly, after restricting the samples to single-family, first-lien mortgages, no additional cleaning steps are applied, so there remain notable outliers in both samples (e.g., the standard deviation on the LTV measures are 24k to 37k for a measure that should mostly be between 0 and 100).

Table S4: Balance table between McDash property insurance sample and mortgage sample

	Insurance sample	No insurance data
FICO Origination	727.64 (79.31)	716.22 (72.68)
Debt/Income	34.14 (12.37)	31.62 (13.80)
Appraisal amount ($)	340005.29 (538343.37)	318756.39 (647219.11)
Loan/Value	82.92 (24242.25)	90.15 (37122.53)
Origination amount ($)	232882.40 (240716.30)	221463.60 (257985.56)
Count	175868957	73555037

Source: ICE, McDash®
Notes: Table reports mean of selected mortgage and borrower characteristics, with standard deviation in parentheses and the observation count. Both samples are restricted to single-family homes and first-lien mortgages. The "insurance sample" denotes mortgages that have insurance data reported while the "no insurance data" column denotes mortgages without reported insurance data.

Table S5 compares the mortgages that we were able to match with CoreLogic property characteristics with mortgages that were unmatched as described in Section 3. The matched and unmatched groups are similar on observable characteristics, showing matching to the CoreLogic AAL data does not create a biased sample.

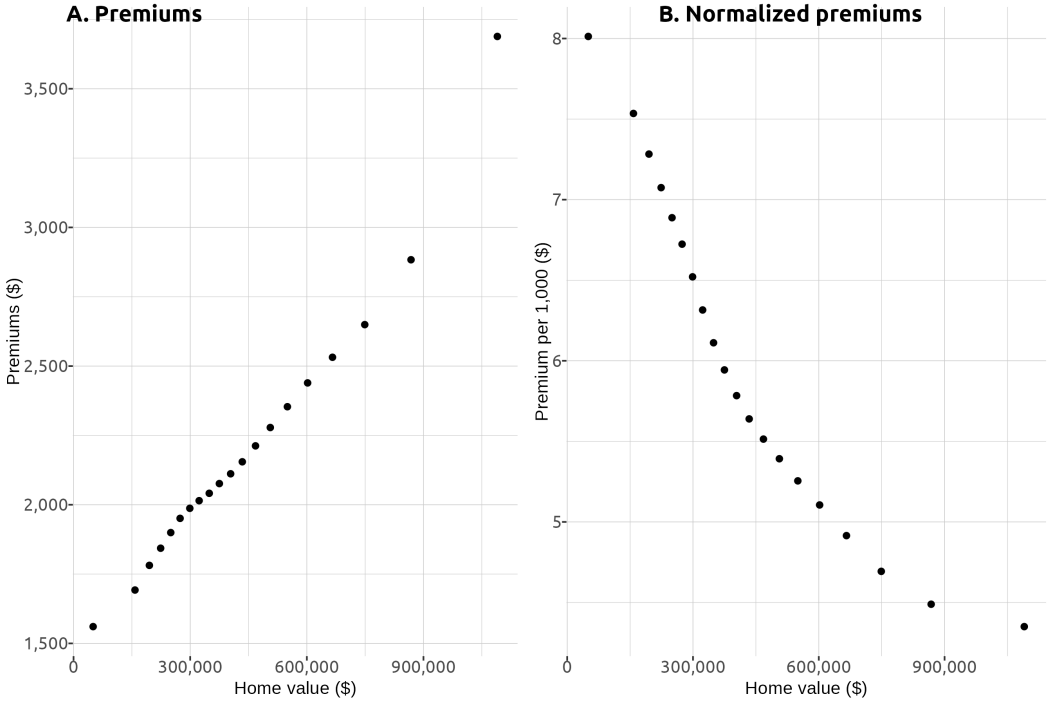
Table S5: Balance table between McDash-CoreLogic matched and unmatched samples

Variable	Not matched	Matched CL
Annual premium ($)	1,542.6 (1,084)	1,550 (1,081)
Coverage ($1k)	343 (207)	331 (188)
Prem. per 1k	5.1 (3.4)	5.2 (3.4)
Deductible ($)	1,444.3 (10,973.8)	1,565 (7,659)
Appraisal ($1k)	306 (251)	297 (225)
Debt-to-Income (%)	34.1 (12.7)	34.9 (11.6)
Loan-to-Value (%)	76.3 (19.3)	80.2 (18)
Insurance-to-loan (%)	15 (12.3)	14.6 (11.7)
Origination ($1k)	217 (160)	224 (151)
Annual mortgage ($)	13,442.5 (9,220.6)	13,498.3 (8,806.6)
Count	43,773,312	75,322,323

Source: ICE, McDash®
Notes: Table reports mean of selected mortgage and borrower characteristics, with standard deviation in parentheses and the observation count. “Matched sample” denotes mortgages that were matched with CoreLogic property information. ”Unmatched sample” denotes mortgages that were not matched with CoreLogic property information. The two groups are similar on observable characteristics.

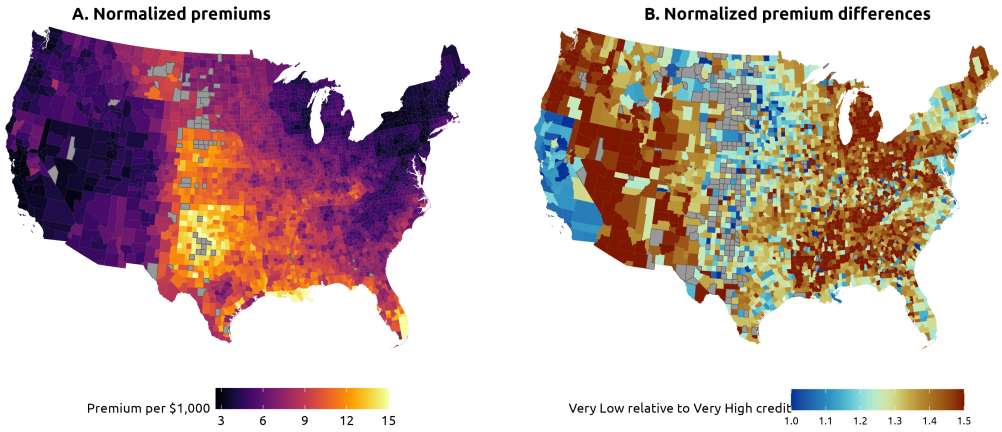
A.4 Additional Tables and Figures

Figure S1: Premiums and normalized premiums by home value quantiles



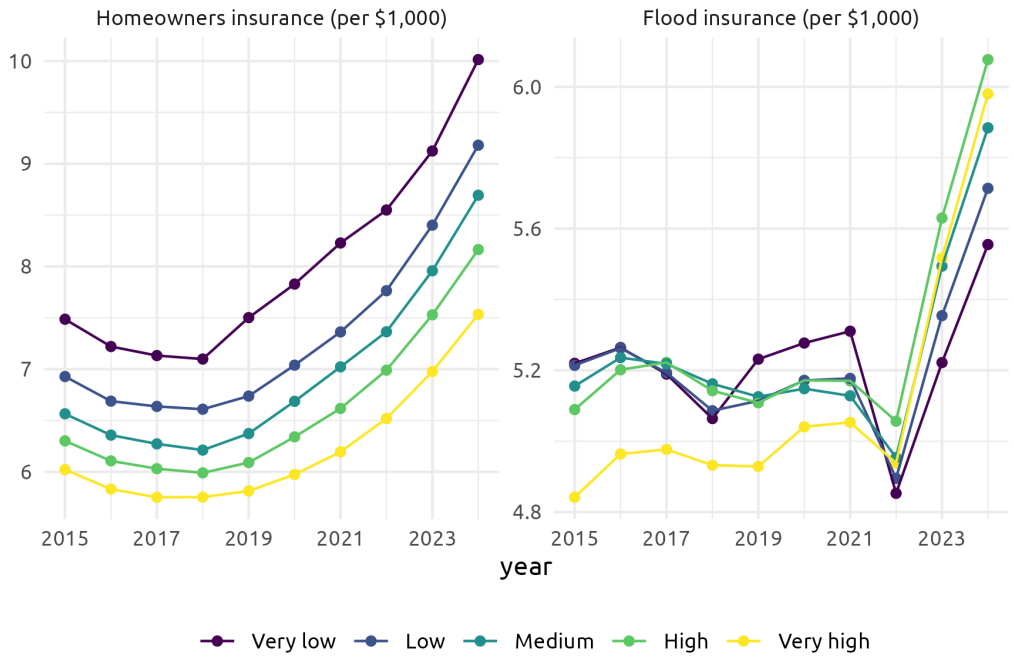
Source: ICE, McDash®
Notes: Home values are based on CoreLogic's appraisal values and are expressed in 2023 USD using the FHFA Housing Price Index. Premiums are in annual dollars.

