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PRICING PROTECTION:
CREDIT SCORES, DISASTER RISK, AND HOME INSURANCE AFFORDABILITY

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ABSTRACT

We use 70 million policies linked to mortgages and property-level disaster risk to show that credit scores impact homeowners insurance premiums as much as disaster risk. Homeowners with low credit pay 24% more for identical coverage than high–credit score homeowners. Leveraging a natural experiment in Washington State, we find that banning the use of credit information considerably weakens the relationship between credit score and pricing. We discuss the role of credit information in pricing and show that, although insurance is often overlooked in discussions of home affordability, a low credit score increases premiums roughly as much as it raises mortgage rates.

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1 Introduction

Debates about homeownership affordability tend to focus on mortgage availability and interest rates, and how these costs impact financially-constrained households. Yet, the rising cost of homeowners insurance is quickly becoming an additional burden of owning a home, especially in disaster-prone areas. In addition to disaster risk and property characteristics, insurers report setting premiums based on a policyholder's credit information, with homeowners who have lower credit scores tending to pay more. However, compared to the large literature on credit scores and mortgage financing, there is little research on the relationship between credit scores and homeowners insurance premiums. The extent to which credit affects home insurance premiums and the mechanisms driving this relationship remain open questions.

To answer these questions, we use granular, contract-level homeowners insurance policy data to study how geography and household characteristics shape insurance premiums. 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, comparable in magnitude to disaster risk itself. Leveraging a temporary ban on credit-based pricing in Washington State, we show that restricting the use of credit information in setting insurance prices causally weakens the relationship between credit scores and premiums, and reallocates costs across households. We explore potential mechanisms driving the relationship between credit scores and premiums, which we call the "credit-premium gradient," finding some evidence that policyholders with lower credit scores are more likely to file claims when experiencing damages. 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 importance of the credit-premium gradient on home affordability.

We first document that home insurance is becoming an increasing share of homeownership expenses. Unlike mortgage payments on long-term fixed-rate loans, insurance contracts are renewed annually, leading to potentially large unanticipated changes in housing expenses. For the average US homeowner, the "insurance burden," or the home insurance premium's share of a household's monthly principal and interest payment, has increased from around 12% in 2020 to 15% in 2024. For policyholders with low credit scores, the insurance burden has increased faster over the same period, from 17% to 24%. If the 2020 to 2024 trends continue, the insurance burden for homeowners with low credit could reach as high as 35%

by 2030.

Next, we quantify the relationship between credit scores and premiums. 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, 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 score distribution paid approximately $550 higher average annual premiums than those in the top credit score quintile–about 24% of the average premium. Even after accounting for location and disaster risk, the credit-premium gradient remains unchanged, suggesting that lower-credit borrowers pay more for reasons other than physical risk exposure.

The empirical credit-premium gradient that we estimate is likely driven by a combination of explicit credit-based pricing and unobserved variables that could also cause homeowners with lower credit scores to pay higher premiums. To better understand the role of credit on home insurance pricing, 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 natural experiment allows us to control for unobserved individual characteristics, such as claim history or bundling of home and auto insurance, that could affect premiums.

We find that after the Washington State ban on credit-based pricing went into effect, homeowners with low credit scores 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. These findings suggest that policymakers can reduce but not entirely eliminate the credit-premium gradient. We find no effect of the credit-pricing ban on coverage decisions, mortgage delinquency, or prepayment. While our estimates from the Washington state policy reflect a specific context, they provide the first quasi-experimental evidence on the causal effects of restricting insurance pricing.

Our results show that insurers use credit information as an economically meaningful signal to differentiate between otherwise observably similar policyholders. We next explore possible mechanisms that might explain why insurers use credit information to set premiums.

Because our policy-level data do not include claim information, we turn to the first publicly available ZIP code-level aggregate data on homeowners claims rates (2018–2022) from the U.S. Treasury. We find that claim rates and realized losses relative to coverage are higher in areas with lower average credit scores.

What, then, is a potential justification for credit scores being such a meaningful determinant of premiums? Turning back to the policy-level data, we document that homeowners with lower credit scores are charged higher premiums per dollar of predicted disaster risk. This pricing pattern suggests that insurers anticipate a higher likelihood of a claim for the same amount of expected damage. The higher claim frequency of people with low credit scores is consistent with liquidity constraints, where filing a claim may be the cheapest, if not the only way, to cover immediate unavoidable expenses.

To investigate further potential drivers of the relationship between premiums and credit, we consider the hypothesis that policyholders with weak credit defer maintenance on older homes, thereby driving up eventual claims. However, we find the credit-premium gradient remains even among new homes that require less maintenance. We next consider if homeowners with lower credit scores are more likely to file contested claims that insurers have to legally challenge. We find the opposite: the credit-premium gradient is modestly flatter, rather than steeper, in states where insurers incur greater legal expenses.

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 score 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 both mortgage interest payments and 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. The finding puts the economic significance of our results in context, showing 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 home ownership costs. The high and increasing cost of home insurance for people with low credit highlights the growing importance of insurance premiums in discussions about home affordability.

This paper advances the literature on insurance pricing by analyzing how insurers use granular data on people-based and place-based factors. Researchers have long studied how forces such as asymmetric information, risk classification, and capital market constraints affect insurance market equilibria (Rothschild and Stiglitz, 1978; Crocker and Snow, 1986; Cummins and Sommer, 1996; Einav, Finkelstein and Cullen, 2010; Koijen and Yogo, 2015). Related empirical work in health and life insurance have typically focused on the trade-offs of pricing restrictions and related policies around adverse selection and reclassification risk (Einav, Finkelstein and Cullen, 2010; Handel, Hendel and Whinston, 2015). In a growing literature on homeowners and disaster insurance, pricing-related research has focused on the role of disaster risk, reinsurance, and inflation driving recent premium increases (Keys and Mulder, 2024), the use of sophisticated catastrophic risk models (Boomhower et al., 2024), the interaction between private markets and last-resort insurers (Taylor, Turland and Weill, 2025), or pricing policy in the public National Flood Insurance Program (Wagner, 2022; Weill, 2023; Mulder, 2022; Mulder and Kousky, 2023). Related research studies how price shocks and insurer insolvencies in insurance markets affect housing markets and homeowners through home price declines, mortgage delinquencies, and underinsurance (Sastry, Sen and Tenekedjieva, 2023; Ge, Lam and Lewis, 2022; Eastman, Kim and Zhou, 2024; Ge, Johnson and Tzur-Ilan, 2025; Cookson, Gallagher and Mulder, 2025; Biswas, Hossain and Zink, 2023; Amornsiripanitch et al., 2025).

We focus on how insurers use credit history to indirectly price predicted losses, adding novel empirical evidence on the distributional impacts of risk classification. Our findings show that policyholders' credit histories are approximately as important as disaster risk in driving premiums. The fact that homeowners with weaker credit histories pay higher premiums is especially important given a growing literature that shows poorer households buy less insurance in general and are more likely to be underinsured (Armantier, Foncel and Treich, 2023; Gropper and Kuhnen, 2025; Sastry et al., 2024). It is unclear ex-ante how limiting credit-based insurance pricing would affect the distribution of insurance costs given that insurers may adjust the contract space or change their pricing around other factors that are correlated with credit score (Finkelstein, Poterba and Rothschild, 2009; Pope and Sydnor, 2011; Bartlett et al., 2022). In our setting, we find that bans on credit-based pricing can significantly narrow the credit-premium gradient without evidence of short-run changes in contract features or mortgage delinquencies and prepayment.

Second, our paper directly contributes to the literature on who bears the costs of disaster risk (Barreca et al., 2016; Massetti and Mendelsohn, 2018; Botzen, Deschenes and Sanders, 2019; Kelly and Molina, 2023; Sastry, 2026). A growing body of research documents disparities in household exposure to disaster risks, adaptation investments, and post-disaster recovery (Bakkensen and Ma, 2020; Bradt and Aldy, 2023; Cain et al., 2024; Billings, Gallagher and Ricketts, 2022; Cookson, Gallagher and Mulder, 2023). Our findings show that even though the the credit-premium gradient is not caused by people with lower credit living in higher disaster risk areas, homeowners with lower credit scores pay more per dollar of predicted disaster risk. While insurers may be able to more efficiently predict expected losses using credit history, such actuarial pricing has distributional consequences and can distort homeowners' incentives to invest in adaptation.

Finally, our results deepen our understanding of how credit scores affect housing affordability. This literature has naturally 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). Given longstanding US goals to promote homeownership, this has led to a number of policies to expand credit access for homeowners with weak credit. We show that the relationship between credit scores and homeowners insurance premiums is approximately as large as its relationship with interest rates. Thus, any analysis of credit and housing affordability must also account for credit-based insurance pricing. The credit-premium gradient means that lower credit score individuals may face higher homeownership barriers through both mortgage lending and insurance pricing. That is, insurance premiums operate as a "second credit channel" and could price low score households out of homeownership as premiums continue rising.

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).[1]

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). These credit-based insurance scores are derived from a person's credit history and are very similar to the better-known FICO credit scores.[2] 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.[3] Credit-based insurance scores are used because they are correlated with claims. This correlation could reflect lower claim frequency, lower conditional severity, or both: limited evidence suggests claim frequency is the dominant margin (Texas Department of Insurance, 2005).[4]

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

[1] 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 2022, wind and hail accounted for 41% of incurred losses, water damage (excluding flooding) and freezing for 28%, and fire and lightning for 22% (see Appendix Table S6). 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.

[2] 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*).

[3] 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.

[4] Credit-based insurance scores are similarly used in setting automobile insurance rates (Federal Trade Commission, 2007).

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 $Claim_{ipke}$ 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, $P(\text{File Claim}_{ike}|\text{Damages}_{pke})$.[5] 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 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.[6]

[5] 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.

