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

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Abstract

This paper estimates the role of disaster risk and credit scores in home insurance pricing. Using novel data on 15 million insurance policies matched to a property-level disaster risk model used by insurers, we estimate that disaster risks are, on average, passed through almost one for one to home insurance premiums. Surprisingly, we find that credit scores have an even larger effect on premiums: Individuals with subprime credit pay 30% more for the same coverage than individuals with super-prime credit. Our results show that premiums can depend more on who lives in a home than on the home's disaster risk.

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1 Introduction

Recent extreme weather events have disrupted home insurance markets, triggering a level of turmoil unseen in decades. This upheaval has attracted intense media scrutiny and led to congressional investigations into the so-called "climate-driven insurance crisis" (Senate Budget Committee, 2024).[1] Despite its crucial role in managing disaster risks, the homeowners insurance market remains frustratingly opaque and understudied. The scarcity of data and research leaves key questions unanswered: How do insurance premiums vary across the United States, and are disaster risks accurately reflected in insurance pricing?

In this paper, we quantify many of the determinants of insurance pricing using novel data on 15 million US homeowners insurance policies linked to mortgage performance data. These data allow us to observe a rich set of characteristics of purchased insurance contracts, such as price, coverage amount, and deductible choice, along with homeowners' credit scores and mortgage characteristics. We match the insurance policies to their corresponding property characteristics and property-level modeled disaster risk, using estimates that are frequently used by the insurance industry.

We estimate that disaster risks are passed through to insurance prices almost dollar for dollar on average, but we find that homeowners' credit scores currently have a larger effect on insurance premiums than disaster risks. Differences in insurance pricing based on credit score are substantial: People with subprime credit (credit scores below 620) pay about 30% more than people with super-prime credit (credit scores above 720), or around $593 per year, even after accounting for disaster risk, state regulation, and insurance policy characteristics. These differences in premiums based on credit score are, on average, larger than the costs of modeled disaster risk. Even in states with high disaster risk like Florida and Louisiana, the premium discount in our sample for having super-prime credit compared to subprime ($894) is larger than the average share of the insurance premium that is attributable to disaster risk ($682).

Differences in insurance pricing by credit score, which we refer to as the "credit-premium gradient," are widespread. The insurance industry is upfront about using credit scores in pricing, arguing that people with lower credit scores are more likely to file claims when their home is damaged, and are therefore more expensive to insure (Todoroff, 2024).[2] To better understand the credit-premium gradient, we leverage state-level policy variation – California, Massachusetts, and Maryland all limit the use of credit information in insurance pricing. We find that the gradient flattens substantially in states that limit the use of credit information but does not completely disappear. This finding suggests that insurers use both credit scores as well as unobserved characteristics correlated with credit to price insurance contracts.

We find that, on average, disaster risks are priced into insurance premiums at about their expected damages at the property level. Our measure of disaster risk is CoreLogic's property-level modeled Average Annual Loss (AAL) measure, which captures the expected losses from a property each year. We use a composite AAL measure that only includes losses from the disasters covered by a standard home insurance contract (wildfires, severe convective storms, winter storms, hurricane winds, and fires following earthquakes – flooding

[1] For example, The New York Times published 40 articles and essays discussing homeowners insurance in 2024 – compared to five per year over the 2016-2019 period.

[2] Unfortunately, there is no available data on individual-level claims to test the relationship between credit scores and claims in homeowners insurance. Flood insurance claims data are available for the National Flood Insurance Program, but credit scores do not impact the price of flood insurance.

is excluded). While insurance companies are passing through AALs to premiums almost dollar for dollar, we estimate that expected natural disaster damage is less than 25% of the average insurance premium in the US. Even in Florida and Louisiana – the states with the highest natural disaster risk – the AAL is only around a third of premiums on average. Despite the relatively small share of current premiums, our estimated pass-through of the AAL shows that any future increases in disaster risk have the potential to meaningfully increase home insurance prices.

We also find an interaction between the pricing of disaster risks and the credit-premium gradient. Individuals with lower credit scores have AAL pass-through rates of 134%, while people with high credit scores have a pass-through rate of 94%, although there is substantial heterogeneity across states. Our results imply that for a property facing the average AAL in our sample of $358, people with low credit scores would pay $479 towards the AAL in their premiums, while a person with super-prime credit living in the same house would only pay $336. These findings suggest that not only do people with low credit score currently pay more for insurance, but that their premiums are likely to increase at a faster rate as disaster risks increase.

The cost of insurance for low credit score people is of particular importance given the large role home insurance can play in home affordability. The average premium costs 17% of their monthly principal and interest payment in 2023, but the ratio is higher for people with lower credit scores: Individuals with subprime credit pay 32% of their monthly principal and interest to insurance. In high-cost insurance states such as Oklahoma, Louisiana, and Florida, people with subprime credit pay insurance premiums that are 44%, 54%, and 60% of their monthly principal and interest, respectively. Future increases in disaster risk are likely to increase the burden of insurance premiums and reduce home affordability, especially for people with lower credit scores.

Our paper makes three contributions. First, to the best of our knowledge, this is the first paper to quantify the role of credit scores and disaster risk in home insurance premiums. Because of previous data availability constraints, there is a relatively small but growing literature on home insurance. Two other studies offer nationwide analyses of homeowners insurance: Oh et al. (2022) points out large state-level regulatory frictions, while a recent report by the Federal Insurance Office highlights the link between disaster risk and premiums (Federal Insurance Office, 2025). Both studies use aggregate climate risk data and do not study the role of homeowners' characteristics. Other papers have focused on California and wildfire risk using Zip code level data (Boomhower et al., 2024; Taylor et al., 2024). More closely related to our work, Ge et al. (2025) use McDash insurance data to show that higher premiums increase mortgage delinquencies, while Sastry et al. (2024) show that underinsurance is a significant issue. Keys and Mulder (2024) use premiums imputed from escrow data to study the recent evolution of homeowners insurance pricing at the Zip code level, focusing on the role of reinsurance costs in increasing premiums. Our paper builds on previous work by using property-level insurance data matched with disaster risk data to quantify the policy-level pass-through of disaster risk to premiums. Our analysis allows us to quantify the previously unexplored role of the credit-premium gradient in overall pricing and how it interacts with disaster risk.

Second, our findings contribute to the literature on the capitalization of disaster risks into real estate markets. Papers that have examined home insurance find significant but relatively small housing price declines for wildfire risk (Garnache (2023) and Ma et al. (2024)) and relatively small price premiums for hurricane-resistant homes Petrolia et al. (2023). Our findings on the magnitude of the credit-premium gradient suggest a new explanation for the

low estimates of disaster risk capitalization: The price of homeowners insurance is currently more sensitive to who lives in the home than to where the home is located (and its predicted disaster risk). The current home insurance pricing system, which gives discounts to people with higher credit scores, could create incentives for people with higher credit scores to sort into high-risk areas.