Figure S2: Premium per $1,000 and credit differences at the county level



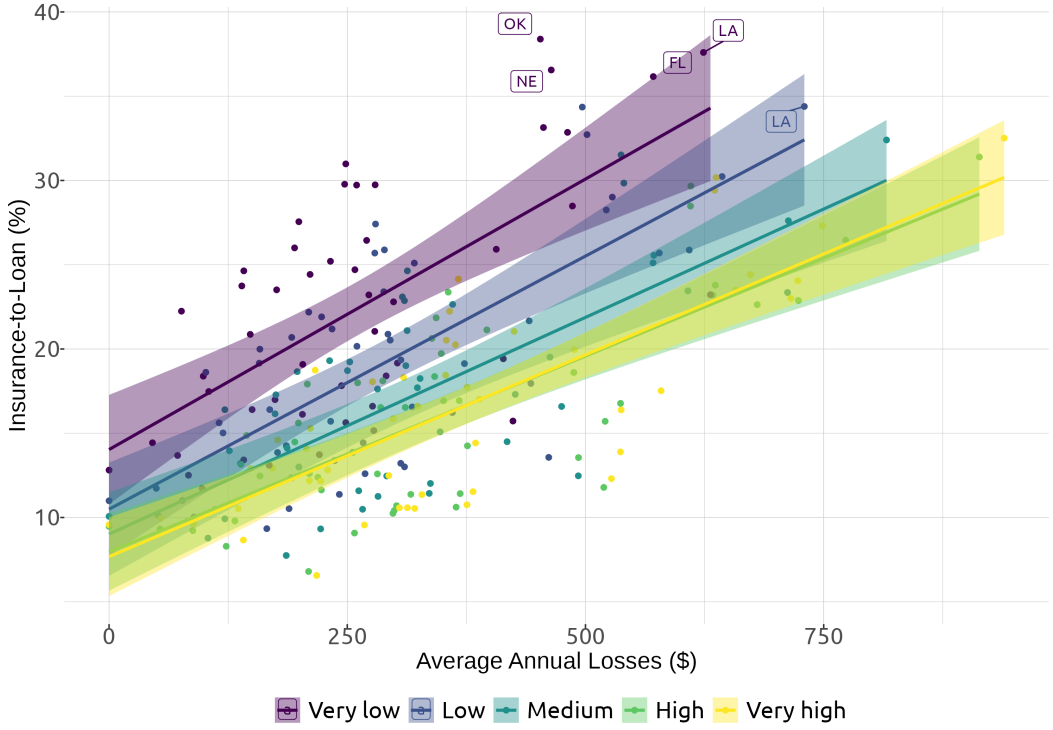
Source: ICE, McDash®
Notes: The figure displays county-level maps showing average premiums per thousand dollars of coverage ("normalized premiums," panel A) and average differences in normalized premiums between the top and bottom quintiles of the credit score distribution (panel B). Scale is bounded between 1 and 1.5 for clarity. Statistics based on fewer than 20 observations are omitted for confidentiality.

Figure S3: Homeowners insurance and flood insurance premiums by credit score



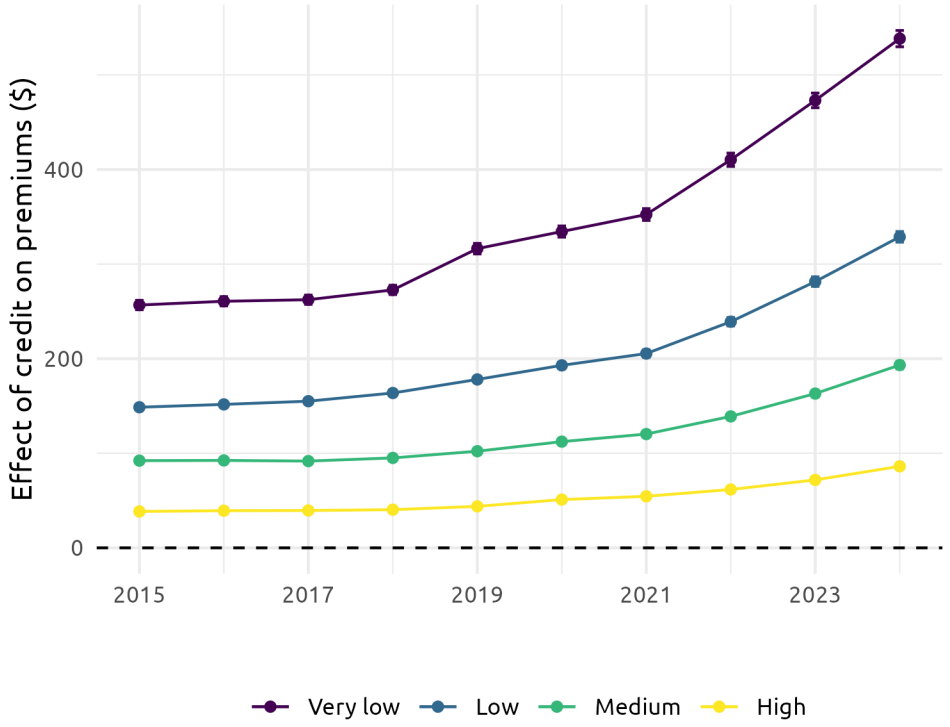
Source: ICE, McDash®
Notes: Premiums are expressed per $1,000 of structure coverage. Flood insurance policies are subset to those with a structure coverage limit equal to the National Flood Insurance Program (NFIP) maximum ($250,000) in order to screen out private flood insurance policies. The NFIP writes the vast majority of flood insurance policies over our sample period (Kousky et al., 2018). Note that the NFIP fully implemented its "Risk Rating 2.0" pricing starting in 2023, where we see both a premiums trend break and the emergence of a modest *positive* relationship between credit scores and premiums.