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

The McDash property insurance dataset reports monthly insurance premiums, coverage limits, and deductible choices for homeowners insurance policies and any escrowed flood insurance policy.[7] 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 131 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.

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., 2024).[8] 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).[9]

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). 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

[7] 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.

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

[9] 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).

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: Summary statistics

Variable	Mean	SD	Min	Max	N
Coverage (USD1k)	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 (USD1k)	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 (USD1k)	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.

Table 1 reports summary statistics for homeowners policies in our sample. Average coverage is \$331k with an average annual premium of \$1,550. At the property level, the average "normalized premium" is \$5.26 per \$1,000 of coverage. AALs are small on average (0.11% of insured value, which corresponds to \$340 in expected annual losses property), but the variation in AAL is substantial.[10] Households face average annual mortgage payments of \$13,459; 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.[11] There are two likely drivers of the differences in cost across states. First, these differences can partially be

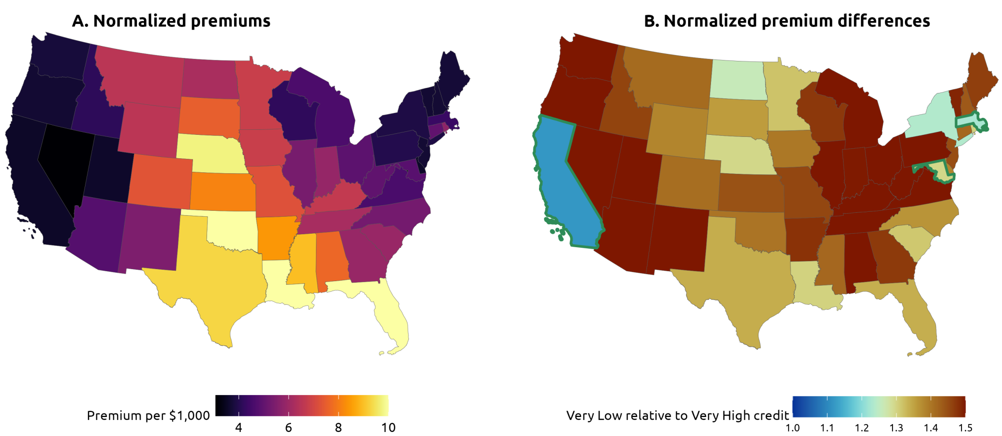
[10] AALs are only calculated for natural disasters and do not include other sources of claims such as kitchen fires, burst pipes, or liability claims (e.g., dog bites).

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

explained by disaster risk: The Great Plains are subject to severe convective storms' hail and tornadoes, while the Gulf Coast is vulnerable to hurricanes. However, several disaster-prone states, in particular states exposed to high wildfire risk (e.g., California), appear to have low premiums. Second, differences in state-level regulation generate distortions in insurance pricing, leading some states to have higher or lower premiums than expected based on their risk (Oh, Sen and Tenekedjieva, 2022).

Figure 1, panel B shows the difference between the normalized premiums for individuals 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.[12]

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 than ban the use of credit information in homeowners' insurance pricing (CA, MA, and MD).

Figure 2 shows the insurance-to-loan ratio, or insurance burden, by year and credit score

[12]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.

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 2025, an increase of around 1.7 percentage points per year. If the insurance burden follows the same trajectory as it has between 2020 and 2024, it could reach as high as 35% for homeowners with very low credit by 2030.[13]

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 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 policies data, rather than insurers' quotes (Todoroff (2024, 2025); Graetz (2025)), allows us to quantify the existing association between premiums and credit.

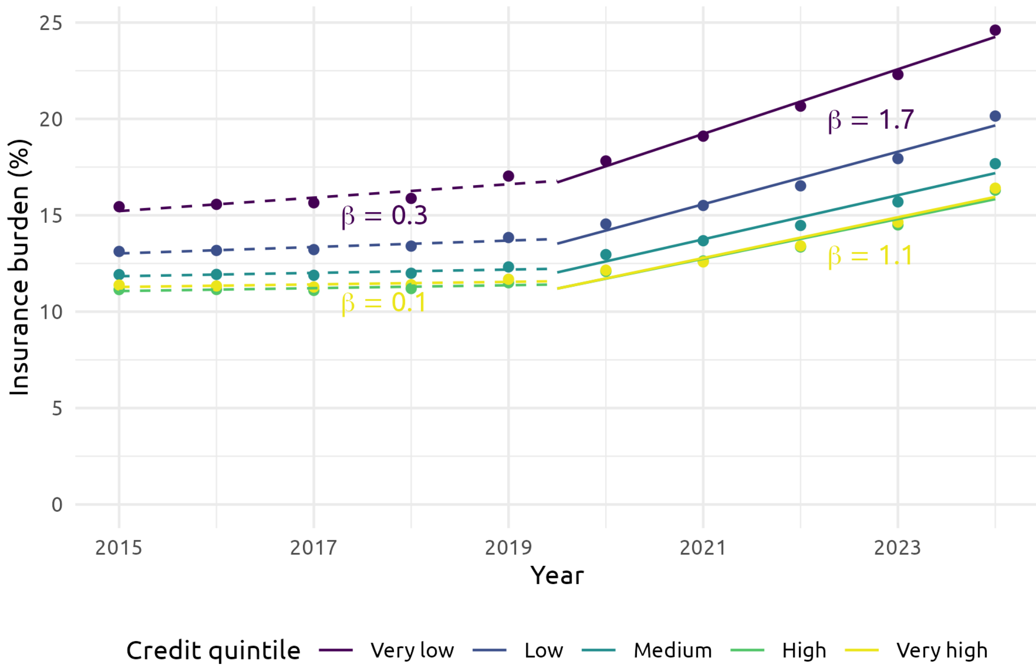
To decompose the relationship between premiums, credit scores, and disaster risk, we first estimate the following specification:

$$P_{igt} = \sum_{k=1}^{4} \beta_{1k} Credit_{ik} + \beta_2 AAL_i + \gamma_1 Deductible_{it} + \gamma_2 Coverage_{it} + \eta_t + \lambda_g + \epsilon_{igt}. \tag{2}$$

where P_{igt} is the annual insurance premium of homeowners insurance policy i in geography

[13]According to a 2016 survey by the Insurance Information Institute, in 2016, 31% of respondents considered homeowners insurance to be a financial burden. Given the growth in premiums since then, it is likely that this share has grown over the past decade (Insurance Information Institute, 2017).

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 divided by the sum of the monthly principal and interest payments) by credit score bin between 2015 and 2024. The 5-year rate of increase is shown for people with very low (in purple) and very high (in yellow) credit scores as the β coefficients on the figure.

g (state or census blockgroup) during year t. The sample spans insurance policies active between 2015 and 2024. $Credit_{ik}$ is an indicator for an individual being in a particular credit score group 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 (672-716), Medium (717-756), High (756-787), and Very high (greater than 788).[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 ($Deductible_i$, which includes \$500 bins for deductible choice and is top coded at \$10,000), and coverage choice ($Coverage_i$,

[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 are not automatic. Appendix Table S7 conducts the analysis with current FICO scores and finds similar results.

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

which includes \$50,000 bins for coverage amount and is top coded at \$2 million). η_t and λ_g are year and geography fixed effects, respectively, and errors are clustered at the ZIP code level. The $\{\beta_{1k}\}$ coefficients report the conditional associations between credit score and premiums, while β_2 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 \$335 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 effects 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 ($P(\text{Event}_{pe})$) and the observable condition of the property ($\text{Damages}_{pke}|\text{Event}_{pe}$) in one annual dollar measure. If the credit-premium gradient is driven by a correlation between expected losses — whether driven by the underlying risk of the property or its condition — we would expect for 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 lowest bins becomes slightly larger. The relatively small changes in the credit-premium gradient when AAL is added as a control shows that, on average, the higher prices paid by homeowners with lower credit scores cannot be explained by disaster risk exposure or observable property condition. The coefficient estimate on AAL indicates that predicted disaster losses are passed through to premiums at about 55 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 \$360, 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

Table 2: Premiums and credit scores

Dependent Variable:	Annual premium (USD)			
Model:	(1)	(2)	(3)	(4)
Variables				
Very low	335.9***	354.2***	326.7***	381.8***
	(3.274)	(2.955)	(1.655)	(3.149)
Low	201.0***	210.4***	191.9***	228.1***
	(2.053)	(1.813)	(1.068)	(1.944)
Medium	120.5***	124.4***	113.3***	134.7***
	(1.474)	(1.259)	(0.7759)	(1.372)
High	55.60***	54.87***	50.65***	59.52***
	(0.9950)	(0.8516)	(0.5860)	(0.9434)
AAL (USD)		0.5576***	0.3198***	0.5588***
		(0.0207)	(0.0131)	(0.0208)
Very low × Credit ban				-212.1***
				(6.301)
Low × Credit ban				-123.4***
				(4.219)
Medium × Credit ban				-69.40***
				(2.926)
High × Credit ban				-29.85***
				(1.791)
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	61,532,320	61,532,320	61,532,320	61,532,320
R^2	0.46991	0.51103	0.60168	0.51154
Within R^2	0.01948	0.09554	0.03414	0.09647
Dep Var Mean	1,558.8	1,558.8	1,558.8	1,558.8

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 (672-716), Medium (717-756), High (756-787), and Very high (greater than 788). The Very high credit group is the omitted reference category.

scores have similar average effects on homeowners insurance premiums.