Third, our paper directly contributes to the disaster adaptation literature Barreca et al. (2016); Massetti and Mendelsohn (2018); Botzen et al. (2019); Kelly and Molina (2023); Carleton et al. (2022). A growing literature highlights the existence of income and racial disparities in household exposure to disaster risks and adaptation investments (Bakkensen and Ma, 2020; Bradt and Aldy, 2023; Cain et al., 2024). While the use of credit scores may help insurance companies more efficiently price homeowners insurance policies, the consequences for disaster recovery and housing markets could be significant. Increasing disaster risk, combined with the credit-premium gradient, is likely to result in disproportionately higher housing costs for lower income people, exacerbating insurance coverage gaps by income and reducing home ownership rates for people with lower credit scores. (Sastry et al., 2024).

2 Homeowners Insurance Background

Homeowners with a mortgage are typically required by their lender to purchase and maintain enough home insurance throughout the duration of the mortgage (Fannie Mae, 2024; Freddie Mac, 2024). Most insurers offer comprehensive property coverage under the HO-3 policy, which covers all perils except those explicitly excluded (floods, earthquakes, and wars are the most common exclusions). The largest share of incurred losses come from wind and hail (40.7% of losses in 2022), followed by water damage (excluding flooding) and freezing (27.6%), and fire and lightning (21.9%) (see Appendix Table S4). Wildfires are only responsible for around 5% of fire and lighting claims, with the majority coming from cooking and other appliances (U.S. Fire Administration, 2024). All other claim types (theft, vandalism, liability) are unrelated to disaster risk.

Insurance companies use collected premiums to pay out incurred losses (claims), to cover other costs associated with writing policies, and to obtain an adequate rate of return on capital. Incurred losses make up between 50% and 75% of the collected premiums depending on the year (Insurance Information Institute, 2024). It is not possible with the available aggregate data to pin down the exact share of incurred losses that come from disasters. However, aggregate data indicate that natural hazards are responsible for between 20% and 35% of collected premiums depending on claims filed in a year.

Insurers set the price of insurance contracts in part by considering the expected claims that homeowners are going to file. These claims depend on the replacement cost value of potential property damages as well as contract characteristics such as deductible and coverage amounts (Todoroff, 2024). Insurers also consider homeowner characteristics and past claims to inform their pricing. Homeowner characteristics that are correlated with a higher claim rate can indicate a higher likelihood of filing a claim in the future, which often leads to a higher proposed insurance premium.

Starting in the 1990s, insurance companies incorporated credit-based insurance scores to help set insurance prices. Credit-based insurance scores are based on a person's credit history and are very similar to the better-known FICO credit scores.[3] We refer to the use

[3]While we do not directly observe credit history or the credit-based insurance scores used by insurers,

of credit-based insurance scores to price policies as "credit scoring." Actuaries use historical data to correlate credit-based insurance scores with past claim payments, which results in people with higher insurance scores often receiving a price discount. The correlation between credit-based insurance scores and past claims could stem from people with higher credit-based insurance scores being (1) less likely to file a claim, (2) more likely to maintain their property, and (3) more likely to pay their insurance bills on time.[4] Three states – California, Massachusetts, and Maryland – limited the use of credit scores in setting home insurance rates in the early 2000s.

3 Data

We use insurance policy data from the McDash residential mortgage service database and property insurance dataset. The McDash mortgage data cover about two-thirds of all residential mortgages in the U.S. and are frequently used in economics research (Fuster et al., 2022; Elul et al., 2010; Foote et al., 2010; Ghent and Kudlyak, 2011). Insurance records are collected from mortgage servicers who agreed to share insurance data with McDash and are available for around about 75% of those mortgages. For our analysis, we restrict our data to standard homeowners insurance policies that were active in September 2023.

The McDash property insurance dataset contains information on monthly insurance premiums, coverage limits, and deductible choices for a range of homeowners insurance policies. It also includes the credit score of the homeowner at mortgage origination and the zip code of the property. We exclude condominiums because many condos are also covered by a master condominium policy obtained by the condo association. We also exclude homes that do not escrow their insurance payments, because while servicers still monitor insurance compliance, they may not collect accurate premium or deductible information since they are not disbursing the funds for the insurance policy from an escrow account. After cleaning the data (detailed in Appendix Table S2), we observe 15.3 million policies totaling $6.2 trillion in total coverage and $30 billion in annual premiums collected.

One advantage of our policy-level data is that we can disentangle changes in insurance expenditure from changes in insurance coverage. Existing work has primarily used insurance expenditure, which is a useful measure but can miss how differences in coverage and credit scores affect the cost of insurance (Keys and Mulder, 2024; Sastry et al., 2024). Appendix Figure S1, panel A shows a positive correlation between home values and insurance premiums and shows that, on average, more expensive homes cost more to insure. However, panel B shows that the cost per dollar of coverage decreases with home value, showing a cost decrease per dollar of insurance purchased for more expensive homes.

We merge the McDash insurance policies with CoreLogic properties using a one-to-one match on zip code, origination amount, and closing date. With this simple method, we can match about 8.5 million of the McDash mortgages. Our matched McDash-CoreLogic sample has similar observable characteristics to the full McDash sample, suggesting that the matching provides a representative sample of homeowners policies (see Appendix Table S3 for balance characteristics of the matched and unmatched mortgages). We also

these scores are highly correlated with the credit scores that we use in our analysis. The relative weights of new credit (10%), length of credit history (15%), and amounts owed (30%) are the same for FICO scores and FICO insurance scores. Only the weights of payment history (35% for FICO and 40% for FICO insurance) and credit mix (10% for FICO and 5% for FICO insurance) differ (FICO, 2025a,b).

[4]Credit-based scores are similarly used in setting automobile insurance rates.

leverage CoreLogic's 2023 property-level estimates of AAL.[5] While several vendors now provide property-level estimates of catastrophic models, CoreLogic's AALs have three main benefits: (1) They include all disaster-related losses; (2) they separate the predicted losses due to flooding from other losses, which allows us to focus on disasters covered by homeowners insurance policies; and (3) they are used by several insurers. Despite its advantages, CoreLogic's AAL is only one of many potential sources of disaster risk information available to insurers. Using insurance policy data matched to AALs allows us to conduct our analyses based on the precise insurance contracts and property-level AALs in our sample. Given that predicted disaster losses can vary substantially over space, even within relatively small geographies such as zip codes, using a property-level match allow us to avoid spatial aggregation bias(Boomhower et al., 2024).

Table 1 presents summary statistics for insurance contracts and for borrower and covered building characteristics. We split mortgages into four bins based on the credit score of the borrower at the time of the origination: subprime (less than 620), near-prime (620 to 659), prime (660 to 719), and super-prime (greater than 720).[6] The table shows meaningful differences in home insurance prices for each credit score bin. Super-prime borrowers purchase the most building coverage on average, but they pay the lowest average annual premiums of the four credit score bins. When accounting for differences in coverage using the premium paid per thousand dollars (third row), we find that super-prime individuals pay 38% less than subprime individuals. This difference in the premium cannot be explained by lower predicted disaster losses: Individuals with super-prime credit are exposed to higher AALs from disasters than individuals with lower credit. However, individuals with super-prime credit choose slightly higher deductibles, which could marginally reduce their premiums. Table 1 also reports the insurance-to-loan ratio, which is the monthly premium as a share of a household's monthly principal and interest mortgage payments. We find that people with subprime credit have insurance payments that are 31% of their monthly mortgage payments – almost double what people with super-prime credit pay despite them having higher mortgage payments on average. Finally, the last row in the table shows that most of the people in our sample have super-prime credit, as people with better credit are more likely to have a mortgage.