Figure S4: Insurance burden and disaster risk by state in 2024



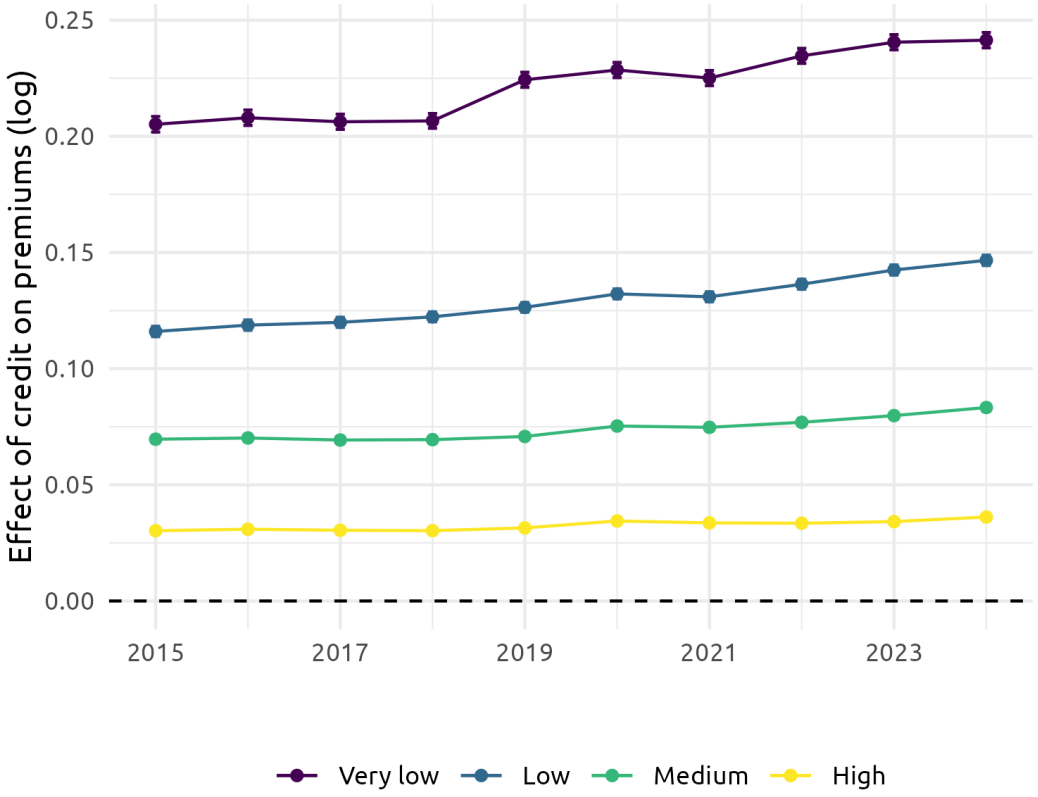
Source: ICE, McDash®; CoreLogic
Notes: The figure displays states by credit quintile averages of the insurance burden in 2024 plotted against the CoreLogic AALs. Shaded bands represent 95% confidence intervals. The insurance burden is the monthly premium divided by the sum of the monthly principal and interest payments. The AALs exclude flooding.

Figure S5: Time-varying premium coefficients on credit quintiles



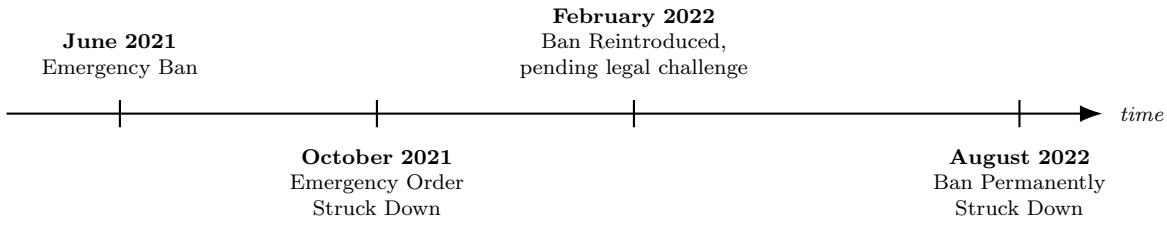
Source: ICE, McDash®; CoreLogic;
Notes: Figure plots the time-varying credit quintile coefficients from a modified version of Equation 2, which regresses insurance premium on credit score quintile, disaster risk, policy characteristics, time fixed effects, and geography fixed effects and allows for time-varying coefficients on credit quintile. Credit score quintiles are: Very low (less than 671), Low (671-715), Medium (716-755), High (756-786), Very high (greater than 786). The Very High credit group is the omitted reference category.

Figure S6: Time-varying log premium coefficients on credit quintiles



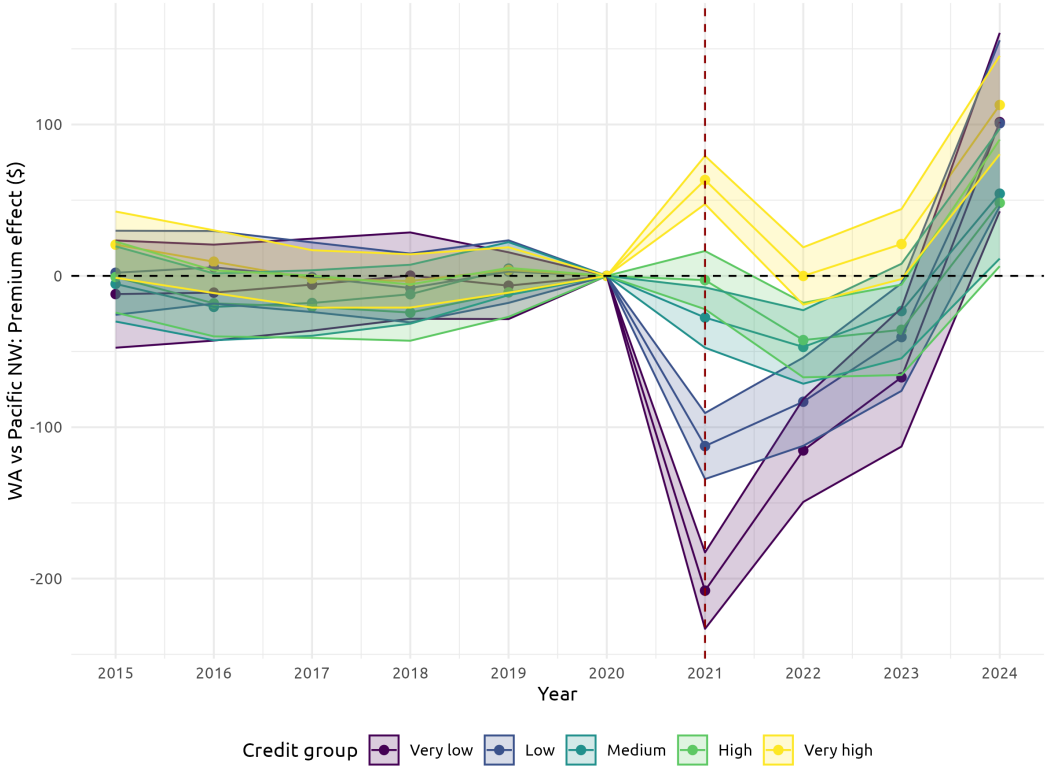
Source: ICE, McDash®; CoreLogic;
Notes: Figure plots the time-varying credit quintile coefficients from a modified version of Equation 2, which regresses log insurance premium on credit score quintile, disaster risk, policy characteristics, time fixed effects, and geography fixed effects and allows for time-varying coefficients on credit quintile. Credit score quintiles are: Very low (less than 671), Low (671-715), Medium (716-755), High (756-786), Very high (greater than 786). The Very High credit group is the omitted reference category.