In column 3, we include 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.[16]

To benchmark the amount of the credit-premium gradient that is attributable to credit pricing per se, as opposed to correlated factors, we leverage state-level policy variation. Column 4 of Table 2 interacts the credit score quintile coefficients with indicator variables for states that ban the use of credit-based pricing (California, Massachusetts, and Maryland). The credit score ban interaction terms are negative and statistically significant, and reduce the magnitude of the credit-premium gradient by over 50%. However, the credit-premium gradient does persist in the states that ban the use of credit scores.[17] Such pricing differences could reflect the use of insurance claims history (not banned) and other characteristics that are correlated with credit scores that affect premiums, or limitations in the scope of the credit ban laws themselves.

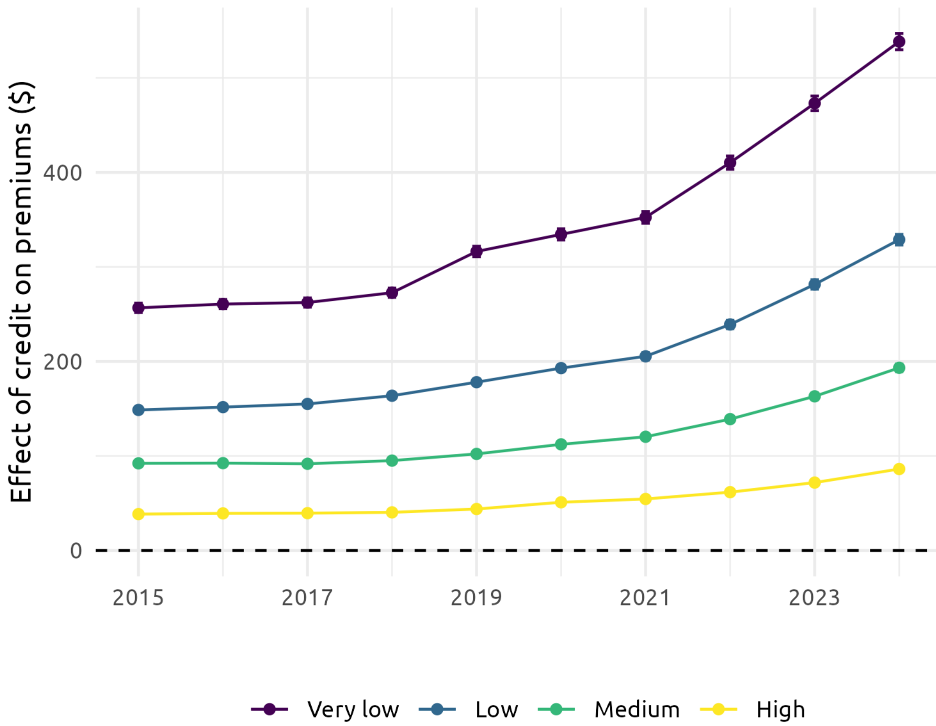
In Figure 3, we estimate time-varying annual credit score coefficients by estimating a modified version of the specification in column 2 of Table 2. Our estimates show an increasing cost paid by people with lower credit scores over time, with policyholders in the bottom credit score quintile paying an average $550 more in average annual premiums as of 2024. Appendix Figure S6 shows that increase in the credit-premium gradient over time is smaller in logs. People 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.

In Appendix A.6 we conduct a robustness test using property fixed effects and focusing on homes with multiple owners during our sample window. We find that most of the credit–premium gradient persists even after controlling for time-invariant property characteristics. While the analysis is conducted with a small and selected sample that is not

[16] 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 find evidence of this in Appendix Figure S10, 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.

[17] Appendix Figure S5 plots state-specific credit-premium gradients.

Figure 3: 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 (672-716), Medium (717-756), High (756-787), Very high (greater than 788). The Very High credit group is the omitted reference category.

necessarily representative of active mortgages, the findings provide additional evidence that the gradient is driven primarily by homeowner characteristics rather than by fixed features of the property.

Our results establish novel evidence that homeowners with lower credit scores pay substantially higher average premiums than people with higher scores, conditional on disaster risk, deductible choice, coverage limits, and geographic fixed effects. However, we caveat that these results are a correlational decomposition of actual premiums based on observable characteristics. There are many factors that could produce the credit-premium gradient that we cannot fully account for. For example, policyholders with lower credit scores may live in unobservably (to the econometrician, but not the insurer) lower quality homes, which would cause us to overestimate the gap. The credit-premium gradient could also 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. Homeowners with higher credit scores may also be more likely to receive bundling discounts from buying auto insurance policies with the same company. To rule out these possibilities, in the next section, we turn to a natural experiment in Washington state.

5 Washington State 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 eliminate the use of 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 basis that the Commissioner did not have a justification to implement the rule on an emergency basis.[18] 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.[19] The rule was finally overturned in court in August 2022 without further appeal from the Commissioner.[20] The upshot of this series of rules and court decisions was that credit-based insurance pricing was officially banned between

[18] https://www.insurancebusinessmag.com/us/news/breaking-news/judge-overturns-credit-score-ban-for-calculating-premiums-312729.aspx

[19] https://apnews.com/article/legal-proceedings-washington-olympia-f5b54526201d94abebca0c0734db4047

[20] https://www.apci.org/media/news-releases/release/72956/

June and October of 2021, while the possibility of a renewed ban remained in effect until August 2022. 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.[21]

The causal effects of a credit-pricing ban on the distribution of premiums are not ex-ante obvious, even conditional on the fact that insurers use credit history in their pricing. Under a ban, insurers may still be able to replicate credit-based prices using other correlated factors or by changing the set of contracts offered (Finkelstein, Poterba and Rothschild, 2009; Pope and Sydnor, 2011). Although we observe attenuated credit-premium gradients in the states that ban credit-based pricing throughout our sample (Table 2, column 4), such differences may reflect other factors of those states' regulatory regimes or insurance markets, rather than the restriction on credit-based pricing per se.

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:

$$\begin{aligned} Premium_{ist} = & \sum_{k=Jan2018, k \neq June2021}^{Jan2024} \beta_{kb} \, CreditBin_b \cdot RenewalMonth_{ik} \\ & + Mortgage_i + RenewalMonth_t + \epsilon_{ist} \end{aligned} \tag{3}$$

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 ($Mortgage_i$), which captures 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 ($RenewalMonth_{ik}$) to isolate the effect of the credit score ban on premiums. We estimate the treatment coefficient β_{kb} for each month of sample k 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 credit score group compared to the medium credit score group.

[21] https://www.insurance.wa.gov/about-us/news/2022/kreidler-acted-good-faith-followed-steps-exceeds-authority-credit-score-ban-court-rules

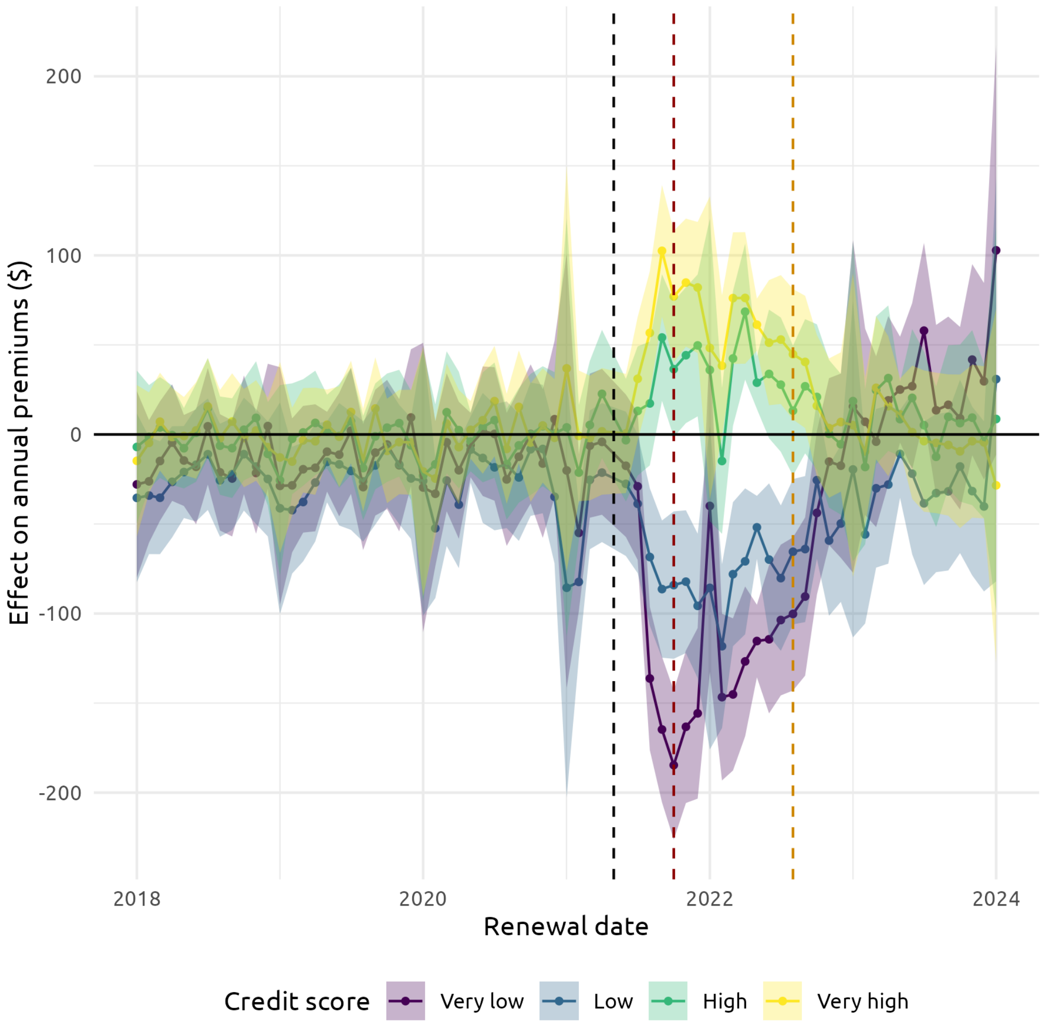
Our identification strategy assumes that, conditional on fixed effects, premiums for each credit score group were moving in parallel and would have continued to do so in the absence of the credit pricing ban. It also leverages the quasi-random timing of policy renewals, with similar homeowners having 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 all credit score groups, 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 is 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 2021. 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 validity 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

[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. 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.