Figure 1, panel A shows the average premium per thousand dollars of coverage ("normalized premiums"), which allows us to more directly compare premiums across areas of the country with different housing values. There are large spatial differences in insurance pricing: Individuals in the Great Plains, Louisiana, Mississippi, and Florida pay the most for insurance, whereas individuals in the Western and Northeastern states pay the least. There are two likely drivers of the differences in cost across states. First, these differences can partially be explained by disaster risk: The Great Plains are subject to convective storms with hail damage and tornadoes, while the Gulf Coast is subject to hurricanes and high wind speeds. However, several disaster-prone states, in particular states exposed to high wildfire risk (e.g., California), appear to have low premiums.[7] Second, Oh et al. (2022)

[5]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) – see Davis et al. (2021) for details – reported in 2023 dollars using the FHFA Housing Price Index.

[6]Current credit score is reported for only a subset of observations and is similar to the credit score at origination. Our results do not meaningfully change when using the current credit score variable (see Appendix Table S5).

[7]Wind and hail damage account for about 40% of insurance losses each year while fire (including house

Table 1: Summary statistics by credit score group

Variable	Subprime	Near-Prime	Prime	Super-Prime
Annual premium ($)	2180.2	1994.9	1926.7	1900.1
	(1524.6)	(1287.4)	(1305.9)	(1346.2)
Coverage ($1k)	318	324	362	432
	(169)	(153)	(182)	(226)
Prem. per 1k	7.9	6.9	6.0	4.9
	(5.6)	(4.6)	(4.1)	(3.4)
Deductible ($)	1564.5	1651.9	1658.4	1719.6
	(1125.3)	(1225.5)	(1250.9)	(1347.2)
Average Annual Losses (%)	0.1	0.1	0.1	0.1
	(0.1)	(0.1)	(0.1)	(0.1)
Average Annual Losses ($)	291.6	286.6	308.0	351.0
	(378.6)	(328.2)	(389.2)	(460.5)
Year Built	1972.0	1974.1	1974.8	1978.0
	(28.7)	(29.5)	(29.7)	(29.8)
Loan-to-Value (%)	86.7	84.7	80.7	73.6
	(19.1)	(17.3)	(17.7)	(18.4)
Debt-to-Income (%)	37.6	38.0	37.1	33.1
	(13.9)	(10.8)	(10.7)	(11.0)
Origination ($1k)	179	193	224	274
	(122)	(133)	(146)	(188)
Appraisal ($1k)	215	239	294	393
	(160)	(160)	(208)	(286)
Annual mortgage ($)	9897.2	11503.8	13419.6	16290.3
	(6839.2)	(6988.1)	(8423.6)	(10737.5)
Insurance-to-loan (%)	30.8	22.4	18.5	15.1
	(30.8)	(18.7)	(15.7)	(13.0)
Count	566,351	1,443,518	3,663,118	9,624,381

Source: ICE, McDash®; CoreLogic
Notes: Mean of selected mortgage, borrower, and property characteristics, with standard deviation in parentheses and the observation count. The four groups are based on the credit score of the borrower at the time of the mortgage origination: subprime (less than 620), near prime (620 to 659), prime (660 to 719), and super prime (greater than 720).

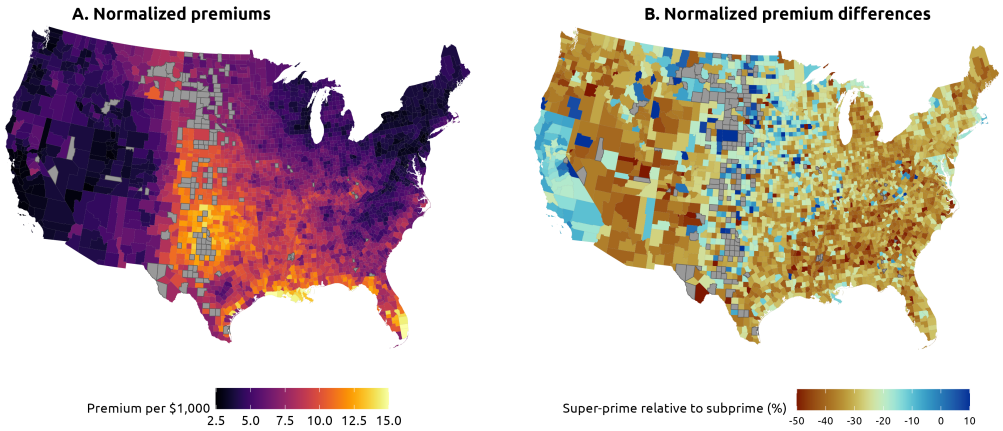
showed that differences in state-level regulation generate distortions in insurance pricing, leading some states to have higher or lower premiums than expected based on their risk.

Figure 1, panel B shows the percent difference between the super-prime and the subprime normalized premiums at the county level. Despite the differences in premium levels observed in panel A, we see that people with super-prime credit pay around 30%-40% less than people with sub-prime credit for most counties. The main exceptions are California, Maryland, and Massachusetts, which limit the use of credit information in insurance pricing and have

fires and wildfires) only account for 20-25% of insurance losses each year (Insurance Information Institute, 2024). In the case of wildfires, they only account for about 3% of residential building fires compared to 48% of residential fires caused by cooking based on 2021 data (U.S. Fire Administration, 2024).

a much flatter credit-premium gradient.

Figure 1: 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 super-prime and subprime borrowers (panel B). Statistics based on fewer than 20 observations are omitted for confidentiality.

Figure 2 presents state-level credit bin averages of insurance-to-loan ratios plotted against AALs. This simple state-level summary figure provides three insights. First, there is significant heterogeneity in insurance-to-loan ratios: People with subprime credit in several states have insurance-to-loan ratios higher than 40%, and the ratios in Florida and Louisiana are over 50%. Second, there is a positive correlation between insurance-to-loan ratios and AALs, suggesting that expected disaster losses partially explain the higher insurance burdens. Third, for a given level of disaster risk, the insurance-to-loan ratio is in general much higher for people with subprime credit compared to those with super-prime credit (we also find that this pattern holds within each state). Overall, these results highlight that insurance payments can be a substantial financial burden in many states, particularly for homeowners with lower credit scores.