Figure S7: WA Credit Ban Timeline



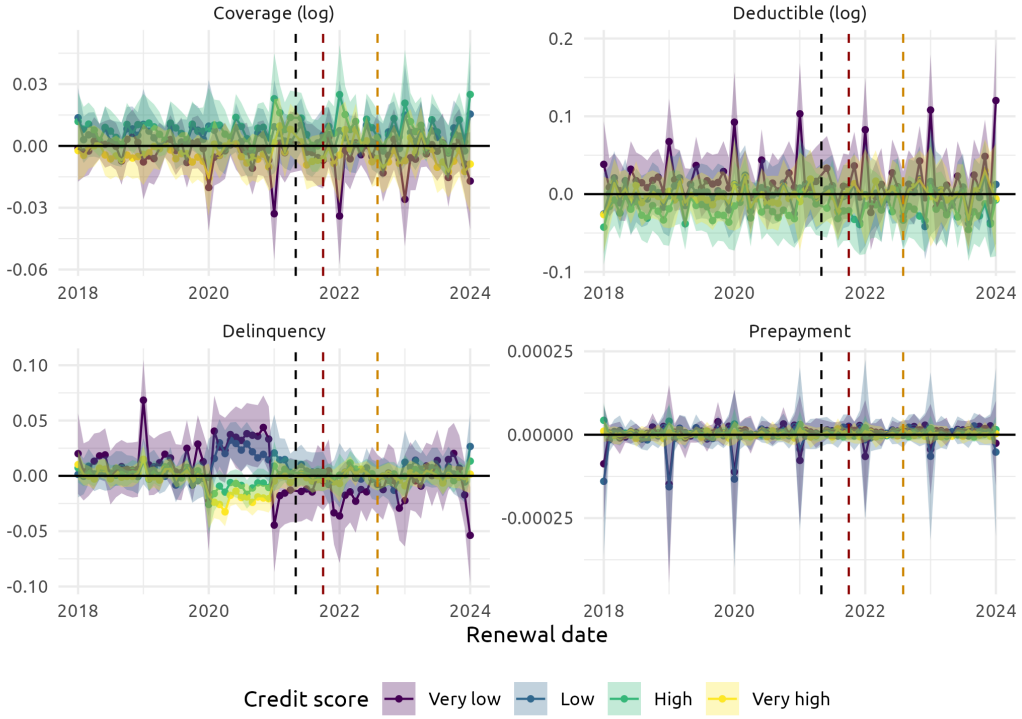
Notes: Timeline of proposed bans on credit-based insurance pricing and court rulings in Washington state.

Figure S8: Washington state credit ban with Pacific Northwest control group



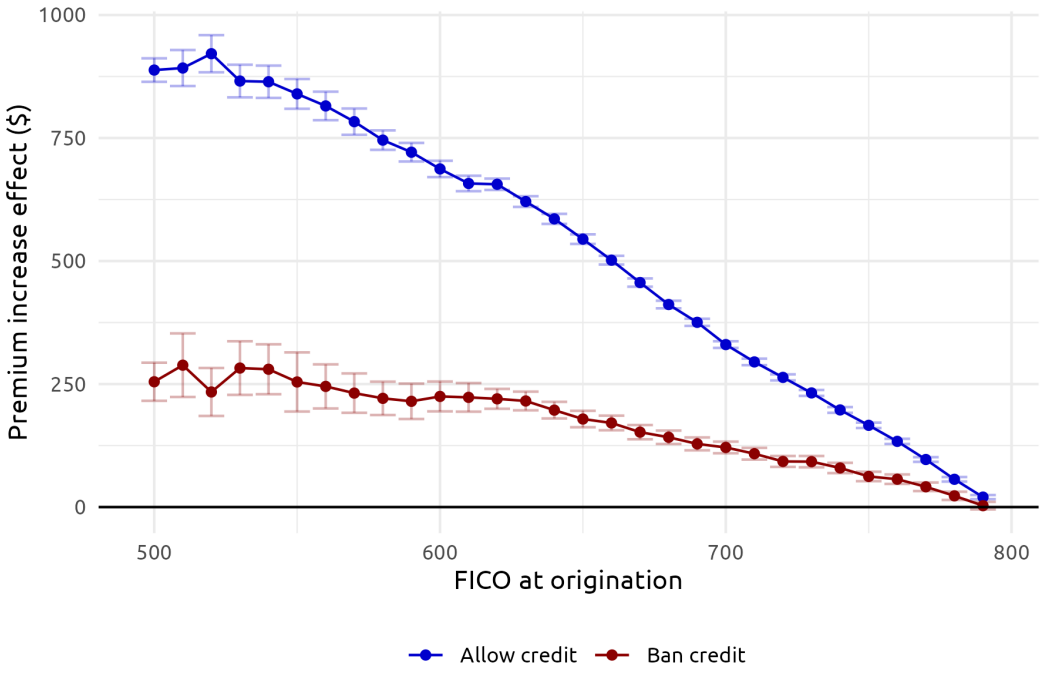
Source: ICE, McDash®; CoreLogic;
Notes: Figure plots the time-varying credit quintile coefficients from a modified version of Equation 2 subset to policies in Oregon, Idaho, and Washington state that renew in October. Plotted coefficients are on the interaction between a Washington state indicator, year, and credit quintile with 2020 interactions as the omitted category. Specification includes disaster risk, policy characteristics, time fixed effects, and ZIP code fixed effects. Credit score quintiles are: Very low (less than 671), Low (671-715), Medium (716-755), High (756-786), and Very high (greater than 786).

Figure S9: Washington state credit ban, other outcomes



Source: ICE, McDash®; CoreLogic;
Notes: Figure plots the time-varying credit quintile coefficients from a modified version of Equation 3, which regresses an outcome of interest of the respective panel on a loan fixed effects, and a renewal month fixed effect and allows for time-varying coefficients. Credit score quintiles are: Very low (less than 671), Low (671-715), Medium (716-755), High (756-786), and Very high (greater than 786). The Medium credit group is the omitted reference category.

Figure S10: Flexible estimation of the effect of credit scores on premiums



Source: ICE, McDash®; CoreLogic
Notes: The figure displays estimates of Equation 6 with credit score bins that are divided into increments of 10 points. All estimates are relative to the omitted bin (having a credit score of 800 and above). Standard errors are clustered at the ZIP code level; the figure shows 95% confidence intervals around the point estimates. States that ban credit in insurance pricing (in red) are CA, MA, and MD. All the other states allow the use of credit information in insurance pricing. The sample is restricted to 2024 insurance policies.

A.5 Additional models

We benchmark the relationship between disaster risk and premiums using the following regressions:

$$P_{igt} = \beta_1 AAL_i + \beta_2 Deductible_{it} + \beta_3 Coverage_{it} + \lambda_i + \lambda_t + \lambda_g + \epsilon_{igt} \tag{6}$$

where P_{igt} is the annual insurance premium of homeowners insurance policy i in geography g during year t. All insurance policies are active between 2015 and 2024. Our main coefficient of interest is β_1, which measures the pass-through of predicted disaster losses to premiums, where AAL_i is the AAL for property i in dollars per year derived from CoreLogic. We control for deductible choice ($Deductible_i$, which includes \$500 bins

for deductible choice and is top-coded at $10,000), and coverage choice ($Coverage_i$, which includes $50,000 bins for coverage amount and is top-coded at $2 million).[35] λ_i, λ_t, and λ_g are insurer, year, and geography fixed effects, respectively, and errors are clustered at the ZIP code level. When considering how the pricing of disaster risk has evolved over time, we estimate a slightly modified version of equation 6 with $\sum_{t=2015}^{2024} \beta_t AAL_i$, thus allowing the pass-through coefficients to vary each year.

Table S7 presents the results of estimating equation 6. Column 1 does not include any geography fixed effects, and we find that a $1 increase in AAL results in a $0.87 increase in premiums on average across our sample. The estimated coefficient on AAL attenuates sharply to $0.55 where we add state fixed effects (column 2), and further diminishes to $0.35 with ZIP fixed effects in column 3, and remains stable around $0.32 with the addition of blockgroup fixed effects in column 4.