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, 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 (672-716), Medium (717-756), High (756-787), and Very high (greater than 788). The Medium credit group is the omitted reference category. Dotted lines indicate the passage of the emergency rule (June 2021, black dashed line), its initial pause (Oct 2021, red dashed line), and final overturning (Oct 2022, orange dashed line). 95% confidence intervals with standard errors clustered at the ZIP code level are shaded.

(CA, MA, MD, see column 4 of Table 2).

Finally, in Appendix Figure S7, we examine how the credit pricing ban impacted a broader set of insurance and mortgage market outcomes, such as coverage choices and

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 (672-716), Medium (717-756), High (756-787), and Very high (greater than 788). The Medium credit group is the omitted reference category.

mortgage performance. We plot the credit bin event study coefficients on log coverage limit (panel a), deductible (panel b), 90-day delinquency (panel c), or 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 S7 suggest that explanations such as claims history, shopping behavior, bundling discounts, or underinsurance, all of which are likely unchanged before and after the ban, are unlikely driving factors of the credit-premium gradient. In the next section, we discuss other mechanisms that could be responsible for the credit-premium gradient.

6 Mechanisms Behind the Credit-Premium Gradient

Our results so far show that insurers' use of credit-based pricing causes policyholders with lower credit scores to pay substantially larger premiums. This suggests that credit information is a useful proxy for some unobserved (or difficult to observe) characteristic that is predictive of expected claims, aligning with the insurance industry's most common justification for the practice (NAIC, 2008).

In this section, we provide additional evidence on why insurers find credit information to be a valuable proxy for setting insurance premiums. We emphasize that these tests are suggestive but not conclusive. Furthermore, our analysis focuses on the accounting mechanisms insurers use to set prices. There may be economic mechanisms that help explain these accounting relationships, but we cannot test them because we do not observe policyholder-level variation in factors such as financial literacy, precautionary savings, or other characteristics that may affect the propensity to file claims.[23] However, we believe the tests in this section tests provide novel evidence on the potential factors that lead to credit-based insurance pricing, and point towards potential directions for new research.

[23] It is also unlikely that insurers can observe or use these factors in setting prices.

In section 6.1, we use aggregate claims data to show how claim frequency and losses relate to average ZIP code credit scores. In section 6.2 we test for differential pass-through of expected disaster losses by credit score. In section 6.3, we consider the role that home age could play in the credit-premium gradient. Finally, section 6.4 examines the potential role of spurious claims in home insurance pricing.

6.1 Summary claim data

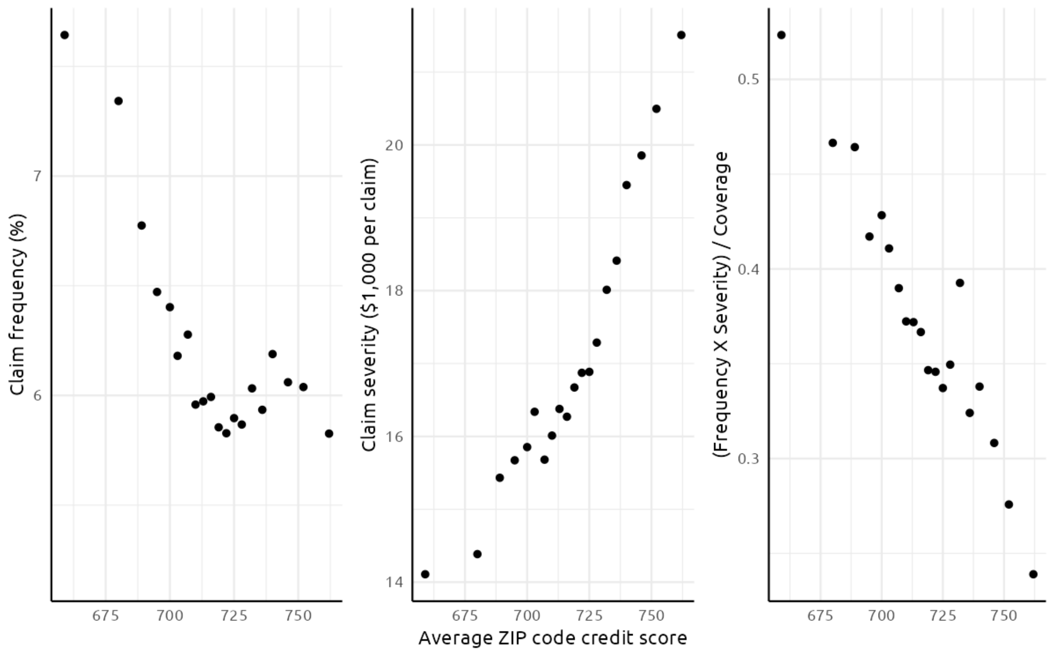
Because our policy-level data do not include claim information, we leverage the first publicly available ZIP code-level aggregate data on homeowners claims rates from 2018 to 2022, collected and aggregated by the National Association of Insurance Commissioners and shared with the US Treasury (U.S. Department of the Treasury, 2025). The data provide annual information on insurance claim frequency and average claim severity by ZIP code. To create a measure of expected loss rates, we multiply the claim frequency by average claim severity and divide by the corresponding average ZIP 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.

The left panel of Figure 6 shows the relationship between average ZIP code claim frequency and ZIP code average credit score across 20 credit score bins. The figure shows that ZIP codes with lower average credit scores file claims more frequently, while the relationship flattens out at ZIP codes with average credit scores above 725. This pattern supports the hypothesis that individuals with lower credit scores file claims more frequently. In the language of our expected claims framework, insurers may price on credit score, in part, because it is a useful predictor of $P(\text{File Claim}_{ike}|\text{Damages}_{pke})$ from equation 1.

Liquidity constraints provide a potential explanation for why people with lower credit scores may be more likely to file claims. Homeowners with lower credit scores typically have lower precautionary savings and can find it harder to borrow affordably (Toh, 2023). After a damage event, policyholders with lower credit scores may have fewer options for how to finance their repairs. As a result, for smaller damage events, filing a claim to finance repairs may be the cheapest option for homeowners with lower credit scores.

The middle panel of Figure 6 shows the relationship between ZIP code average claim severity and credit score. The positive relationship between credit score and claim severity suggests that policyholders with higher credit scores are more likely to file larger claims,

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



Source: ICE, McDash®; U.S. Treasury;

or that policyholders with lower credit file smaller claims more frequently. The positive correlation could reflect that homeowners with higher credit scores live in more valuable properties, leading to higher average claim severity. The right panel of Figure 6 shows the relationship between ZIP code average expected loss rates and credit score, where we find a downward sloping relationship. Although using ZIP code averages provides an indirect measure of the relationship between claims and credit scores, these data nonetheless offer the first evidence based on publicly available data that credit scores are an informative proxy for expected home insurance claims.

6.2 Disaster risk pricing by credit score

In this section, we use our policy-level data to provide additional supporting evidence that insurers charge homeowners with lower credit scores more because they expect them to file more claims. We focus on how insurance contracts price disaster risk based on the credit score of the policyholder. If policyholders with lower credit scores are more likely to file claims, then insurance companies will charge them a higher price per dollar of expected disaster risk. To test this prediction in our policy data, we estimate the following equation:

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

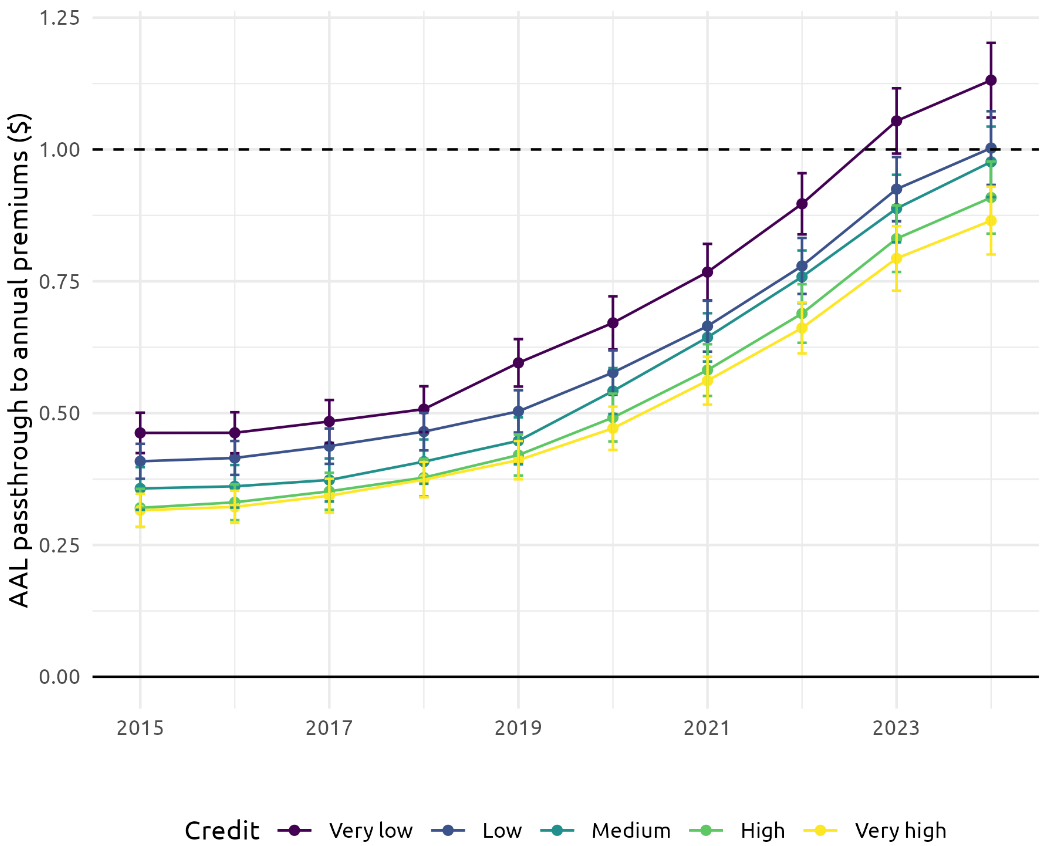
The specification modifies Equation (2) by estimating annual coefficients and allowing the AAL term to vary by credit score bin. The β_{3kh} coefficients show how disaster risk is priced for each credit score bin.