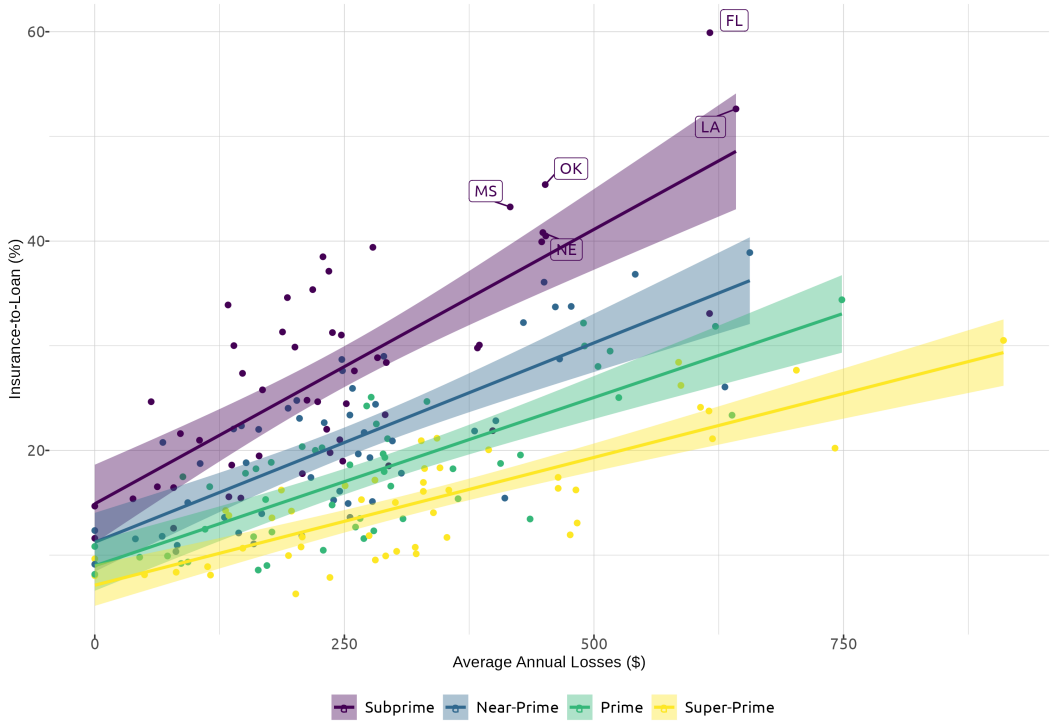
4 Empirical Strategy

To examine the determinants of homeowners insurance premiums, we estimate a cross-sectional descriptive regression of the following form:

$$P_{is} = \sum_{k=1}^{3} \beta_{1k} Credit_i + \beta_2 Deductible_i + \beta_3 Coverage_i + \lambda_s + \epsilon_{is} \tag{1}$$

where P_{is} is the annual insurance premium of homeowners insurance policy i in state s. All insurance policies are active in September 2023. $Credit_i$ is an indicator for an individual being in a particular credit bin – near prime, prime, or super prime – with the subprime bin being omitted. Our main coefficients of interest are the β_{1k} coefficients, which show the relative discount that people with near-prime, prime, and super-prime credit receive on

Figure 2: Insurance burden and climate risk



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

their insurance contract relative to people with subprime credit. We control for deductible choice using $Deductible_i$, which includes \$500 bins for deductible choice and is top coded at \$10,000. We control for coverage choice using $Coverage_i$, which includes \$50,000 bins for coverage amount and is top coded at \$2 million. λ_s is a state fixed effect, and errors are clustered at the zip code level.

We next consider the role that property structure characteristics and disaster risk play in insurance premiums using our McDash-CoreLogic merged sample. We modify equation (1) and estimate the following model:

$$P_{is} = \sum_{k=1}^{3} \beta_{1k} Credit_i + \beta_2 AAL_i + \sum_{k=1}^{4} \beta_{3k} Credit_i * AAL_i + Deductible_i + Coverage_i + \lambda_s + \epsilon_{is} \tag{2}$$

where AAL_i is the AAL for property i in dollars per year derived from CoreLogic. The interaction between AAL_i and $Credit_i$ allows us to estimate how the AAL is passed through to people in our four credit bins.

5 Results

Table 2 shows results from estimating the relationship between credit scores and insurance premiums. Column 2 shows the credit-premium gradient for our full sample accounting for deductible, coverage, and state fixed effects. People with super-prime credit have a $546 per year discount on their insurance contract compared to subprime individuals – a 28% discount compared to the average premium. Discounts for prime and near-prime people are smaller than for super-prime but are still statistically and economically significant. We use premiums in levels to help with interpretation, but our results are similar when we use normalized premiums as the outcome (Appendix Table S6), and when adding additional loan-level controls such as appraisal and loan-to-value at origination (Appendix Table S7).

Table 2: Estimates of the impacts of credit scores and disaster risks

Dependent Variable:	Annual premium (USD)					
Sample:		All		CA, MA, MD	Credit scoring	FL, LA
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Near-Prime	-204.4***	-202.0***	-215.0***	-90.44***	-156.6***	-578.7***
	(6.657)	(4.534)	(6.210)	(7.997)	(19.13)	(61.98)
Prime	-361.1***	-347.6***	-382.4***	-144.7***	-321.9***	-701.2***
	(7.257)	(5.156)	(7.021)	(7.525)	(18.71)	(56.89)
Super-Prime	-554.7***	-546.1***	-593.3***	-206.0***	-526.3***	-893.8***
	(8.987)	(6.322)	(8.175)	(8.960)	(19.93)	(63.34)
AAL (USD)			0.9387***			
			(0.0305)			
Subprime × AAL (USD)				0.5943***	1.338***	1.251***
				(0.0635)	(0.0664)	(0.0942)
Near-Prime × AAL (USD)				0.6370***	1.075***	1.240***
				(0.0486)	(0.0437)	(0.0670)
Prime × AAL (USD)				0.5945***	1.023***	1.070***
				(0.0504)	(0.0362)	(0.0596)
Super-Prime × AAL (USD)				0.5370***	0.9396***	0.9578***
				(0.0438)	(0.0336)	(0.0564)
Fixed effects						
Deductible	Yes	Yes	Yes	Yes	Yes	Yes
Coverage	Yes	Yes	Yes	Yes	Yes	Yes
State		Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	15,297,368	15,297,368	7,141,018	949,556	6,191,462	739,847
R^2	0.19414	0.43315	0.49478	0.44819	0.49349	0.33862
Within R^2	0.01422	0.01958	0.12755	0.06169	0.13399	0.15707
Dep Var Mean	1,925.8	1,925.8	1,954.7	1,572.6	2,013.3	3,441.0
AAL Mean			333.1	171.1	358	681.8

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

Source: ICE, McDash®; CoreLogic
Notes: The table displays estimates of regression equations 1 and 2. Credit bins are defined as subprime (less than 620), near prime (620 to 659), prime (660 to 719), and super prime (greater than 720), with subprime being the omitted category.

It is possible that these large credit score discounts are driven by differences in the risk of the homes that people with higher credit scores reside in relative to lower-credit individuals.

To better understand how disaster risk affects premiums, in column 3 we use our matched McDash-CoreLogic sample and include disaster risk in the regression. Including the AAL in the regression results in a small increase in the coefficients on the credit bin indicators, suggesting that it is not the disaster risk profile of homes that is driving the credit score premium. The coefficient on the AAL is 0.94, which shows that the AAL is passed through to annual insurance premiums at around \$0.94 for every dollar of increased AAL. We do not know what share of insurers use the CoreLogic AAL estimates, but our findings suggest that this measure currently is close to being priced into insurance premiums on average.