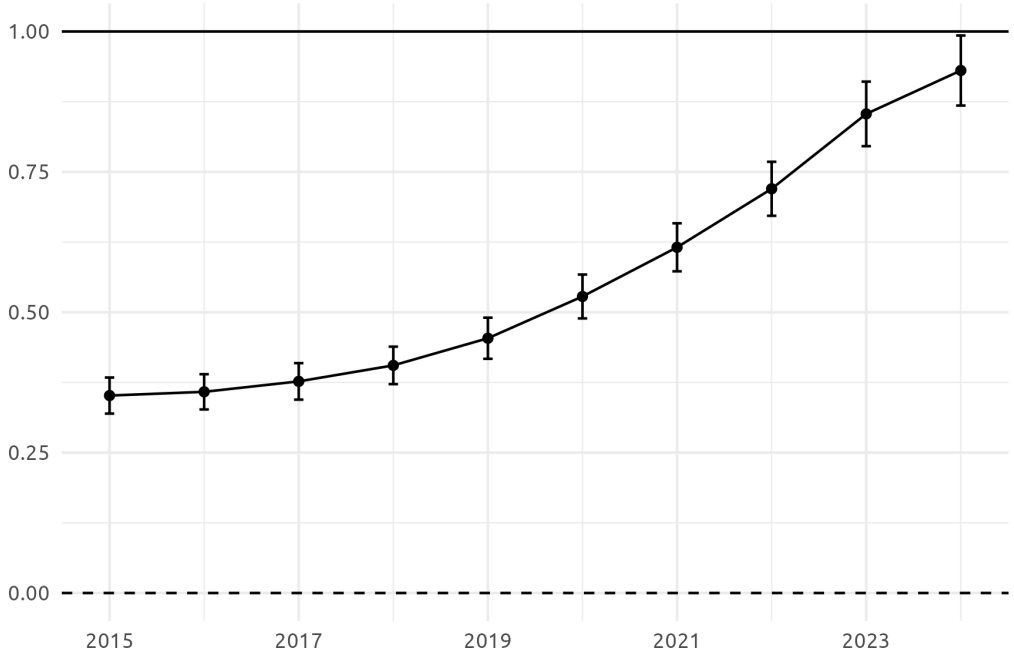
One plausible explanation for the sensitivity of the estimated AAL coefficient to geographic fixed effects is that many insurers use ZIP code factors rather than property level estimates of risk to price expected losses. To test this interpretation, we re-estimate Equation 6 with two successive changes: First, we allow time-varying annual coefficients on the relationship between AAL and premiums. Second, we introduce a new term that is the ZIP-average AAL across all the loans in our estimation sample also with annual coefficients.

The results show several striking trends. Figure S11 shows that the overall pass-through of AAL into premiums is increasing sharply over our estimation period. From 2015 to 2024, the AAL coefficient increased from $0.35 to $0.95 conditional on policy state, year, coverage bin, and deductible fixed effects. This increase in the risk-premium gradient is consistent with Keys and Mulder (2024), who also find an increase in the relationship between ZIP code level premiums and risk over the same period driven, in part, by the increasing price of insuring correlated risks. Our results highlight that this relationship holds with more granular microdata and may also be driven by the adoption of increasingly geographically precise data and sophisticated risk models.

Figure S12 shows the estimation results when including ZIP code average AAL in the estimating equation. Through 2019, a property's own AAL and the AAL of other homes in the same ZIP code had approximately equal weight on its premium. Beginning in 2020, the coefficient on property-level AAL begins to have more weight on premiums. These

[35] Our results are unchanged if we use $20,000 bins of coverage amount.

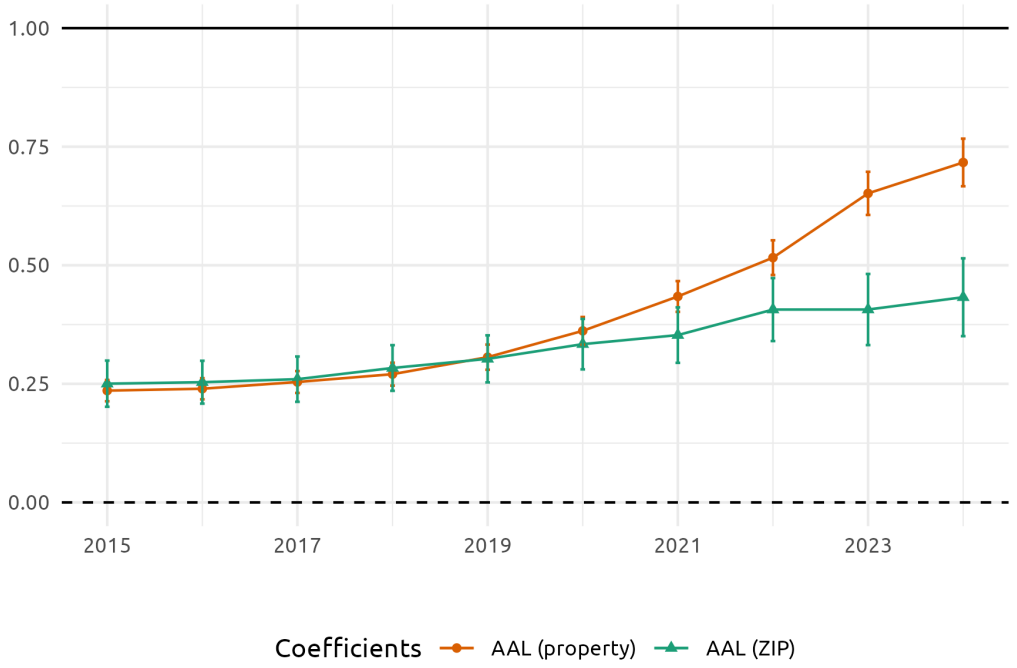
Figure S11: Time-varying premium coefficients on expected losses



Source: ICE, McDash®; CoreLogic;
Notes: The figure displays estimates of a modified version of Equation 6 which allows for time varying coefficients and regresses annual premiums on policy characteristics, average annual losses, and geography fixed effects. Standard errors are clustered at the ZIP code level; the figure shows 95% confidence intervals around the point estimates.

national-level findings are consistent with results from Boomhower et al. (2024), who study California and show that, although many insurers use relatively simple ZIP code factors to price wildfire risk, there is an increasing trend towards the use of property-level catastrophic risk models over the same period. While some of the weight on the ZIP code AAL coefficients could be a function of measurement error, the divergence in the two coefficients is relatively sudden and large in magnitude.

Figure S12: Time-varying premium coefficients on expected losses, ZIP and property AAL



Source: ICE, McDash®; CoreLogic;
Notes: The figure displays estimates of a modified version of Equation 6 which allows for time varying coefficients and regresses annual premiums on policy characteristics, ZIP code and property-level average annual losses, and geography fixed effects. ZIP code averages constructed using Leave-one-out. Standard errors are clustered at the ZIP code level; the figure shows 95% confidence intervals around the point estimates.

Table S6: Premiums and current credit score

Dependent Variable:	Annual premium (USD)			
Model:	(1)	(2)	(3)	(4)
Variables				
Very low	303.4***	320.8***	300.2***	342.5***
	(2.911)	(2.633)	(1.576)	(2.806)
Low	161.4***	171.3***	158.2***	182.3***
	(1.765)	(1.571)	(0.9605)	(1.716)
Medium	103.1***	109.3***	100.3***	116.3***
	(1.255)	(1.108)	(0.7018)	(1.220)
High	50.87***	53.79***	48.91***	56.89***
	(0.8883)	(0.7678)	(0.5093)	(0.8594)
AAL (USD)		0.5354***	0.3048***	0.5363***
		(0.0208)	(0.0139)	(0.0208)
Very low × Credit ban				-178.7***
				(5.756)
Low × Credit ban				-82.53***
				(3.634)
Medium × Credit ban				-49.74***
				(2.541)
High × Credit ban				-20.61***
				(1.601)
Fixed-effects				
Deductible	Yes	Yes	Yes	Yes
Coverage	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
State	Yes	Yes		Yes
Blockgroup			Yes	
Fit statistics				
Observations	44,467,090	44,467,090	44,467,090	44,467,090
R^2	0.47896	0.51962	0.61109	0.51997
Within R^2	0.01730	0.09398	0.03252	0.09465
Dep Var Mean	1,538.5	1,538.5	1,538.5	1,538.5

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

Source: ICE, McDash®; CoreLogic
Notes: Table reports the results of Equation 2, which regresses insurance premium on current credit score quintile, disaster risk, policy characteristics, time fixed effects, and geography fixed effects. The analysis uses current credit score instead of credit score at origination used in table 2. Current credit score is not reported for every observation, resulting in a lower number of observations. Credit score quintiles are: Very low (less than 671), Low (671-715), Medium (716-755), High (756-786), and Very high (greater than 786). The Very high credit group is the omitted reference category.