We plot the combined AAL coefficients for each credit score group ($\beta_{2h} + \beta_{3kh}$) in Figure 7. 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 shows 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. The findings are consistent with insurance companies pricing policies with the expectation that homeowners with lower credit scores are more expensive to insure because they are more likely to file claims. Figure 7 also 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.

6.3 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 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

Figure 7: AAL coefficients by credit quintile



Source: ICE, McDash®; CoreLogic;
Notes: Notes: Figure plots the time-varying coefficients of credit quintile crossed with Average Annual Losses (disaster risk) from Equation 4, 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 (672-716), Medium (717-756), High (756-787), and Very high (greater than 788). The Very high credit group is the omitted reference category.

could be correlated with credit.

Table 3 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.

Column 4 restricts the sample to houses that are less than 15 years old. By focusing on

Table 3: 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 (672-716), Medium (717-756), High (756-787), and Very high (greater than 788). The Very high credit group is the omitted reference category.

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 \$50 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 3 suggest that home age and maintenance are not meaningful drivers of the credit-premium gradient.

6.4 Spurious Claims

Another reason for lower credit score policyholders to have higher claim rates is if they are more likely to file "fraudulent claims."[24] 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).

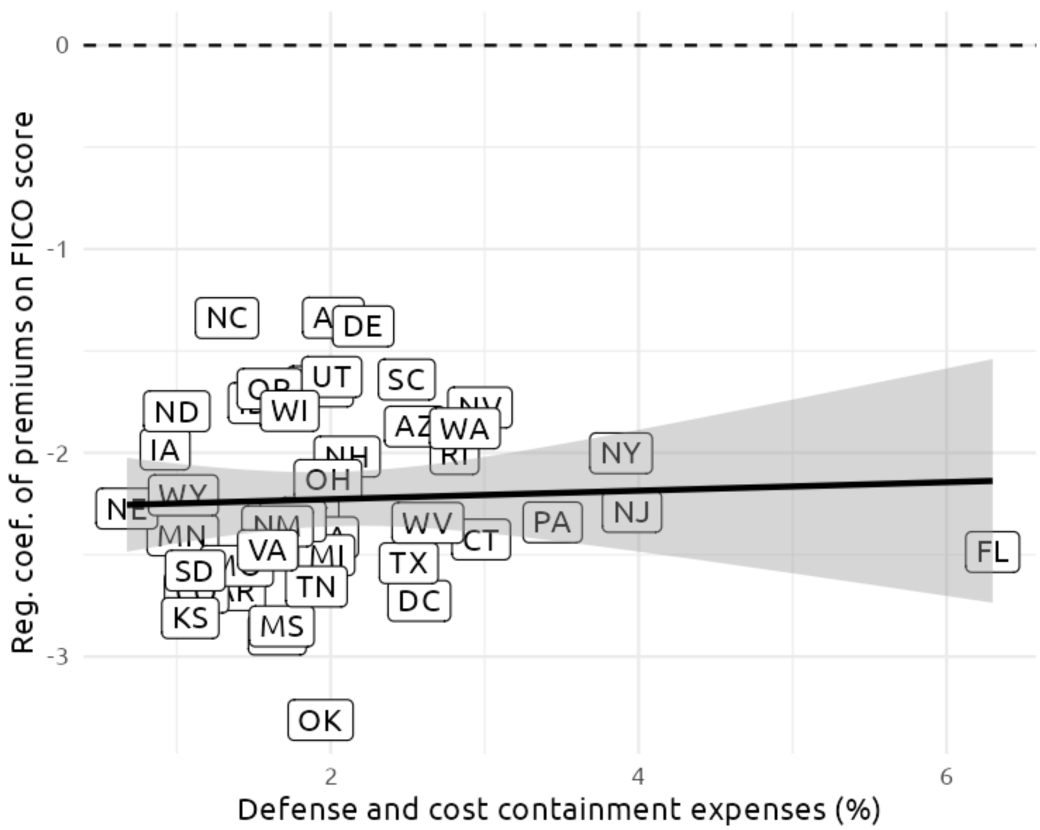
To test whether insurers expect customers with worse credit histories to be more likely to file claims that are subsequently challenged in court—thus increasing DCC expenses—we estimate a state-specific credit-premium gradient over our sample and compare it against the average DCC expenses in each state. The results, presented in Figure 8, do not show a meaningful relationship between states that spend more resources litigating claims and the credit-premium gradient.

7 The Impact of Credit on Housing Affordability

Homeownership affordability is a long standing, albeit controversial, US 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

[24]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 8: 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: $P_{igt} = \beta_1 Credit_i + \beta_2 AAL_i + \gamma_1 Deductible_{it} + \gamma_2 Coverage_{it} + \eta_t + \epsilon_{igt}$., where $Credit_i$ is measured in continuous FICO points. The scatterplot excludes states that ban the use of credit-based pricing (CA, MA, MD).

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 impact of credit scores on mortgage interest rates. We estimate the following regression on our sample of loans active in 2024:

$$r_{is} = \alpha_0 + \beta_1 X_i + \gamma_b Credit_{ib} + \lambda_s \epsilon_{is}. \tag{5}$$

where r_{is} is the current interest rate on loan i in state s, and the controls X_i include debt to income and loan to value at origination, as well as binned loan origination fixed effects. $Credit_{ib}$ include bins of the credit score at origination, in 10-point FICO bins.

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:

$$P_{is} = \alpha_0 + \alpha_1 X_i + \beta_b Credit_{ib} + \beta_2 AAL_i + Deductible_{it} + Coverage_{it} + \epsilon_{it}, \qquad (6)$$

where the only difference with Equation (2) is that $Credit_{ib}$ is expressed in 10-point FICO bins.

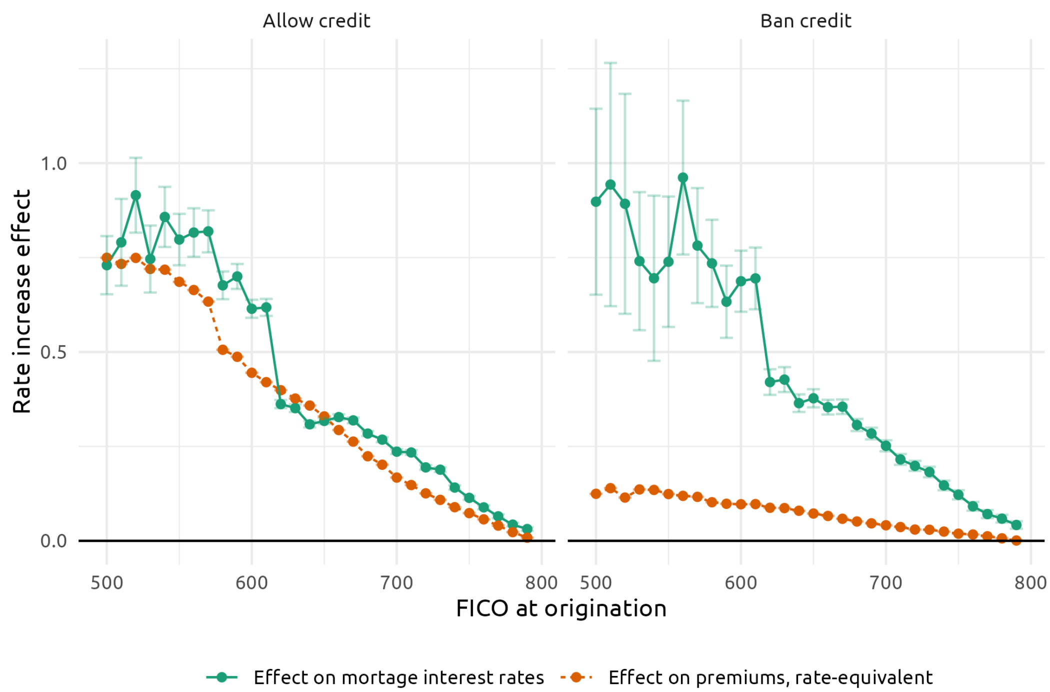
The two sets of coefficients γ_b and β_b from the regressions above capture the effects of credit scores on two channels of homeownership costs. However, the coefficient estimates are expressed in different units. For comparability, we divide the estimates and standard errors in Equation (6) by the remaining 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.[25]

Figure 9 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 effects of credit bins on current interest rates are in green, while the effects of credit bins on rate-equivalent are in orange. We note two striking

[25] 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. This reflects the fact that homeowners insurance premiums are a permanent cost of homeownership, whereas interest payments only extend through the life of a loan.

results.[26]

Figure 9: FICO scores and housing affordability: interest rates and premiums



Source: ICE, McDash®; CoreLogic;
Notes: Figure plots the credit bin coefficients from Equation 5 (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 6 (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-level. The sample is restricted to 2024 insurance policies.