We next leverage state-level policy variation to better examine the role of credit scores in insurance pricing. Column 4 restricts the sample to the three states that limit credit scoring (California, Massachusetts, and Maryland), while column 5 restricts the sample to the other 47 states. These two specifications provide several key insights. First, in the states that limit credit scoring, the coefficients on the credit score bins are less than half the size of the coefficients in states that use credit scoring (column 5). Even accounting for the relatively lower premiums in California, Massachusetts, and Maryland, the discount for people with super-prime credit is only 13% compared to 26% in the credit scoring states. The much smaller coefficients on credit scores in California, Massachusetts, and Maryland suggest that limiting credit scoring meaningfully flattens the credit-premium gradient. However, the persistence of discounts for people with higher credit scores in California, Massachusetts, and Maryland also shows that limiting the use of credit scores will not remove all credit-based pricing discounts in insurance pricing.[8] Such pricing differences could reflect the use of insurance claims history (not banned), limitations in the law of fully banning the use of credit scores, or other characteristics that are correlated with credit scores that affect premiums.

Second, column 5 shows that states that allow credit scoring display different pass-through rates of the AAL into premiums by credit score bin. People with subprime credit scores have around 134% of the AALs passed through to their premiums, which is significantly higher than a pass-through of 100%. The AAL pass-through rate declines as credit scores increase, with super-prime people only experiencing around a 94% pass-through rate. The average AAL in credit scoring states is \$358, showing that while people with subprime credit scores pay \$479 towards the AAL in their premiums, a super-prime person in the same house would only pay \$336 towards the AAL.

Third, pass-through of the AAL to premiums in California, Massachusetts, and Maryland is between 54% and 64% and does not have a distinct pattern across credit score bins. The lack of a credit score pattern likely reflects the limit of credit scoring in California, Massachusetts, and Maryland, but it could be due to different regulations in those states and the rest of the country (Oh et al., 2022; Boomhower et al., 2024; Taylor et al., 2024).[9] Appendix Figure S3 shows that there is heterogeneity in pass-through rates across states, but that there is the higher pass-through of the AAL to lower-credit-score individuals for most states where credit scoring is allowed.

Column 6 shows our results that focus on the highest premium and risk states: Florida and Louisiana. The discounts for people with higher credit scores are larger in these states, but they are a similar share of the average insurance premium – \$3,441. For example, the super-prime credit score discount is 26% for all the credit scoring states in column 5 and is also 26% in Florida and Louisiana (column 6). Florida and Louisiana also have pass-through

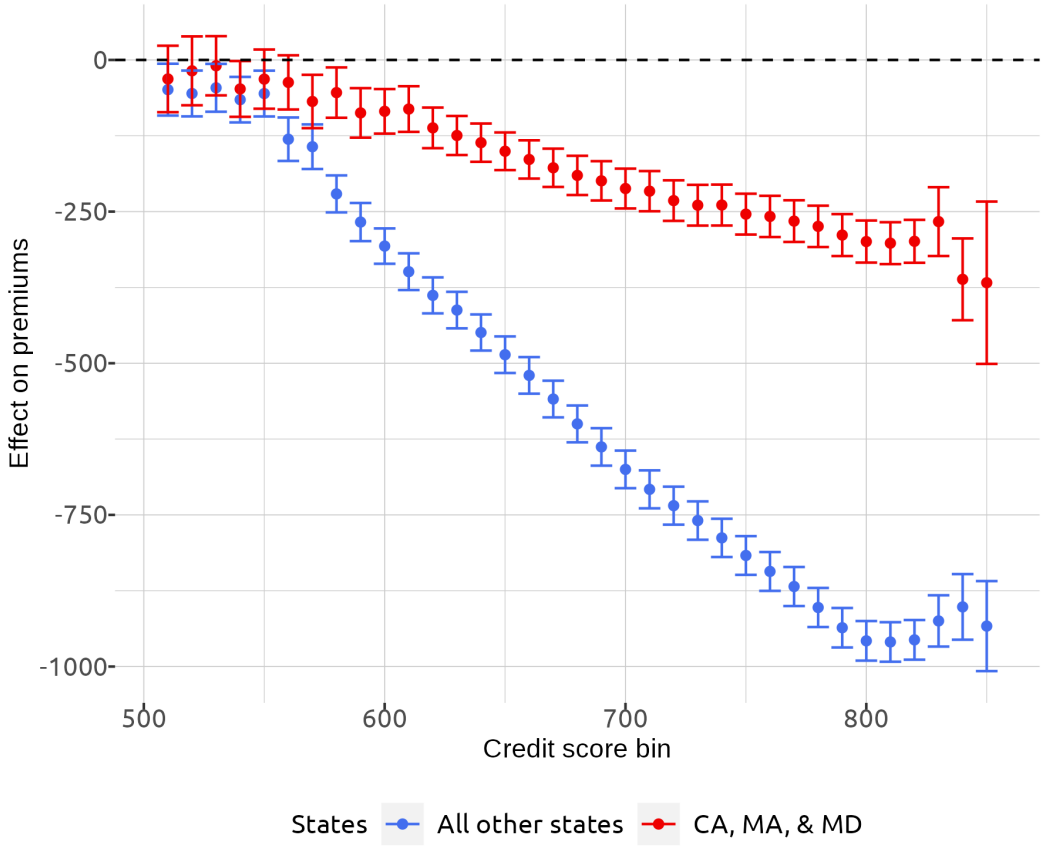
[8] Appendix Figure S2 shows that the credit-premium gradient exists to some extent in every state.

[9] For example, California bans the use of catastrophe models in setting home insurance rates, which could affect AAL pass-through.

rates similar to all of the credit scoring states, which shows that insurance companies are passing through risk similarly for both higher- and lower-risk states.

Figure 3 estimates columns 4 and 5 of Table 2 using 10 point credit score bins instead of the four bins used in the main analysis. The discounts are reported relative to the omitted bin, where people have a credit score between 500 and 510. The figure gives three additional insights. First, there is a large difference between the credit score discount between the credit scoring states (in blue) and the states that limit the use of credit scores in insurance pricing (in red) for credit scores above 550. Second, the main specification using four credit bins does not show the full extent of the potential credit score discount, which can be as high as $900 when comparing people with credit scores over 800 to people with credit scores below 500. Third, the credit score discount monotonically decreases – from a credit score of 550 down to around 800 – providing evidence that insurance companies are likely using a customer's exact credit-based insurance score in their pricing decisions.

Figure 3: Flexible estimation of the effect of credit scores on premiums



Source: ICE, McDash®; CoreLogic
Notes: The figure displays estimates of equation (2) with FICO bins that are divided into increments of 10 points. All estimates are relative to the omitted bin (having a credit score of 500 and below). Standard errors are clustered at the zip code level; the figure shows 95% confidence intervals around the point estimates.

6 Discussion

This section summarizes our findings about the homeowners insurance market and offers three conjectures about their larger implications. First, for most people with low credit scores, homeowners insurance is already a substantial portion of their total housing expenses. People with lower credit are already less likely to be approved for a mortgage, and high home insurance prices are likely to further decrease the share of people with lower credit scores who can afford home ownership. If insurances prices continue to rise, homeownership will become even less affordable for individuals with lower credit scores. Moreover, we find that the AALs are passed through to people with lower credit scores at rates above one, which suggests that as disaster risks rise, the insurance burden will rise faster for homeowners with lower credit scores.