Table S7: Premiums and disaster risk

Dependent Variable:	Annual premium (USD)			
Model:	(1)	(2)	(3)	(4)
Variables				
AAL (USD)	0.8703***	0.5493***	0.3547***	0.3157***
	(0.0277)	(0.0204)	(0.0133)	(0.0129)
Fixed-effects				
Deductible	Yes	Yes	Yes	Yes
Coverage	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
State		Yes		
ZIP			Yes	
Blockgroup				Yes
Fit statistics				
Observations	62,060,201	62,060,201	62,060,201	62,060,201
R^2	0.39091	0.49959	0.57234	0.59272
Within R^2	0.16837	0.07395	0.02000	0.01182
Dep Var Mean	1,559.1	1,559.1	1,559.1	1,559.1

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

Source: ICE, McDash®; CoreLogic
Notes: Table reports the results of equation 6 which regresses annual premiums on Average Annual Losses, policy characteristics, year fixed effects, and geography fixed effects.

A.6 A Structural Model of Claim Filing

Environment

Homeowners are indexed by a credit-score group $b \in \{1, 2, 3, 4\}$: Poor/Fair (300–669), Good (670–739), Very Good (740–799), and Excellent (800–850). Their population shares, measured in the policy data, are $(\pi_1, \pi_2, \pi_3, \pi_4) = (0.197, 0.318, 0.381, 0.104)$. Homeowners experience a loss with probability θ^b each year. Losses are lognormally distributed with a common dispersion parameter and a location parameter that can vary linearly with credit score group according to the parameter δ:

$$L \mid \text{loss} \sim \text{Lognormal}(\mu_L + \delta(b-1),\ \sigma_L), \qquad \sigma_L = 1.2, \tag{7}$$

Homeowners in each credit group also belong to one of three shadow deductible types, $j \in \{low, med, high\}$. A share β_j^b of group b is of type j, and these shares sum to one within each group. Upon experiencing a loss, a homeowner files a claim if it is above their filing threshold $m_j D$, where $(m_{low}, m_{med}, m_{high}) = (1, 1.5, 3)$, and $D = 1500$ is their contract deductible, which is close to this value in every credit group in the policy data.[36] The threshold m_j may be influenced by a number of factors that affect the perceived costs of claim filing, such as hassle costs, liquidity constraints, and beliefs about whether filing will cause future premiums to rise.

Calibration and Estimation

We first calibrate the shadow deductible type shares β_j^b directly from the survey data (Table 3), which reports the same four credit score groups as the model. Next, the model fits six parameters based on eight moments from the claims data. The eight moments are the claim frequency and severity means of the four credit groups, shown in Figure S13. The parameters are:

$$\gamma = (\theta^b,\ \mu_L,\ \delta). \tag{8}$$

Given γ, the predicted moments follow from the loss distribution (7) and the type shares.

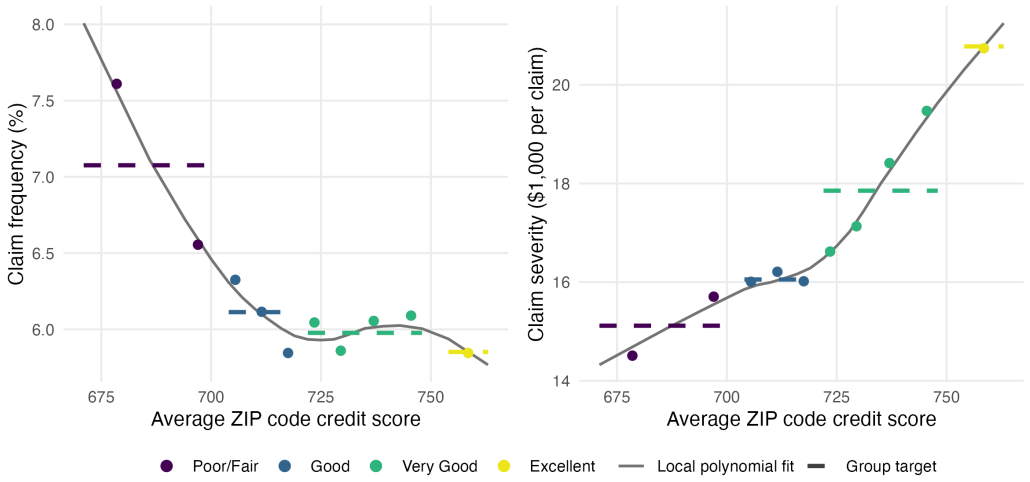
[36] We use $m_{high} = 3$ because the survey left the top category of the shadow deductible open-ended– we only asked if households would wait for damages to be at least 200% of their deductible before filing. Our results are robust to using higher values of m_{high}.

A homeowner of type j files when the loss exceeds $m_j D$, and the insurer then pays the loss net of the deductible, so the predicted claim frequency and severity of group b are

$$\hat{r}^b = \theta^b \sum_j \beta_j^b \, P(L > m_j D), \qquad \hat{s}^b = \frac{\sum_j \beta_j^b \, E[(L - D)\,\mathbf{1}\{L > m_j D\}]}{\sum_j \beta_j^b \, P(L > m_j D)}, \tag{9}$$

where L follows (7) for group b and both terms have closed forms under the lognormal. Claim frequency is the loss probability times the share of losses that are filed, and claim severity is the average payout per filed claim.

Figure S13: Calibration targets by credit score



Notes: Dots are ZIP code deciles of average credit score in the policy data, showing annual claim frequency (left) and average claim severity (right). Colors mark the credit group each decile is assigned to: the underlying data are allocated to Poor/Fair, Good, Very Good, and Excellent in increasing order of credit score, in proportion to the population shares π_b.

We use a minimum distance approach with proportional weighting so that frequency (percent) and severity (dollar) moments are comparable:

$$\min_{\gamma} \sum_{b=1}^{4} \left(\frac{\hat{r}^b - r_*^b}{r_*^b} \right)^2 + \sum_{b=1}^{4} \left(\frac{\hat{s}^b - s_*^b}{s_*^b} \right)^2, \tag{10}$$

where $\hat{r}^b, \hat{s}^b$ are the predicted moments of equation (9) and r_*^b, s_*^b the targets, corresponding to panels of Figure S13 aggregated by the four credit score groups. Since θ^b cancels in $\hat{s}^b$, the severity moments identify (μ_L, δ) and each θ^b then sets its group's claim frequency equal to the target.

Parameter estimates and fit

Table S8 reports the model's estimated and calibrated parameters. Estimated loss rates decrease from 8.73% among policyholders with Poor/Fair credit to 6.67% for those with excellent credit while claim severity increases from $14,800 to $20,300. Panel A of Table 4 (main text) shows that the model mechanically matches the claim frequency moments by construction when the loss rates are free, and matches the four severity moments closely. The model closely reproduces the (non-targeted) gap in expected incurred losses per dollar of coverage across credit groups: from $4.52 per $1,000 of coverage for Poor/Fair to $2.34 for Excellent in the model, against $4.63 and $2.40 in the data.

Table S8: Estimated and calibrated parameters

Parameter	Description	Value
Estimated		
μ_L	log loss location, intercept (Poor/Fair)	8.79
δ	log loss location trend per credit group	0.120
$\theta^1, \theta^2, \theta^3, \theta^4$	annual loss probability by credit group	8.73%, 7.33%, 7.00%, 6.67%
Calibrated		
D	contractual deductible, all groups	$1,500
$(m_{low}, m_{med}, m_{high})$	filing thresholds, multiples of D	$(1, 1.5, 3)$
σ_L	log loss dispersion	1.2
$Cov^1, Cov^2, Cov^3, Cov^4$	average coverage limit by credit group ($1,000)	231, 265, 343, 507

Notes: Estimated parameters minimize equation (10). The loss probabilities θ^1 to θ^4 and the coverage limits Cov^1 to Cov^4 are listed in credit group order, Poor/Fair, Good, Very Good, Excellent. Coverage limits are the average dwelling coverage of each credit group in the policy data, measured at the ZIP code level like the claim moments.