First, the effects of credit score on rate equivalent premiums is very similar to the effects of credit score on current interest rates — but only in states that allow credit-based 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 history is comparable through the mortgage cost channel and the insurance pricing channel: A borrower with a FICO score of 620 pays roughly 40 more basis points

[26] Appendix Figure S8 in the appendix presents the unscaled $\hat{\beta}_b$ coefficients.

per year in *both* interest and insurance premium. The comparable effects of credit scores on mortgage rates and home insurance premiums highlights the large role that credit-based pricing of home insurance pricing can play in home affordability. The second credit channel through which credit history affects insurance premiums merits further study given its comparable size to the relationship between credit scores and mortgage rates. If current increases in home insurance prices persist, insurance premiums may surpass mortgage costs as the main way credit scores influence home affordability.

8 Conclusion

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.

We investigate several mechanisms that might explain why credit history 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. However, we find no evidence that these higher costs are driven by deferred maintenance on older properties or spurious claims. Instead, we find that insurers price expected disaster damages to policyholders with low credit scores at a higher rate, suggesting that they are more likely to file claims on realized damages. Our tests point to liquidity constraints as a likely channel through which limited credit access increases claim likelihood, although they do not directly distinguish among alternative mechanisms.

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.

The use of credit pricing involves tradeoffs for policymakers. On the one hand, allowing insurers to use credit information to set prices could allow for more accurate pricing and reduce adverse selection. On the other hand, there are distributional consequences which make home ownership less affordable for people with low credit scores. Furthermore, credit-based pricing may reduce homeowners' incentives to invest in risk-reducing property improvements. If costly improvements that could lower future premiums also lower a homeowner's credit score, the net effect could be higher premiums. Further research is needed to understand the full consequences of credit-based pricing on housing markets.

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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 history 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

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.

$5775. However, since we have all of the rating factors, we can trace out the premium as we 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,

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.

Travelers, and USAA have all indicated "yes".

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.[27] 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.

[27] 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.

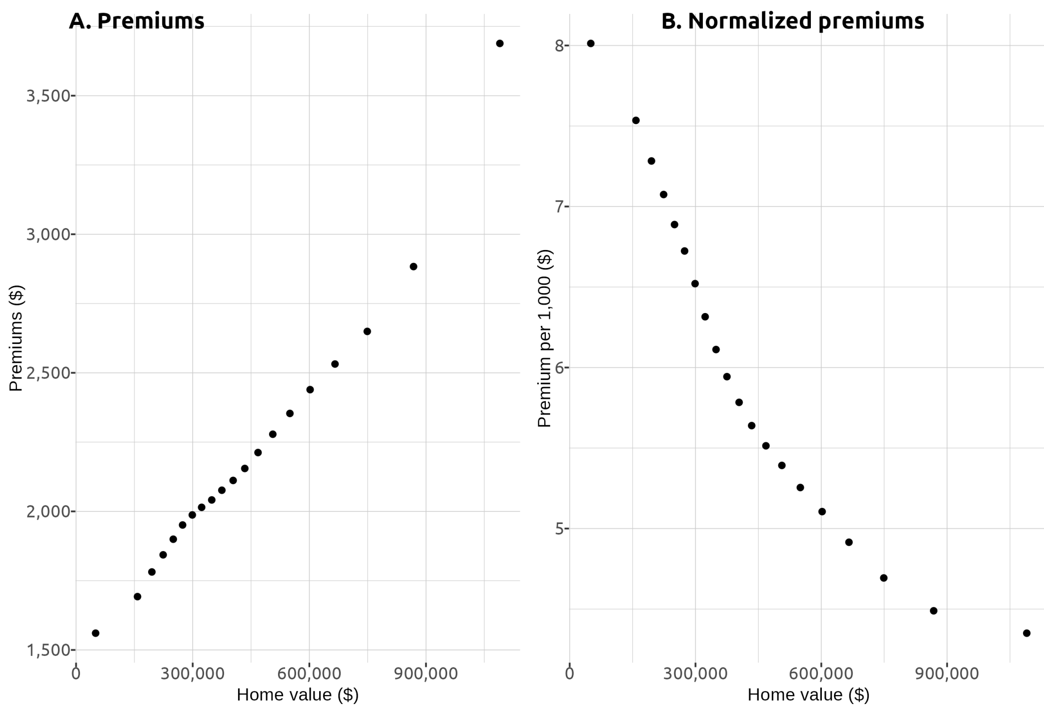
A.4 Additional Tables and Figures

Table S6: Causes of insurers' losses in 2022

Cause of Loss	2022
Property Damage	97.8%
Wind and hail	40.7%
Fire and lightning	21.9%
Water damage and freezing	27.6%
Theft and other property damage	7.6%
Liability, credit card, and other	2.2%

Source: Homeowners Insurance Losses by Cause. Insurance Information Institute; see https://www.iii.org/fact-statistic/facts-statistics-homeowners-and-renters-insurance. Accessed 10/21/2024.

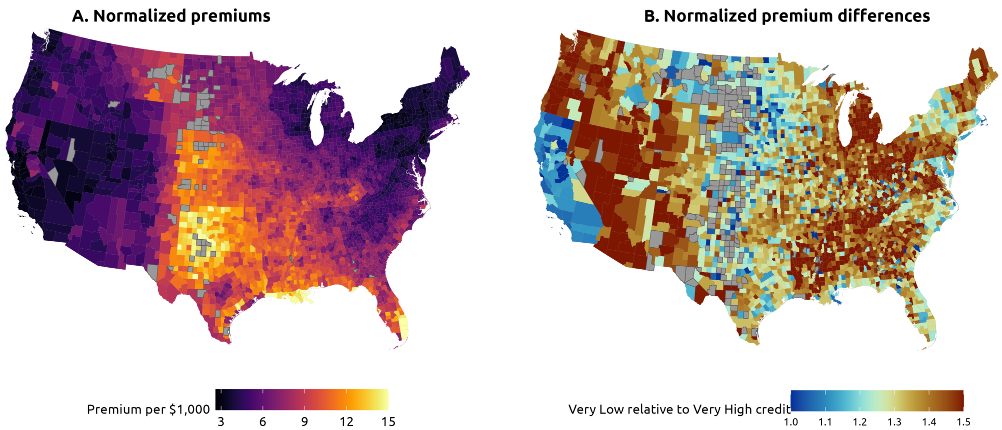
Figure S1: Premiums and normalized premiums by home value quantiles



Source: ICE, McDash®

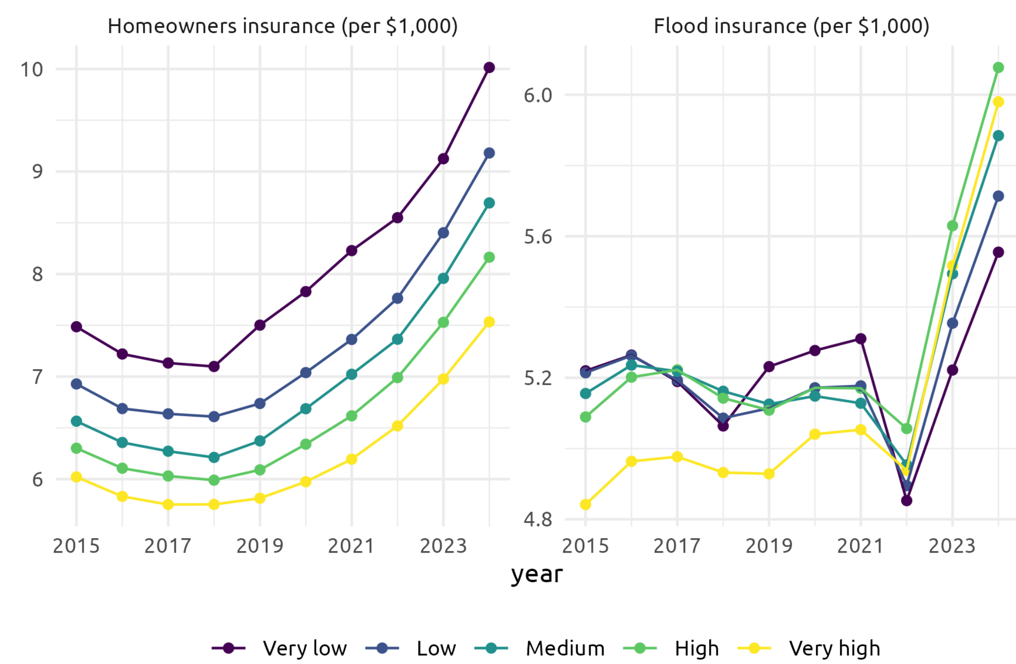
Notes: Home values are based on CoreLogic's appraisal values and are expressed in 2023 USD using the FHFA Housing Price Index. Premiums are in annual dollars.