Second, our results show that while disaster risk does factor into insurance pricing, at the policy level it is currently a smaller driver of premiums than an individual's credit score. The average AAL in our data is $333, which suggests that the average person pays around $313 (333*.94) of their premium towards the AAL-related risks. Our results also provide evidence that disaster risks are currently passed through almost dollar for dollar to insurance premiums on average, although there is large heterogeneity between states and much uncertainty about the vendors' AAL measures. Insurance pricing depends on many things, including non-disaster risks, reinsurance costs, state-level regulation, capital reserve requirements for insurers, fixed costs, and reconstruction costs. Given that we do not observe these characteristics, we do not take a stand on whether current AAL pass-through rates are appropriate. However, these AAL pass-through rates may soon change in some states: Recent disasters have already led to state-level policy changes that will likely affect future pass-through (see, for instance, the California Department of Insurance REG-2023-00010, which aims to amend previous regulations to allow insurers to use catastrophe models in rate setting).

Third, the use of credit scoring means that the price of homeowners insurance depends both on the characteristics of the home and on who lives in that home. We find that the AAL premium is smaller than the discount someone gets from having a high credit score. For example, if a person with subprime credit lived in a home that had its disaster risk increased from an AAL of $50 (17th percentile) to $400 (75th percentile) within the same state, that would result in a premium increase of $329. If that person was replaced by someone with prime credit, they would actually see a net decrease in their premium of $197, despite the increase in expected disaster losses. While credit scoring may be the efficient way to price insurance, it has implications for how disaster risks are capitalized into housing values. With insurance pricing being based on people's characteristics, the capitalization of disaster risks in housing values does not only depend on the disaster beliefs of insurers (which are typically based on catastrophe models), but also on the beliefs of households. Given previous research that finds large heterogeneity in household beliefs on disaster risk (Bakkensen and Barrage, 2021), pricing based on individual characteristics provides incentives for people with higher credit scores to buy homes in places with higher disaster risk.

7 Conclusion

In this paper, we use U.S. homeowners insurance policies linked to mortgage performance data and property-level disaster risk estimates to better understand the role of credit scores and disasters in insurance pricing. We find that disaster risk is passed through to home

insurance prices almost dollar for dollar on average. However, we also show that the discount given to people with high credit scores is on average larger than the disaster component of insurance prices. The pass-through of AAL is also higher for people with lower credit scores, suggesting that future increases in disaster risk are likely to be larger for people with low credit scores.

Our findings are based on a cross-sectional analysis and are descriptive in nature. However, given the large share of the housing market that our data cover, we believe these findings have implications that beg future investigation. First, it is unclear how the current home insurance policy landscape, which relies on credit history data in most states, will interact with increasing disaster risks. It is possible that credit scoring will reduce the natural disaster price signal, leading to resorting and home values that do not necessarily reflect disaster risks. Future work is needed to determine the extent to which insurance pricing and credit scoring are affecting the capitalization of disaster risks into home prices.

Second, we find that while disaster risk is not currently a large share of premiums on average, it has the potential to be a significant diver of premium increases going forward. Unlike mortgage rates that are set for 30 years, insurance premiums change annually. For some people, large insurance price increases could lead to mortgage delinquencies if people are no longer able to afford the increasing premiums.

Finally, our paper also raises questions around the optimal pricing of insurance and state-level insurance regulation. We show that there is state-level heterogeneity in pass-through of disaster risk to premiums, but further research is needed to pin down the driver of the heterogeneity and the optimal level of the disaster risk pass-through. Furthermore, state insurance regulators may change regulations to address increasing disaster risk. Given the quickly evolving insurance landscape, more work is needed to better understand how state-level regulations are affecting premiums and disaster risk pass-through.

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Online Appendix

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 while only weakly predicting the size of the claim (Monaghan, 2000; Miller et al., 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 scoring on premiums, with two studies finding that credit scoring impacts the allocation of premium changes without changing aggregate premiums (Lacy, 2017; Federal Trade Commission, 2007).

Data cleaning

The full McDash mortgage dataset includes around 35.5 million unique mortgages in 2023. After basic cleaning (e.g. removing missing observations and mortgages with credit scores outside the correct range), there are around 28 million mortgages. Our insurance sample is taken from the 28 million McDash mortgage observations based on three conditions: (1) The servicer has agreed to share their insurance information with ICE/McDash; (2) the mortgage is for a non-condo property; and (3) the premiums are escrowed. Table S1 compares the approximately 18 million observations we have with insurance data (middle column) to the remaining 10.6 million observations that do not meet the three above criteria (right column). Overall, the two samples are broadly comparable, with the most notable difference being that the insurance sample has homes that have lower appraisal and origination values. This is likely due to our requirement that mortgages in the insurance sample are escrowed. For mortgages with a loan-to-value ratio of less than 80%, escrowing insurance payments becomes optional. Wealthier home buyers are more likely to have a loan-to-value ratio of less than 80%, which is likely driving the higher origination and appraisal values in the mortgages not in insurance sample.

Table S1: Balance table between McDash property insurance sample and mortgage sample

Variable	Insurance sample	Mortgages not in insurance sample
Appraisal value ($)	355,257 (283,968)	469,352 (482,717)
Debt/Income	34 (11)	33 (12)
FICO at orig.	733 (61)	743 (59)
Loan/Value	77 (19)	70 (23)
Origination ($)	255,536 (184,107)	296,136 (276,069)
N	17,930,128	10,635,928

Source: ICE, McDash®
Notes: Table reports mean of selected mortgage and borrower characteristics, with standard deviation in parentheses and the observation count. "Insurance sample" denotes mortgages that satisfy three conditions: insurance data is reported, premiums are escrowed, and the property is not flagged as a condo. "Mortgages not in insurance sample" denotes mortgages that fail at least one of the three conditions.

Table S2 shows the cleaning process starting with almost 21 million observations of mortgages that include any insurance information.[10] The insurance data cleaning process removes observations with missing information or with potential outlier values values.

Table S2: Cleaning steps

Step	Observations
Starting count	20,970,725
Drop missing premiums	20,957,981
Keep credit score in [350, 850]	18,415,996
Keep Coverage in [$50k, $2M]	18,273,406
Keep Appraisals in [$50k, $5M]	18,108,496
Keep Deductibles in [$500, $10k]	15,302,631
Keep Valid Zip Codes	15,302,509
Keep 50 States + DC	15,300,189
Drop Premiums More Than 5% of Coverage	15,297,368

Source: ICE, McDash®
Notes: Cleaning of the McDash mortgage dataset and observation counts

Table S3 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

[10]The starting count is higher than the insurance sample reported in Table S1 because Table S2 includes some of the cleaning steps used to create table S1.

and unmatched groups are similar on observable characteristics, showing matching to the CoreLogic AAL data does not create a biased sample.

Table S3: Balance table between McDash-CoreLogic matched and unmatched samples

Variable	Matched sample	Unmatched sample
Appraisal value ($)	339,722 (250,206)	358,529 (277,769)
Debt/Income	35 (11)	34 (11)
FICO at orig.	733 (60)	733 (63)
Loan/Value	78 (41)	75 (34)
Origination ($)	249,694 (165,911)	252,332 (186,110)
N	8,581,890	6,715,478

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.