Panel B of Table 4 (main text) uses the model estimates to decompose the credit group differences in coverage-adjusted incurred losses across the different model parameters. For loss probabilities and shadow deductibles, we impose uniform rates and shares equal to the population-weighted mean across the four groups ($\sum_b \pi_b \theta^b = 7.41\%$, $\sum_b \pi_b \beta^b_{low} = 0.289$, $\sum_b \pi_b \beta^b_{med} = 0.566$, and $\sum_b \pi_b \beta^b_{high} = 0.145$), and for claim severity, we impose a common coverage limit ($(\sum_b \pi_b Cov^b = \$313\text{k})$) and $\delta = 0$. Differences in loss rates, conditional severity per dollar of coverage, and shadow deductibles explain 41%, 59%, and (approximately) 0% of the disparity in coverage-adjusted incurred losses between the highest and lowest credit score group.

A.6.1 Robustness

Table S9 shows the results of the decomposition of the differences in coverage-adjusted incurred losses across credit groups as we re-estimate the model under a variety of different assumptions. We consider calibrating the high shadow deductible filing threshold m_{high} to be lower (2) or higher (4), let m_{high} rise with credit score to ten times the deductible for the three upper groups, and set the loss dispersion σ_L to 1.0 or 1.4. Across these specifications, differences in P(Loss) explain between 26% and 47% of the gap and differences in E(Damages | Loss) between 53% and 69%, and differences in shadow deductibles explain at most 5% of differences in coverage-adjusted claims.

Table S9: Robustness of the decomposition of coverage-adjusted incurred losses

	Share of cost gap (%)		
Scenario	P(Loss)	E(Dam. | Loss)	Shadow deductibles
Baseline	41	59	0
$m_{high} = 2$	40	60	0
$m_{high} = 4$	42	58	0
Group $m_{high} = (2, 10, 10, 10)$	26	69	5
$\sigma_L = 1.0$	35	65	0
$\sigma_L = 1.4$	47	53	0

Notes: Each row re-estimates the model and repeats the decomposition of Table 4, panel B, under the stated change to the baseline calibration. In the "Group m_{high}" row, the high shadow deductible threshold is 2 for Poor/Fair and 10 for the other three groups, so in that row the shadow deductible channel includes the threshold differences as well as the type-share differences: equalizing the channel sets both the type shares and the threshold to their population-weighted means.

A.7 Robustness Checks and Supplemental Analyses of Credit-Premium Gradient Decomposition

A.7.1 Disaster risk pricing by credit score

In this section, we test how the cost of disaster risk varies based on the credit score of the policyholder with the following equation:

$$P_{igt} = \sum_{h=2015}^{2024} \left(\sum_{k=1}^{4} \beta_{1kh} \, Credit_{ik} + \beta_{2h} AAL_i + \sum_{k=1}^{4} \beta_{3kh} \left(Credit_{ik} \cdot AAL_i \right) \right) + \gamma_1 Deductible_{it} + \gamma_2 Coverage_{it} + \lambda_i + \lambda_t + \lambda_g + \epsilon_{igt}. \tag{11}$$

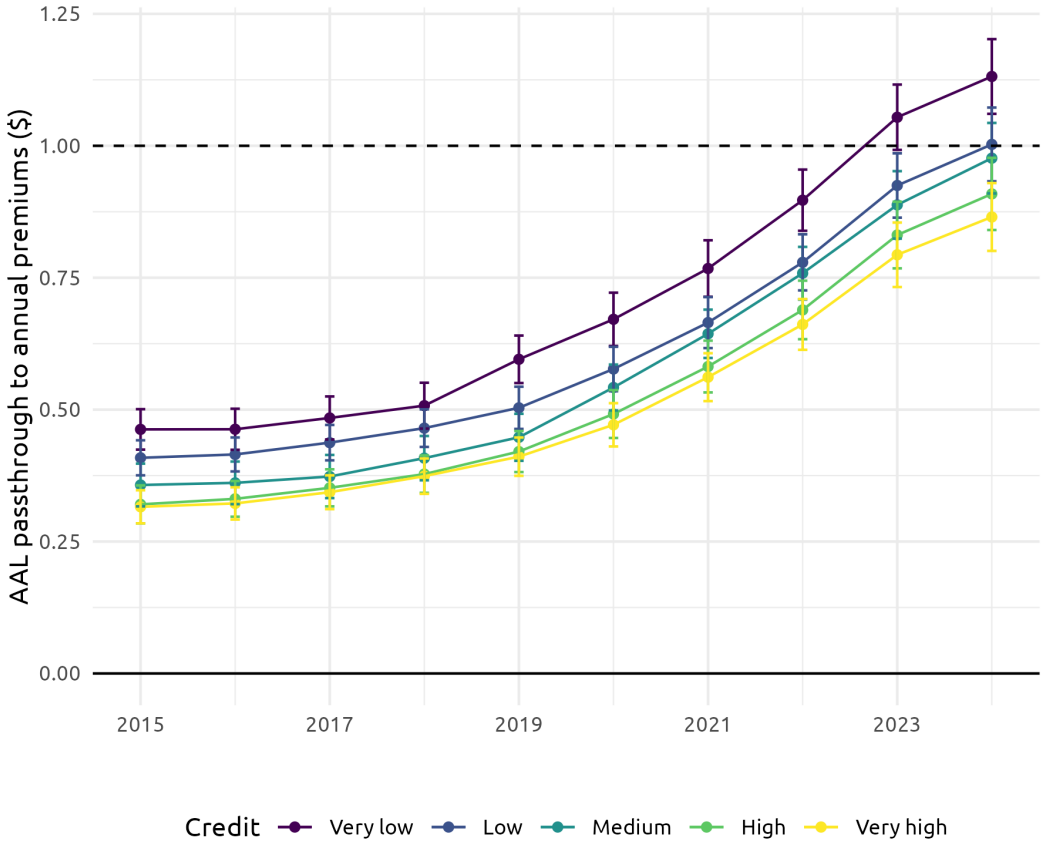
The specification modifies Equation (2) by estimating annual coefficients and allowing the AAL term to vary by credit score bin. The β_{3kh} coefficients show how disaster risk is priced for each credit score bin.

We plot the combined AAL coefficients for each credit score group ($\beta_{2h} + \beta_{3kh}$) in Figure S14. The AAL pass-through is higher for people with lower credit scores over our whole sample. By 2024, homeowners with very low credit scores have a coefficient around 1.1, while those with very high credit scores are closer to 0.9. The different pass-through coefficients show that a person with lower credit score will be charged more for the same amount of disaster risk than a person with higher credit score, conditional on coverage, deductible, and state. Figure S14 allows us to estimate how the higher pricing of disaster risk for policyholders with lower credit contributes to the credit-premium gradient. At the sample average AAL of $340, we find that the differential pass-through of disaster risk contributes around $68, or 19%, of the difference between homeowners with very high and very low credit scores. The higher cost of disaster risk may reflect differences in how insurers expect policyholders with low credit to file claims conditional on a loss, or differences in expected loss size or frequency given differences in unobserved property maintenance or adaptation. We separate these channels more formally in Section A.6.

A.7.2 Home Age and Maintenance

In this section, we consider whether the mechanism driving the relationship between credit and claims might be related to a correlation with a home's age, in particular unobserved

Figure S14: AAL coefficients by credit quintile



Source: ICE, McDash®; CoreLogic;
Notes: Figure plots the time-varying coefficients of credit quintile crossed with Average Annual Losses (disaster risk) from Equation 11, which regresses insurance premium on credit score quintile, disaster risk, policy characteristics, time fixed effects, and geography fixed effects and allows for time-varying coefficients. Credit score quintiles are: Very low (less than 671), Low (671-715), Medium (716-755), High (756-786), and Very high (greater than 786). The Very high credit group is the omitted reference category.

home maintenance and condition. If homeowners with low credit scores invest less in maintenance, it is possible that they are more likely to experience positive or larger damage events ($\mathbb{E}(Damages_{pk}|Event_p)$ in equation 1), leading to higher claim rates. Although our CoreLogic AAL measure includes some disaster-relevant aspects of a home's physical condition, other aspects of property maintenance may be less easily observed by insurers and could be correlated with credit.