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



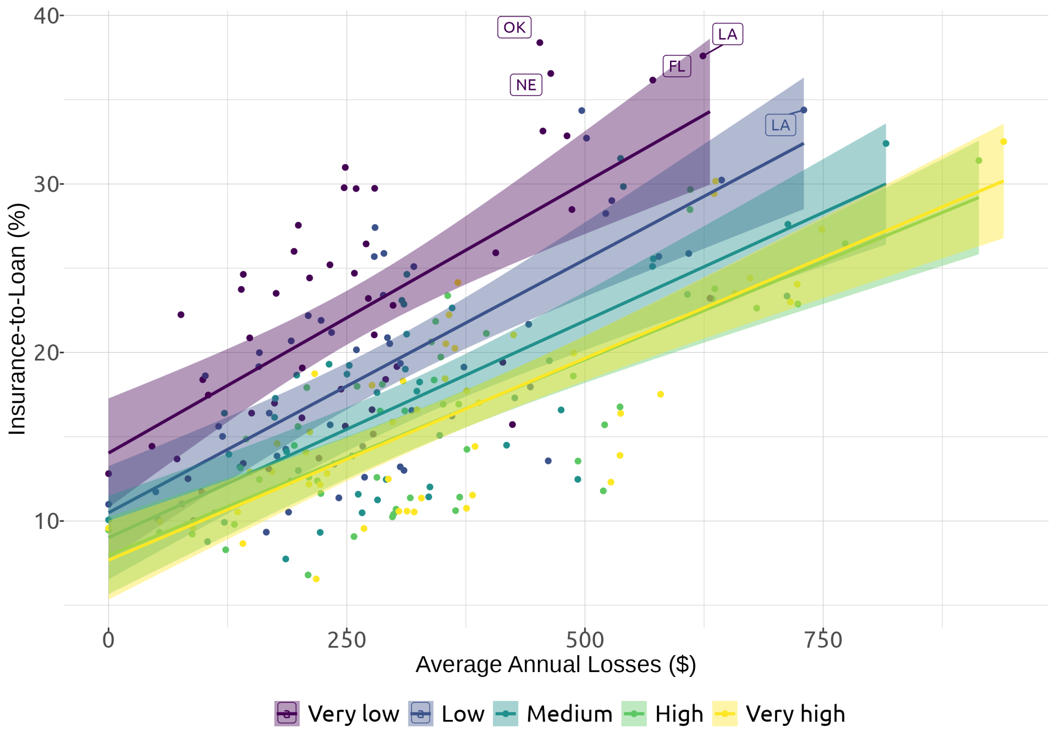
Source: ICE, McDash®
Notes: The figure displays county-level maps showing average premiums per thousand dollars of coverage ("normalized premiums," panel A) and average differences in normalized premiums between the top and bottom quintiles of the credit score distribution (panel B). Scale is bounded on 1 – 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

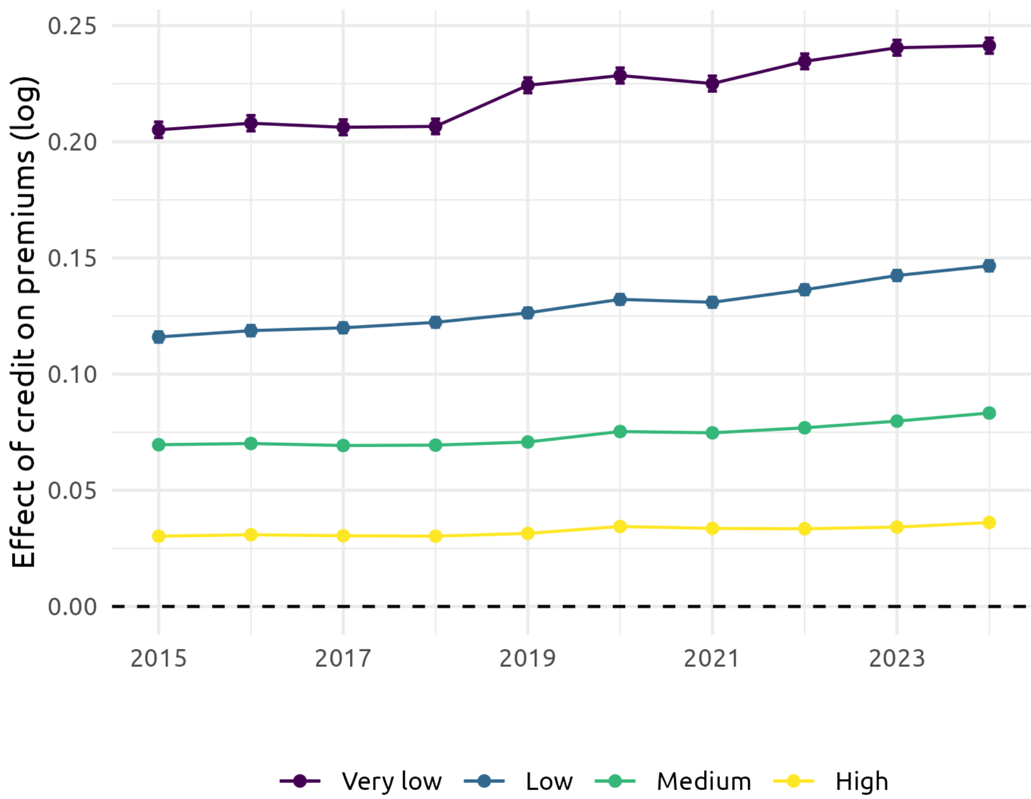
Notes: The figure displays states by credit quintile averages of the insurance burden in 2024 plotted against the CoreLogic AALs. Shaded bands represent 95% confidence intervals. The insurance burden is the monthly premium divided by the sum of the monthly principal and interest payments. The AALs exclude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

Figure S5: Credit-premium gradient by state

Source: ICE, McDash®; CoreLogic

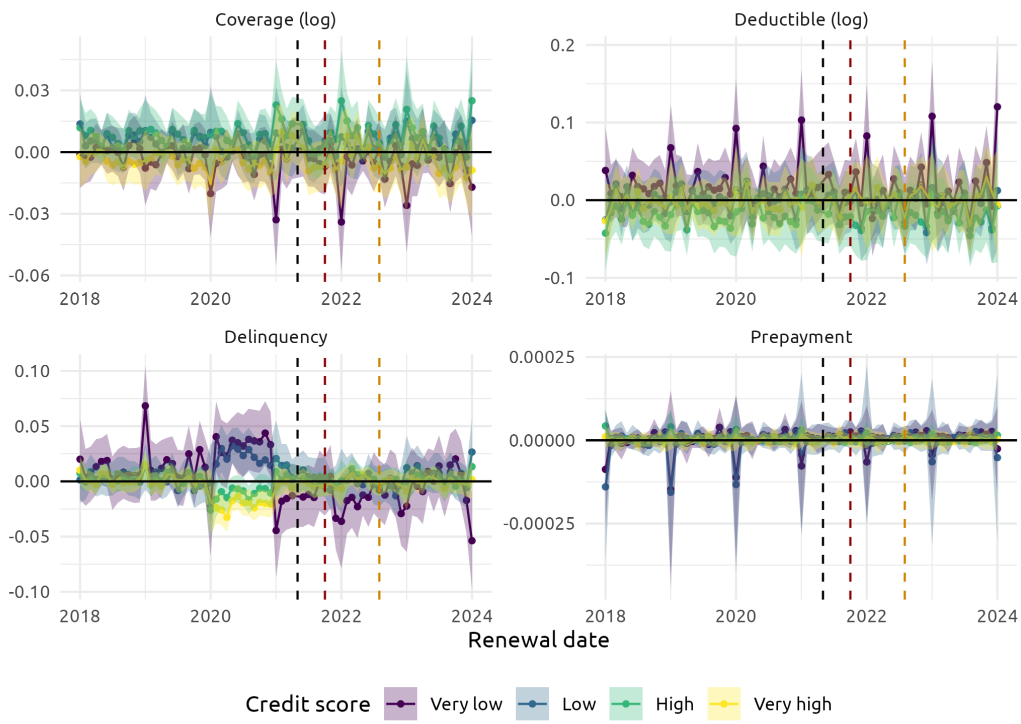
Notes: The figure displays the within-state coefficient estimates of Equation 7, including AALs. The three coefficients show the effect of credit bins on annual insurance premiums. Credit bins are defined as subprime (less than 620, omitted), near prime (620 to 659 – the first coefficient on the left), prime (660 to 719), and super prime (greater than 720 – the last coefficient on the right). Standard errors are clustered at the ZIP code level, and the figure shows 95% confidence intervals around point estimates.

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



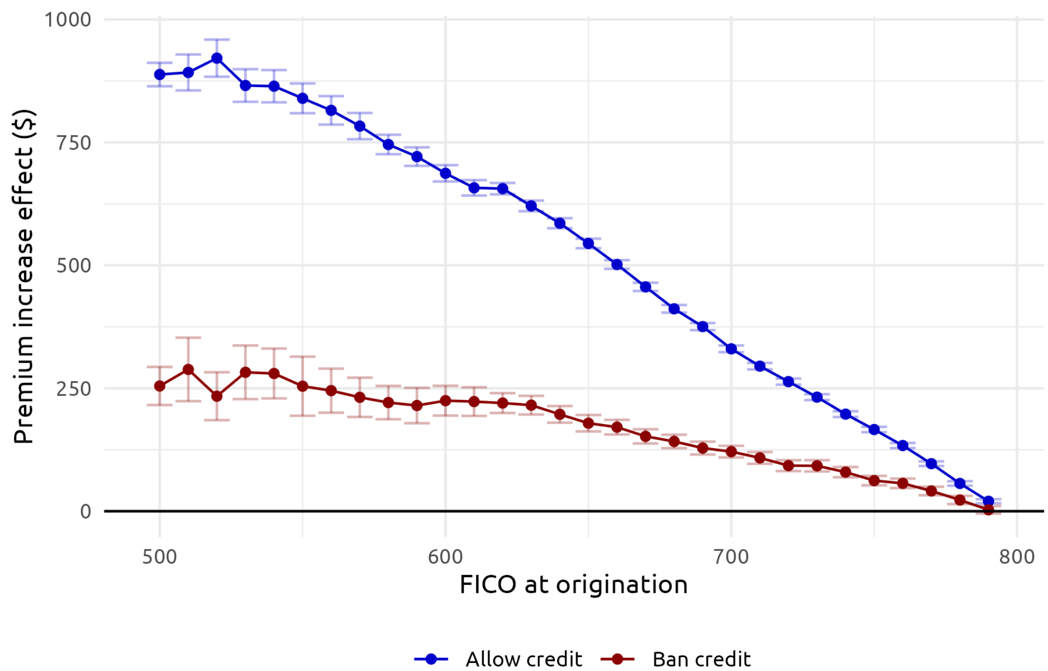
Source: ICE, McDash®; CoreLogic;
Notes: Figure plots the time-varying credit quintile coefficients from a modified version of Equation 2, which regresses log insurance premium on credit score quintile, disaster risk, policy characteristics, time fixed effects, and geography fixed effects and allows for time-varying coefficients on credit quintile. Credit score quintiles are: Very low (less than 671), Low (672-716), Medium (717-756), High (756-787), Very high (greater than 788). The Very High credit group is the omitted reference category.