Additional Tables and Figures

Table S4: 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.

Table S5: Estimates of the impacts of credit scores and disaster risks – robustness to current FICO scores

Dependent Variable:	Annual premium (USD)					
Sample:		All		CA, MA, MD	Credit scoring	FL, LA
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Near-Prime (curr.)	-134.8***	-136.7***	-157.3***	-48.89***	-156.3***	-303.8***
	(2.959)	(2.406)	(3.427)	(11.91)	(17.56)	(48.40)
Prime (curr.)	-249.0***	-248.0***	-290.5***	-96.69***	-266.9***	-345.4***
	(3.318)	(2.713)	(3.488)	(9.891)	(10.78)	(38.62)
Super-Prime (curr.)	-438.2***	-430.4***	-485.6***	-155.0***	-444.9***	-454.5***
	(4.906)	(3.775)	(4.504)	(10.78)	(11.70)	(43.14)
AAL (USD)			0.9341***			
			(0.0311)			
Subprime (curr.) × AAL (USD)				0.6654***	1.189***	1.241***
				(0.0797)	(0.0450)	(0.0831)
Near-Prime (curr.) × AAL (USD)				0.6679***	1.136***	1.329***
				(0.0669)	(0.0529)	(0.0554)
Prime (curr.) × AAL (USD)				0.6101***	1.034***	1.092***
				(0.0525)	(0.0364)	(0.0571)
Super-Prime (curr.) × AAL (USD)				0.5395***	0.9362***	0.9355***
				(0.0481)	(0.0343)	(0.0558)
Fixed-effects						
Deductible	Yes	Yes	Yes	Yes	Yes	Yes
Coverage	Yes	Yes	Yes	Yes	Yes	Yes
State		Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	9,951,770	9,951,770	4,609,261	571,348	4,037,913	473,940
R^2	0.20495	0.44430	0.50656	0.46187	0.50569	0.35715
Within R^2	0.01059	0.01430	0.12774	0.05704	0.13314	0.15253
Dep Var Mean	1,943.4	1,943.4	1,984.9	1,610.8	2,037.8	3,520.9
AAL Mean			333.1	171.1	358	681.8

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

Source: ICE, McDash®; CoreLogic
Notes: Estimates of regression equations (1) and (2), with credit bins based on current (rather than origination) FICO scores. Credit bins are defined as subprime (less than 620), near-prime (620 to 659), prime (660 to 719), and super-prime (greater than 720), with subprime being the omitted category.

Table S6: Estimates of the impacts of credit scores and disaster risks – normalized premiums

Dependent Variable:	Premium per 1,000 (USD)					
Sample:		All		CA, MA, MD	Credit scoring	FL, LA
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Near-Prime	-0.8273***	-0.8138***	-0.8378***	-0.2123***	-0.7112***	-2.382***
	(0.0263)	(0.0190)	(0.0276)	(0.0184)	(0.0705)	(0.2248)
Prime	-1.415***	-1.373***	-1.430***	-0.3602***	-1.174***	-2.668***
	(0.0287)	(0.0212)	(0.0308)	(0.0198)	(0.0679)	(0.2091)
Super-Prime	-1.990***	-1.955***	-2.024***	-0.4932***	-1.620***	-3.050***
	(0.0334)	(0.0243)	(0.0344)	(0.0245)	(0.0719)	(0.2261)
AAL (USD)			0.0017***			
			(7.39×10^{-5})			
Subprime × AAL (USD)				0.0012***	0.0036***	0.0033***
				(0.0001)	(0.0003)	(0.0004)
Near-Prime × AAL (USD)				0.0013***	0.0028***	0.0036***
				(9.78×10^{-5})	(0.0001)	(0.0002)
Prime × AAL (USD)				0.0011***	0.0022***	0.0028***
				(9.31×10^{-5})	(0.0001)	(0.0002)
Super-Prime × AAL (USD)				0.0009***	0.0016***	0.0021***
				(7.71×10^{-5})	(7.46×10^{-5})	(0.0001)
Fixed-effects						
Deductible	Yes	Yes	Yes	Yes	Yes	Yes
Coverage	Yes	Yes	Yes	Yes	Yes	Yes
State		Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	15,297,368	15,297,368	7,141,018	949,556	6,191,462	739,847
R^2	0.22123	0.46899	0.49001	0.24262	0.47996	0.25127
Within R^2	0.02017	0.02825	0.07371	0.05201	0.08292	0.11670
Dep Var Mean	5.442	5.442	5.405	3.456	5.704	10.66
AAL Mean			333.1	171.1	358	681.8

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

Source: ICE, McDash®; CoreLogic
Notes: Estimates of regression equations (1) and (2), with credit bins based on current (rather than origination) FICO scores, with normalized premiums as the outcome. Credit bins are defined as subprime (less than 620), near-prime (620 to 659), prime (660 to 719), and super-prime (greater than 720), with subprime being the omitted category.

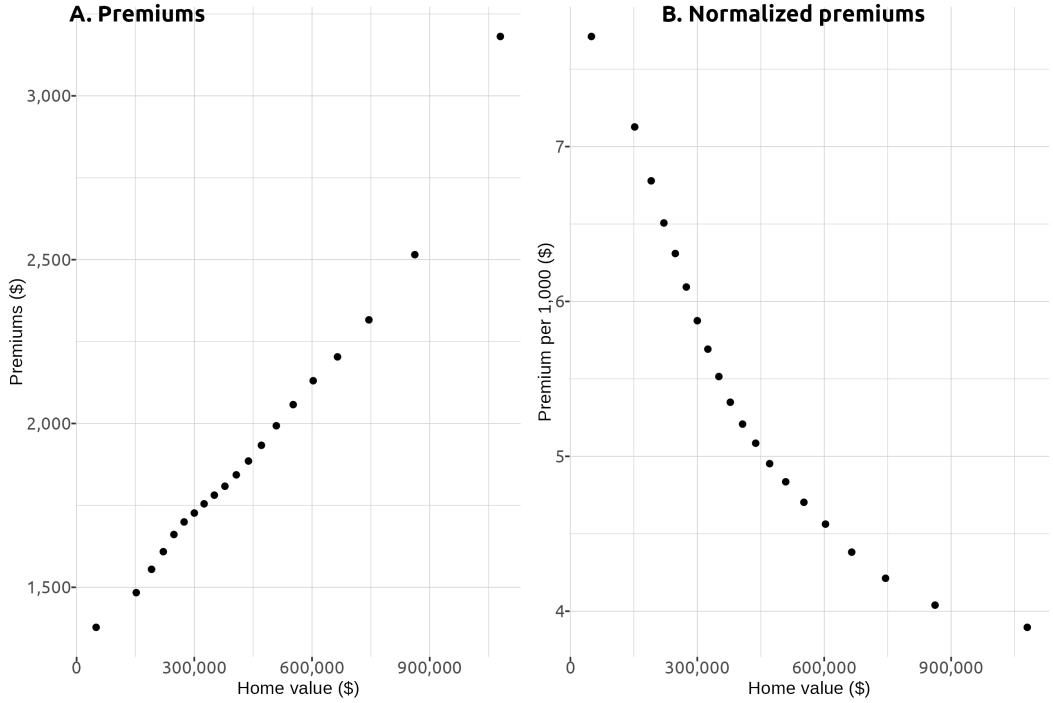
Table S7: Estimates of the impacts of credit scores and disaster risks – robustness to appraisals and LTV