Table S10 re-estimates equation 2 with a variety of home age controls excluding the states that consistently ban credit-based pricing (CA, MD, MA). Column 1 reproduces our baseline

specification (Column 2 of Table 2), showing the credit-premium gradient conditional on AAL and block group fixed effects. Columns 2 and 3 add a linear age control and year-built five-year bin fixed effects, respectively. The addition of these controls has little effect on the credit-premium gradient.

Table S10: The effect of credit score and home age on premiums

Dependent Variable:	Annual premium (USD)			
		All		Built past 15-y
Model:	(1)	(2)	(3)	(4)
Variables				
Very low	360.0***	352.2***	348.1***	305.1***
	(1.430)	(1.477)	(1.462)	(2.417)
Low	213.5***	206.4***	206.1***	173.7***
	(0.9543)	(0.9818)	(0.9790)	(1.682)
Medium	125.8***	121.4***	124.3***	92.36***
	(0.7618)	(0.7794)	(0.7729)	(1.355)
High	56.06***	54.54***	58.10***	33.37***
	(0.6293)	(0.6441)	(0.6294)	(1.152)
AAL (USD)	0.3232***	0.3095***	0.2868***	0.2406***
	(0.0141)	(0.0142)	(0.0133)	(0.0189)
Property Age		4.471***		
		(0.0713)		
Fixed-effects				
Deductible	Yes	Yes	Yes	Yes
Coverage	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Blockgroup	Yes	Yes	Yes	Yes
Year built			Yes	
Fit statistics				
Observations	53,326,143	50,031,520	50,031,520	8,851,963
R^2	0.60058	0.60545	0.61560	0.59472
Within R^2	0.03753	0.04563	0.03387	0.03250
Dep Var Mean	1,598.8	1,603.8	1,603.8	1,464.1

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

Source: ICE, McDash®; CoreLogic
Notes: Table reports the results of Equation 2, which regresses insurance premium on credit score quintile, disaster risk, policy characteristics, time fixed effects, and geography fixed effects. Estimation samples exclude states that consistently ban credit-based pricing (CA, MD, MA). Columns 2 and 3 include controls for year built and column 4 restricts the sample to homes built in the previous 15 years. Credit score quintiles are: Very low (less than 671), Low (671-715), Medium (716-755), High (756-786), and Very high (greater than 786). The Very high credit group is the omitted reference category.

Column 4 restricts the sample to houses that are less than 15 years old. By focusing on newer homes, this restriction limits the sample but strengthens internal validity by reducing potential bias from unobserved maintenance and depreciation. The results show that the credit-premium gradient remains even in this subsample of newer homes. While the premium surcharge drops by around $40 for homeowners with very low credit scores relative to those with the best credit, the credit-premium gradient is similar as a share of the lower average premium among newer homes as in the overall sample. Taken together, the results in Table S10 explain only 2%-11% of the gradient.

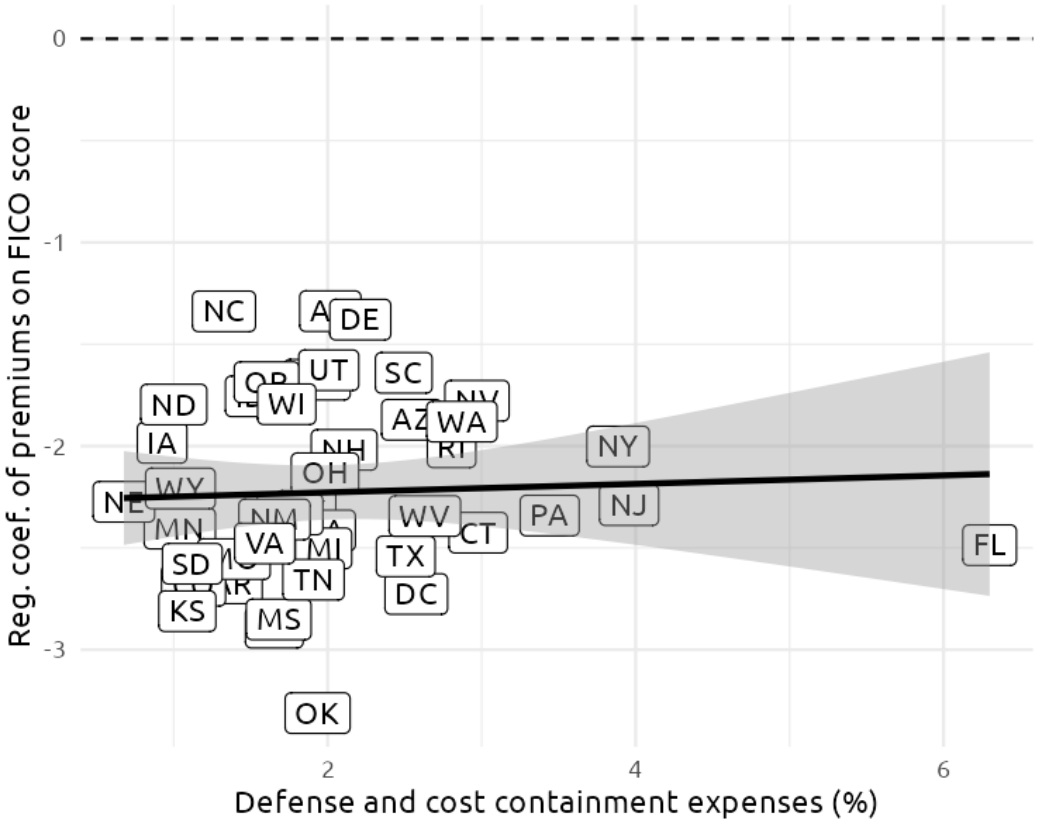
A.7.3 Spurious Claims

Insurers may expect lower credit score policyholders to be more likely to file "fraudulent claims."[37] Such claims are more likely to be contested by insurers, thereby increasing "defense and cost containment" expenses (DCC) (Insurance Information Institute, 2022). DCC expenses are specifically the associated investigation and legal fees that go into settling a claim. Some states, particularly Florida, have seen particularly adverse trends in litigation between homeowners claimants and insurers, which have led to rising DCC expenses (Johnson et al., 2023).

To test whether insurers expect customers with worse credit histories to be more likely to file claims that are subsequently challenged in court—thus increasing DCC expenses—we estimate a state-specific credit-premium gradient over our sample and compare it against the average DCC expenses in each state. The results, presented in Figure S15, do not show a meaningful relationship between states that spend more resources litigating claims and the credit-premium gradient.

[37] In our framework, this would correspond to $P(\text{File Claim}_{ike}|\text{Damages}_{pke} = 0) > 0$, or to a situation where the reported Damages_{pke} amount is inflated, leading to higher reported claim severity.

Figure S15: Relationship between defense cost containment expenses and the pricing of credit risk



Source: ICE, McDash®; CoreLogic; NAIC
Notes: Figure plots the state-specific credit gradients against the average defense and cost containment expenses incurred by insurers in that state. The credit-premium gradients are estimated separately for each state with the following specification: $P_{igt} = \beta_1 Credit_i + \beta_2 AAL_i + \gamma_1 Deductible_{it} + \gamma_2 Coverage_{it} + \lambda_t + \epsilon_{igt}.$, where $Credit_i$ is measured in continuous credit score points. The scatterplot excludes states that ban the use of credit-based pricing (CA, MA, MD).