Figure S7: 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 (672-716), Medium (717-756), High (756-787), and Very high (greater than 788). The Medium credit group is the omitted reference category.

Figure S8: Flexible estimation of the effect of credit scores on premiums



Source: ICE, McDash®; CoreLogic
Notes: The figure displays estimates of Equation 7 with FICO 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:

$$P_{igt} = \beta_1 AAL_i + \beta_2 Deductible_{it} + \beta_3 Coverage_{it} + \eta_t + \lambda_g + \epsilon_{igt} \qquad (7)$$

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).[28] η_t and λ_g are year and geography fixed effects, 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 7 with $\sum_{t=2015}^{2024} \beta_t AAL_i$, thus allowing the pass-through coefficients to vary each year.

Table S8 presents the results of estimating equation 7. 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 from 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.

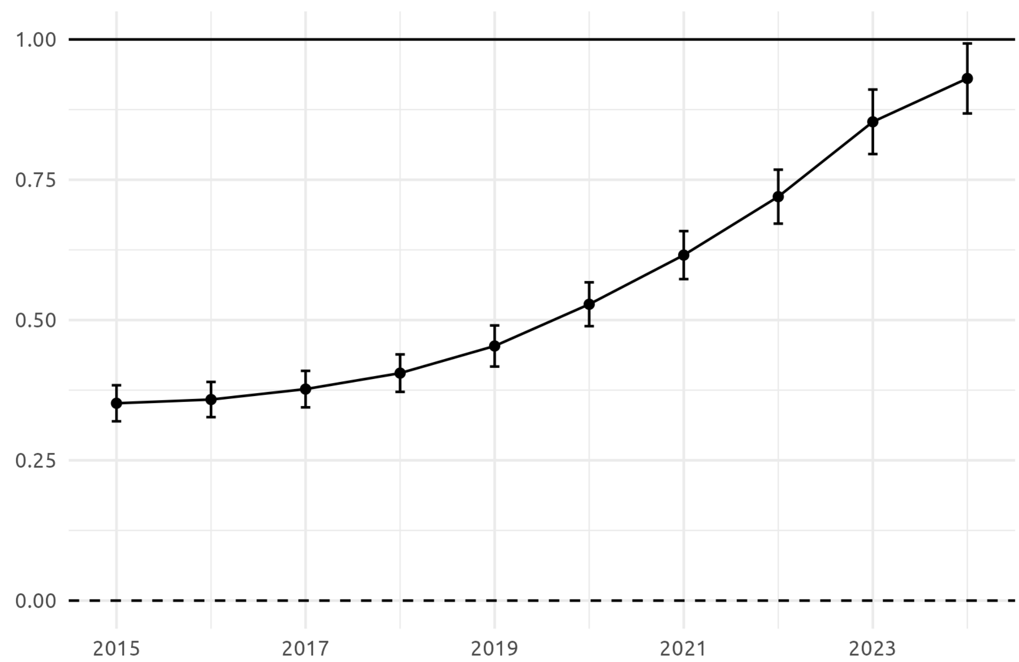
One plausible explanation for the sensitivity of the estimated AAL coefficient to geographic fixed effects is that many insurers use ZIP code factors rather than property level estimates of risk to price expected losses. To test this interpretation, we re-estimate Equation 7 with two successive changes: 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 S9 shows that the overall pass-through of AAL into premiums is increasing sharply over our estimation period. From 2014 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 S10 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

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

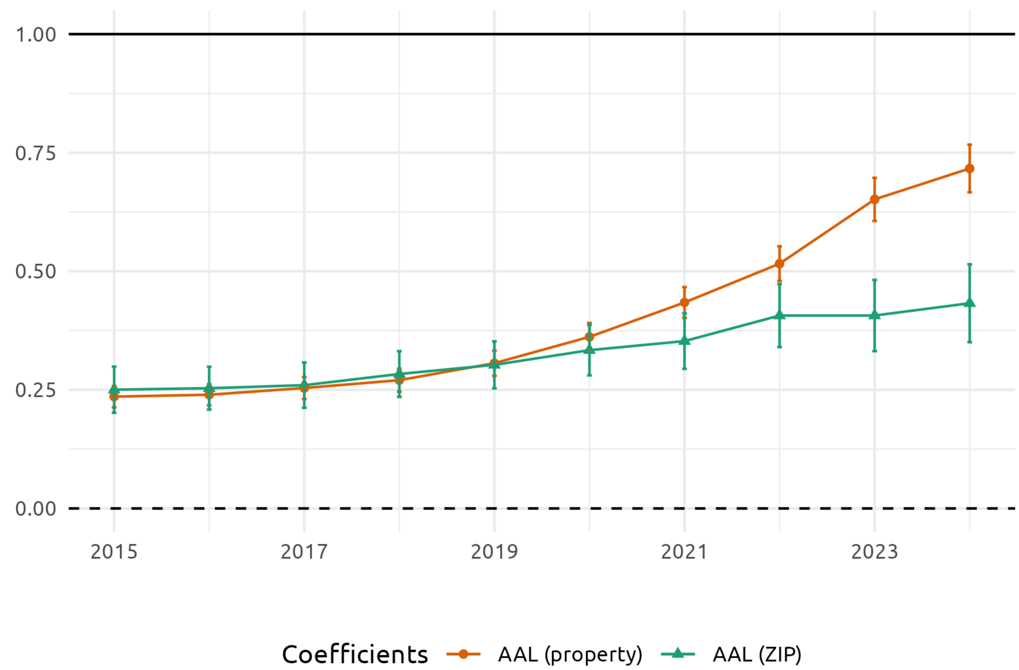
Figure S9: Time-varying premium coefficients on expected losses



Source: ICE, McDash®; CoreLogic;
Notes: The figure displays estimates of a modified version of Equation 7 which allows for time varying coefficients and regresses annual premiums on policy characteristics, average annual losses, policy characteristics, 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 S10: 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 7 which allows for time varying coefficients and regresses annual premiums on policy characteristics, zip-code and property-level average annual losses, policy characteristics, 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 S7: 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 (672-716), Medium (717-756), High (756-787), and Very high (greater than 788). The Very high credit group is the omitted reference category.

Table S8: 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 7 which regresses annual premiums on Average Annual Losses, policy characteristics, year fixed effects, and geography fixed effects.

A.6 Property fixed effects analysis

In this section, we estimate a modified version of Equation 2 using property fixed effects. The analysis leverages identifying variation from properties that were sold during our sample window, and compares premiums charged to owners with different credit scores on the same property. As a result, the "sales sample" is smaller and not representative of the full McDash dataset and mortgage market.

Column 1 of Table S9 first shows the results of estimating Equation 2 on the sales sample without using property fixed effects. It is comparable to column 1 of Table 2, and yields qualitatively similar results. The credit-premium gradient appears to be somewhat flatter in the sales sample, with people in most credit bins paying a somewhat smaller premium compared to the omitted very high credit score bin.

Column 2 adds property fixed effects, which reduces but does not eliminate the credit-premium gradient. Column 3 limits the analysis to only states that allow for credit-based pricing and column 4 examines California, Maryland, and Massachusets which ban credit-based pricing. The results show that a substantial credit-premium gradient remains even when conditioning on property fixed effects. The findings support that most of the variation in premiums due to credit score are based on the people living in the homes, rather than the homes themselves.

We caution that the results in Table S9 should not be interpreted as representative of the overall credit-premium gradient. Homes that sold during our sample window are likely not representative of the national sample of homeowners. The sales sample also requires that the home shows up in the McDash data for both the buyer and the seller, which could introduce additional selection. It is also possible that insurance prices could have affected home sales, making the precise magnitudes of the coefficients difficult to interpret. Despite these caveats, the findings support that the credit-premium gradient is primarily driven by characteristics of the homeowners, rather than the homes they live in.

Table S9: Premiums and credit score, property fixed effects

Dependent Variable:	Annual premium (USD)			
Sample:	All		Credit scoring	Ban credit
Model:	(1)	(2)	(3)	(4)
Variables				
Very low	293.2***	218.2***	238.8***	55.40***
	(1.751)	(2.079)	(2.108)	(3.540)
Low	184.5***	138.0***	152.2***	33.85***
	(1.327)	(1.710)	(1.798)	(3.061)
Medium	113.8***	87.05***	96.02***	22.54***
	(1.105)	(1.515)	(1.646)	(2.749)
High	55.52***	43.03***	47.79***	10.18***
	(0.9672)	(1.369)	(1.510)	(2.711)
Fixed-effects				
Deductible	Yes	Yes	Yes	Yes
Coverage	Yes	Yes	Yes	Yes
Blockgroup	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Property FE		Yes	Yes	Yes
Fit statistics				
Observations	14,621,914	14,621,914	12,681,820	1,940,094
R^2	0.62349	0.82631	0.82532	0.83103
Within R^2	0.01967	0.00676	0.00774	0.00070
Dep Var Mean	1,531.0	1,531.0	1,567.0	1,295.4

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 at origination quintile, disaster risk, policy characteristics, time fixed effects, and geography fixed effects. The analysis also uses property fixed effects, which cuts the sample from the analysis in Table 2 to only homes that transact over the sample period. Credit score quintiles are: Very low (less than 671), Low (672-716), Medium (717-756), High (756-787), and Very high (greater than 788). The Very high credit group is the omitted reference category.