Dependent Variable:	Annual premium (USD)					
Sample:		All		CA, MA, MD	Credit scoring	FL, LA
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Near-Prime	-198.2***	-196.6***	-207.6***	-84.71***	-150.5***	-507.7***
	(6.391)	(4.377)	(6.027)	(8.089)	(20.90)	(58.76)
Prime	-361.7***	-352.5***	-373.8***	-138.9***	-309.3***	-675.4***
	(7.454)	(5.119)	(6.919)	(7.518)	(19.91)	(54.98)
Super-Prime	-565.3***	-574.1***	-587.6***	-205.3***	-510.2***	-930.6***
	(9.661)	(6.361)	(8.093)	(8.804)	(21.00)	(61.68)
AAL (USD)			0.9241***			
			(0.0319)			
Subprime × AAL (USD)				0.5942***	1.341***	1.097***
				(0.0640)	(0.0717)	(0.0952)
Near-Prime × AAL (USD)				0.6340***	1.086***	1.078***
				(0.0482)	(0.0457)	(0.0713)
Prime × AAL (USD)				0.5910***	1.018***	0.9320***
				(0.0499)	(0.0385)	(0.0609)
Super-Prime × AAL (USD)				0.5330***	0.9215***	0.8372***
				(0.0435)	(0.0357)	(0.0593)
Fixed-effects						
Deductible	Yes	Yes	Yes	Yes	Yes	Yes
Coverage	Yes	Yes	Yes	Yes	Yes	Yes
Appraisal value	Yes	Yes	Yes	Yes	Yes	Yes
LTV ratio	Yes	Yes	Yes	Yes	Yes	Yes
State		Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	15,205,482	15,205,482	7,100,139	944,035	6,156,104	735,056
R^2	0.19603	0.43929	0.49576	0.45106	0.49445	0.34826
Within R^2	0.01415	0.02142	0.11792	0.06145	0.12105	0.10491
Dep Var Mean	1,925.4	1,925.4	1,954.2	1,572.3	2,012.8	3,438.6
AAL Mean			333.1	171.1	358	681.8

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

Source: ICE, McDash®; CoreLogic
Notes: Estimates of regression equations (1) and (2), including $50,000 appraisal bins for robustness. Credit bins are defined as subprime (less than 620), near-prime (620 to 659), prime (660 to 719), and super-prime (greater than 720), with subprime being the omitted category.

Figure S1: Premiums and normalized premiums by home value quantiles



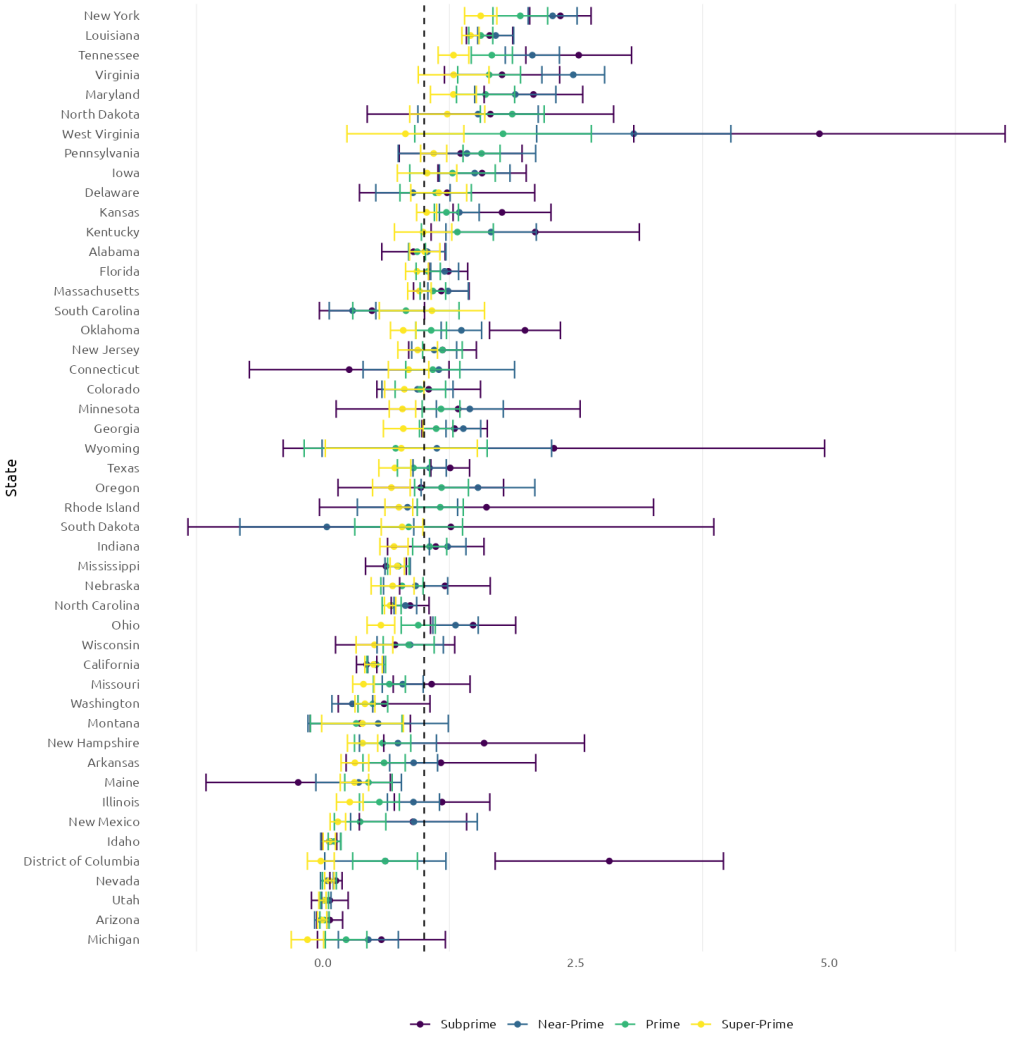
Source: ICE, McDash®
Notes: Home values are based on CoreLogic's appraisal values and are expressed in 2023 USD using the FHFA Housing Price Index. Premiums are in annual dollars.

Figure S2: Credit-premium gradient by state



Source: ICE, McDash®; CoreLogic
Notes: The figure displays the within-state coefficient estimates of equation (1), 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 S3: AAL pass-through rates by state and credit bin



Source: ICE, McDash®; CoreLogic
Notes: The figure displays the within-state coefficient estimates of equation (2). For each state the four coefficients show the effect of the AAL on annual insurance premiums by credit bins. Credit bins are defined as subprime (less than 620), near prime (620 to 659), prime (660 to 719), and super prime (greater than 720). Standard errors are clustered at the zip code level, and the figure shows 95% confidence intervals around the point estimates.